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RESEARCH ARTICLE

Linear mathematical models for yield estimation of baby corn (*Zea mays* L.)

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Abstract

Linear mathematical models have been developed for predicting baby corn yield in terms of cob volume for two cycles of maize (*Zea mays* L.). Cob volume is directly proportional to morphological parameters such as length, weight, and girth; hence, linear mathematical models have been developed. Primary data for a random selection of 60 cobs for each cycle were collected, and lab work was carried out to measure the corn ears and cob growth parameters. An irregular distribution was observed among all six growth parameters examined in the study. Descriptive statistical measures were employed to facilitate the description of growth parameters. The final volume of the baby corn cob was used for crop yield estimation. The water displacement method was employed to measure the actual volume of cobs, which was then compared with the volumes estimated using the developed mathematical models. For both cycles, similar trends were observed in both estimated and actual volumes of cobs, providing numerical confirmation for the validity of the developed mathematical models. The theoretical validity of these models was also established using statistical measures such as R^2, adjusted R^2, F-test, P-value, and correlation coefficient. Any deviations between estimated and actual volumes would indicate changes in the dependent variables of the model, attributed to the effects of climate change, as other internal and external factors are held constant. These models offer a critical predictive tool for stakeholders, enabling improved yield predictions and optimized resource allocation. As a result, they facilitate strategic planning for increased profitability.

Keywords

Baby corn; crop yield estimation; maize; mathematical modeling; regression-based models; yield prediction

Introduction

Farmers need to upscale agricultural produce by at least 70% to feed an estimated population of around nine billion by 2050 (1). However, this goal is confronted by a series of challenges, including a growing population, diminishing cultivable land, decreasing seed setting, and reduced crop yields caused by the impacts of climate change (2-7). To overcome these hurdles, strategies such as crop diversification, the adoption of advanced agricultural tools, and the implementation of sustainable technologies emerge as potential solutions. One crucial aspect is the ability to forecast production, which plays a pivotal role in enabling farmers to formulate effective pre- and post-production strategies. Achieving this involves intricate processes such as satellite remote sensing-based methods (8), mathematical modelling (9), and various other independent or combined approaches for predicting crop yields (10, 11).

The present study attempts to develop a mathematical model to estimate the yield of baby corn, or ear of maize (*Zea mays* L.), which holds substantial popularity in both domestic and international markets. This crop has garnered significant attention from farmers due to its notable nutritional and economic value (12). Being a C4 crop, it also has the benefit of growing in diverse climatic conditions. This feature positions maize cultivation as a potentially advantageous endeavour for farmers, particularly those facing economic constraints. By enabling multiple harvests within a single year, maize farming exhibits the capacity to substantially augment farmers' income while concurrently addressing the imperative need for crop diversification.

Mathematical modelling plays a pivotal role in the realm of crop production, offering a dynamic array of mathematical applications. Employing these mathematical tools to scrutinize and enhance crop yield, along with providing reasonably precise estimates, holds the potential to assist farmers in adeptly preparing for the upcoming harvesting season (13-21). In the context of escalating global food demand and climate change, the present study is significant. The hypothesis tested in this study is that linear mathematical models can accurately predict baby corn yield based on cob volume for two maize growth cycles. The study holds significant economic implications, as accurate yield predictions can lead to optimized resource allocation, reduced wastage, and improved farmers' income stability. Environmentally, improved yield predictions could lead to more sustainable farming practices, reducing unnecessary resource exploitation and its associated environmental impact. Therefore, the environmental-economic nexus in this research is that optimizing agricultural yield predictions not only carries potential economic benefits but also promotes more sustainable and climate-resilient farming practices.

Materials and Methods

Experimental sites

The work for the present investigation was carried out at a farmer's field in Aterna village, which is situated in the Rai block of Sonipat district. This village is located southeast of the district of Sonipat in Haryana (Figure 1). Latitude 28.9031185 and longitude 77.1549874 are the geo-coordinates of the Aterna (http://wikiedit.org/India/Aterna/28894/).

The experimental site is famous for baby corn production. The variety studied in the present investigation was G-5414 (Syngenta) in both crop seasons. Primary data was collected through field and laboratory experiments involving the measurement of various parameters that served as the basis for this study. To raise the crop, all the agronomic practices were carried out uniformly. Field trips were conducted at regular intervals to gather growth-related data for two baby corn crops in different seasons within the same year. Two crop cycles, I and II, were examined in February-April 2021 and July-September 2021, respectively. The average high-low temperature varies between 24°C and 11°C in the month of February with a relative humidity (RH) of 58%. In July, the average high-low temperature spanned between 35°C and 28°C, with an RH of 68%. The average rainfall in the district is 24.6mm and 190mm in the months of February and July, respectively. The mean day lengths for these months were 11.2 hours (February) and 13.8 hours (July) (https://www.weather-atlas.com/en/india/sonipat-climate).

Considering the financial analysis, the integration of mathematical models might entail initial costs for activities such as data collection, analysis, and model development. However, these costs are likely to be counterbalanced by the prospective advantages offered by the models. By providing accurate yield predictions, the models can aid in efficient resource allocation, potentially reducing waste and associated costs. Further, accurate yield predictions would also allow for better market planning and risk management, leading to a more stable income for farmers.

Fig. 1. Experimental Field Site (in red boxes) and team working in laboratory https://en.wikipedia.org/wiki/Sonipat_district

Collection of primary data

Data regarding the growth parameters of baby corn were gathered from the farmers' fields at specific time points. For the winter crop (February-April), observations were taken at 25 days, 45 days, and 85 days after sowing (DAS), with harvesting done at 85 DAS. In contrast, due to the accelerated growth during the summer season (July-September), observations were recorded at 5, 15, 25, and 55 DAS. Harvesting occurred at 55 DAS. For data collection, sixty plants were randomly selected at the mentioned DAS and harvesting stages. All biometric observations were recorded. The spacing between rows and individual plants within a row was consistent for both seasons. Plant height was recorded from the base of the plant to the tip of the terminal leaf on the main stem and expressed in cm.

Results

Cycle-I (February-April 2021)

The length and diameter of both cobs and corn ears from a randomly selected sample of 60 plants were measured from harvested yields at the end of the field experiment for cycle-I, as illustrated in Figure 2. Meanwhile, the weights of both cobs and corn ears in these samples are presented in Figure 3. All these growth parameters exhibit an irregular distribution spread over a wide range. Table 1 shows some descriptive statistical measures such as the arithmetic mean, median, variance, standard deviation, minimum, and maximum values for the baby corn samples to better describe growth parameters in cycle-I. These descriptive statistical analyses were carried out using the R software.

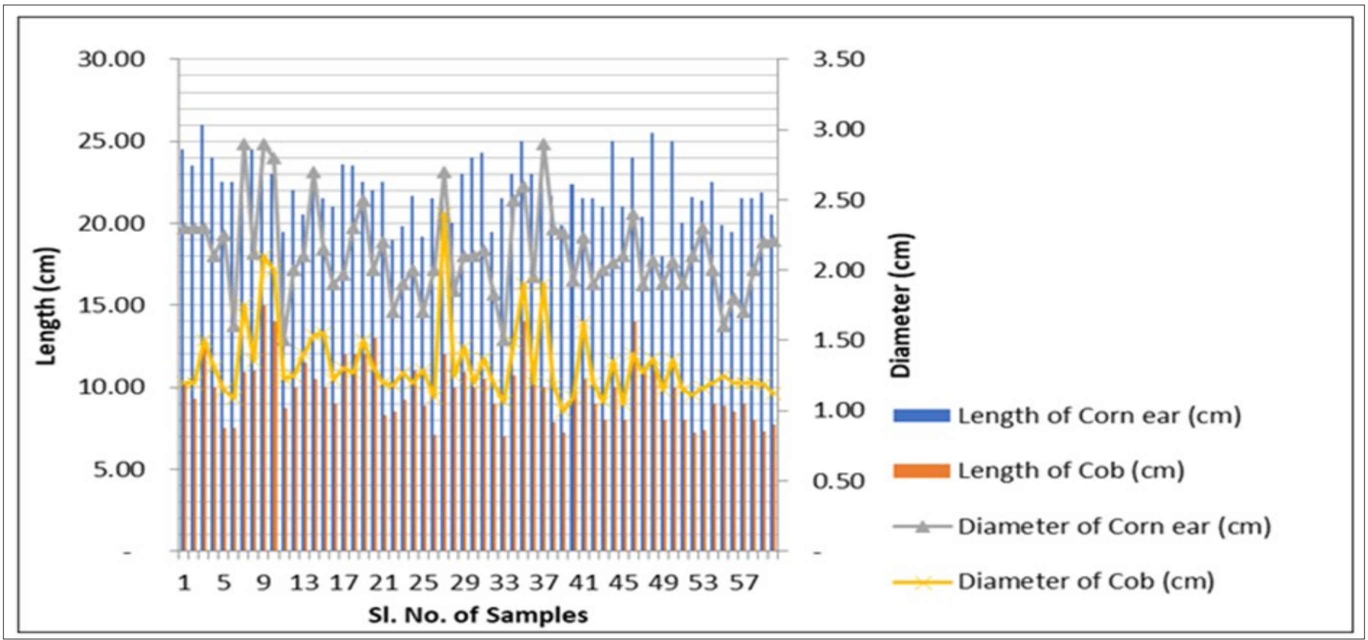

Fig. 2. Length and Diameter of Cob and Corn of 60 randomly selected samples at harvest of Cycle-I (February-April 2021)

Laboratory work

Laboratory experiments were conducted to assess the growth parameters of baby corn cobs (as shown in Figure 1). These parameters included length, weight, girth, and volume. The cobs were harvested on the 85th day for cycle-I and the 55th day for cycle-II, representing the initial harvest. From a selection of representative plants, measurements were taken to determine the mean values. For each representative plant, the corn ear sheath was carefully removed. Subsequently, the length, diameter, and weight of the cobs contained within the sheath were measured. Additionally, the total count of cobs from the plants was tallied, and the mean number was computed based on these counts.

Two crop cycles I and II, in February-April 2021 and July-September 2021, respectively, were studied to develop the mathematical models for corn yield estimation. Randomly selected samples of 60 corn ears were taken from both the harvested crops in the field experiment, and then the lab experiments were carried out to evaluate the length, diameter, and weight of cobs and corn ears. Additionally, the volume of the cobs was also measured using the water displacement method.

The trends of the volume of cobs, as estimated by the model, and the measured volume of cobs from lab experiments are illustrated in Figure 4. Similar trends are evident in both volume measurements of cobs. The distribution of cob samples as per the percentage error in the estimated volume of sampled cob has been shown in Table 2 for cycle-I. Analysis of this distribution revealed that the percentage error in the estimated volume of sampled cobs falls within the range of 0-9% for 80% of the sampled cobs.

Cycle-II (July-September 2021)

The length and diameter of both cobs and corn ears from a randomly selected sample of 60 plants, which were measured from harvested yields at the conclusion of the field experiment for cycle-II, are illustrated in Figure 5, whereas the weights of both cobs and corn ears of these samples are shown in Figure 6. All these growth parameters exhibit an irregular distribution spread over a wide range. Table 3 shows some descriptive statistical measures like the arithmetic mean, median, variance, standard deviation, and minimum and maximum values for the baby corn samples to better describe growth parameters in cycle-II. These descriptive statistical analyses were performed using the R software.

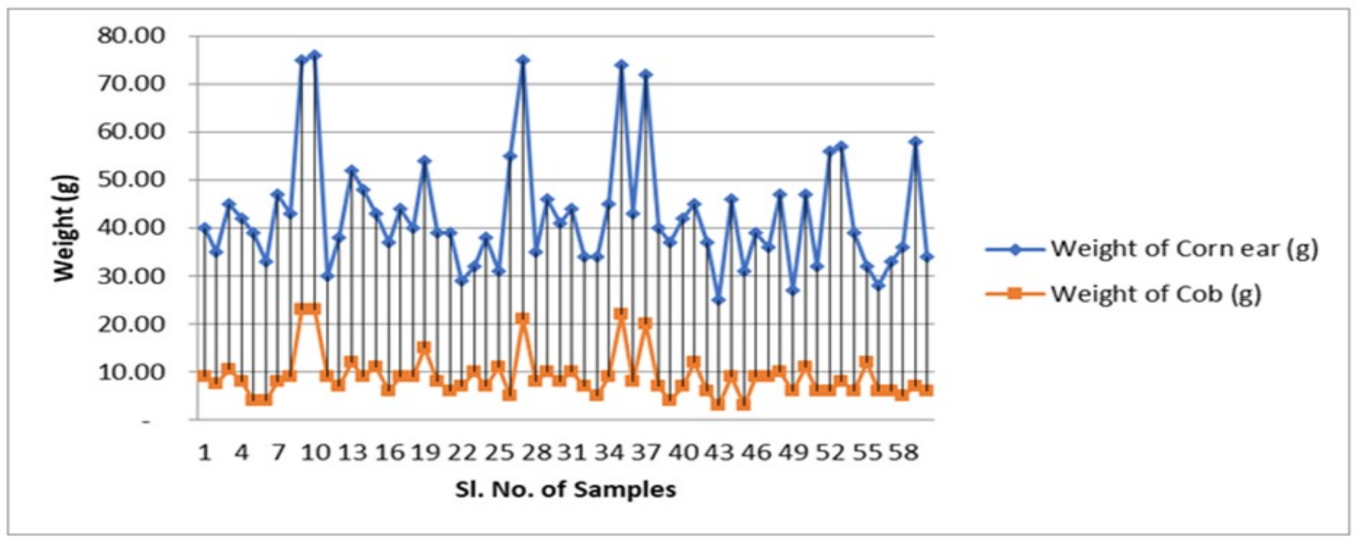

Fig. 3. Weight of Cob and Corn of 60 randomly selected samples at harvest of Cycle-I (February-April 2021)

Table 1. Cycle-I (February-April 2021): Descriptive Statistical Measures of Baby Corn Samples.

Descriptive Statistical Measures	Length of Corn Ear L_1 (cm)	Length of Cob L_2 (cm)	Diameter of Corn Ear D_1 (cm)	Diameter of Cob D_2 (cm)	Weight of Corn Ear W_1 (g)	Weight of Cob W_2 (g)
Arithmetic Mean	22.1	9.84	2.121	1.33	42.85	8.99
Median	22	10	2.1	1.24	40	8
Variance	3.17	3.66	0.11	0.007	145.66	20.49
Standard Deviation	1.78	1.91	0.32	0.27	12.06	4.52
Minimum	18	7	1.5	1	25	3
Maximum	26	15	2.9	2.4	76	23

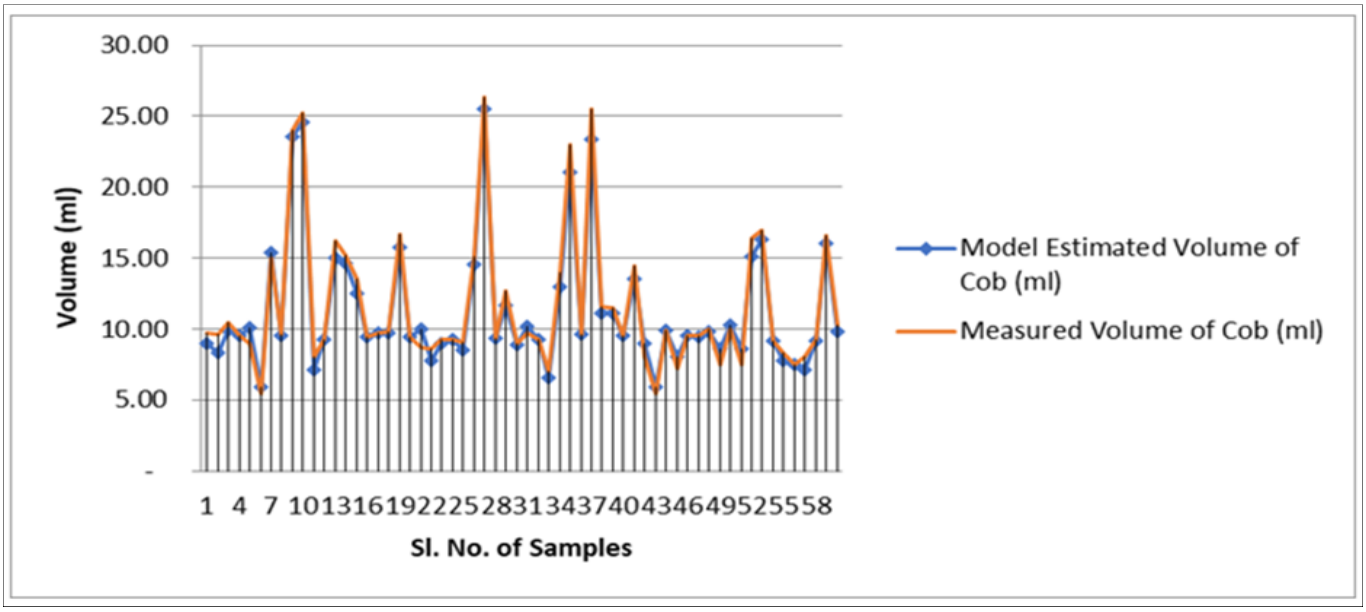

Fig. 4. Estimated Volume of Corn by Model and Measured Volume of Corn of 60 randomly selected samples at harvest of Cycle-I (February-April, 2021)

Table 2. Cycle-I (February-April 2021): Distribution of Cob Samples as per the Percentage Error in Estimated Volume of Sampled Cob.

Sl. No.	Interval of Percentage Error in Estimated Volume (%)	Number of Sampled Cob	Ratio of Sampled Cob in Prescribed Interval (%)
1	0-3	24	40
2	3-6	12	20
3	6-9	12	20
4	9-12	6	10
5	12-15	6	10
Total		**60**	**100**

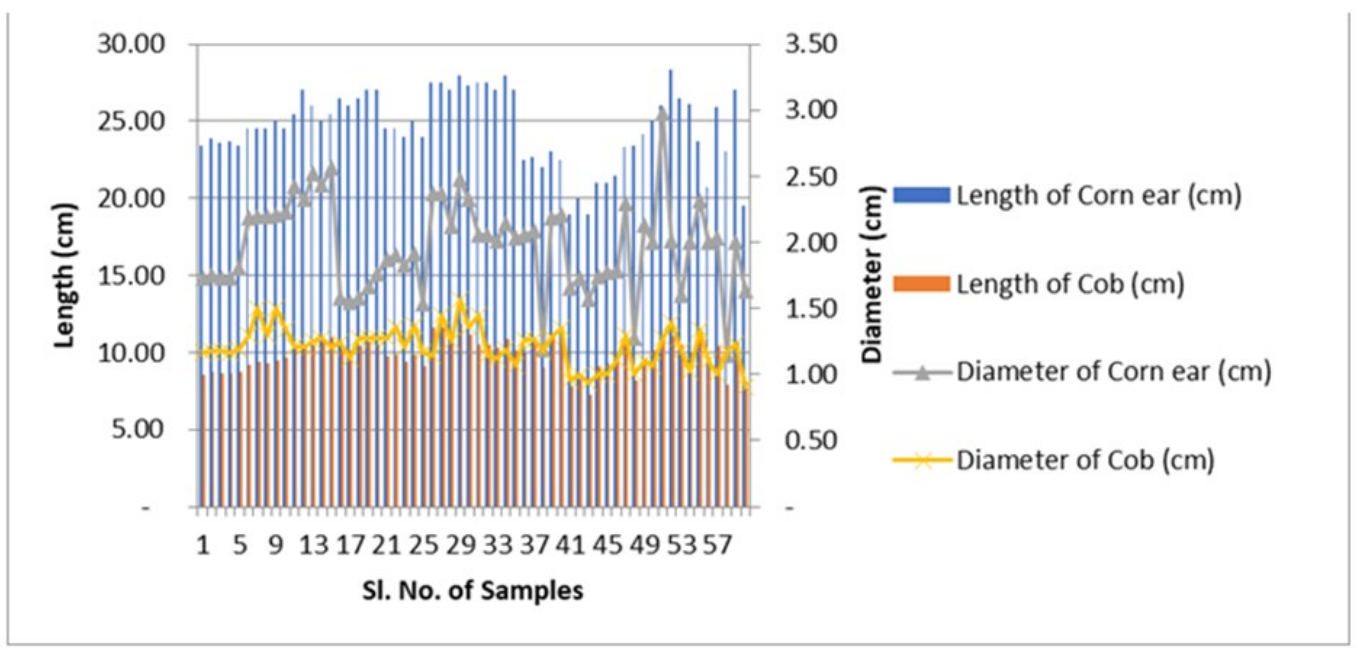

Fig. 5. Length and Diameter of Cob and Corn of 60 randomly selected samples at harvest of Cycle-II (July-September 2021)

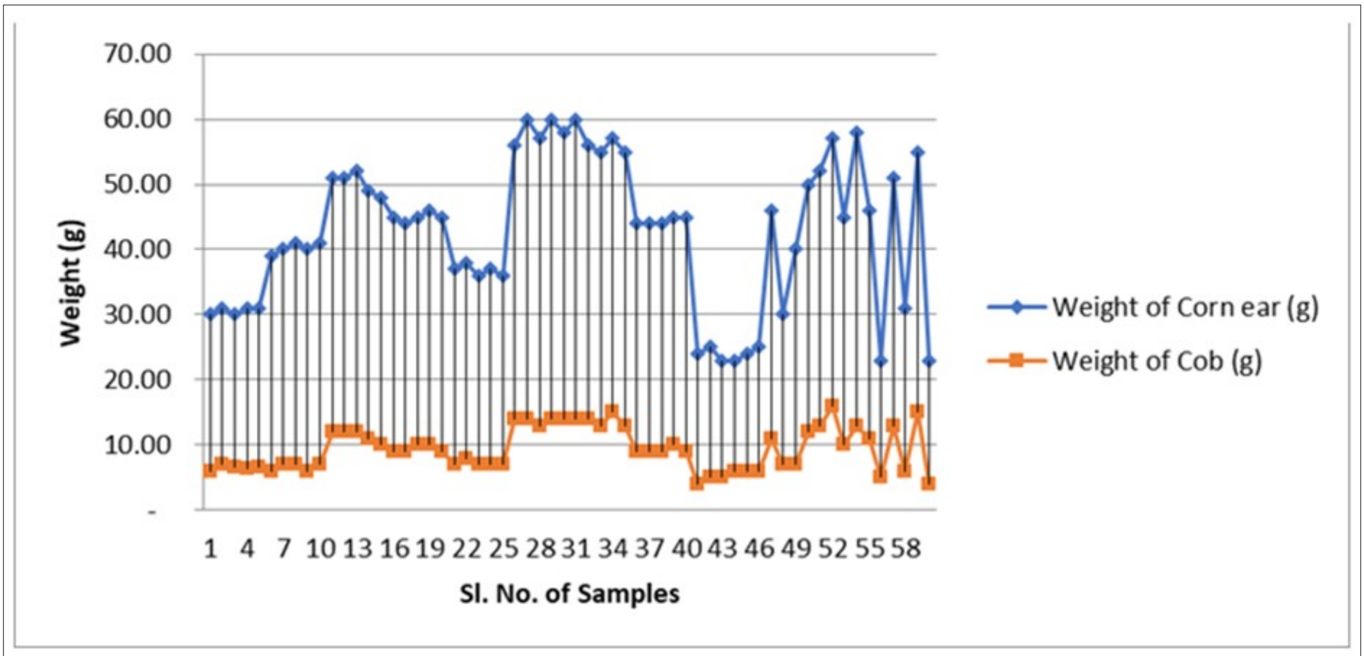

Fig. 6. Weight of Cob and Corn of 60 randomly selected samples at harvest of Cycle-II (July-September 2021)

Table 3. Cycle-II (July-September 2021): Descriptive Statistical Measures of Cob Samples.

Descriptive Statistical Measures	Length of Corn Ear L_1 (cm)	Length of Cob L_2 (cm)	Diameter of Corn Ear D_1 (cm)	Diameter of Cob D_2 (cm)	Weight of Corn Ear W_1 (g)	Weight of Cob W_2 (g)
Arithmetic Mean	24.6	9.93	1.97	1.21	42.68	9.4
Median	24.5	10.1	2.0055	1.2105	44.5	9
Variance	5.6	1.11	0.12	0.02	124.78	10.522
Standard Deviation	2.36	1.05	0.34	0.1419	11	3.24
Minimum	19	7.3	1.147	0.9	23	4
Maximum	26	15	2.9	2.4	76	23

The trends of the estimated cob volume generated by the model and the actual cob volume measured in the lab experiment are shown in Figure 7. Similar trends are generally observed in both volume measurements of the cobs. The distribution of cob samples, based on the percentage error in the estimated volume of the sampled cobs, is presented in Table 4 for cycle-II. This distribution analysis reveals that the percentage error in the estimated volume of sampled cobs falls within the range of 0% to 6% for approximately 86.67% of the sampled cobs.

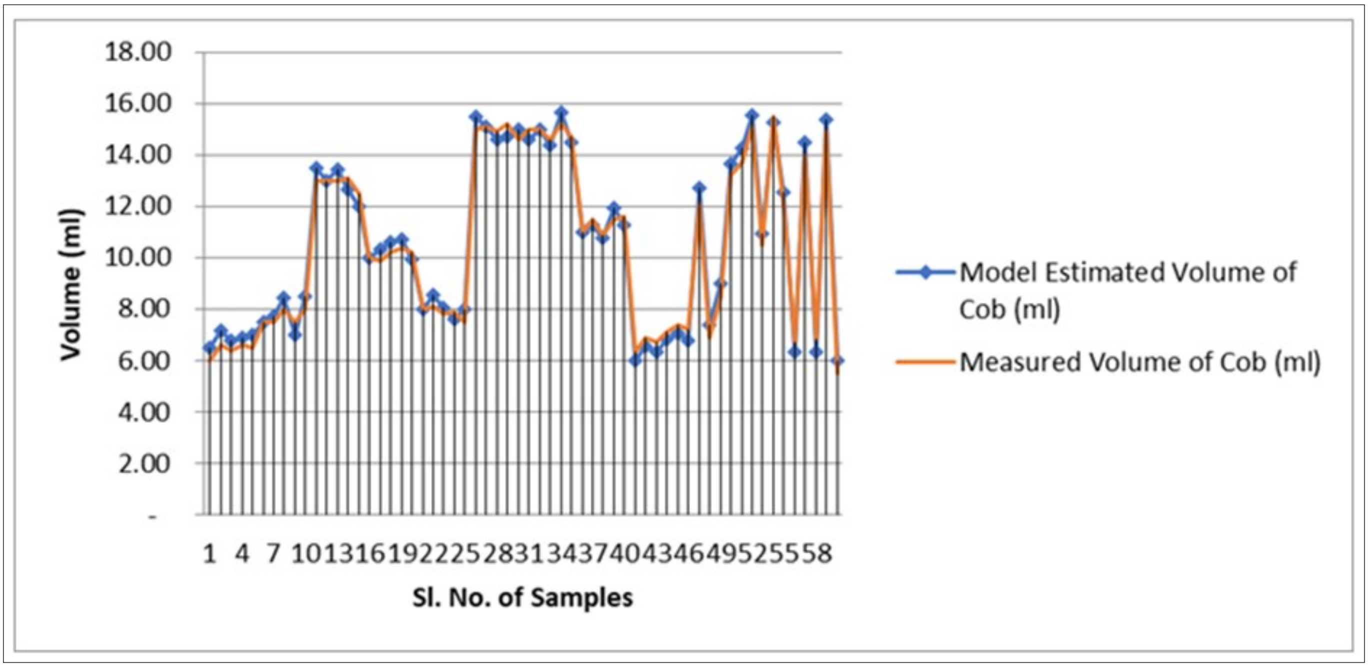

Fig. 7. Estimated Volume of Corn by Model and Measured Volume of Corn of 60 randomly selected samples at harvest of Cycle-II (July-September 2021)

Table 4. Cycle-II (July-September 2021): Distribution of Cob Samples as per the Percentage Error in Estimated Volume of Sampled Cob.

Sl. No.	Interval of percentage Error in Estimated Volume (%)	Number of Sampled Cob	Ratio of Sampled Cob in Prescribed Interval (%)
1	0-2	13	21.67
2	2-4	26	43.33
3	4-6	13	21.67
4	6-8	5	8.33
5	8-10	3	5.00
Total		**60**	**100**

Analysis

Cob volume, being a significant indicator of yield, is considered a dependent variable. The growth parameters such as length, diameter, and weight of both cobs and corn ears, which play a pivotal role in the growth of baby corn, are treated as independent variables. These are used to develop a mathematical model based on the linear algebra technique. The general form of the model for the specific crop growth being studied is defined as,

$$V_{est}^{i} = \alpha_0 + \alpha_1 L_1^i + \alpha_2 L_2^i + \alpha_3 D_1^i + \alpha_4 D_2^i + \alpha_5 W_1^i + \alpha_6 W_2^i \quad \text{....................(1)}$$

Where, the superscript *i* represents the *i*th cob or corn ear,

V_{est}^{i} = Estimated volume of cob in ml

L_1^i = Length of corn ear in cm

L_2^i = Length of cob in cm

D_1^i = Diameter of corn ear in cm

D_2^i = Diameter of cob in cm

W_1^i = Weight of corn ear in g

W_2^i = Weight of cob in g

α_0 = fixed term in the model taken as an error term that may arise due to parameters (environmental or climatic or physiological) affecting the crop growth but not taken into account in the present model,

$\alpha_1, \alpha_3, \alpha_5$ = Coefficients for the corn ear's length, diameter, and weight, respectively, and

$\alpha_2, \alpha_4, \alpha_6$ = Coefficients for the cob's length, diameter, and weight, respectively.

A system of seven linear simultaneous equations involving seven unknowns α_j ($0 \le j \le 6$)are to be obtained from the data collected which is then to be solved by any linear algebra technique like the Gauss Jordan elimination method. The software *Mathematica* was used to solve this system of seven linear equations, thus providing the required mathematical model for corn volume estimation.

Mathematical Model for Cycle-I

The system of linear equations used to estimate the values

$$\begin{aligned}
&\alpha_0 + 24\alpha_1 + 10\alpha_2 + 2.1\alpha_3 + 1.3\alpha_4 + 42\alpha_5 + 8\alpha_6 = 9.5 \\
&\alpha_0 + 22\alpha_1 + 10\alpha_2 + 2.0\alpha_3 + 1.25\alpha_4 + 38\alpha_5 + 7\alpha_6 = 9.3 \\
&\alpha_0 + 22\alpha_1 + 13\alpha_2 + 2.0\alpha_3 + 1.3\alpha_4 + 39\alpha_5 + 8\alpha_6 = 9.4 \\
&\alpha_0 + 20\alpha_1 + 10\alpha_2 + 1.85\alpha_3 + 1.25\alpha_4 + 35\alpha_5 + 8\alpha_6 = 9.35 \\
&\alpha_0 + 23\alpha_1 + 11\alpha_2 + 1.95\alpha_3 + 1.2\alpha_4 + 43\alpha_5 + 8\alpha_6 = 9.6 \\
&\alpha_0 + 25\alpha_1 + 10\alpha_2 + 2.05\alpha_3 + 1.35\alpha_4 + 46\alpha_5 + 9\alpha_6 = 9.9 \\
&\alpha_0 + 22.5\alpha_1 + 9\alpha_2 + 2\alpha_3 + 1.2\alpha_4 + 39\alpha_5 + 6\alpha_6 = 9.2
\end{aligned} \quad \text{....................(2)}$$

of the unknowns α_j ($0 \le j \le 6$) is taken as,

$$\alpha_0 = 4.80625, \alpha_1 = -0.725, \alpha_2 = -0.109375, \alpha_3 = 3.5,$$
$$\alpha_4 = 2.8125, \alpha_5 = 0.290625, \alpha_6 = -0.003125.$$

The solution of this system by the Gauss-Jordan elimination method using software *Mathematica* is given as,

$$V^i_{est} = 4.80625 - 0.725L^i_1 - 0.109375L^i_2 + 3.5D^i_1 + 2.8125D^i_2 + 0.290625W^i_1 - 0.003125W^i_2 \quad \text{...............................(3)}$$

Thus, the mathematical model for estimation of cob volume during cycle-I is described as,

Mathematical Model for Cycle-II

$$\alpha_0 + 24.5\alpha_1 + 9.2\alpha_2 + 2.183\alpha_3 + 1.3\alpha_4 + 39\alpha_5 + 6\alpha_6 = 7.5$$
$$\alpha_0 + 27\alpha_1 + 10.4\alpha_2 + 2.325\alpha_3 + 1.21\alpha_4 + 51\alpha_5 + 12\alpha_6 = 13$$
$$\alpha_0 + 26.5\alpha_1 + 10.2\alpha_2 + 1.577\alpha_3 + 1.24\alpha_4 + 45\alpha_5 + 9\alpha_6 = 10$$
$$\alpha_0 + 24.5\alpha_1 + 9.8\alpha_2 + 1.868\alpha_3 + 1.272\alpha_4 + 37\alpha_5 + 7\alpha_6 = 8$$
$$\alpha_0 + 27.5\alpha_1 + 11.6\alpha_2 + 2.373\alpha_3 + 1.45\alpha_4 + 60\alpha_5 + 14\alpha_6 = 15.1$$
$$\alpha_0 + 27.5\alpha_1 + 10.5\alpha_2 + 2.06\alpha_3 + 1.14\alpha_4 + 56\alpha_5 + 14\alpha_6 = 15$$
$$\alpha_0 + 22.5\alpha_1 + 10\alpha_2 + 2.06\alpha_3 + 1.264\alpha_4 + 44\alpha_5 + 9\alpha_6 = 11$$

.......................(4)

The system of linear equations used to estimate the values of the unknowns α_j ($0 \le j \le 6$) is taken as,

$$\alpha_0 = 5.17302, \alpha_1 = -0.284353, \alpha_2 = 0.344897, \alpha_3 = 0.328469,$$
$$\alpha_4 = -3.17866, \alpha_5 = 0.150797, \alpha_6 = 0.609121.$$

$$V^i_{est} = 5.17302 - 0.284353L^i_1 + 0.344897L^i_2 + 0.328469D^i_1 - 3.17866D^i_2 + 0.150797W^i_1 + 0.609121W^i_2 \quad \text{........................(5)}$$

The solution of this system by the Gauss-Jordan elimination method using the software *Mathematica* is given as,

Thus, the mathematical model for estimation of cob volume during cycle-II is described as,

Validity of the Mathematical Model for Cycle-I

To check the validity of the mathematical model derived for cycle-I, the requirement is to determine the relationship between the cob volume (dependent variable) and

$$R^2 = \frac{\alpha_1\sum L^i_1 V^i_{est} + \alpha_2\sum L^i_2 + \alpha_3\sum D^i_1 V^i_{est} + \alpha_4\sum D^i_2 V^i_{est} + \alpha_5\sum W^i_1 V^i_{est} + \alpha_6\sum W^i_1 V^i_{est}}{\sum (V^i_{est})^2} \quad \text{.......................(6)}$$

the growth parameters length, diameter, and weight of both the cob and corn ear (independent variables). This relation was determined by R^2, the multiple determination coefficient (22, 23) which is defined as,

Here, all parameters were calculated as per the mean origin axis. The value of R^2 was found to be 0.9875 which shows that cob volume is well described by the growth parameters length, diameter, and weight of both cobs and corn ears. Then, to check the effect of any additional new

$$\text{Adjusted } R^2 = 1 - \left(1 - R^2\right)\left[\frac{n-1}{n-(k+1)}\right] \quad \text{........................(7)}$$

parameter on the mathematical model, adjusted R^2,the corrected multiple determination coefficient (22) was used, which is defined as,

where R^2 stands for multiple determination coefficient, n represents the number of samples, and k is the number of independent variables. The value of adjusted R^2 was calculated as 0.986, which was found to be less than R^2. This finding reinforces that introducing a new growth parameter to the model under the same conditions is unlikely to significantly enhance the result's accuracy. The F-test was used to analyze the significance of R^2. With a P-value of ≤ 0.01, it can be concluded that there exists a highly significant relationship between the cob volume and the growth parameters length, diameter, and weight of both the cob and corn ears. Finally, to describe the relationship between the measured volume of cob and the estimated volume of cob using a mathematical model, the correlation coefficient was also calculated and was found to be 0.992. All these statistical analyses were conducted using Microsoft Office Excel. The output summary for cycle-I is shown in Table 5.

Table 5. Cycle-I (February-April 2021): Output Summary

Sl. No.	Statistics Measures	Output
1	Observations	60
2	Multiple R	0.99372462
3	R Square	0.987488621
4	Adjusted R Square	0.986072239
5	df	6
6	F	697.1906471
7	Significance F	1.44944E-48
8	P-value (Intercept)	1.72946E-06
9	Correlation Coefficient	0.992

Validity of the Mathematical Model for Cycle-II

In cycle-II, following the same strategy as in cycle-I to validate the derived mathematical model, the value of R^2 was found to be 0.9883, which again confirms that cob volume is well described by the growth parameters: length, diameter and weight of both the cob and corn ear. To assess the impact of any additional new parameter on the mathematical model, the adjusted R^2 was calculated, yielding a value of 0.9869, which once again demonstrated a slight decrease compared to R^2. This finding reinforces that introducing a new growth parameter to the model under the same conditions is unlikely to significantly enhance result accuracy. Subsequently, the F-test was calculated to analyze the significance of R^2. With a P-value of ≤ 0.01, it confirms the highly significant relationship between cob volume and the growth parameters length, diameter, and weight of both cobs and corn ears during July-September. Lastly, the relationship between the measured volume of cob and the estimated volume of cob from the mathematical model was described by calculating the correlation coefficient, which was found to be 0.993. All these statistical analyses were conducted using Microsoft Office Excel. The summary of results for cycle-II is presented in Table 6.

Table 6. Cycle-II (July-September 2021): Output Summary

Sl. No.	Statistics Measures	Output
1	Observations	60
2	Multiple R	0.994132569
3	R Square	0.988299566
4	Adjusted R Square	0.986949516
5	df	6
6	F	732.0465761
7	Significance F	2.19231E-48
8	P-value (Intercept)	2.92542E-08
9	Correlation Coefficient	0.993

Discussion

After individually analyzing the two crops, Figure 8 shows a comparison of cob sample volume data from both cycles to address seasonal variations in the crop. It is observed from Figure 8 that cycle-I exhibits a broader volume distribution as compared to cycle-II. The mathematical model derived in cycle-II demonstrates greater accuracy in comparison to the volume accuracy obtained in cycle-I. This improved performance of the mathematical model in cycle-II could be attributed to the shorter growth time span of 55 days at the time of harvest as compared to 85 days at the time of harvest in cycle-I. Thus, the present study introduces a unique approach to yield prediction, which contrasts with much of the existing literature, which often focuses on experimental or observational studies. The high correlation coefficients and low P-values in this study reinforce the accuracy of the developed mathematical models, surpassing many conventional methods in precision. This significant improvement could be attributed to the detailed consideration of six fruit traits in the models, enhancing their specificity and predictive accuracy.

The results observed in the presented model were compared with those of models already employed for crop yield prediction. In a study (24), a mathematical model was derived to study the biomass production of crops across various regions of the Republic of Kazakhstan. The model consisted of eight coupled non-linear equations involving six parameters, namely a positive dimensionless parameter, optimum temperature for photosynthesis, the optimum moisture content in the meter layer of soil, a constant representing consumption of biomass at zero temperature, the basic respiration temperature, and an empirical coefficient varying with region and crops. These parameters were calculated for each region of the Republic of Kazakhstan for twenty-one years, from 2000 to 2021. A correlation of 84% was observed between the estimated yield and the actual yield. For cross validation, the model was applied to the spring wheat crop, leading to a reduced correlation of 70%. This indicates that the model was unsuitable for predicting the yield of various crops produced under variable meteorological conditions. Furthermore, in our paper, the estimated and actual yield values exhibit a stronger correlation compared to this study. Kumar (25) presented a mathematical model based on fuzzy logic to forecast rice crop yield. Time series yield and weather data for 27 years from 1981 to 2007 for the Pantnagar region in India were used. To develop the model, six weather average weekly parameters, namely temperature, relative humidity, sunshine hours, total rainfall, number of rainfall days, and pan evaporation, were used. During the testing phase, the root mean square error between the observed and estimated crop yields was

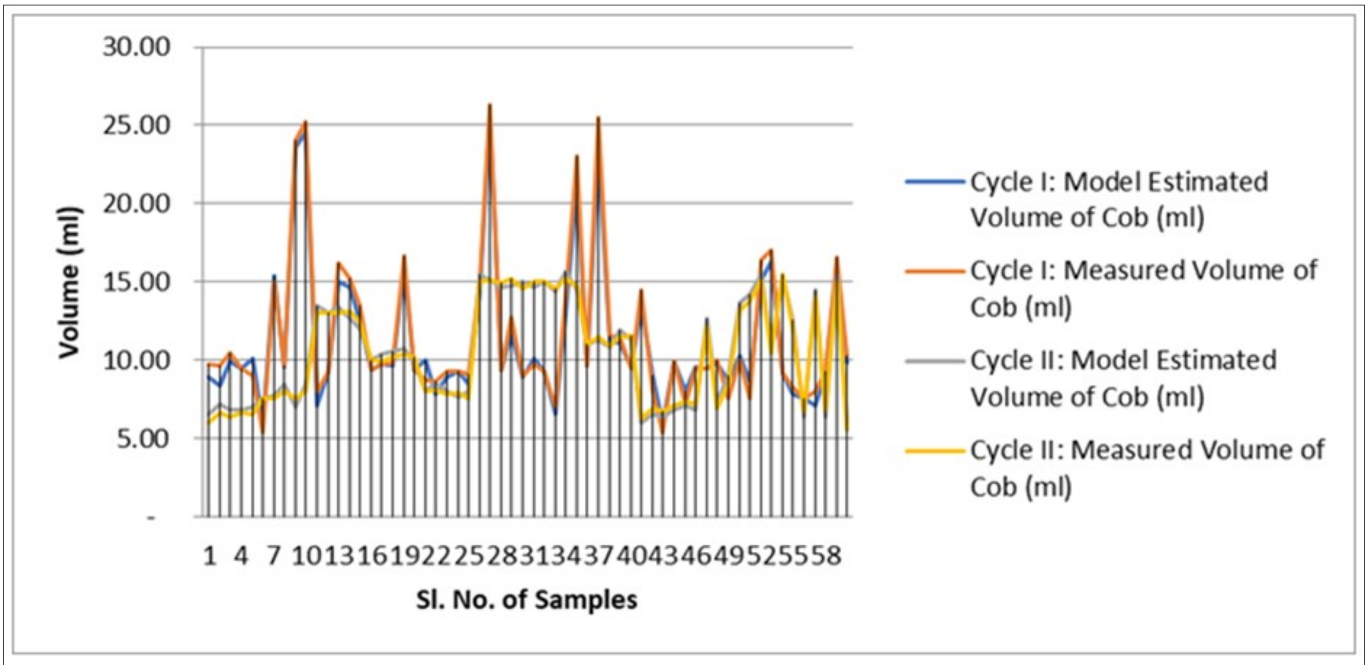

Fig. 8. Comparison of Estimated Volume of Corn by Model and Measured Volume of Corn of 60randomly selected samples at harvest of Both Cycles

measured as 1.756, further validating our presented model as accurate or potentially superior in terms of precision and the parameters used for model derivation.

Conclusion

The main driving mechanism behind the results of this research on baby corn yield estimation revolves around mathematical models derived from six fruit traits. These models are used to estimate the cob volume, demonstrating a high degree of accuracy with correlation coefficients of 0.992 and 0.993 for two crop cycles. A deeper synthesis of the results suggests that the models' validity is confirmed by statistical measures like R^2, adjusted R^2, F-test, P-value, and correlation coefficient. The significant agreement between actual and estimated cob volumes in both crop cycles supports this. One original finding from this research is the models' potential to detect the impacts of climate change on baby corn yields. This is inferred from any deviations in estimated volume from the actual volume, considering other internal and external factors remain constant. Moreover, the successful application of these models to baby corn indicates potential for their use in other crops, especially those with cone-shaped or cylindrical fruit volumes. The irregular distribution observed in the six growth parameters underscores the complexity of yield prediction, reinforcing the importance of this research. This study also exemplifies the integration of advanced mathematics and traditional agriculture, potentially setting a new standard for efficient, sustainable farming practices. In conclusion, the research hypotheses are confirmed, as suggested by the high correlation coefficients between the estimated and measured cob volumes in both crop cycles (0.992 and 0.993 respectively) and the P-value $\leq$ 0.01, indicating high statistical significance. Furthermore, the similarity in trends between estimated and actual cob volumes for both cycles strengthens the validity of the developed mathematical models, thus confirming the original research hypotheses.

Scope of Future Research

Having a mathematical understanding of patterns in baby corn crop production can help formulate effective and efficient solutions to these issues in the short term. The work could be extended by modifying the mathematical model to take into consideration vegetative growth stages or other growth parameters in future studies. This adjustment would allow for estimating the growth trajectory and yield of this crop many days before the final harvest in subsequent crops of the same season, considering the prevailing agro-climatic conditions. Such an approach would yield both economic and ecological benefits for society. The use of mathematical tools in estimation can also contribute to reducing manpower, optimizing resource utilization, and minimizing energy waste in the field.

The present mathematical models derived in this study could be beneficial for any crop having a cone-shaped or cylindrical-shaped fruit volume. This model is applicable under specific field conditions and agro-climatic conditions, thus expanding its utility. However, research by Maroušek and coworkers (26, 27) suggests that the inclusion of factors such as agro-climatic conditions could financially optimize a model and enhance production. Along with this, more research is required for crop yield estimation in the case of crops exhibiting irregular or non-geometrical fruit or vegetable shapes. Additionally, the derivation of non-linear mathematical models could also provide a better understanding of other mathematical concepts and techniques by enhancing the accuracy of crop yield estimation.

The field of agriculture has been experiencing numerous advancements and innovations recently, driven by the increasing challenges of climate change, food security, and sustainability. A key trend is the intersection of agriculture and nanotechnology to improve the various aspects of plant growth and developmental phases, beginning with seed germination (28). The application of nanotechnology in agriculture represents an exciting direction, potentially improving crop yields, enhancing resource efficiency, and mitigating environmental impact. The use of artificial intelligence (29) and advanced analytics could improve the precision of existing models. Furthermore, a cyber-physical system approach can be taken to incorporate real-time agro-climatic data for better yield prediction (30-31).

The current study reflects the integration of advanced mathematical techniques into agriculture. By developing precise models for yield estimation based on cob volume, the study addresses the need for improved crop yield prediction, which is crucial for resource management and food security. All these trends - nanotechnology, use of artificial intelligence, cyber-physical production networks, deep learning-assistance, real-time advanced analytics, and mathematical modeling, epitomize the growing importance of cross-disciplinary approaches in modern agriculture.

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Authors contributions

The study was conceived by KB and NR. The material preparation and field work were designed by JSB, KB and NR. All authors were involved in data collection. NR, AS, KB and SG (Savita Garg) did data analysis. KB and NR drafted and critically revised the work and all authors approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None.

References

1. Solomon S, Qin D, Manning M,Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL, editors. Climate change 2007: The physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.2007;p.1-10.
2. Challinor AJ, Watson J, Lobell DB, Howden SM, Smith DR, Chhetri N. A meta-analysis of crop yield under climate change and adaptation. Nat Clim Change. 2014;4:287-91. https://doi.org/10.1038/nclimate2153
3. Liu Y, Li N, Zhang Z, Huang C, Chen X, Wang F. The central trend in crop yields under climate change in China: A systematic review. Sci of the Total Environ. 2020;704:1353-55. https://doi.org/10.1016/j.scitotenv.2019.135355
4. Talwar S, Tayal P, Kumar S, Bamel K, Prabhavathi V. Climate change: A threat to biodiversity. In: Proceedings of National Conference on “Climate Change: Impacts, Adaptation, Mitigation Scenario and Future challenges in Indian Perspective”. 2015;p. 84-93.
5. Talwar S, Bamel K, Prabhavathi. Impact of elevated temperature and carbon dioxide on seed physiology and yield. Plant Science Today. 2022a;9(sp):85-91. https://doi.org/10.14719/pst.2059
6. Talwar S, Bamel K, Prabhavathi, Mal A. Effect of high temperature on reproductive phases of plants- A review’. Nat Env Poll Tech. 2022b;21(4):1887-92. https://doi.org/10.46488/NEPT.2022.v21i04.043
7. Wing IS, De Cian E, Mistry MN. Global vulnerability of crop yields to climate change. J Environmental Economics and Management. 2021;109:1024-62. https://doi.org/10.1016/j.jeem.2021.102462
8. Bamel K, Bamel JS, Rani N, Pathak SK, Gahlot S, Singh RN. Crop yield prediction using satellite remote sensing based methods. Int J of Botany Stud. 2022a;7:35-40. https://www.botanyjournals.com/assets/archives/2022/vol7issue2/7-1-125-326.pdf
9. Rani N, Bamel K, Shukla A, Singh N. Analysis of five mathematical models for crop yield prediction. South Asian J Exp Biol. 2022;12(1):46-54. https://doi.org/10.38150/sajeb.12(1).p46-54
10. Basso B, Liu L. Seasonal crop yield forecast: Methods, applications and accuracies. In: D.L. Sparks (eds) Advances in Agronomy, Academic Press. 2019;154:201-55. https://doi.org/10.1016/bs.agron.2018.11.002
11. Bamel K, Rani N, Bamel JS, Gahlot S, Singh RN, Pathak SK. Current approaches and future perspectives in methods for crop yield estimation. Bull Environ Pharmacol Life Sci. 2022b;1:243-47. https://bepls.com/special_issue(1)2022/37.pdf
12. Singh AK, Kumar R, Bohra JS, Kumawat N. Fodder yield, nutrient uptake and quality of baby corn (*Zea mays* L.) as influenced by NPKS and Zn fertilisation. Res Crops. 2015;16:243-49. http://dx.doi.org/10.5958/2348-7542.2015.00036.4
13. Aggarwal PK, Kalra N, Chander S, Pathak, H. Info Crop: a dynamic simulation model for the assessment of crop yields, losses due to pests and environmental impact of agro-ecosystems in tropical environments. I. Model description. Agric Syst. 2006;89:1-25.https://doi.org/10.1016/j.agsy.2005.08.001
14. Bozokalfa MK, Kilic M. Mathematical modelling in the estimation of pepper (*Capsicum annuum* L.) fruit volume. Chilean J Agricultural Res. 2010;70:626-32. https://doi.org/10.4067/S0718-58392010000400013
15. Bresler E, Dagan G. Variability of yield of an irrigated crop and its causes: 1. Statement of the problem and methodology. Water Resour Res. 1988;24:381-87. https://doi.org/10.1029/WR024i003p00381
16. Hochmuth GJ, Cantliffe DJ, Soundy P. A comparison of three mathematical models of response to applied nitrogen: A case study using lettuce. Hort Sci. 1998;33:5. https://doi.org/10.21273/HORTSCI.33.5.833
17. Kropff MJ. Modelling the effects of weeds on crop production. Weed Res. 1998;28:465-71.https://doi.org/10.1111/j.1365-3180.1988.tb00829.x
18. Madadgar S, Kouchak A, Farahmand A, Davis SJ. Probabilistic estimates of drought impacts on agricultural production. Geophys Res Lett. 2017;44:7799-7807. https://doi.org/10.1002/2017GL073606
19. Magaji AS, Nasir MO. A discrete-time mathematical model for the control of weeds population density towards improving crop yields. Sci World J. 2019;14:74-77.
20. Osama S, Elkholy M, Kansoh RM. Optimization of the cropping pattern in Egypt. Alex Eng J. 2017;56:557-66.https://doi.org/10.1016/j.aej.2017.04.015
21. Overmars KP, de Groot WT, Huigen MG. Comparing inductive and deductive modeling of land use decisions: Principles, a model and an illustration from the Philippines. Human Ecol. 2007;35:439-52.https://doi.org/10.1007/s10745-006-9101-6
22. Green JR, Margerison D. Statistical treatment of experimental data. Elsevier Scientific Publishing Company, New York, USA; 1978.
23. Spiegel MR, Stephens LJ. Schaum’s Outline of Statistics, 3rd ed., McGraw-Hill, Columbus, Ohio, USA; 1998.
24. Sadenova MA, Beisekenov NA, Rakhymberdina MY, Varbanov PS, Klemes JJ. Mathematical modelling in crop production to predict crop yields. Chem Eng Transac. 2021;88:1225-30. https://doi.org/10.3303/CET2188204
25. Kumar P. Crop yield forecasting by adaptive neuro fuzzy inference system. Math TheoryMod. 2011;1:1-7.
26. Maroušek J, Minofar B, Maroušková A, Strunecký O, Gavurová B. Environmental and economic advantages of production and application of digestate biochar. Environ TechInnov. 2023;30:103-09. https://doi.org/10.1016/j.eti.2023.103109
27. Maroušek J, Trakal L. Techno-economic analysis reveals the untapped potential of wood biochar. Chemos. 2022;291:133000. https://doi.org/10.1016/j.chemosphere.2021.133000
28. Maroušek J, Maroušková A, Periakaruppan R, Gokul GM, Anbukumaran A, Bohatá A, Kříž P, Bárta J, Černý P, Olšan P. Silica nanoparticles from coir pith synthesized by acidic sol-gel method improve germination economics. Polymers. 2022;14(2):266. https://doi.org/10.3390/polym14020266
29. Durana P, Perkins N, Valaskova K. Artificial intelligence data-driven internet of things systems, real-time advanced analytics and cyber-physical production networks in sustainable smart manufacturing. Econ Manag Financ Mark. 2021;16:20-30. https://doi.org/10.22381/emfm16120212
30. Zvarikova K, Rowland M, Krulicky T. Sustainable industry 4.0 wireless networks, smart factory performance and cognitive automation in cyber-physical system-based manufacturing. J Self-Govern Manag Econ. 2021;9(4). https://doi.org/10.22381/jsme9420211
31. Kovacova M, Lăzăroiu G. Sustainable organizational performance, cyber-physical production networks and deep learning-assisted smart process planning in Industry 4.0-based manufacturing systems. Econ, Manag Finan Mar. 2021;16(3):41-54.