International Research Journal of Education and Technology

Peer Reviewed Journal, **ISSN 2581-7795**

Effect of Rainfall Factor In Production of Large Cardamom in Sikkim

[1]Ms. Purnima Chettri, [2]Ms. Depika Chettri,

[1] Assistant Professor, Department of IT, Sikkim Skill University, Sikkim.

[2] Vocational Educator IT, Government Secondary School Sardong, Sikkim.

ABSTRACT

The research-based project aims to develop a predictive model for cardamom production in Sikkim using historical rainfall data and the area under cultivation. Given the critical role of agriculture in the region, this project provides a valuable tool for farmers and agricultural planners to forecast production and make informed decisions. The dataset used for this study was obtained from various agricultural records and includes information on actual rainfall in different periods and cardamom production metrics. A linear regression model was trained to predict cardamom production based on four rainfall periods and the area under cultivation. The model's performance was evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2), yielding promising results with an R^2 value of 0.80, indicating a strong predictive capability. To enhance user accessibility, a graphical user interface (GUI) was developed; this interface allows users to input rainfall and area data to obtain predictions for cardamom production. It also provides a detailed analysis page where users can view the actual data, standardized data, and correlation matrices.

Overall, this project demonstrates a comprehensive approach to data analysis and model development, offering a practical application for predicting agricultural yields. The integration of a user-friendly interface further extends the project's utility, making it a valuable resource for stakeholders in Sikkim's agricultural sector.

Keywords- Large Cardamom, Sikkim, Cultivation, Analysis, Climatic Factor, Production, graphical user interface (GUI).

I. INTRODUCTION

The state of Sikkim in northeastern India is tucked away in the eastern Himalayas and is well known for its breath taking landscapes, profusion of animals, and vibrant culture. The main stay of Sikkim's economy and the source of its people's livelihoods is agriculture. The state was proclaimed India's first entirely organic state in 2016 after making impressive progress in organic farming. Large cardamom (Amomum subulastum), one of its many crops, is very important, especially in Sikkim and the West Bengali region of Darjeeling. With 84% of the country's huge cardamom produced in Sikkim, it is the biggest producer in India.

Sikkim has made remarkable strides in organic farming and was declared India's first fully organic state in 2016.Cardamom is widely used as a flavoring agent and is widely used in medicine, including all opathy and Ayurveda (Sunil C. Ketal., 2022) Organic agriculture can be more clearly defined compared to sustainable agriculture and takes its reference point in environmental protection (Chubakumzuk Jamir., 2021). Large cardamom (Amomum subulatum) holds a significant position in agricultural practices, particularly in regions like Sikkim, India. However, the cultivation of large cardamom is intricately tied to the region's climatic conditions, which exert a profound influence on its production. Understanding the impact of climatic factors on large cardamom cultivation in Sikkim is paramount for ensuring sustainable production and addressing challenges posed by climate variability and change. This study aims to delve into the intricate relationship between climatic variables and large cardamom production, shedding light on the key drivers shaping its cultivation landscape in Sikkim. Through a comprehensive analysis, this research endeavors to provide valuable insights into optimizing agricultural practices and mitigating risks associated with climatic fluctuations, thereby fostering the resilience and prosperity of large cardamom farmers in Sikkim. It is generally assumed that the option of organic farming is a practice leading to agricultural development. It is one of the highly priced and expensive spices and rightly called as the ‘green gold’ (Chubakumzuk Jamir.,2021). Sikkim constitutes the lion's share (84%) of large cardamom production in India, where its varieties are cultivated in diverse agro- ecosystems and climatic regimes (Bhawana Kapkoti Negi et al., 2018) Climate change is a global threat to the food and nutritional security of the world.

As greenhouse gas emissions in the atmosphere are increasing, the temperature is also rising due to the greenhouse effect. (Malhi, Kaur and Kaushik, 2021). In recent times, the cultivation of cardamom in Sikkim has witnessed a noticeable decline. The climatic conditions of Sikkim, characterized by its diverse topography ranging from subtropical to alpine zones, pose both opportunities and challenges for large cardamom.

Factors such as temperature, rainfall, humidity, and altitude play critical roles in shaping the growth patterns and productivity of this spice crop. International Centre for Integrated Mountain Development (ICIMOD), 2016, reported that “Agricultural landscape of Sikkim a rapid transformation due to the impact of globalization” (Sushmita Chakraborty et al., 2019). Temperature regimes influence the phonological stages of large cardamom, including flowering, fruit set, and maturation, thereby impacting its yield and quality. While the plant thrives in a moderate temperature range, extreme temperatures can disrupt its growth and development, leading to reduced yields and susceptibility to diseases and pests. Rainfall patterns, another crucial climatic factor, directly influence soil moisture levels, which are essential for the germination, growth, and flowering of large cardamom plants. Excessive rainfall during the monsoon season may lead to water logging and soil erosion, adversely affecting plant health and productivity.

Conversely, inadequate rainfall or drought conditions can result in water stress and stunted growth, thereby limiting yield potential. Humidity levels, particularly during the monsoon and post-monsoon seasons, influence disease incidence and spread, posing significant challenges to large cardamom cultivation. High humidity coupled with warm temperatures creates favorable conditions for fungal and bacterial diseases, such as rhizome root and leaf spot, which can cause extensive damage to crops if left unchecked. Altitude is a defining factor in large cardamom cultivation, with optimal growing conditions typically between 800 to 1500 meters above sea level. Higher altitudes provide cooler temperatures and well- drained soil to the cultivation of high quality cardamom, while lower altitudes may experience higher pest pressure and disease incidence. Accurate models mapping weather to crop yields are important not only for projecting impacts to agriculture, but also for projecting the impact of climate change on linked economic and environmental outcomes, and in turn for mitigation and adaptation policy.

However, over the past few decades, the production of large cardamom has faced numerous challenges, primarily due to changing climatic conditions. Temperature fluctuations pose a significant threat, as the ideal growth of large cardamom is highly sensitive to temperature changes. Extreme heat or cold can affect the flowering and fruiting stages, leading to reduced yields. Additionally, rainfall variability has become a critical concern. Large cardamom requires specific moisture levels, and inconsistent rainfall patterns, including both droughts and excessive rainfall, can disrupt the water balance, affecting plant health and productivity. Moreover, changes in climate can lead to new pest and disease challenges. Warmer temperatures and increased humidity create favorable conditions for pests and pathogens, posing significant threats to large cardamom crops. The primary objective of this study is to explore the intricate relationship between climatic variables (such as temperature and rainfall) and large cardamom production. By understanding these dynamics, the study aims to identify which climatic variables have the most significant impact on large cardamom yields.

Additionally, rainfall variability has become a critical concern. Large cardamom requires specific moisture levels, and inconsistent rainfall patterns, including both droughts and excessive rainfall, can disrupt the water balance, affecting plant health and productivity. Moreover, changes in climate can lead to new pest and disease challenges. Warmer temperatures and increased humidity create favorable conditions for pests and pathogens, posing significant threats to large cardamom crops.

This study aims to delve into the intricate relationship between climatic variable rainfall and large cardamom production. Understanding how these climatic factors impact cardamom cultivation is crucial for developing strategies to enhance productivity and mitigate adverse effects. Ultimately, our research seeks to contribute to the resilience and prosperity of large cardamom farmers in Sikkim.

OBJECTIVE OF THE STUDY

- To compile data from multiple sources systematically.
- To analyze the production based on different climatic factors.
- To analyze the production levels of Sikkim with production of India.

II. REVIEW OF LITERATURE

The following are the investigation of the different scholarly articles for the study of Crop Production:

Sarkar et al. (2024): The paper focused on the conceptualization and characterization of large cardamom cultivation in the Eastern Himalayas of West Bengal. They basically search into understanding the conceptual framework surrounding of large cardamom cultivation in this region, examining factors such as geographical, ecological, and socio-economic aspects. Their study contributed insights into the challenges, opportunities, and potential strategies for enhancing large cardamom cultivation in the region, thus aiding farmers, researchers, and policymakers in optimizing agricultural practices and promoting sustainable development. **Shrijana Poudyal et al. (2023):** The paper conducted a survey paper on "Land Suitability for Large Cardamom in West Sikkim". The study likely aimed to assess the suitability of land for large cardamom cultivation in the region of West Sikkim. Large cardamom is cash crop grown in the Sikkim region, and understanding the factors that influence its growth and productivity is essential for sustainable agriculture. Additionally, the study may have identified potential challenges and opportunities for improving large cardamom cultivation practices in the region, contributing to the sustainable development of agriculture in Sikkim. **Patrush Lepcha et al. (2023):** The paper proposed the relationship between elevation and large cardamom productivity in Sikkim, examining how factors such as temperature, precipitation, and soil quality vary with altitude and influence crop yield. The study aims to provide insights for optimizing cultivation practices to maximize productivity at different elevations. It may also discuss how farmers can optimize their practices based on elevation to maximize productivity.

Muthusamy Murugan et al. (2023): The paper focused the connections between cardamom cultivation practices and the surrounding environmental conditions common in the Indian cardamom hills. By investigating these interrelationships, the paper aims to shed light on sustainable agricultural practices that can be employed in the region. **Sunil C. K. et al. (2022):** The paper focused on detecting diseases in cardamom plants, specifically Colletotrichum Blight and Phyllosticta Leaf Spot, using deep learning techniques. It employed the U2-Net for background removal and the Efficient Net V2 model for disease detection. The proposed approach achieved a high detection accuracy of 98.26%, highlighting the efficacy of deep learning in this domain. However, limitations such as data availability, model interpretability, computational resources, and transferability should be considered when interpreting the results. **Colombo-Mendoza et al. (2022):** The paper introduces an innovative smart farming system that harnesses Internet of Things (IoT) sensors and cloud analytics to revolutionize agricultural practices. By integrating IoT technology, the system enables real-time monitoring of various environmental parameters crucial for crop growth, such as soil moisture, temperature, and humidity. Furthermore, the utilization of cloud analytics allows for the aggregation and analysis of vast amounts of data collected by the sensors, providing farmers with actionable insights and decision support tools.

Vineeta et al. (2021): The paper proposed an examination of the ecosystem services of traditional large cardamom-based agro forestry in the Sikkim and Darjeeling Himalayas. Their study likely discusses the ecological and socio-economic advantages of these systems, underscoring their significance for sustainable development in the region. Overall, the study likely aims to highlight the importance of preserving and promoting traditional agro forestry practices for sustainable development in the Himalayan region. **Gurdeep Singh Malhi et al. (2021):** The paper conducts a comprehensive review of the current body of literature related to the impact of climate change on agriculture. It arrange findings from various studies to make clear how rising temperatures and increasing levels of carbon dioxide (CO_2) in the atmosphere influence key aspects of agricultural systems. Specifically, the review highlights the physiological responses of plants to these environmental changes, including changes in growth patterns, photosynthesis rates, and water use efficiency. Additionally, it discusses the implications of climate change-induced shifts in pest populations and their potential consequences for crop yields and food security. **Saranya et al. (2020):** The paper proposes the application of machine learning techniques to classify soil types based on their nutrient composition, with the ultimate goal of assisting farmers in predicting suitable crops for different soil conditions. This innovative approach holds the potential to significantly enhance India's agricultural productivity by providing farmers with valuable insights into soil characteristics and crop suitability. The paper's proposal to use machine learning for soil classification represents a promising advancement in agricultural technology with significant implications for India's agricultural sector. By harnessing the power of data-driven insights, this approach has the potential to revolutionize how farmers manage their land, leading to increased productivity, profitability, and resilience in the face of evolving environmental challenges.

Kabita Gurung et al. (2020): The paper proposed the emergence of Curvulariaera grostidisas a new threat to large cardamom cultivation in Sikkim, specifically causing leaf blight. The paper probably discusses the symptoms, spread, and impact of this fungal pathogen on large cardamom plants. Additionally, it may delve into the epidemiology of the disease, including factors contributing to its spread and methods for its management. Overall, the study likely aims to raise awareness about the threat posed by Curvulariaera grostidisas and provide recommendations for mitigating its impact on large cardamom production in Sikkim.

Mayank Champaneri et al. (2020): The paper employs the Random Forest algorithm in conjunction with weather data for the prediction of crop yields, offering valuable support to both farmers and policy makers in making informed decisions. By leveraging machine learning techniques, particularly Random Forest, the study aims to provide accurate forecasts of crop yields based on historical weather data. This approach holds promise for enhancing agricultural productivity and informing policy interventions aimed at addressing food security and rural development. **T Raghav Kumar et al. (2018):** The paper proposes a Smart IoT-based Agriculture system integrating IoT, machine learning, and Arduino technology. It aims to enhance crop management by providing real-time data on temperature and soil moisture content. The system seeks to improve yield and product quality while reducing wastage. However, it may face limitations such as reliance on internet connectivity, particularly in rural areas. **Andrew Crane-Droesch (2018):** The paper introduces as parametric deep neural network to model crop yield dependence on weather, showing superior predictive performance over classical methods. It forecasts climate change impacts on corn yield, offering less pessimistic projections in warm regions compared to traditional statistical approaches.

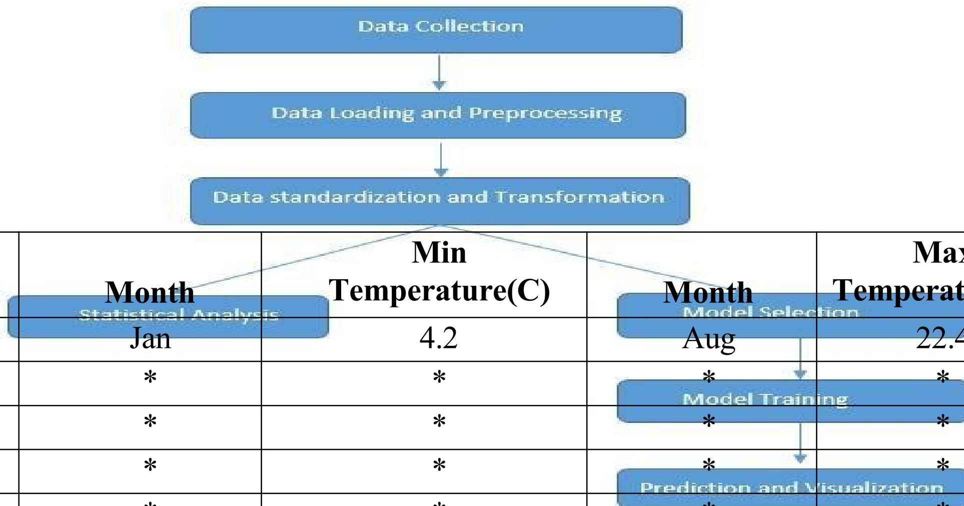
Liakos et al. (2018): The paper offers a comprehensive review of the applications of machine learning in agriculture, emphasizing its pivotal role in various aspects of farm management, including crop, livestock, water, and soil management .By leveraging machine learning algorithms, farmers and agricultural stakeholders can harness the power of data-driven insights to optimize production practices, improves our allocation, and enhance decision-making processes across the agricultural value chain. **Bhawana Kapkoti Negi et al. (2018):** The paper proposed the status of large cardamom farming in Sikkim within the context of modern economic changes. It show traditional farming practices are adapting to factors like globalization and technological advancements, aiming to understand the challenges and opportunities for sustainable cultivation. Overall, the paper likely aim stop insights into the intersection of traditional farming practices with modern economic forces in the context of large cardamom cultivation in Sikkim.

Jharna Majumdar et al. (2017): The paper employs a variety of data mining techniques, including Partitioning. Around Partitioning Around Medoids, Clustering Large Applications (CLARA), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Multiple Linear Regression (MLR), to optimize crop production parameters and enhancer to climate change. By leveraging these techniques, the study aims to extract valuable insights from agricultural data sets, ultimately improving decision-making processes and increasing agricultural resilience in the face of climate variability.

Anjana YA et al. (2016): The paper research utilized machine learning methods like k-NN and Decision Trees, along with image processing, to automate cardamom grading. It improved efficiency and accuracy, potentially reducing costs and processing time.

III. RESEARCH METHODOLOGY

The secondary data were collected from the different sources like Agricultural Department, Horticulture Department, Spices Board, Krishi Bhawan etc. Raw data were collected directly from its sources without any processing, formatting and analysis. It can forms such as numbers, alphabets and more. Researcher showed the analysis of past year Data of Temperature, Rainfall and Production of Large cardamom in Sikkim thorough this systematic study.



Year	Month	Min Temperature(C)	Month	Max Temperature(C)
2000	Jan	4.2	Aug	22.4
2001	*	*	*	*
2002	*	*	*	*
2003	*	*	*	*
2004	*	*	*	*
2005	Jan	1	Jun	31
2006	Jan	5	May	27
2007	Feb	2	May	26
2008	Jan	0	Jun	26
2009	Jan	5	Jun	25
2010	Jan	3	Jun	27
2011	Jan	1.6	May	25.6
2012	Jan	2.2	May	25.5
2013	Oct	2.6	Jun	25
2014	Jan ,Feb	3.6	Nov	29.2

Followings are the created datasets from the collected data from different sources as Agricultural Department, Horticulture Department, Spices Board, Krishi Bhawan.

2015	Mar	1	Jun	25.3
2016	Jan	3.3	Oct	26.3
2017	Jan	2.5	Jul	26.4
2018	Jan, Dec	2.1	Jul	26.8
2019	Dec	2.9	Jun	27.5
2020	Apr	2.2	Jun	26.1
2021	Dec	2.8	May	26.6
2022	May	1.1	Jun	28
2023	*	*	*	*

Raw Data of Rainfall and Production of Large Cardamom in Sikkim:

Raw data of Temperature of Sikkim from past 23 years (2000- 2023) are collected directly from its source without any processing, formatting and analysis. It has many forms such as numbers, alphabets, etc.

		Temperature						Rainfall				
Year	Min Temp	Month	Month	Max Temp	Month	Actual Rainfall	Month	Actual Rainfall	Month	Actual Rainfall	Month	Actual Rainfall
2000	4.2	Jan	Aug	22.4	*	*	*	*	*	*	*	*
2001	*	*	*	*	*	*	*	*	*	*	*	*
2002	*	*	*	*	*	*	*	*	*	*	*	*
2003	*	*	*	*	*	*	*	*	*	*	*	*
2004	*	*	*	*	*	*	*	*	*	*	*	*
2005	1	Jan	Jun	31	Mar-May	509	June-Sept	1813	Oct-Dec	291	Jan-Feb	12
2006	5	Jan	May	27	Mar-May	433	June-Sept	1708	Oct-Dec	145	Jan-Feb	91
2007	2	Feb	May	26	Mar-May	405	June-Sept	2063	Oct-Dec	86	Jan-Feb	36
2008	0	Jan	Jun	26	Mar-May	195	June-Sept	2098	Oct-Dec	112	Jan-Feb	4
2009	5	Jan	Jun	25	Mar-May	473.9	June-Sept	1530	Oct-Dec	264.6	Jan-Feb	6.5
2010	3	Jan	Jun	27	Mar-May	492.9	June-Sept	2194	Oct-Dec	116.4	Jan-Feb	25.3
2011	1.6	Jan	May	25.6	Mar-May	375.6	June-Sept	1865.1	Oct-Dec	64.8	Jan-Feb	30.1
2012	2.2	Jan	May	25.5	Mar-May	217.1	June-Sept	2103.8	Oct-Dec	91.1	Jan-Feb	594.9
2013	2.6	Oct	Jun	25	Mar-May	266.3	June-Sept	1434.1	Oct-Dec	59.5	Jan-Feb	807.7
2014	3.6	Jan,Feb	Nov	29.2	Mar-May	65.1	June-Sept	1925.5	Oct-Dec	19.3	Jan-Feb	617
2015	1	Mar	Jun	25.3	Mar-May	162.2	June-Sept	1980.2	Oct-Dec	42.9	Jan-Feb	763.8
2016	3.3	Jan	Oct	26.3	Mar-May	128.3	June-Sept	1818	Oct-Dec	76.9	Jan-Feb	733.4
2017	2.5	Jan	Jul	26.4	Mar-May	178.3	June-Sept	1997.1	Oct-Dec	29.2	Jan-Feb	669
2018	2.1	Jan, Dec	Jul	26.8	Mar-May	198.1	June-Sept	2156.6	Oct-Dec	57.4	Jan-Feb	693.1
2019	2.9	Dec	Jun	27.5	Mar-May	110	June-Sept	1825.1	Oct-Dec	90.3	Jan-Feb	714.6
2020	2.2	Apr	Jun	26.1	Mar-May	183.4	June-Sept	2416.3	Oct-Dec	86.4	Jan-Feb	664
2021	2.8	Dec	May	26.6	Mar-May	347.7	June-Sept	1798	Oct-Dec	68.9	Jan-Feb	828.8
2022	1.1	May	Jun	28	Mar-May	300.5	June-Sept	2000	Oct-Dec	175.8	Jan-Feb	826.9
2023	*	*	*	*	Mar-May	303.4	June-Sept	1753.6	Oct-Dec	99.9	Jan-Feb	655.6

Raw Data of Temperature of Sikkim

The production of Large Cardamom in Sikkim has experienced notable fluctuations over the past two decades. This variation is a subject to significant interest for stakeholders, including farmers, policymakers, and researchers. To understand and predict these changes, data has been meticulously collected from various authoritative sources such as the Agricultural Department, Horticulture Department, Spices Board, and Krishi Bhawan. This data spans from 2005 to 2023 and encompasses various factors affecting cardamom production, including temperature, rainfall, and cultivation area. For this study, we focus on predicting the future production of Large Cardamom by analyzing two critical variables: the cultivated area and rainfall. These two factors are chosen due to their direct and significant impact on the growth and yield of cardamom plants. While other variables like temperature and soil quality also play crucial roles, the scope of this model is confined to area and rainfall to simplify the analysis and enhance the model's predictive capabilities. The raw data, obtained directly from its sources, contains a mix of formats including numerical figures, alphabets, and possibly other forms. Before building the predictive model, this raw data undergoes extensive preprocessing to ensure accuracy and consistency. The preprocessing steps include cleaning, formatting, and handling missing values, which are essential for generating reliable predictions. The objective of this predictive model is to provide actionable insights into future cardamom production based on historical data trends of cultivated area and rainfall. However, cardamom cultivation is highly sensitive to climatic conditions, particularly rainfall and the area of cultivation. Understanding these dynamics is crucial for maintaining and potentially increasing production levels.

The study found the vast difference between the past year and present production of Large cardamom in Sikkim, West Bengal, Kerala, Tamil Nadu and Karnataka. we aim to create a predictive model for Sikkim's large cardamom production. It has developed a user-friendly tool where user can input data and get production projections in order to improve usability. For farmers and agricultural planners, this tool is an invaluable resource that helps with well-informed decision-making in Sikkim's agriculture sector.

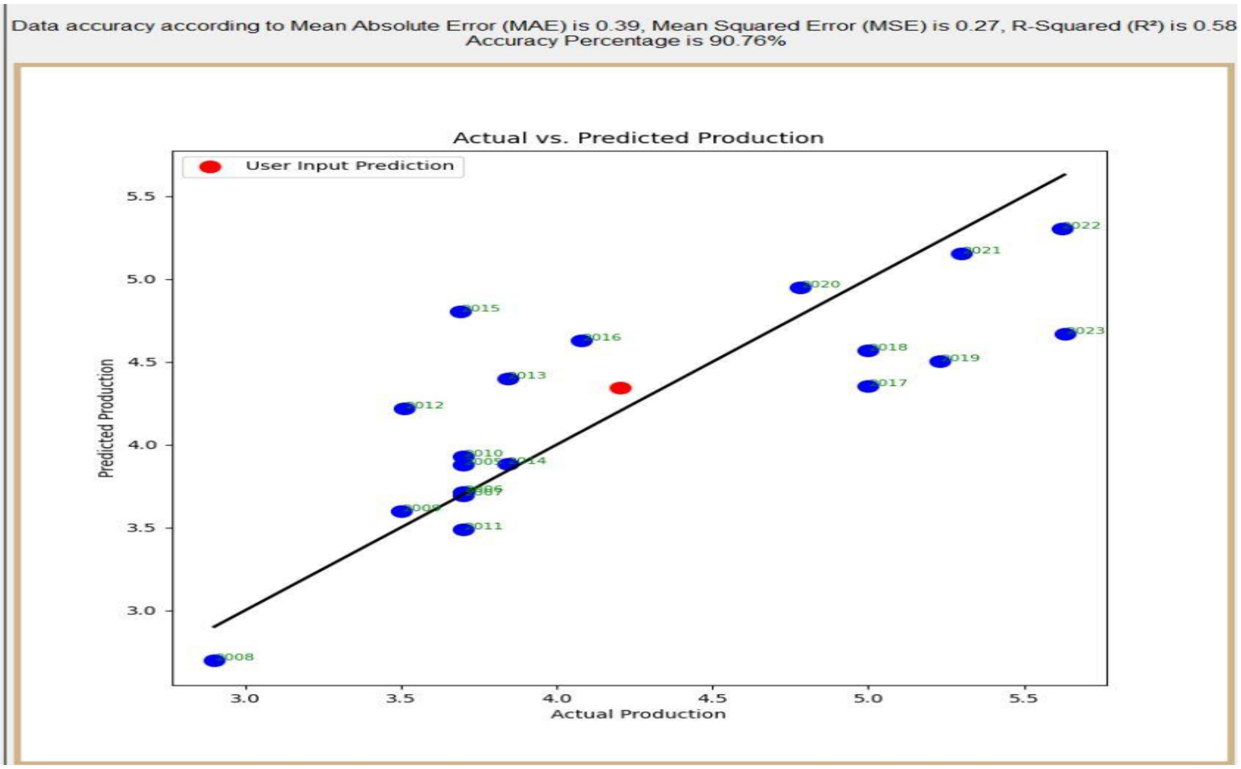
IV. RESULT AND DISCUSSION

This table appears to contain data related to production of large cardamom with various variables. The rainfall data, given in columns B to E, reflects different periods which are crucial for assessing the impact of precipitation on production. This data, before standardization, varies in scale and units, highlighting the need for preprocessing to Snormalize the values for meaningful analysis and comparison.

◢		B	C	D	E	F	G	H
1		Actual Rai	Actual Rai	Actual Rai	Actual Rai	Area	Productior	Yield
2	5	509	1813	291	12	24.8	3.7	0.15
3	6	433	1708	145	91	24.8	3.7	0.15
4	7	405	2063	86	36	24.8	3.7	0.15
5	8	195	2098	112	4	12.8	2.9	0.23
6	9	473.9	1530	264.6	6.5	24.7	3.5	0.14
7	0	492.9	2194	116.4	25.3	24.8	3.7	0.15
8	1	375.6	1865.1	64.8	30.1	24.8	3.7	0.15
9	2	217.1	2103.8	91.1	594.9	15.02	3.51	0.23
10	3	266.3	1434.1	59.5	807.7	16.01	3.84	0.24
11	4	65.1	1925.5	19.3	617	16.01	3.84	0.24
12	5	162.2	1980.2	42.9	763.8	22.76	3.69	0.16
13	6	128.3	1818	76.9	733.4	23.08	4.08	0.18
14	7	178.3	1997.1	29.2	669	18	5	0.28
15	8	198.1	2156.6	57.4	693.1	18	5	0.28
16	9	110	1825.1	90.3	714.6	21.8	5.23	0.24
17	0	183.4	2416.3	86.4	664	23.31	4.78	0.21
18	1	347.7	1798	68.9	828.8	22.35	5.3	0.23
19	2	300.5	2000	175.8	826.9	22.15	5.62	0.25
20	3	303.4	1753.6	99.9	655.6	22.17	5.63	0.25

International Research Journal of Education and Technology

Peer Reviewed Journal, **ISSN 2581-7795**



The standardized data table has the same variables as the raw data but has been transformed to have a mean of zero and a standard deviation of one. This transformation makes the data consistent and comparable across different variables.

	A	B	C	D	E	F	G	H
1	Year	Actual Rai	Actual Rai	Actual Rai	Actual Rai	Area	Productio	Yield
2	2005	1.705184	-0.4689	2.67214	-1.3377	0.956723	-0.6602	-1.1746
3	2006	1.136027	-0.9291	0.585048	-1.1027	0.956723	-0.6602	-1.1746
4	2007	0.926338	0.626958	-0.2584	-1.2663	0.956723	-0.6602	-1.1746
5	2008	-0.6463	0.780376	0.113308	-1.3615	-2.2028	-1.6517	0.509729
6	2009	1.442323	-1.7094	2.294748	-1.354	0.930393	-0.908	-1.3851
7	2010	1.584612	1.201178	0.176207	-1.2981	0.956723	-0.6602	-1.1746
8	2011	0.706164	-0.2405	-0.5614	-1.2838	0.956723	-0.6602	-1.1746
9	2012	-0.4808	0.805799	-0.1855	0.395927	-1.6183	-0.8957	0.509729
10	2013	-0.1124	-2.1297	-0.6372	1.028809	-1.3576	-0.4866	0.720269
11	2014	-1.6191	0.024247	-1.2119	0.461654	-1.3576	-0.4866	0.720269
12	2015	-0.892	0.264016	-0.8745	0.898247	0.419605	-0.6726	-0.9641
13	2016	-1.1458	-0.447	-0.3885	0.807836	0.503859	-0.1892	-0.543
14	2017	-0.7714	0.338095	-1.0703	0.616306	-0.8337	0.951104	1.562429
15	2018	-0.6231	1.03724	-0.6672	0.687981	-0.8337	0.951104	1.562429
16	2019	-1.2829	-0.4158	-0.1969	0.751923	0.166844	1.236174	0.720269
17	2020	-0.7332	2.175598	-0.2526	0.601435	0.564416	0.678428	0.088648
18	2021	0.497224	-0.5346	-0.5028	1.091562	0.311655	1.322935	0.509729
19	2022	0.143748	0.350807	1.025338	1.085911	0.258997	1.719554	0.930809
20	2023	0.165465	-0.7293	-0.0597	0.576453	0.264263	1.731949	0.930809

Correlation matrix

The correlation coefficients between various variables Rainfall and area of cultivation are represented numerically in the matrix. The range of these coefficients is -1 to +1, with a perfect negative correlation being represented by a value of -1 (as one variable increases, the other variable decrease). A perfect positive correlation is shown by a value of 1, meaning that so variable rises, the other does too.

	Actual Rainfall	Actual Rainfall	Actual Rainfall	Actual Rainfall
	1	-0.2487	-0.68505	-0.6863
	-0.2487	1	-0.2724	0.00892
	0.68505	-0.2724	1	-0.5231
	-0.6863	0.00892	0.5231	1
Yield	-0.6358	0.14961	-0.4631	0.6987

Model performance metrics

Performance Metrics	Percentage%
Mean Absolute Error (MAE)	0.38
Mean Squared Error (MSE)	0.25
R-squared (R^2)	0.62
Result Accuracy	91 %

Mean Absolute Error (MAE): Measures the average magnitude of errors in predictions, providing a straightforward indication of prediction accuracy. Mean Squared Error (MSE): Penalizes larger errors more than MAE, useful for highlighting significant prediction deviations. R-squared (R^2): Indicates the proportion of variance in the dependent variable that is predictable from the independent variables. Higher values suggest better model performance.

Visualization

Scatter Plot (Actual vs. Predicted Production): A graphical representation showing how closely the model's predictions match actual production values. The closer the points lie to the diagonal line, the better the model's predictions.

Prediction Results

The system predicts cardamom production based on user inputs for rainfall and area, providing a specific production estimate. The predicted value is dynamically displayed in the GUI, offering real-time feedback.

Correlation Analysis

Correlation Matrix: Indicates the strength and direction of relationships between variables, with values ranging from -1 to 1. Higher absolute values suggest stronger relationships.

Discussion

- **Model accuracy and reliability**

The model's performance metrics indicate its ability to predict cardamom production accurately. MAE and MSE, combined with a high R^2 value, suggest that the model is reliable and effective for this task. The accuracy percentage derived from MAPE confirms the model's predictive power, with higher percentages indicating better performance.

- **Influence of input variables**

The correlation matrix provides insights into how different rainfall periods and area size influence cardamom production. Strong correlations between specific rainfall periods and production can guide agricultural planning.

- **User interface and usability**

The Tkinter GUI enhances user interaction by allowing stakeholders to input data easily and receive immediate predictions. The validation of numeric inputs ensures data integrity and usability. The detailed analysis page enables users to explore the dataset, standardized values, and correlation matrices, promoting a deeper understanding of the underlying data.

- **Practical implications**

The system offers valuable predictions that can aid farmers, policymakers, and agricultural planners in making informed decisions about cardamom production. By understanding the impact of rainfall and area on production, stakeholders can optimize resource allocation and improve yield outcomes.

- **Limitations and future directions**

While the current model performs well, it is based on historical data and may not fully account for future changes in climate patterns or other unforeseen factors.
Future enhancements could involve integrating more sophisticated models, incorporating additional variables, and using real-time data for continuous model updates.

V. CONCLUSION

The research project successfully developed a predictive model for large cardamom production in Sikkim using historical rainfall data across four critical periods and the area under cultivation. The use of a linear regression model yielded a high R^2 value of **0.80**, indicating that rainfall patterns and cultivation area significantly influence cardamom yields. The study highlights that both the timing and quantity of rainfall have a measurable impact on agricultural output in this ecologically sensitive region. Furthermore, the development of a **Graphical User Interface (GUI)** enhances the accessibility and usability of the predictive model. This interactive tool enables farmers, researchers, and policymakers to input relevant data and receive accurate forecasts of production, making it an effective instrument for planning and risk mitigation in agriculture.

The research not only confirms the strong dependency of large cardamom yields on rainfall distribution and cultivated area but also showcases the power of data-driven agricultural planning. The practical outcomes of the model reinforce the importance of integrating technology into traditional farming practices in hill regions like Sikkim.

VI. SUGGESTIONS AND EDUCATIONAL IMPLICATIONS

Suggestions

1. **Wider Adoption of Predictive Tools**: Promote the use of the GUI-based predictive model at the community and cooperative levels to assist farmers in planning sowing, irrigation, and harvesting strategies.

2. **Integration with Government Schemes**: Align this model with agricultural planning schemes under the Ministry of Agriculture or Sikkim State Government to support subsidy distribution, crop insurance, and resource allocation.
3. **Real-time Data Integration**: Incorporate real-time rainfall data and satellite observations to make the prediction model dynamic and more responsive to changing weather patterns.
4. **Expansion to Other Climatic Factors**: Include other climatic variables such as temperature, humidity, and soil moisture to improve the model's robustness and overall accuracy.
5. **Farmer Training Programs**: Conduct capacity-building sessions for local farmers to train them in using the GUI tool and interpreting predictive outputs.
6. **Cloud-Based Access**: Develop a cloud-based or mobile app version of the GUI to ensure widespread use, especially in remote villages with limited computing infrastructure.
7. **Community Data Sharing Network**: Establish village-level data recording and sharing systems to continuously update the model with new and accurate field data.

Educational Implications:

1. **Inclusion in Agricultural Curriculum**: This research model can be integrated into university-level syllabi for agricultural science, environmental studies, and data analytics to provide students with hands-on experience in applied predictive modeling.
2. **Skill Development in Agri-Tech**: Encourage students to learn data analysis, machine learning, and interface design through such real-world applications, fostering interdisciplinary skill sets.
3. **Research Extension**: The study opens avenues for further academic research in climate-smart agriculture, offering a framework for future projects involving AI, GIS, and crop simulation modeling.
4. **Use in Farmer Field Schools (FFS)**: Educational institutions and Krishi Vigyan Kendras (KVKs) can use this model as a training tool for farmer field schools to improve digital literacy and predictive farming skills.
5. **Awareness of Climate-Agriculture Link**: This research can help promote awareness about the increasing sensitivity of agriculture to climatic variations and the importance of adaptive, evidence-based strategies.
6. **Policy-Oriented Learning**: The project findings can be used in policy education modules to demonstrate how scientific research and technological tools can guide public policy in agricultural planning and rural development.

DECLARATION OF INTEREST

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Author has participated in the research and writing process independently and have approved the final manuscript.

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to all those who have contributed to the development of this research. Their invaluable insights, guidance, and technical expertise have been instrumental in refining the methodology and enhancing the quality of this work. I appreciate the support and resources that I got from respected Dr. Pradeep Kumar Tiwari, Associate Professor, Sikkim Skill University for his regular support and also the ICFAI University Sikkim. I acknowledge the contributions that have made this research possible. No Agency funded to complete this work.

REFERENCES:

1. A, A.Y.*etal.* (2016) 'IRJCS: Mendeley (Elsevier Indexed) Cite Factor Journal Citations Impact Factor cardamom grading using machine learning', *International Research Journal of Computer Science (IRJCS)*, https://doi.org/10.26562/IRJCS.2019.JNCS10112
2. Ben Ayed, R. and Hanana, M. (2021) 'Artificial Intelligence to Improve the Food and Agriculture Sector', *Journal of Food Quality*. Hindawi Limited. https://doi.org/10.1155/2021/5584754
3. Champaneri, M. *et al.* (2018) 'Crop Yield Prediction Using Machine Learning', *International Journal of Science and Research* [Preprint]. https://doi.org/10.21275/SR20402185927
4. Colombo-Mendoza, L.O.*etal.*(2022): 'Internet of Things-Driven Data Mining for Smart Crop Production Prediction in the Peasant Farming Domain', *Applied Sciences (Switzerland)*, 12(4). https://doi.org/10.3390/app12041940.
5. Crane-Droesch, A. (2018): 'Machine learning methods for crop yield prediction and climate change impact assessment in agriculture' *Environmental Research Letters*, 13 (11). https://doi.org/10.1088/1748-9326/aae159.
6. Golay, S. and Singh, S. B. (2021): *Production and Marketing of Organic Large Cardamom in West District of Sikkim*, *Indian Res. J. Ext. Edu*.
7. Gurung, K. *et al.* (2020) 'Curvulariaera grostidis, a new threat to large cardamom (Amomum subulatum Roxb.) causing leaf blight in Sikkim',*Journal of Bio sciences*, 45(1). https://doi.org/10.1007/s12038-020-00086-7.
8. Hemming, S. *et al.* (2019) 'Remote control of greenhouse vegetable production with artificial intelligence—greenhouse climate, irrigation, and crop production', *Sensors (Switzerland)*, 19(8). Available at: https://doi.org/10.3390/s19081807.
9. Jamir, C. (no date) *Black Sea Journal of Agriculture ORGANIC LARGE CARDAMOM FARMINGINLONGLENGDISTRICT: PROMOTING GROWTH WITH POVERTY REDUCTION*. https://orcid.org/0000-0002-1414-0413.
10. Khaki,S. and Wang, L. (2019): Crop yield prediction using deep neural networks' *Frontiers in Plant Science*, 10. https://doi.org/10.3389/fpls.2019.00621.
11. 'Land suitability for large cardamom' (2023) *International Research Journal of Modernization in Engineering Technology and Science* https://doi.org/10.56726/irjmets43140.
12. Lepcha, P. *et al.* (2023) 'Elevation determines the productivity of large cardamom (Amomum subulatum Roxb.) cultivars in Sikkim Himalaya', *Scientific Reports*, 13(1). https://doi.org/10.1038/s41598-023-47847-6.
13. Liakos, K.G. *et al.* (2018) 'Machine learning in agriculture: A review', *Sensors (Switzerland)*. MDPI AG. https://doi.org/10.3390/s18082674.
14. Lingitz, L., Sihn, W. and Ciani, L. (2020) *Number 1 | 32 of Production Plans using Machine Learning*, *Acta IMEKO*. www.imeko.org.
15. Majumdar, J., Naraseeyappa, S. and Ankalaki, S. (2017) 'Analysis of agriculture data using data mining techniques: application of big data', *Journal of Big Data*, 4(1). https://doi.org/10.1186/s40537-017-0077-4.
16. Malhi, G.S., Kaur, M. and Kaushik, P. (2021) 'Impact of climate change on agriculture and its mitigation strategies: A review', *Sustainability (Switzerland)*. MDPI, pp. 1–21. https://doi.org/10.3390/su13031318.

17. Murugan, M.*etal.*(2023): 'Cardamom agro-environmental inter relationships analysis in Indian cardamom hills', *Frontiers in Climate*, 5. https://doi.org/10.3389/fclim.2023.1107804.
18. Negi, B.K., Joshi, R.K. and Pandey, A. (2018) *Case Study STATUS OF LARGE CARDAMOM (AMOMUM SUBULATUM ROXB.) FARMING SYSTEMS IN THE CHANGINGSCENARIOOFMODERNECONOMICSOFSIKKIM,HIMALAYA*. http://www.sikkimagrisnet.org/General/en/Cardamom_Varieties.aspx.
19. Palanivel,K .and Suria narayanan, C., 'An Approach for Prediction of Crop Yield Using Machine Learning and Big Data Techniques', *International Journal of Computer Engineering and Technology (IJCET)*, 10(3), pp.110–118. http://www.iaeme.com/IJCET/index.asp110.