International Journal of Bio-resource and Stress Management https://ojs.pphouse.org/index.php/IJBSM

Crossref

IJBSM September 2025, 16(9): 01-12

Article AR6261

Research Article

Natural Resource Management

DOI: HTTPS://DOI.ORG/10.23910/1.2025.6261

Development and Validation of Stoichiometric Model in Groundnut (*Arachis hypogaea* L.)

V. Arpitha[1], M. H. Manjunatha[2], M. N. Thimmegowda[2], T. C. Yogesh[3], M. B. Rajegowda[2], R. Jayaramaiah[2], Lingaraj Huggi[2], D. V. Soumya[2], R. S. Pooja[2], G. S. Sathisha[2] and L. Nagesha[2]

[1]Dept. of Agricultural Meteorology, [2]AICRP on Agro-Meteorology, University of Agricultural Sciences, Bangalore, Karnataka (560 065), India

[3]Dept. of Agronomy, Agricultural Research Station, VC Farm, Mandya, Karnataka (571 405), India

Open Access

Corresponding kargalavh@gmail.com

0009-0009-2462-5471

ABSTRACT

The experiment was conducted during 2023 in *kharif* season (June–September) at GKVK, Bangalore, Karnataka, India aimed to develop a stoichiometric model for groundnut. Regression equations were formulated using historical data on key weather parameters, including Growing Degree Days (GDD), Solar Radiation (SR), Actual Evapotranspiration (AET) and pod yield from the years 2001 and 2003–2014. The observed total dry matter at the end of first four stages i.e., 30 DAS, 50% flowering, pod initiation, pod filling and predicted dry matter at harvest which was used as one of the independent variables to predict the pod yield. The model showed good agreement between observed and predicted values with higher coefficient of determination (R^2=0.77) at pod filling stage and it was lower at 30 days after sowing stage (R^2=0.08). The developed model was validated for two dates of sowing over four years (2015–2018). To assess its reliability, the model was validated over four years (2015–2018) for two different sowing dates. The validation results indicated a strong predictive accuracy for the first sowing date across all years, except in 2018, where the second sowing date exhibited better alignment with observed values. The developed model was as an effective tool for predicting total dry matter production at various growth stages and estimating pod yield well before harvest, with an accuracy of up to 77%.

KEYWORDS: Groundnut, regression, drymatter production, pod yield, stoichiometric model

Citation* (VANCOUVER)*: Arpitha et al., Development and Validation of Stoichiometric Model in Groundnut (*Arachis hypogaea* L.). *International Journal of Bio-resource and Stress Management,* 2025; 16(9), 01-12. HTTPS://DOI.ORG/10.23910/1.2025.6261.

Data Availability Statement: Legal restrictions are imposed on the public sharing of raw data. However, authors have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

Conflict of interests: The authors have declared that no conflict of interest exists.

RECEIVED on 02nd April 2025 RECEIVED in revised form on 14th August 2025 ACCEPTED in final form on 06th September 2025 PUBLISHED on 18th September 2025

1. INTRODUCTION

Agriculture in India is a dynamic and evolving sector that remains a cornerstone of the country's economic development (Vinaya et al., 2017). Approximately 60% of the Indian population depends on agriculture for their livelihood and it is the largest source of income & employment for rural households. Weather plays a crucial role in determining the success or failure of agricultural activities from land preparation to realization of the yield (Mudalagiriyappa et al., 2022). According to Jasna et al. (2014), crop yields in India will decline by 4.5 to 9.0% as a result of weather abnormalities. The yield is directly affected by the unfavourable weather conditions (Thimmegowda et al., 2023).

Understanding crop phenology is crucial as biomass output and seed yield depend heavily on environmental variables during different phenophases (Alsubhi and Alzahrani, 2024). Phenological development is strongly influenced by meteorological variations during the growing season (Krupashree et al., 2022). Thus, examining phenological events in groundnut helps understand growth processes related to weather parameters, radiation balance, dry matter production, and yield. Accurate yield prediction models are essential for minimizing crop losses due to extreme weather (Elbasi et al., 2023). Crop models are computer equations that mimic crop growth and development.

Crop weather modelling forms a vital link between data science, meteorology, and agriculture. Predicting crop responses to changing weather is essential in an era of increasingly unpredictable climate patterns. This forecasting ability is key to ensuring food security, promoting sustainable farming, and addressing challenges posed by a changing environment. Crop weather models are "the product of two or more factors, each representing the simplified functional relationship between a particular plant response (e.g., yield) and the variations in selected weather parameters at different plant development phases" (Baier, 1979). These models serve as valuable decision-support tools, helping farmers to optimize crop management practices, enhance resource-use efficiency, reduce risks, and maximize yield in response to weather variation and climate change. These are useful to farmers to decide in advance their future prospects and course of action.

Groundnut (*Arachis hypogaea* L.) is one of the most important oilseed crops of India. It is a leguminous plant and widely cultivated in the tropics and subtropics (Thimmegowda et al., 2007). It is also known as 'peanut' 'earthnut' and 'monkey nut'. It is valued for its higher oil content and edible seeds. It is the 4th most important source of edible oil and 3rd most important source of vegetable protein in the world. Groundnut covers 32.7 mha with the production of 53.9 mt with the productivity of 1.648 t ha^{-1} (Anonymous, 2022). According to Anonymous (2021), the potential average yield of groundnuts is 2.5 to 2.7 t ha^{-1}, but the low production is caused by diverse abiotic and biotic factors. Extreme temperatures, drought stress and other weather factors affecting groundnut production (Daudi et al., 2018).

Despite its economic and agricultural importance, research on growth models for groundnut remains limited (Rajegowda et al., 2010). In response to this gap, an effort was made to develop a stoichiometric crop weather model specifically for groundnut. This model aimed to predict dry matter accumulation at different growth stages and estimate pod yield well before harvest. The study examined the influence of key weather parameters, including actual evapotranspiration (AET), growing degree days (GDD), and solar radiation (SR), on dry matter production and final pod yield. The primary objective was the development and validation of a stoichiometric model in groundnut to quantitatively relate these weather variables with crop growth dynamics, enabling accurate prediction of dry matter accumulation and pod yield across different phenological stages and sowing dates.

2. MATERIALS AND METHODS

2.1. *Study location*

The research work was conducted during 2023 in *kharif* season (June–September) at GKVK, Bangalore which is situated in the Karnataka state, India with the latitude of 13° 05' N, longitude of 77° 34' East with altitude of 930 m msl. The district comes under Agro Climatic Zone-V: Eastern Dry Zone with normal annual rainfall of 941.5 mm and the normal maximum and minimum temperature of 29.2°C and 17.9°C, respectively. The mean bright sunshine hour is 7.1 hr. day^{-1}. The major land use cover includes groundnut, finger millet, pigeon pea etc.

2.2. *Nature and source of data*

The long-term data of weather parameters like rainfall, maximum and minimum temperature, bright sunshine hour, potential evapotranspiration and groundnut yield during 2000–2018 was collected from All Coordinated Research Project on Agrometeorology (AICRPAM), GKVK, Bangalore. The accumulated weather parameters were calculated at the end of each growth stage by summing the respective values over time, providing a comprehensive assessment of meteorological influences on groundnut productivity. To ensure robust model development, the dataset was divided into two subsets: 75% of the data was allocated for calibration, helping to establish the predictive relationships between weather parameters and yield, while the remaining 25% was reserved for validation to test the accuracy and reliability of the developed models. This method aligns with established modeling practices (Uno et al., 2005; Li et al., 2017; Montaseri et al., 2018), ensuring that the models are not only well-fitted to historical data but also capable of accurately forecasting yield outcomes under varying climatic conditions.

2.3. Treatment and varietal details

The phenological growth stages of the groundnut crop were categorized into five distinct phases: T_1, from sowing to 30 days after sowing (30 DAS); T_2, from 30 DAS to 50% flowering; T_3, from 50% flowering to the pod initiation stage; T_4, from pod initiation to the pod filling stage; and T_5, from the pod filling stage to harvest. The variety used in the study was TMV-2, which has a crop duration of 125 days. For the development and validation of the model, two sowing dates were considered for each year from 2000 to 2018-D_1 in July and D_2 in August.

2.4. Model description

A stoichiometric crop weather model, also known as a crop weather relationship model, is a type of mathematical model that relates weather variables to crop growth and development. It is used to predict groundnut growth and pod yield based on the dry matter accumulated at each stage. These models are typically based on empirical relationship derived from field observation. Models provide insight into how changes in weather patterns may impact crop productivity by quantifying the stoichiometric relationship between meteorological variables and crop growth processes. Stoichiometric crop weather models can be useful tools in agricultural research and management. They can help farmers and agronomists to make decisions about planting date, irrigation schedule, and nutrient management. These models can also be used to assess the potential impact of climate change on crop production and identify strategies for adaptation.

2.5. Inputs used for development of the model

The derived weather parameters like growing degree days (GDD), solar radiation (SR) and actual evapotranspiration (AET) were derived using weather data of maximum temperature, minimum temperature, bright sunshine hours, rainfall and potential evapotranspiration. The data on dry matter accumulation at the end of each stage and final pod yield was used for the development of coefficients in the model. The daily weather data was used to calculate the following indices.

2.6. Growing degree days (GDD)

Growing degree days at different phonological stages were calculated by summation of daily mean temperature and subtracting with base temperature for a corresponding period from sowing.

$$\text{GDD } (^{0}\text{days}) = \sum \frac{(T_{max}+T_{min})}{2} - T_b$$

Where,

T_{max} and T_{min} are maximum and minimum temperature, respectively

T_b=Base temperature below which crop growth ceases Groundnut=10°C (Rao et al., 1992).

2.7. Solar radiation (SR)

Solar radiation refers to the energy emitted by the sun in the form of electromagnetic waves. The data on bright sun shine hour was used to calculate the solar radiation. The DSSAT (Decision Support System on Agro technology Transfer) model was used to convert the bright sunshine hours (hrday^{-1}) into solar radiation (MJm^{-2}day^{-1}) using the following formula,

$$Q = Q_o \left(a + \frac{bn}{N}\right)$$

Where,

Q=solar radiation (MJ m^{-2} day^{-1})

Q_o=maximum solar energy on clear cloudy day (constant)

a and b=constants for the specific location

n=actual bright sunshine hour (hr day^{-1})

N=maximum possible bright sun shine hour (hr day^{-1})

2.8. Actual evapotranspiration (AET)

"Actual Evapotranspiration" (AET) is the total amount of water that is evaporated from the earth's surface and transpired by plants into the atmosphere. AET was calculated by following the FAO water balance method (Doorenbos and Pruitt, 1977). Soil water storage (mm) at the end of ith day has been calculated using the equation:

$$S_i = S_{i-1} + P_i - WR_i$$

Where,

S_i= Water retained (mm) in the soil at the end of ith day

S_{i-1}= Water available (mm) in the beginning of the ith day

P_i= Precipitation (mm) during the ith day

WR_i= water requirement of the crop during ith day

Where,

$AET_i = WR_i$, when $S_i > WR_i$

$AET_i = S_i$, when $S_i < WR_i$

Actual evapotranspiration (AET) is equal to potential water requirement (WR) as long as the soil moisture content is greater than or equal to WR and the actual ET (AET) is equal to soil moisture content (S) when the soil moisture content is less than water requirement.

Water requirement (WR_i) by the crop was computed using the equation:

$WR_i = Kc_i * PET_i$

Where,

WR_i=Evapotranspiration by the crop during i^{th} day

Kc_i=Crop coefficient during i^{th} day

PET_i=Potential Evapotranspiration during i^{th} day

2.9. Development of stoichiometric model

The field experiment data of 2001, 2003–2014 (i.e., two sets of data in each year) were used to formulate multiple linear regression equations relating to the GDD, SR and AET with the accumulated dry matter at each phenological growth stage as well as the ultimate pod yield. The coefficients of determinant indicate the climatic parameters considered and the initial TDM (total dry matter) used to estimate the final TDM in each stage.

Crop weather relationships have been generated to know the influence of weather parameter on accumulation of the dry matter. The initial TDM (Total Dry Matter) of the crop being exposed to the environment has been considered as one of the independent parameters along with the GDD, SR, and AET to know the bio-mass accumulated at the end of each stage.

The multiple linear regression equations (noted below) by considering parameters such as GDD, SR, and AET as well as the initial TDM as independent parameters and the Total Dry Matter accumulated at the end of each stage as a dependent parameter for all the stages have been generated in order to understand the influence of these crucial parameters on the growth of crops in each stage.

$T_1=(A_1X_1+B_1Y_1+C_1Z_1)$ ....(1)

$T_2=T_1S_2+(A_2X_2+B_2Y_2+C_2Z_2)$ ....(2)

$T_3=T_2S_3+(A_3X_3+B_1Y_3+C_3Z_3)$ ....(2)

$T_4=T_3S_4+(A_4X_4+B_4Y_4+C_4Z_4)$ ....(4)

$T_5=T_4S_5+(A_5X_5+B_5Y_5+C_5Z_5)$ ....(5)

Where,

Subscript indicates the respective stages,

T_1, T_2, T_3, T_4 and T_5=dry matter accumulated at the end of each stage

A, B and C=Coefficient of determinants of the variables i.e., GDD, SR, AET

X (GDD), Y (SR), Z (AET),=coefficients of determinants of input accumulated.

S_2, S_3, S_4, S_5=coefficients of initial TDM for respective stage of the crop

The pod yield as influenced by the dry matter accumulated at the end of each stage is related in the multiple linear regression equation,

$Yg=IT_1\ (O)+JT_2\ (O)+KT_3\ (O)+LT_4\ (O)+MT_5\ (P)$

Where,

T_1 (O), T_2 (O), T_3 (O) and T_4 (O)=observed TDM at the end of first four stages

T_5 (P)=predicted total dry-matter for 5^{th} stage.

I, J, K, L, M and N=coefficients of TDM for respective stages

2.10. Model calibration and validation

Calibration is the process of adjusting the model parameters to improve the agreement between model simulations and observed data. The model was calibrated with the data (that included phenology, biomass and yield components) collected from AICRP on Agro-Meteorology, GKVK, Bengaluru.

Validation involves the comparison of model output with independent field observation or experimental data that were not included during model development. The developed stoichiometric model was validated with the data from 2015–2018 for two dates of sowing (D_1, D_2).

2.11. Statistical approach of model evaluation

Statistical approaches for model evaluation involve using various techniques to assess the performance of a predictive model.

2.12. Coefficient of determination (R^2 value)

It is a statistical measure which represents the proportion of variance in the dependent variable that can be explained by the independent variable in a regression model. It is used to evaluate the goodness of fit. The value ranges from 0–1. The higher value indicates better fit of the model.

2.13. Correlation coefficient (r)

It quantifies the strength and direction of the linear relation between two variables. The value ranges from -1 to +1.

$$r = \frac{\sum(x_i - \bar{x})\ (y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})}^2}$$

Where,

r=Correlation coefficient

x, y=two variables

x_i, y_i=values of two variables

$\bar{x}$, $\bar{y}$=mean of two variables

2.14. Root mean square error (RMSE)

RMSE is used to assess the accuracy and precision of a model's performance. A lower RMSE indicates better accuracy and smaller average prediction error. Higher

RMSE indicate greater variability and larger prediction error. The RMSE is calculated by taking the square root of the mean of the squared differences between the predicted and actual values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}((y_i - \bar{y})^2)}$$

Where,

n=number of data points

y_i= actual value of the target variable for the i^{th} data point

$\bar{y}_i$= predicted value of the target variable for the i^{th} data point

2.15. Standard error

The standard error of the mean is a probabilistic statement about how the sample size provides a better bound on estimates of the population mean. The standard error is calculated by dividing the standard deviation from square root of sample size.

$$\mathrm{SE} = \frac{\sigma}{\sqrt{n}}$$

2.16. Per cent deviation

Per cent deviation measures the degree to which individual data points in a statistic deviate from the average measurement of that statistic.

$$\text{Per cent deviation} = \left(\frac{\text{Observed value-Simulated value}}{\text{Simulated value}}\right)\times 100$$

2.17. Multiple linear regression (MLR)

It is the measure of average relationship between more than two variables at a time.

$Y=b_0+b_1x_1+b_2x_2+\ldots+b_px_p$

Where,

Y=dependent variable

$x_1, x_2, \ldots xp$=independent variables

$b_0, b_1, b_2, \ldots b_p$=coefficients corresponding to the independent variables

3. RESULTS AND DISCUSSION

3.1. Development of the stoichiometric crop weather model

The observed total dry matter at end of first four stages i.e., 30 DAS, 50% flowering, pod initiation, pod filling stage and predicted dry matter at harvest stage was used as independent variable (initial biomass) along with the derived weather parameters and pod yield was used as dependent variable for the development of regression equation. The multiple regression equations emerged between weather parameters, TDM and pod yield is presented in Table 1.

The regression equations (Table 1) developed for predicting dry matter accumulation at different phenological stages of groundnut demonstrated varying levels of accuracy based on the coefficient of determination (R^2). The lowest R^2 value (0.08) was observed at 30 DAS, indicating a weak relationship between initial biomass, growing degree days (GDD), solar radiation (SR), and actual evapotranspiration (AET) with dry matter accumulation. This may be attributed to the early stage of crop growth when environmental factors such as soil moisture availability, temperature fluctuations, and initial establishment conditions have a higher degree of variability (Reddy et al., 2017). As the crop advanced to the pod filling stage, the R^2 value increased to 0.77, indicating a stronger correlation between the weather parameters and dry matter accumulation, which can be explained by more stable plant growth conditions and efficient utilization of accumulated biomass (Patil et al., 2021).

The moderate R^2 values at 50% flowering (0.33), pod initiation (0.44) and harvesting (0.67) stages suggested that environmental variability had a moderate impact on dry matter accumulation. At these stages, factors such as nutrient availability, pest and disease infestation and variations in sunshine hours contributed to deviations from the predicted values (Sharma et al., 2019). The relatively higher accuracy at the harvesting stage (R^2=0.67) indicated that cumulative weather effects over the entire crop cycle provides a better prediction of final biomass as environmental fluctuations tend to stabilize over time. This finding was supported by

Table 1: Multiple regression equations between the derived weather parameters and total dry matter production and pod yield

Stages	Regression Equations	R^2
30 DAS (T_1)	$y=5.07-0.04 (X_1)+0.16 (Y_1)-0.02 (Z_1)$	0.08
50% flowering (T_2)	$y=26.76+1.16 (T_1)-0.08 (X_2)+0.05 (Y_2)+0.52 (Z_2)$	0.33
Pod initiation (T_3)	$y=-271.05+1.59 (T_2)+1.19 (X_3)-0.66 (Y_3)+3.34 (Z_3)$	0.44
Pod filling (T_4)	$y=-181.54+0.81 (T_3)-0.11 (X_4)+0.3 (Y_4)+3.76 (Z_4)$	0.77
Harvesting (T_5)	$y=-815.52+2.96 (T_4)+0.48 (X_5)+0.13 (Y_5)-1.09 (Z_5)$	0.67
Pod yield (Yg)	$y=315.03-0.38\ T_1(O)+0.002\ T_2(O)-0.11\ T_3(O)-0.61\ T_4(O)+0.24\ T_5(P)$	0.38

For development of regression equations crop and weather datasets from 2001–2014 were exploited; X: Growing degree days (degree days); Y: Solar radiation (MJ $m1^{-2}$ day^{-1}); Z: Actual evapotranspiration (mm day^{-1}); T_1, T_2, T_3, T_4, T_5: Total dry matter at the end of each stage (g^{-2}); (O): Observed dry matter (gm^{-2}); (P): predicted dry matter (g^{-2})

previous research indicating that long-term weather patterns significantly influence groundnut biomass accumulation and yield potential (Vinu et al., 2020).

For pod yield prediction, the regression model showed an R^2 value of 0.38, suggesting a moderate fit. The moderate predictive capability could be due to the combined influence of multiple factors, including soil fertility, pest attacks and physiological stress caused by varying meteorological conditions. Previous studies have also reported similar levels of predictability in crop yield models where environmental variables play a significant role in influencing final yield (Padmalatha and Reddy, 2006).

3.2. Validation of developed stoichiometric crop weather model

Model validation is the process of comparing predictions of model with the field experiment data to evaluate the performance of a model on the data which was not used during the model development. In the present study, the developed Stoichiometric model was validated for 2015–2018 with two dates of sowing in each year.

The validation of the stoichiometric crop weather model for the year 2015 showed variations in dry matter accumulation predictions (Table 2). For the first date of sowing, the model performed well with a high coefficient of determination (87%) (Figure 1) and a lower RMSE

Table 2: Validation of the stoichiometric crop weather model for the year 2015 (Date of sowing-I)

Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			430	537.4	39.89	86.58	73.05
T_2	86.58		142.5	182	87.58	202.02	170.43
T_3	202.02		278.2	345.2	73.16	388.5	397.74
T_4	388.5		127.8	170	74.7	330.78	450.95
T_5	330.78		404.5	493.8	42.31	404.04	375.82
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5 (P)	Yg (O)	Yg (P)
	86.58	202.02	388.5	330.78	375.82	172.26	128.22
% dev.		8.32		RMSE		55.44	

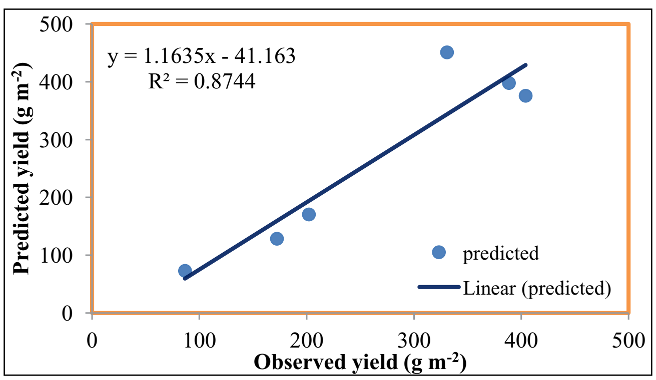

Figure 1: Coefficient of determination between observed and predicted yield for the year 2015 date of sowing I

(55.44 g m^{-2}). These findings align with the earlier research conducted by Muralidhara and Rajegowda (2002). However, underestimations were observed at 30 DAS, 50% flowering and harvesting stages, while overestimations occurred at pod initiation and pod filling stages. These variations can be attributed to differences in soil moisture availability and temperature fluctuations, which are critical for groundnut growth, particularly during the reproductive stage (Ahmed et al., 2020).

The outcome of the model validation for the second date of sowing during 2015 is shown in Table 3. A moderate fit was recorded (R^2=40%) (Figure 2), with an RMSE of 127.34 g m^{-2}. The discrepancies were attributed to variations in climatic conditions affecting crop growth and development, as groundnut is highly sensitive to temperature and water stress during its vegetative and reproductive phases (Craufurd et al., 2002). Additionally, delayed sowing can expose crops to increased temperatures and reduced soil moisture, leading to lower photosynthetic efficiency and impaired pod development (Kakani et al., 2015). The lower RMSE and per cent deviation (8.32) for the first date of sowing indicate better predictability than the second date of sowing (RMSE=127.34 g m^{-2}; % dev.=14.31).

The finding of the model validation for the first date of sowing during 2016 is displayed in Table 4. Overestimation of the dry matter accumulation at T_1, T_2, T_5 stage and

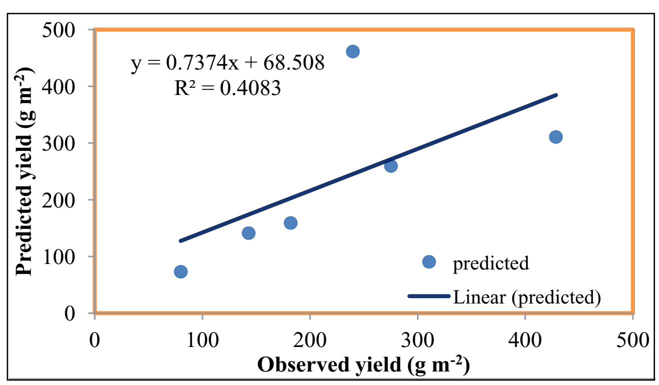

Figure 2: Coefficient of determination between observed and Predicted yield for the year 2015 date of sowing II

Table 3: Validation of the stoichiometric crop weather model for the year 2015 (Date of sowing-II)

Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			434.60	540.00	39.62	79.92	73.29
T_2	79.92		133.70	157.20	81.80	182.04	159.16
T_3	182.04		283.60	309.30	92.70	239.76	461.35
T_4	239.76		121.70	152.70	57.00	275.28	259.40
T_5	275.28		426.30	418.20	43.56	428.46	310.81
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5 (P)	Yg (O)	Yg (P)
	79.92	182.04	239.76	275.28	210.80	142.94	141.32
% dev.		14.31		RMSE		127.34	

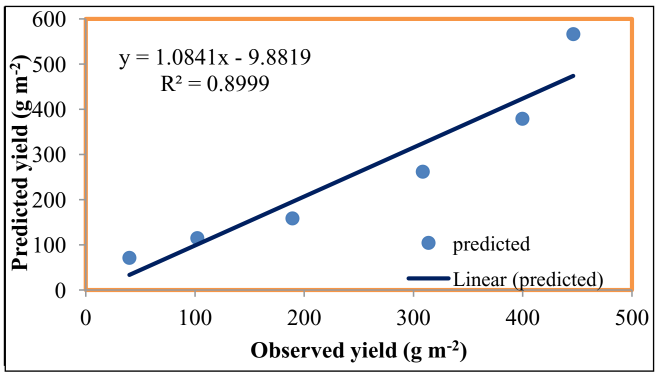

Figure 3: Coefficient of determination between observed and predicted yield for the year 2016 date of sowing I

underestimation of the accumulation of the dry matter was observed at T_3, T_4 stages. Pod yield was also underestimated by the model. The underestimation and overestimation of the model was mainly due to the environmental variations. However, the model was within the acceptable range, indicated good agreement between the observed and anticipated yield with coefficient of determination of 89% (Figure 3). A lower RMSE and per cent deviation was also observed (56.54 g m^{-2}, -5.56, respectively). Groundnut growth is highly influenced by soil temperature and photoperiod, which play crucial roles in regulating flowering and pod filling (Nautiyal, 2022).

Table 5 presented the results of the model validation for the second sowing date during 2016. During T_1, T_2, and T_4 stage, dry matter accumulation was overestimated and at the T_3 and T_5 stage, dry matter accumulation was underestimated. The model overestimated the pod yield. The environmental fluctuations or climatic variability throughout 2016 was the primary cause of the model's deviation. Although the model was within the acceptable range, yield predicted and observed was well-aligned with a coefficient of determination of 71% (Figure 4). The per cent deviation and root mean square error showed lower values (71.81 g m^{-2} and -11.44, respectively) indicating a good fit. This result was in accordance with Giridhar (2019). These deviations were linked to variations in growing degree

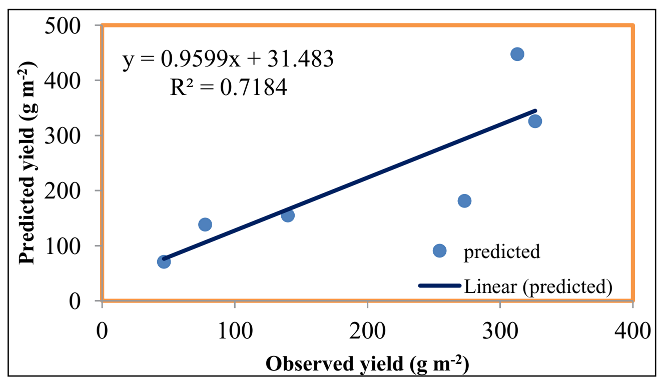

Figure 4: Coefficient of determination between observed and Predicted yield for the year 2016 date of sowing II

Table 4: Validation of the stoichiometric crop weather model for the year 2016 (Date of sowing-I)

Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			400.00	518.40	39.89	39.96	71.21
T_2	39.96		144.10	197.80	83.80	102.12	115.05
T_3	102.12		269.90	279.90	70.01	308.58	261.60
T_4	308.58		141.50	181.40	72.20	399.60	378.73
T_5	399.60		372.60	585.10	51.20	446.22	566.39
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5 (P)	Yg (O)	Yg (P)
	39.96	102.12	308.58	399.60	566.40	189.16	158.28
% dev.		-5.56		RMSE		56.54	

Table 5: Validation of the stoichiometric crop weather model for the year 2016 (Date of sowing-II)

Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			413.70	519.30	37.51	46.62	70.85
T_2	46.62		139.32	492.24	84.72	77.70	138.36
T_3	77.70		273.61	434.90	86.90	273.06	181.28
T_4	273.06		137.80	420.00	78.95	313.02	447.33
T_5	313.02		460.30	365.90	49.20	326.34	325.90
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5(P)	Yg (O)	Yg (P)
	46.62	77.70	273.06	313.02	325.90	140.00	154.70
% dev.		-11.44		RMSE		71.81	

days (GDD) and soil moisture conditions, as groundnut requires optimal GDD accumulation for effective biomass production and yield formation (Reddy et al., 2003). The lower predictability for the second date of sowing may be due to increased temperatures and moisture stress, which adversely affect root development, nodulation, and pod formation in groundnut (Prasad et al., 2003).

The results of the model validation for the year 2017 at first date of sowing are presented in Table 6. The model underestimated the dry matter accumulation at pod initiation (T_3), pod filling (T_4), harvesting (T_5) and overestimated the accumulation of dry matter at 30 DAS (T_1), 50% flowering (T_2) and Pod yield (Yg). However, the model was within the acceptable range, indicated good agreement between the observed and predicted yield. In this model, a good agreement has been realized between the predicted and observed yield of groundnut with coefficient of determination 98% as indicated in Figure 5. Lower root mean square error (RMSE) and per cent deviation was observed i.e., 34.59 g m^{-2} and -2.96%, respectively. The improved accuracy was likely due to stable weather conditions, minimal climatic variations, and consistent solar radiation influencing crop growth positively. Groundnut has a high requirement for solar radiation, especially during the flowering and pod development stages, as inadequate light can reduce biomass accumulation and yield (Nigam et al., 2005).

Table 6: Validation of the stoichiometric crop weather model for the year 2017 (Date of sowing-I)

Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			410.40	520.30	34.50	68.82	71.21
T_2	68.82		139.40	490.20	79.90	126.54	161.49
T_3	126.54		269.90	434.20	81.80	259.74	237.96
T_4	259.74		121.50	400.80	59.60	377.40	359.82
T_5	377.40		323.70	342.10	45.60	517.26	451.72
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5(P)	Yg (O)	Yg (P)
	68.82	126.54	259.74	377.40	451.70	109.20	138.76
% dev.		-2.96		RMSE		34.59	

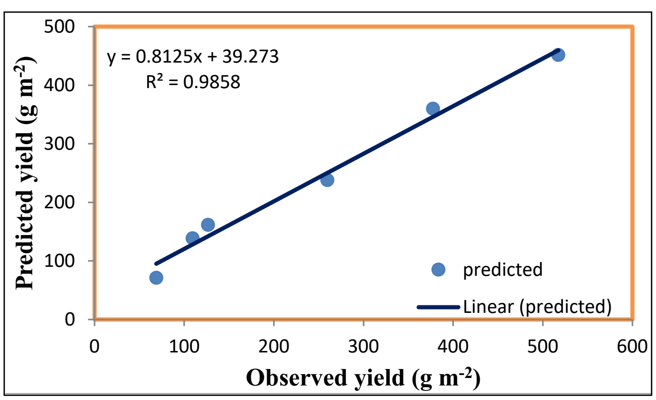

Figure 5: Coefficient of determination between observed and Predicted yield for the year 2017 date of sowing I

The outcome of the model validation for the second date of sowing during 2017 is shown in Table 7. The dry matter accumulation at pod initiation (T_3) and harvesting stage (T_5) was underestimated by the model and overestimated at 30 DAS (T_1), 50% flowering (T_2), pod filling stages (T_4). However, the model was within the permissible range and showed considerable agreement between the observed and predicted yields. Further, the model predictive ability was evaluated with R^2 value, RMSE and per cent deviation. The model has good fit to the data with coefficient of

Table 7: Validation of the stoichiometric crop weather model for the year 2017 (Date of sowing-II)							
Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			413.70	519.30	37.51	46.62	70.85
T_2	46.62		139.30	492.24	84.72	77.70	138.36
T_3	77.70		273.60	434.90	86.90	273.06	181.28
T_4	273.06		137.80	420.00	78.95	313.02	447.33
T_5	313.02		460.30	365.90	49.20	326.34	325.90
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5(P)	Yg (O)	Yg (P)
	46.62	77.70	273.06	313.02	325.90	185.80	154.70
% dev.		-6.20		RMSE		72.68	

determination value of 69% (Figure 6), lower RMSE and per cent deviation of about 72.68 g m^{-2} and -6.20%, respectively. Although the accuracy was lower compared to the first sowing date, the model's moderate predictability for the second date of sowing could be attributed to slightly higher temperatures and reduced soil moisture availability (Kukal, 2024). Delayed sowing often exposes groundnut crops to increased water stress and suboptimal growing conditions, affecting biomass accumulation and pod filling (Prasad et al., 2003)

The findings of the model validation for the first date of sowing during 2018 are displayed in Table 8. Overestimation of the dry matter accumulation at T_1, T_4, T_5 stages and underestimation at T_2, T_3 stages, respectively was observed. Pod yield was also overestimated by the model. The underestimation and overestimation of the model was mainly due to the environmental variations or climatic variability during 2018. Although, the model showed a good agreement between the observed and predicted values with coefficient of determination of 73% (Figure 7) and lower RMSE and per cent deviation (267.97 g m^{-2} and 2.20, respectively) (Rajegowda et al., 2014).

The outcome of the model validation for the second date of sowing during 2018 is shown in Table 9. The dry matter accumulation at 30 DAS (T_1), 50% flowering (T_2) and harvesting (T_5) was overestimated by the model and

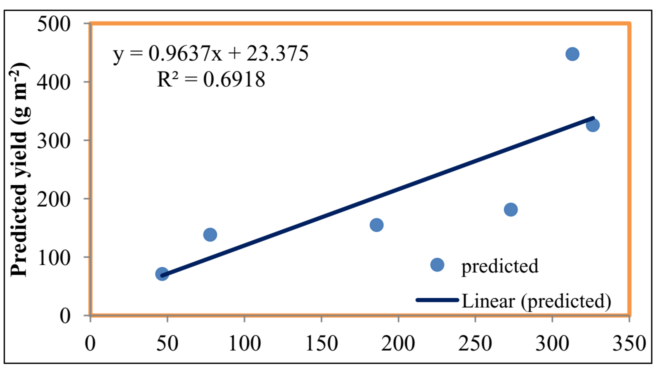

Figure 6: Coefficient of determination between observed and Predicted yield for the year 2017 date of sowing II

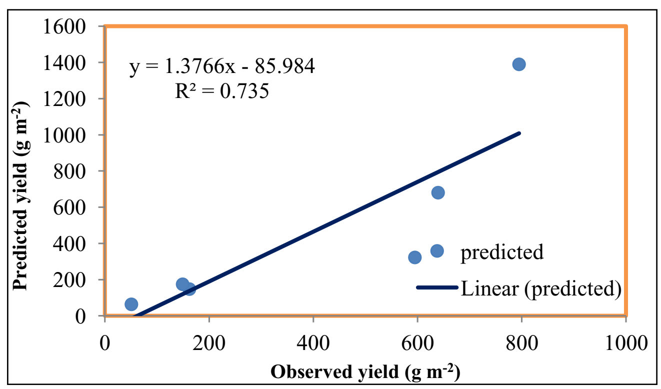

Figure 7: Coefficient of determination between observed and Predicted yield for the year 2018 date of sowing I

Table 8: Validation of the stoichiometric crop weather model for the year 2018 (Date of sowing-I)							
Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			402.10	465.70	36.50	51.06	62.76
T_2	51.06		123.85	467.20	91.28	162.06	146.90
T_3	162.06		267.80	400.40	84.20	594.96	322.27
T_4	594.96		143.40	409.10	72.70	639.36	680.68
T_5	639.36		637.60	472.30	50.32	794.76	1389.58
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5(P)	Yg (O)	Yg (P)
	51.06	162.06	594.96	639.36	1389.60	149.30	173.99
% dev.		2.20		RMSE		267.97	

Table 9: Validation of the stoichiometric crop weather model for the year 2018 (Date of sowing-II)

Stages	Initial TDM		GDD	SR	AET	Observed DM (g m^{-2})	Predicted DM (g m^{-2})
T_1			388.15	443.50	35.00	56.62	59.80
T_2	56.62		140.60	572.80	87.14	138.72	155.14
T_3	138.72		285.10	408.00	81.90	426.22	293.04
T_4	426.22		121.80	449.10	73.07	566.10	559.77
T_5	566.10		439.40	354.20	47.29	839.16	1065.54
Pod yield	TDM1	TDM2	TDM 3	TDM 4	TDM 5(P)	Yg (O)	Yg (P)
	51.06	162.06	594.96	639.36	1389.60	149.30	173.99
% dev.		-2.36		RMSE		108.53	

underestimated at pod initiation (T_3), pod filling stages (T_4). The model has excellent fit to the data with coefficient of determination value of 92% (Figure 8), lower RMSE and per cent deviation of about 108.53 g m^{-2} and -2.36%, respectively. Groundnut is highly susceptible to erratic rainfall, as excessive moisture during flowering can lead to poor pollination, while drought stress reduces pod filling

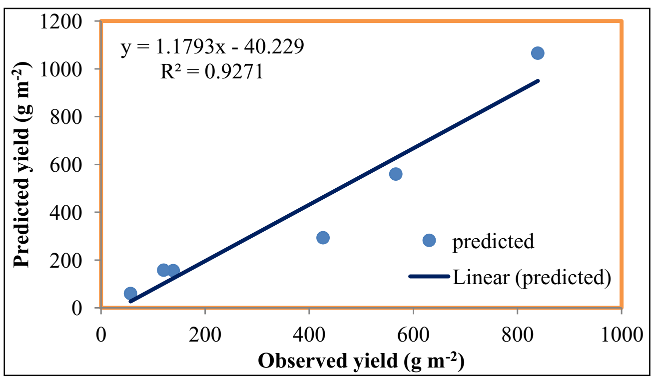

Figure 8: Coefficient of determination between observed and Predicted yield for the year 2018 date of sowing II

(Prasad et al., 2003). The better performance of the second date of sowing highlights the importance of selecting optimal sowing periods to enhance crop yield predictions. The improved predictability in the second sowing date could be due to more stable temperature conditions and better soil moisture retention, which provided a favorable environment for crop establishment and pod development (Ashok et al., 2025). In certain climatic scenarios, delayed sowing can help groundnut avoid excessive heat stress during early growth stages and align reproductive phases with optimal weather conditions, improving biomass accumulation and yield stability (Singh et al., 2012).

4. CONCLUSION

The Stoichiometric crop weather model predicted groundnut dry matter and pod yield using weather-based regression equations. R^2 ranged from 0.08 at 30 DAS to 0.77 at pod filling, with 0.38 for pod yield. Validated from 2015–2018, the model performed best for early sowing, achieving up to 98% accuracy (2017). Accuracy declined with delayed sowing due to heat and moisture stress. Despite some estimation errors, the model showed strong potential for predicting yield under varying climatic conditions.

5. ACKNOWLEDGEMENT

The authors thank the AICRP on Agrometeorology, GKVK, Bangalore for extending their guidance and technical assistance in conducting this research work.

6. REFERENCES

Ahmed, M., Ahmad, S., Raza, M.A., Kumar, U., Ansar, M., Shah, G.A., Parsons, D., Hoogenboom, G., Palosuo, T., Seidel, S., 2020. Models' calibration and evaluation. Systems Modeling, 151–178.

Alsubhi, N.H., Alzahrani, S.M., 2024. Plant phenology: definition, history, and response to environmental factors. Egyptian Journal of Botany 64(4), 49–58.

Anonymous, 2021. Statistical data on crops, groundnut, area, production quantity of Tanzania, Africa & World.

Anonymous, 2022. FAO Stat. Database, 2021. Accessed on 07.08.2023. Available at http://faostat.fao.org

Ashok, K., Malleswari, S.N., Sudheer, K.V.S., Bal, S.K., Manikandan, N., Subba Rao, A.V.M., Sarath Chandran, M.A., 2025. Optimizing groundnut sowing for minimizing dry spell risks over Rayalaseema, a rainfed region of India. Agronomy Journal 117(1), 70020.

Baier, W., 1979. Note on the terminology of crop-weather models. Agricultural Meteorology 20(2), 137–145.

Craufurd, P.Q., Prasad, P.V., Summerfield, R.J., 2002. Dry matter production and rate of change of harvest index at high temperature in peanut. Crop Science 42(1), 146–151.

Daudi, H., Shimelis, H., Laing, M., Okori, P., Mponda, O., 2018. Groundnut production constraints, farming systems, and farmer-preferred traits in Tanzania. Journal of Crop Improvement 32(6), 812–828.

Doorenbos, J., Pruitt, W.O., 1977. Guidelines for predicting crop water requirements, F.A.O. Irrigation and Drainage, 24, 35–41.

Elbasi, E., Zaki, C., Topcu, A.E., Abdelbaki, W., Zreikat, A.I., Cina, E., Shdefat, A., Saker, L., 2023. Crop prediction model using machine learning algorithms. Applied Sciences 13(16), 9288.

Jasna, V.K., Som, S., Burman, R.R., Padaria, R.N., Sharma, J.P., 2014. Socio economic impact of climate resilient technologies. International Journal of Agricultural Science and Food Technology 5(3), 185–190.

Kakani, V.G., Wheeler, T.R., Craufurd, P.Q., Rachaputi, R.C., 2015. Effect of high temperature and water stress on groundnuts under field conditions. Combined Stresses in Plants: Physiological, Molecular, and Biochemical Aspects, 159–180.

Kukal, S., 2024. A machine learning regression model for predicting the occurrence of Aflatoxin in Peanut fields using environmental and field-dependent variables (Master's thesis, University of Georgia).

Krupashree, R., Shivaramu, H.S., Thimmegowda, M.N., Manjunath, B.L., Mallikarjuna Gowda, A.P., Murali Mohan, K., Lingaraj, H., 2022. Studies on crop water balance and yield of mango (Cv. Mallika) as influenced by the weather parameters. Mysore Journal of Agricultural Sciences 56(3), 152–160.

Li, X., Sha, J., Wang, Z.L., 2017. Chlorophyll-a prediction of lakes with different water quality patterns in China based on hybrid neural networks. Water 9, 524.

Montaseri, M., Amirian, S., Mohammadi, K., 2018. Predicting crop yield using machine learning approaches: A case study on groundnut. Computational Agriculture Journal 55(2), 211–223.

Montaseri, M., Zaman Zad Ghavidel, S., Sanikhani, H., 2018. Water quality variations in different climates of Iran: Toward modeling total dissolved solid using soft computing technique. Stochastic Environmental Research and Risk Assessment 32, 2253–2273.

Mudalagiriyappa, Thimmegowda, M.N., Puneetha, K.M., Vasanthi, B.G., Latha, H.S., Devaraja, K., Madan Kumar, M., 2022. National innovation in climate resilient agriculture-A case study at Bangalore Rural district of Karnataka. International Journal of Environment and Climate Change 12(8), 34–42.

Muralidhara, K.S., Rajegowda, M.B., 2002. Stoichiometric crop weather model to predict the finger millet grain yield. Journal of Agrometeorology 4(1), 53–57.

Nautiyal, P., 2022. Seed development in groundnut-floral biology and peg development. Seed Research 50(1), 1–12.

Nigam, S.N., Aruna, R., Vasanthi, R.P., 2005. Groundnut physiology and agronomy. International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, India.

Padmalatha, Y., Reddy, R., 2006. Influence of weather parameters on growth and yield of groundnut. Peanut Science Journal 33(2), 102–110.

Patil, S.D., Gokhale, N.G., Jadhav, P., 2021. Regression models for yield prediction in groundnut under variable agro-climatic conditions. Indian Journal of Agricultural Sciences 91(3), 287–294.

Prasad, P.V.V., Craufurd, P.Q., Summerfield, R.J., 2003. Influence of high temperature on groundnut growth and development. Journal of Experimental Botany 54(392), 625–634.

Rajegowda, M.B., Janardhanagowda, N., Ravindrababu, B.T., Girish, J., 2010. Crop weather model for sustainable groundnut production under dry land condition. Journal of Agrometeorology 12(2), 221–224.

Rajegowda, M.B., Soumya, D.V., Padmashri, H.S., Gowda, N.J., Nagesha, L., 2014. Ragi and groundnut yield forecasting in Karnataka–statistical model. Journal of Agrometeorology 16(2), 203–206.

Rao, M.V., Nigam, S.N., Huda, A.K.S., 1992. The thermal time concept as a selection criterion for earliness in peanut. Peanut Science 19(1), 7–10.

Reddy, K.R., Reddy, V.R., Kakani, V.G., 2003. Interactive effects of temperature and radiation on groundnut. Agricultural and Forest Meteorology 120(1–4), 47–61.

Reddy, K.S., Nageswara Rao, R.C., Kumar, P., 2017. Climate variability and its impact on groundnut productivity in semi-arid tropics. Agricultural Meteorology Journal 72(1), 89–97.

Sharma, V., Singh, R., Yadav, B., 2019. Impact of solar radiation and evapotranspiration on groundnut yield prediction models. Journal of Agro-Meteorology 21(4), 412–419.

Singh, A.L., Basu, M.S., Singh, A.K., 2012. Advances in agronomic management of groundnut. In: Basu, M.S., Singh, N.B. (Eds.), Groundnut research in India. National Research Centre for Groundnut (ICAR), Junagadh, India, 17–136.

Summerfield, R.J., Huxley, P.A., Roberts, E.H., 1993. Environmental physiology of crops. Academic Press.

Thimmegowda, M.N., Manjunatha, M.H., Huggi, L., Shivaramu, H.S., Soumya, D.V., Nagesha, L., Padmashri, H.S., 2023. Weather-based statistical and neural network tools for forecasting rice yields in major growing districts of Karnataka. Agronomy 13(3), 704.

Thimmegowda, M.N., Nanjappa, H.V., Ramachandrappa, B.K., 2007. Influence of tillage and moisture regimes with soil solarization on weed dynamics and yield of baby corn-groundnut crop sequence. Indian Journal

of Weed Science 13(1–2), 13–16.
Uno, Y., Prasher, S.O., Lacroix, R., Goel, P.K., Karimi, Y., Viau, A., Patel, R.M., 2005. Artificial neural networks to predict corn yield from compact airborne spectrographic imager data. Computers and Electronics in Agriculture 47, 149–161.
Vinaya Kumar, H.M., Shivamurthy, M., Lunagaria, M.M., 2017. Impact of rainfall variability and trend on rice yield in Coastal Karnataka. Journal of Agrometeorology 19(3), 286–287.
Vinu, V., Prasad, R., Kumar, A., 2020. Development of crop growth models for groundnut under different sowing dates. Journal of Phytometeorology 9(6), 1203–1215.