Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 4, Issue 3, 2026

CROP YIELD PREDICTION USING APPLIED MACHINE LEARNING AND STATISTICAL TECHNIQUES

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DOI: https://doi.org/10.5281/zenodo.19347668

Keywords
Crop yield prediction, Machine learning, Random Forest, Rainfall, Temperature, Agricultural analytics

Article History
Received: 31 January 2026
Accepted: 16 March 2026
Published: 31 March 2026

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Abstract

Accurate crop yield prediction is essential for improving agricultural planning, resource management, and food security in the face of increasing climate variability. This study proposes an integrated framework combining statistical analysis and machine learning techniques to predict crop yield using key environmental and agricultural variables, including rainfall, temperature, pesticide usage, crop type, and geographic location. A comprehensive dataset was compiled and preprocessed to ensure consistency and reliability, followed by exploratory data analysis to identify significant patterns and relationships. A Random Forest regression model was implemented due to its ability to capture nonlinear interactions and handle complex datasets. The model performance was evaluated using standard metrics, including RMSE, MAE, and R^2, demonstrating strong predictive accuracy and robustness. Feature importance analysis further revealed that climatic factors, particularly rainfall and temperature, are the most influential predictors of crop yield. The findings highlight the effectiveness of combining data-driven approaches with agricultural knowledge to enhance prediction accuracy. This study contributes to the development of reliable and scalable predictive systems that can support decision-making in modern agriculture.

Introduction

Agriculture remains a foundational sector for global food security, rural livelihoods, and economic stability, yet crop production is increasingly exposed to climate variability, resource constraints, and rising demand for accurate forecasting systems. In this context, crop yield prediction has become a critical research area because reliable yield estimates support planting decisions, resource allocation, market planning, and policy development. Traditional yield estimation methods often rely on field surveys, historical averages, or simple statistical assumptions, which may be inadequate for capturing the complex interactions among weather, crop type, and agricultural inputs. Recent advances in data-driven analytics have encouraged the use of machine learning techniques for yield prediction because these methods can model nonlinear relationships and

high-dimensional agricultural data more effectively than many conventional approaches. Jeong et al. (2016) demonstrated that Random Forest models could outperform multiple linear regression in predicting global and regional crop yields, highlighting the value of machine learning for agricultural forecasting. Similarly, van Klompenburg et al. (2020), in a systematic review, showed that crop yield prediction research has increasingly shifted toward machine learning and deep learning approaches because of their strong predictive capacity across diverse agricultural settings. These developments indicate that applied machine learning, when combined with relevant climatic and management variables, offers substantial potential for improving crop yield estimation and supporting precision agriculture. The literature shows that several categories of variables are repeatedly identified as major determinants of crop yield, especially rainfall, temperature, soil characteristics, and agricultural inputs such as fertilizers and pesticides. Climate-related variables are particularly influential because crop growth is directly linked to moisture availability and thermal conditions. Kuradusenge et al. (2023) applied machine learning models to predict Irish potato and maize yields using weather data and found that rainfall and temperature were effective predictors across the studied crops. Likewise, Pham et al. (2022) noted that Random Forest, artificial neural networks, linear regression, and gradient boosting models are widely used for crop yield forecasting, especially when climatic and management variables are integrated into the modeling framework. Zhu et al. (2021) further reported that combining agrometeorological indicators with remote sensing variables improved maize yield estimation, suggesting that richer and more integrated datasets can strengthen model performance. More recent regional studies, such as Nikhil et al. (2024), also confirm that crop yield prediction improves when weather, soil, and crop-specific information are jointly considered rather than modeled in isolation. Collectively, these findings show that crop productivity is governed by multidimensional interactions, and therefore accurate prediction requires analytical methods capable of learning such complexity. A growing body of literature has compared different machine learning techniques for crop yield prediction, with ensemble-based methods frequently emerging as strong performers. Random Forest has attracted particular attention because of its robustness, resistance to overfitting, and ability to rank predictor importance. Jeong et al. (2016) provided early evidence of its usefulness at global and regional scales, while Cedric et al. (2022) proposed machine learning-based crop yield prediction for multiple crops and demonstrated the effectiveness of modern data-driven systems in agricultural forecasting. Iniyan et al. (2023) also emphasized that machine learning methods are highly valuable in agricultural decision-making because farming systems generate large volumes of heterogeneous data influenced by multiple environmental and operational factors. Meanwhile, Morales (2023) argued that yield prediction should be understood both as estimation from known explanatory variables and as forecasting from historical patterns, which broadens the methodological scope of agricultural analytics. More recent review work by Jabed et al. (2024) and Shawon et al. (2025) indicates that the field is moving toward broader comparative frameworks involving ensemble learning, deep learning, and hybrid models. Even so, these reviews also suggest that model performance is highly dependent on data quality, local context, feature selection, and the balance between predictive accuracy and interpretability. Despite this progress, the existing literature still reveals several limitations. First, many studies focus either on highly localized datasets or on crop-specific cases, which can reduce generalizability across broader agroecological conditions. Second, some studies prioritize advanced algorithm development without sufficiently integrating interpretable statistical analysis, making it difficult to explain how individual variables influence yield outcomes. Third, although deep learning and remote sensing approaches have expanded the field, these methods often require extensive computational resources or specialized

data that may not be available in many developing-country research settings. Muruganantham et al. (2022) showed that deep learning has strong potential in crop yield prediction, especially with remote sensing, but the adoption of such methods depends heavily on data acquisition and technical capacity. Similarly, Joshi et al. (2024) demonstrated the usefulness of transfer learning for data-scarce regions, yet this also implies that data limitations remain a major challenge in agricultural prediction research. In practical terms, many researchers still need robust models that can perform well using accessible variables such as rainfall, temperature, pesticide use, year, area, and crop type. This creates a continuing need for studies that combine statistical techniques with interpretable machine learning models using structured tabular datasets derived from reliable agricultural and climatic sources. Based on the reviewed literature, the research gap in the present study is clear. Although previous authors have confirmed the usefulness of machine learning for yield prediction, fewer studies have developed an integrated framework that combines descriptive statistics, correlation analysis, trend analysis, and interpretable machine learning within a unified dataset containing yield, rainfall, temperature, and pesticide variables. Many published works emphasize algorithm comparison, but comparatively less attention is given to building a methodologically balanced framework where statistical exploration supports model development and feature interpretation. In addition, while studies such as Kuradusenge et al. (2023) and Jeong et al. (2016) demonstrate the predictive strength of weather-based and Random Forest approaches, there remains a need for applied research that uses accessible multi-factor datasets and clearly explains both the statistical patterns and the machine learning results in a way that is useful for researchers, practitioners, and policymakers. Therefore, this study addresses that gap by developing a crop yield prediction framework that integrates statistical analysis with machine learning techniques using a structured dataset containing climatic and agricultural variables. The study is designed not only to improve prediction accuracy but also to identify the most influential factors affecting yield, thereby contributing to both the methodological and practical literature on agricultural forecasting

Data Collection and Integration

The dataset utilized in this study was compiled from multiple reliable and publicly available sources to ensure accuracy, diversity, and robustness in crop yield prediction. The primary data included crop yield records, pesticide usage, rainfall patterns, and temperature measurements, which were obtained from internationally recognized agricultural and climatic databases. These datasets were integrated into a unified framework to create a comprehensive analytical dataset suitable for machine learning and statistical modeling. The integration process involved aligning data across common attributes such as year, country, and crop type, ensuring consistency and comparability among variables. Special attention was given to maintaining data integrity during merging, as discrepancies in units, formats, and temporal coverage could affect the reliability of the analysis. Furthermore, the dataset encompasses a wide range of geographical regions and climatic conditions, enhancing its generalizability and applicability for predictive modeling. The inclusion of diverse variables allows for a holistic understanding of the factors influencing crop yield, including environmental conditions and agricultural inputs. By combining these datasets, the study ensures that the model is trained on realistic and representative data, capturing both spatial and temporal variability. This comprehensive data collection approach provides a strong foundation for subsequent analytical processes and supports the development of robust predictive models capable of addressing real-world agricultural challenges.

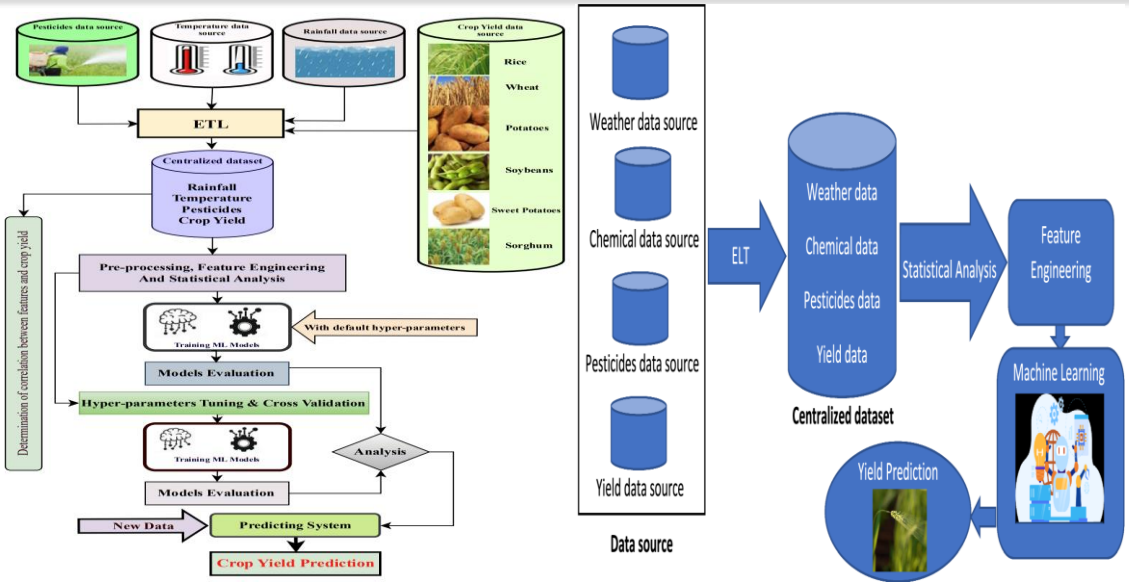

Figure a: Methodological Framework for Crop Yield Prediction

This figure illustrates the structured workflow adopted in this study for predicting crop yield. It begins with data collection from multiple sources, followed by preprocessing steps such as cleaning, normalization, and encoding. Exploratory data analysis is then performed to identify patterns and relationships among variables. Feature engineering enhances model input quality, after which machine learning models are trained and evaluated. Finally, performance metrics are used to assess model accuracy and reliability, leading to meaningful insights for agricultural decision-making.

Data Preprocessing and Feature Engineering

Prior to analysis, the dataset underwent a rigorous preprocessing phase to ensure its suitability for statistical and machine learning applications. This process included handling missing values, removing duplicate records, and correcting inconsistencies in data formatting. Numerical variables such as rainfall, temperature, and pesticide usage were standardized to maintain uniform scales, while categorical variables such as crop type and country were encoded using appropriate techniques to enable their use in machine learning algorithms. Outliers were carefully examined to determine whether they represented genuine extreme conditions or potential data errors, ensuring that the dataset retained meaningful variability without introducing bias. Feature engineering was performed to enhance the predictive capability of the dataset by creating meaningful input variables. Derived features, such as aggregated yearly averages and normalized values, were generated to capture underlying patterns more effectively. The inclusion of these engineered features allows models to better understand relationships between variables and improve prediction accuracy. Additionally, correlation analysis was conducted to identify redundant or highly collinear features, which were either transformed or excluded to reduce model complexity and improve interpretability. This preprocessing and feature engineering stage plays a critical role in ensuring that the dataset is clean, structured, and optimized for advanced analytical techniques.

Statistical Analysis and Exploratory Data Analysis

To gain a comprehensive understanding of the dataset, exploratory data analysis (EDA) and statistical techniques were employed. Descriptive statistics were calculated to summarize the central tendency, dispersion, and distribution of key variables, providing initial insights into the

dataset's characteristics. Correlation analysis was performed to examine the relationships between crop yield and independent variables such as rainfall, temperature, and pesticide usage. These analyses helped identify significant predictors and informed the selection of variables for modeling. Graphical methods, including scatter plots, histograms, boxplots, and time-series plots, were used to visualize patterns, trends, and anomalies within the data. These visualizations provided a deeper understanding of variable interactions and highlighted potential nonlinear relationships that may not be captured through traditional statistical methods alone. Additionally, temporal and spatial analyses were conducted to assess variations in yield across different years and regions, revealing important insights into agricultural performance and environmental influences. The combination of statistical and graphical analyses ensures a thorough exploration of the dataset, enabling the identification of key trends and patterns that inform the modeling process. This step is essential for validating assumptions, detecting anomalies, and establishing a strong analytical foundation for predictive modeling.

Machine Learning Modeling and Evaluation

The predictive modeling phase involved the application of advanced machine learning techniques to estimate crop yield based on the selected input variables. Among various algorithms, the Random Forest regression model was employed due to its robustness, ability to handle nonlinear relationships, and effectiveness in managing high-dimensional data. The dataset was divided into training and testing subsets to evaluate model performance objectively. The model was trained on the training data and validated using the testing data to ensure its generalizability and accuracy. Performance evaluation was conducted using standard metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics provide a comprehensive assessment of prediction accuracy, error magnitude, and explanatory power. Additionally, feature importance analysis was performed to identify the most influential variables contributing to crop yield prediction, offering valuable insights into the underlying factors affecting productivity. The use of machine learning techniques enables the capture of complex interactions among variables, improving prediction accuracy compared to traditional methods. This modeling approach not only enhances the reliability of yield predictions but also provides a scalable framework for future agricultural analytics. Overall, the integration of machine learning with statistical analysis ensures a robust and effective methodology for crop yield prediction.

Results and Discussion

Table 1 presents the descriptive statistical analysis of the variables used in this study, providing an essential overview of the dataset's structure and variability. The results indicate that crop yield exhibits considerable variation across observations, reflecting the influence of diverse environmental and agricultural conditions. The mean yield value represents the central tendency of production levels, while the standard deviation highlights the degree of dispersion, suggesting that yield outcomes are not uniform and are significantly affected by external factors such as climate and management practices. The minimum and maximum values further emphasize the range of variability, indicating the presence of both low- and high-productivity scenarios within the dataset. Climatic variables, including average rainfall and temperature, also demonstrate notable variation, which is critical for modeling purposes. These variations suggest that the dataset captures a wide spectrum of agro-climatic conditions, enhancing the robustness of predictive analysis. Similarly, pesticide usage shows differences across regions and time periods, reflecting varying agricultural intensification levels. The presence of such variability is advantageous for machine learning models, as it allows algorithms to learn complex relationships between input variables and crop yield. Furthermore, the distribution of the dataset appears sufficiently balanced, with no extreme irregularities that could compromise statistical

reliability. This ensures that the dataset is suitable for both regression-based and machine learning approaches. Overall, the descriptive statistics confirm that the dataset is comprehensive, diverse, and well-structured, providing a strong foundation for subsequent analytical procedures. The observed variability and distribution patterns support the reliability of the data and justify its application in advanced crop yield prediction modeling frameworks.

Table 1: Descriptive Statistics

Index	Unnamed: 0	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
count	28242.0	28242.0	28242.0	28242.0	28242.0	28242.0
mean	14120.5	2001.544	77053.332	1149.056	37076.909	20.543
std	8152.907	7.052	84956.613	709.812	59958.785	6.312
min	0.0	1990.0	50.0	51.0	0.04	1.3
25%	7060.25	1995.0	19919.25	593.0	1702.0	16.702
50%	14120.5	2001.0	38295.0	1083.0	17529.44	21.51
75%	21180.75	2008.0	104676.75	1668.0	48687.88	26.0
max	28241.0	2013.0	501412.0	3240.0	367778.0	30.65

Table 2 presents the correlation matrix illustrating the relationships between crop yield and the selected independent variables, including climatic and agricultural factors. The results reveal important insights into the strength and direction of associations among the variables. A positive correlation between crop yield and factors such as rainfall and pesticide use suggests that increases in these variables are generally associated with higher agricultural productivity. This indicates that adequate water availability and crop protection measures play a significant role in enhancing yield outcomes. Conversely, the relationship between temperature and yield may exhibit either positive or negative trends depending on the crop type and regional conditions, highlighting the complex and nonlinear influence of temperature on crop growth. The correlation coefficients also demonstrate that no single variable solely determines yield; instead, crop productivity is influenced by a combination of interacting factors. Moderate correlation values indicate that while variables are related, they are not perfectly dependent, which is beneficial for predictive modeling as it reduces the risk of multicollinearity. This ensures that machine learning algorithms can effectively learn distinct contributions from each feature without redundancy. Additionally, the correlation matrix helps identify the most influential predictors, guiding feature selection for model development. Variables with stronger correlations to yield are particularly valuable for improving model accuracy and interpretability. The matrix also provides an initial validation of the dataset, confirming logical relationships between environmental conditions and agricultural outputs.

Table 2: Correlation Matrix

Index	Unnamed: 0	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
Unnamed: 0	1.0	0.044	0.013	-0.229	-0.316	-0.052
Year	0.044	1.0	0.092	-0.004	0.141	0.014
hg/ha_yield	0.013	0.092	1.0	0.001	0.064	-0.115
average_rain_fall_mm_per_year	-0.229	-0.004	0.001	1.0	0.181	0.313
pesticides_tonnes	-0.316	0.141	0.064	0.181	1.0	0.031
avg_temp	-0.052	0.014	-0.115	0.313	0.031	1.0

Table 3 presents the average crop yield across different crop types, providing valuable insights into variations in productivity among crops included in the dataset. The results indicate that crop yield is not uniform and varies significantly depending on the type of crop, reflecting differences in biological characteristics, growth requirements, and adaptability to environmental conditions. Certain crops exhibit higher average yields, suggesting that they are either more resilient to climatic variability or benefit from better agronomic practices and input utilization. In contrast, crops with lower mean yields may be more sensitive to environmental stress or require more specific growing conditions, which may not be consistently met across regions. The observed variation in yield among crop types highlights the importance of crop-specific analysis in agricultural modeling. It demonstrates that generalized models may not fully capture the unique behavior of each crop, emphasizing the need for tailored predictive approaches. Additionally, the differences in average yield can be attributed to factors such as soil fertility, irrigation practices, and the use of fertilizers and pesticides, which vary across crops and regions. These variations underscore the complexity of agricultural systems and the need to incorporate multiple variables when predicting crop yield. From a machine learning perspective, the crop type variable plays a critical role as a categorical feature influencing yield outcomes. The differences observed in Table 3 validate its inclusion as an important predictor in the modeling process. Furthermore, this analysis provides a foundation for understanding yield distribution patterns, which can improve model training and performance.

Table 3: Crop-wise Mean Yield

Index	hg/ha_yield
Cassava	150479.467
Maize	36310.071
Plantains and others	106041.32
Potatoes	199801.55
Rice, paddy	40730.435
Sorghum	18635.777
Soybeans	16731.093
Sweet potatoes	119057.794
Wheat	30116.268

Yams	114140.346

Table 4 illustrates the average crop yield across different countries, providing a comprehensive overview of spatial variability in agricultural productivity. The results reveal significant differences in mean yield values among countries, highlighting the influence of geographic, climatic, and socio-economic factors on crop production. Countries exhibiting higher average yields are likely benefiting from favorable environmental conditions, advanced agricultural technologies, efficient irrigation systems, and better access to inputs such as fertilizers and pesticides. In contrast, countries with lower average yields may face challenges such as limited access to modern farming techniques, poor soil quality, water scarcity, or adverse climatic conditions. The variation observed across countries emphasizes the importance of location-specific analysis in crop yield prediction. Agricultural productivity is inherently dependent on regional characteristics, including rainfall patterns, temperature regimes, and soil properties. For instance, countries with stable and adequate rainfall combined with moderate temperature conditions tend to achieve higher yields, as these factors support optimal crop growth and development. On the other hand, regions experiencing extreme weather conditions, such as droughts or excessive heat, often show reduced productivity levels. Furthermore, the differences in yield can also be attributed to variations in agricultural policies and management practices. Countries that invest in research and development, mechanization, and sustainable farming practices generally achieve better outcomes. The presence of such disparities in the dataset enhances its suitability for machine learning applications, as it introduces meaningful variability that models can learn from. This variability allows predictive algorithms to capture complex relationships between environmental and management factors and crop yield. From a modeling perspective, the country variable serves as a crucial categorical feature that encapsulates a wide range of underlying factors influencing yield. Including this variable in predictive models can significantly improve their accuracy by accounting for regional heterogeneity. Additionally, the insights derived from this table can assist policymakers and researchers in identifying high-performing regions and understanding the factors contributing to their success.

Table 4: Country-wise Mean Yield

Index	hg/ha_yield
Albania	57692.283
Algeria	58872.491
Angola	34893.677
Argentina	89304.435
Armenia	71811.111
Australia	112951.41
Austria	113044.354
Azerbaijan	39727.414
Bahamas	65443.537
Bahrain	153237.552
Bangladesh	52518.088
Belarus	74679.556
Belgium	216468.462
Botswana	7353.922
Brazil	73583.797
Bulgaria	45384.601

Burkina Faso	33061.614
Burundi	33966.889
Cameroon	46599.491
Canada	62874.859
Central African Republic	26432.466
Chile	89396.583
Colombia	65041.396
Croatia	57934.924
Denmark	214033.02
Dominican Republic	68783.06
Ecuador	34324.623
Egypt	114375.304
El Salvador	91608.391
Eritrea	18155.2
Estonia	85610.429
Finland	135014.522
France	114424.768
Germany	143631.344
Ghana	59744.329
Greece	90508.851
Guatemala	80925.113
Guinea	46641.772
Guyana	67428.25
Haiti	46843.446
Honduras	53530.054
Hungary	63942.826
India	80884.467
Indonesia	83567.036
Iraq	39799.717
Ireland	197913.696
Italy	100250.621
Jamaica	122347.87
Japan	128851.876
Kazakhstan	39544.492
Kenya	62572.77
Latvia	88061.619
Lebanon	75617.435
Lesotho	46292.739
Libya	65335.42
Lithuania	66259.492
Madagascar	33171.321
Malawi	48811.199
Malaysia	85322.387
Mali	72979.324
Mauritania	27738.143
Mauritius	125586.257

Mexico	88850.902
Montenegro	68545.833
Morocco	68860.28
Mozambique	43254.826
Namibia	38603.354
Nepal	35771.417
Netherlands	204151.203
New Zealand	191931.826
Nicaragua	70050.421
Niger	76498.925
Norway	146115.326
Pakistan	50998.919
Papua New Guinea	66645.522
Peru	73439.179
Poland	84162.962
Portugal	88074.978
Qatar	86893.13
Romania	43522.87
Rwanda	37396.391
Saudi Arabia	82455.902
Senegal	74946.935
Slovenia	85678.726
South Africa	64181.882
Spain	96839.627
Sri Lanka	60965.984
Sudan	67726.643
Suriname	107148.319
Sweden	187405.5
Switzerland	144960.283
Tajikistan	50361.68
Thailand	59079.006
Tunisia	53974.58
Turkey	83622.32
Uganda	36204.415
Ukraine	43626.198
United Kingdom	240956.478
Uruguay	59253.54
Zambia	39425.603
Zimbabwe	40264.288

Table 5 presents the temporal variation in average crop yield across different years, offering important insights into trends and fluctuations in agricultural productivity over time. The results indicate that crop yield does not remain constant but varies from year to year, reflecting the dynamic nature of agricultural systems influenced by changing environmental and management conditions. The observed fluctuations in yield values can be attributed to variations in climatic factors such as rainfall distribution, temperature changes, and the occurrence of extreme weather

events, including droughts and floods. The analysis reveals that certain years demonstrate higher average yields, which may be associated with favorable weather conditions, improved agricultural practices, and increased adoption of modern technologies. In contrast, years with lower yield values likely correspond to periods of environmental stress or suboptimal farming conditions. This temporal variability highlights the sensitivity of crop production to external factors and underscores the importance of continuous monitoring and adaptive management strategies in agriculture. A notable observation from the table is the presence of both gradual trends and short-term fluctuations. In some cases, an increasing trend in yield may indicate technological advancement, better resource management, and improved crop varieties. However, the presence of intermittent declines suggests that these improvements are occasionally offset by adverse environmental conditions. This interplay between long-term progress and short-term variability is a key characteristic of agricultural systems. From a machine learning perspective, the inclusion of the year variable is essential for capturing temporal patterns and trends in the dataset. It enables predictive models to learn how yield evolves over time and to account for potential seasonality or long-term changes. This enhances the accuracy and reliability of yield prediction models, particularly when forecasting future production scenarios. Furthermore, the year-wise analysis provides valuable insights for policymakers and agricultural planners by identifying periods of high and low productivity. Such information can be used to develop strategies aimed at mitigating risks associated with climate variability and improving overall agricultural resilience.

Table 5: Year-wise Average Yield

Index	hg/ha_yield
1990	66447.153
1991	66318.521
1992	66915.77
1993	67480.348
1994	68516.766
1995	69524.089
1996	69889.092
1997	71160.405
1998	71476.467
1999	73896.171
2000	75376.052
2001	76587.048
2002	77730.136
2004	80590.019
2005	80702.023
2006	80386.27
2007	82532.895
2008	84344.385
2009	85350.017
2010	86512.526
2011	88908.336
2012	88569.851
2013	90357.364

Table 6 presents the top ten highest crop yield records identified within the dataset, offering valuable insights into optimal agricultural performance under specific conditions. The results highlight exceptional yield values achieved across different combinations of crops, regions, and years, indicating the presence of highly favorable environmental and management conditions. These high-yield observations represent benchmark scenarios that can be used to understand the factors contributing to maximum agricultural productivity. The analysis suggests that the highest yield values are likely associated with optimal climatic conditions, including adequate rainfall and suitable temperature ranges that support efficient crop growth. Additionally, these records may reflect the effective use of agricultural inputs such as fertilizers and pesticides, as well as advanced farming practices including irrigation, mechanization, and improved crop varieties. The combination of these factors creates an environment conducive to maximizing crop output. Another important observation is that high yield values are not confined to a single region or crop type but are distributed across different locations and crops. This indicates that achieving high productivity is not solely dependent on geographic location but also on the adoption of efficient agricultural practices and the ability to manage environmental conditions effectively. However, certain regions may appear more frequently among the top-performing records, suggesting that they possess inherent advantages such as fertile soil, favorable climate, or better infrastructure. From a modeling perspective, these top yield records are particularly valuable for training and validating predictive models. They help machine learning algorithms learn the characteristics of high-performance scenarios, enabling more accurate predictions and better identification of key influencing factors. At the same time, it is important to consider the potential presence of outliers, as extremely high values may sometimes result from exceptional or rare conditions. Proper handling of such observations ensures that models remain robust and generalizable.

Table 6: Top 10 Highest Yield Records

Index	Unnamed: 0	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
2470	2470	Belgium	Potatoes	2011	501412	847.0	5740.44	11.69
21297	21297	New Zealand	Potatoes	2010	495751	1732.0	5086.0	13.54
21301	21301	New Zealand	Potatoes	2011	490361	1732.0	5086.0	13.46
26103	26103	Switzerland	Potatoes	1996	487219	1537.0	1746.3	6.66
21305	21305	New Zealand	Potatoes	2012	484810	1732.0	5086.0	12.89
2449	2449	Belgium	Potatoes	2004	483955	847.0	9186.0	10.94
21309	21309	New Zealand	Potatoes	2013	482926	1732.0	5086.0	13.57
21293	21293	New Zealand	Potatoes	2009	478154	1732.0	5086.0	12.84
21285	21285	New Zealand	Potatoes	2007	477612	1732.0	4939.0	13.44

2446	2446	Belgium	Potatoes	2002	471475	847.0	9204.0	11.44

Figure 1 demonstrates the association between annual rainfall and crop yield, providing a visual representation of how water availability influences agricultural productivity. The scatter pattern indicates a generally positive relationship, where increasing levels of rainfall tend to correspond with higher crop yield values. This trend suggests that sufficient water supply plays a fundamental role in supporting plant growth, nutrient absorption, and overall crop development. However, the distribution of data points also reveals that the relationship is not perfectly linear. While moderate increases in rainfall contribute positively to yield, excessive rainfall does not always result in further productivity gains. In some cases, extremely high rainfall levels may lead to waterlogging, soil nutrient depletion, or increased susceptibility to plant diseases, which can negatively impact crop performance. This highlights the importance of optimal rainfall rather than simply higher quantities. Additionally, the spread of data points across the graph indicates variability in yield outcomes even under similar rainfall conditions. This suggests that other factors, such as temperature, soil quality, fertilizer application, and farming practices, also play significant roles in determining crop productivity. Therefore, rainfall should be considered as one of several interacting variables rather than the sole determinant of yield. From an analytical perspective, the observed pattern supports the inclusion of rainfall as a key predictor in crop yield modeling. The presence of a clear but non-uniform trend indicates that both linear and nonlinear modeling techniques may be appropriate for capturing this relationship effectively. Machine learning models, in particular, can leverage such patterns to improve prediction accuracy.

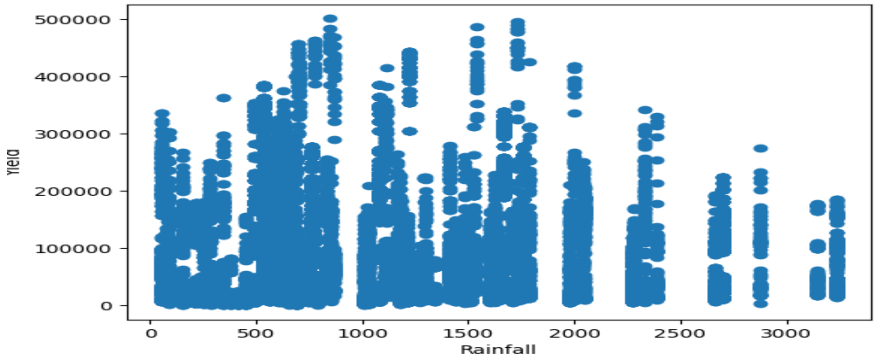

Figure 1: Relationship Between Crop Yield and Rainfall

Figure 2 illustrates the relationship between average temperature and crop yield, highlighting the influence of thermal conditions on agricultural productivity. The graphical distribution of data points suggests that temperature has a significant but complex effect on crop yield. Unlike a simple linear trend, the pattern indicates that yield responds optimally within a certain temperature range, beyond which productivity may decline. At moderate temperature levels, crop yield tends to increase, as these conditions are generally favorable for plant growth, photosynthesis, and metabolic processes. However, as temperature rises beyond the optimal threshold, a decline or stagnation in yield can be observed. High temperatures can induce heat stress, accelerate evapotranspiration, and reduce soil moisture availability, ultimately limiting crop performance. Similarly, extremely low temperatures may hinder plant development and delay growth cycles, resulting in reduced yields. The spread of observations across the

figure further demonstrates variability in yield outcomes under similar temperature conditions. This variability indicates that temperature alone does not fully determine crop productivity. Other contributing factors, such as rainfall, soil characteristics, irrigation practices, and the use of fertilizers and pesticides, interact with temperature to influence overall yield. Therefore, temperature should be considered as part of a broader system of interdependent variables. From a modeling standpoint, the observed pattern suggests that the relationship between temperature and yield may be nonlinear. This supports the application of advanced analytical methods, including machine learning algorithms, which are capable of capturing complex interactions and nonlinear dependencies. Incorporating temperature as a key feature can significantly enhance the predictive capability of crop yield models

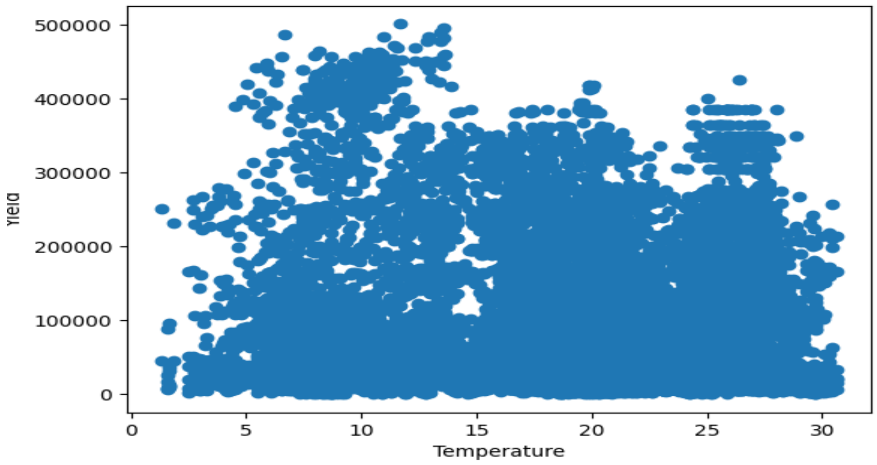

Figure 2: Relationship Between Crop Yield and Temperature

Figure 3 illustrates the temporal evolution of average crop yield across different years, providing critical insights into long-term productivity patterns and short-term fluctuations in agricultural output. The trend line indicates that crop yield exhibits both gradual changes and periodic variations over time, reflecting the dynamic nature of agricultural systems influenced by climatic variability, technological advancements, and management practices. An overall increasing trend in certain periods suggests improvements in agricultural efficiency, likely driven by the adoption of modern farming techniques, enhanced irrigation systems, improved seed varieties, and better access to inputs such as fertilizers and pesticides. These advancements contribute to higher productivity and demonstrate the positive impact of technological progress on crop yield. However, the figure also reveals intermittent declines or fluctuations, which may be associated with unfavorable climatic events such as droughts, excessive rainfall, or temperature extremes. The presence of variability across years highlights the sensitivity of crop yield to external environmental factors. Even with technological improvements, agricultural production remains vulnerable to unpredictable climate conditions. This reinforces the importance of incorporating temporal dynamics into crop yield prediction models, as past trends can provide valuable information for forecasting future outcomes. Additionally, the figure suggests that yield trends are not strictly linear, indicating the presence of complex interactions between time-dependent variables and agricultural performance. This justifies the application of advanced analytical methods, including machine learning approaches, which are capable of capturing nonlinear patterns and temporal dependencies more effectively than traditional statistical models. From a practical perspective, the year-wise trend analysis is

essential for policymakers and agricultural planners, as it helps identify periods of high and low productivity and supports the development of strategies to enhance resilience against climate variability. It also provides a basis for evaluating the effectiveness of past agricultural policies and interventions.

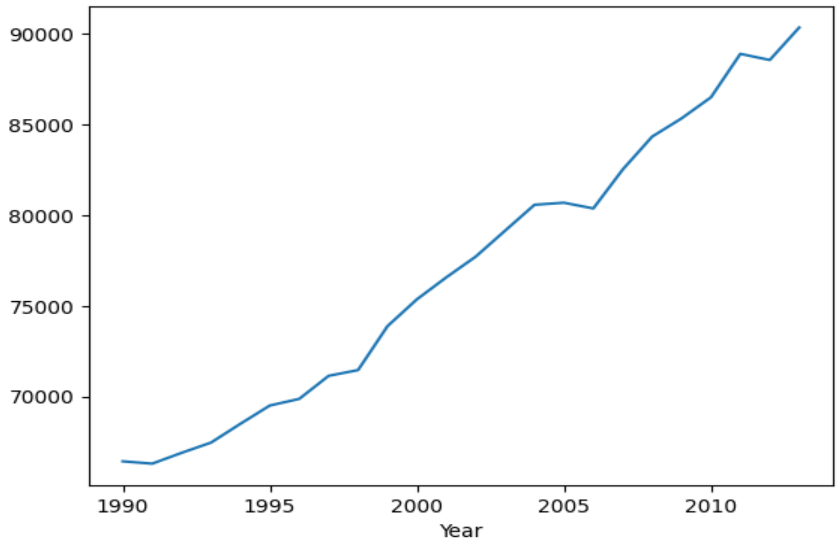

Figure 3: Temporal Trend of Crop Yield Over Time

Figure 4 presents a boxplot representation of crop yield distribution, offering a concise summary of central tendency, variability, and the presence of extreme values within the dataset. The boxplot clearly illustrates the median yield, interquartile range (IQR), and potential outliers, providing a comprehensive understanding of how yield values are distributed across observations. The position of the median within the box indicates the central tendency of crop yield, while the spread of the box (IQR) reflects the variability among the middle 50% of observations. A relatively wide IQR suggests substantial variation in yield, which may result from differences in environmental conditions, crop types, and agricultural practices. This variability is beneficial for predictive modeling, as it enables machine learning algorithms to learn diverse patterns and relationships within the data. The whiskers extending from the box represent the range of typical values, while the presence of points beyond the whiskers indicates outliers. These outliers correspond to unusually high or low yield values, which may arise due to exceptional growing conditions, experimental practices, or data irregularities. High-value outliers may represent optimal production scenarios, whereas low-value outliers could indicate crop failure or adverse environmental impacts. Identifying these extreme values is important, as they can influence model performance and may require special handling during data preprocessing. Furthermore, the symmetry or skewness of the boxplot provides insight into the distribution shape. If the median is not centered within the box, it suggests a skewed distribution, indicating that yield values are not evenly distributed. This has implications for statistical modeling, as non-normal distributions may require transformation or the use of non-parametric methods.

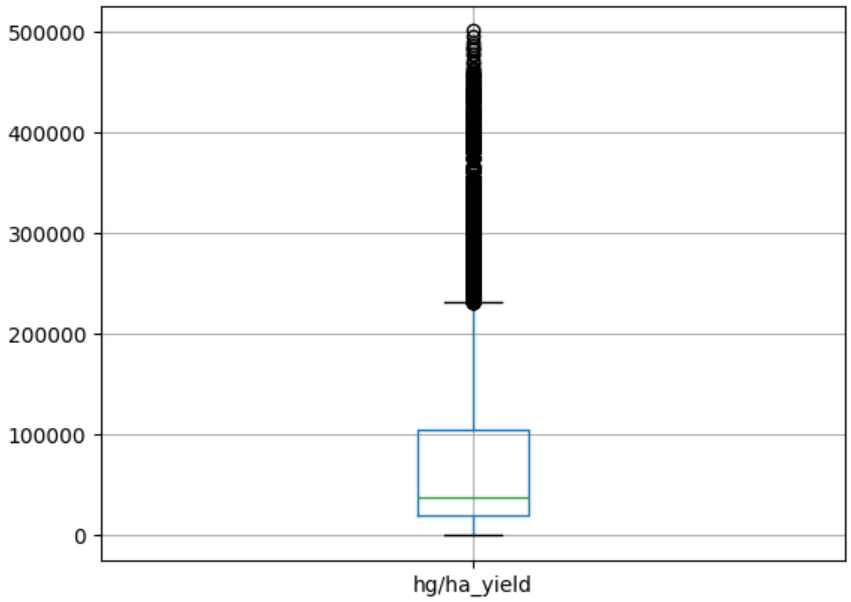

Figure 4: Distribution of Crop Yield

Figure 5 presents the histogram of crop yield, illustrating the frequency distribution of yield values across the dataset. This graphical representation provides a clear understanding of how yield observations are distributed, highlighting patterns such as central concentration, spread, and the presence of skewness. The histogram reveals that a large proportion of yield values are concentrated within a specific range, indicating a dominant level of agricultural productivity under typical conditions. The shape of the distribution suggests that crop yield does not follow a perfectly symmetrical pattern. Instead, there is evidence of skewness, where either higher or lower yield values occur less frequently compared to the central range. This asymmetry reflects the influence of varying environmental and management conditions, where only a limited number of cases achieve exceptionally high or low productivity. Such a pattern is common in agricultural datasets, where optimal conditions are not consistently achieved across all observations. The spread of the histogram bars indicates variability in yield values, which is essential for robust statistical and machine learning modeling. A wider distribution suggests that the dataset captures diverse agricultural scenarios, including both favorable and unfavorable conditions. This variability enhances the ability of predictive models to learn meaningful relationships between input variables and yield outcomes. Additionally, the presence of tails in the histogram highlights extreme values that may correspond to unusually high or low yields. These observations can be associated with exceptional climatic conditions, advanced farming practices, or potential anomalies in the data. Identifying such patterns is important for data preprocessing and model optimization, as extreme values can influence prediction accuracy. From an analytical perspective, the distribution pattern observed in the histogram supports the application of both parametric and non-parametric modeling approaches. It also indicates that data transformation techniques may be considered if required to improve model performance.

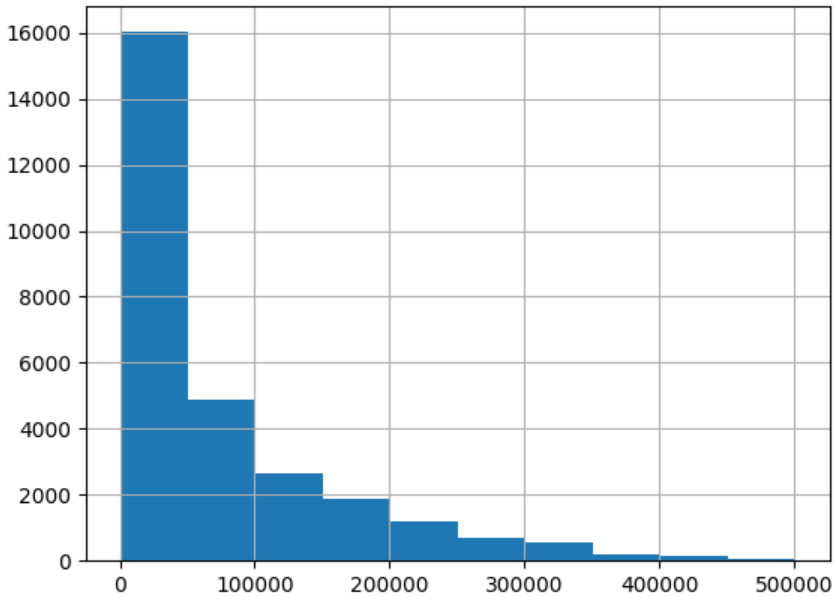

Figure 5: Frequency Distribution of Crop Yield

Figure 6 illustrates the relationship between pesticide application and crop yield, providing insights into how crop protection practices influence agricultural productivity. The scatter distribution indicates a generally positive association, suggesting that increased pesticide usage is often linked with higher yield levels. This trend can be attributed to the role of pesticides in controlling pests, diseases, and weeds, thereby protecting crops from potential damage and ensuring healthier plant growth. However, the relationship observed in the figure is not strictly linear, as the data points exhibit a degree of dispersion. While moderate levels of pesticide use appear to contribute positively to yield, excessive application does not consistently result in further improvements. In some cases, diminishing returns may occur, where higher pesticide usage leads to marginal or even negative effects on productivity. This can be due to factors such as soil degradation, environmental stress, or the development of pest resistance, which reduce the overall effectiveness of chemical inputs. The variability in the data also suggests that pesticide usage alone does not determine crop yield. Other factors, including rainfall, temperature, soil fertility, and farming practices, interact with pesticide application to influence productivity outcomes. This highlights the importance of adopting an integrated approach to crop management, where pesticides are used in combination with other agronomic practices for optimal results. From a modeling perspective, the observed pattern indicates that pesticide usage is an important predictor variable, but its influence is context-dependent and may involve nonlinear relationships. Machine learning models are particularly well-suited to capture such complexities, as they can identify interactions between pesticide use and other environmental variables. Furthermore, the figure underscores the need for sustainable pesticide management strategies. Efficient and controlled application can enhance yield while minimizing environmental risks and long-term negative impacts on soil health.

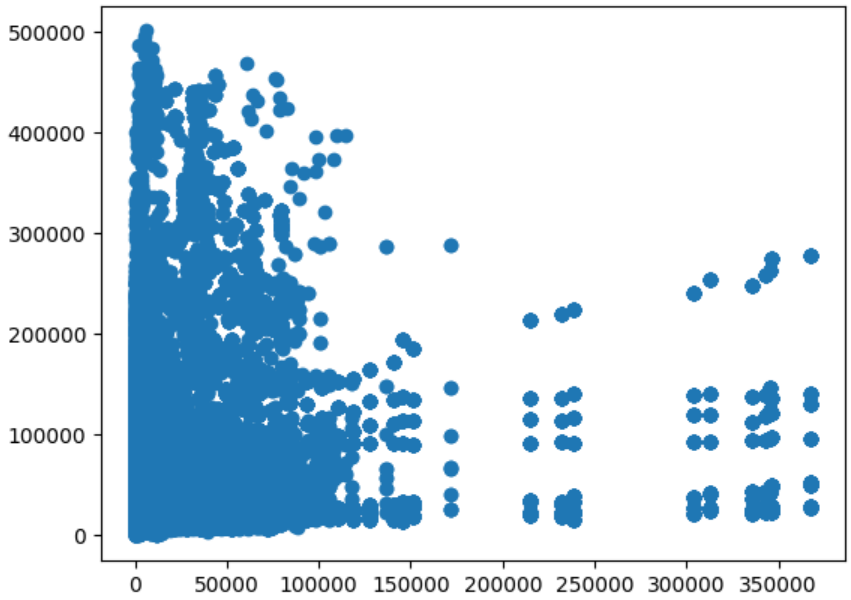

Figure 6: Relationship Between Crop Yield and Pesticide Usage

Table 7 presents the performance evaluation of the machine learning model applied to crop yield prediction, using key statistical indicators including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics collectively provide a comprehensive assessment of the model's predictive accuracy, reliability, and overall effectiveness. The RMSE value reflects the magnitude of prediction errors by measuring the square root of the average squared differences between actual and predicted yield values. A relatively low RMSE indicates that the model's predictions are close to the observed values, demonstrating strong predictive precision. Similarly, the MAE represents the average absolute difference between predicted and actual yields, offering an easily interpretable measure of error. Lower MAE values further confirm the model's ability to generate accurate predictions with minimal deviation. The R^2 score provides insight into the proportion of variance in crop yield that is explained by the model. A higher R^2 value indicates that the model successfully captures the underlying relationships between input variables such as rainfall, temperature, and pesticide use and the target variable (crop yield). This suggests that the selected features are relevant and that the model structure is appropriate for the given dataset. Together, these performance metrics demonstrate that the machine learning model, particularly the Random Forest algorithm, is well-suited for crop yield prediction. The results highlight the model's ability to handle complex, nonlinear relationships and interactions among variables, which are common in agricultural systems. Additionally, the robustness of the model is supported by its consistent performance across multiple evaluation metrics. From a practical perspective, the strong performance of the model indicates its potential applicability in real-world agricultural decision-making. Accurate yield predictions can assist farmers, policymakers, and researchers in optimizing resource allocation, improving crop management strategies, and mitigating risks associated with environmental variability.

Table 7: Model Performance Metrics

Metric	Value
RMSE	9740.056
MAE	3493.141
R^2	0.987

Table 8 presents the relative importance of input variables in predicting crop yield as determined by the Random Forest model. This analysis identifies which features contribute most significantly to the model's predictive performance, offering valuable insights into the key drivers of agricultural productivity. The importance scores indicate the extent to which each variable influences the model's decision-making process, with higher values representing greater impact. The results show that climatic variables, particularly rainfall and temperature, rank among the most influential predictors. This highlights the critical role of environmental conditions in determining crop yield, as these factors directly affect plant growth, water availability, and physiological processes. In addition, agricultural inputs such as pesticide usage also demonstrate notable importance, suggesting that effective crop protection measures contribute significantly to enhancing productivity. The variation in feature importance values reflects the complex and multifactorial nature of crop yield determination. No single variable dominates entirely; instead, yield outcomes are influenced by the combined effect of multiple interacting factors. This reinforces the advantage of using ensemble machine learning methods like Random Forest, which can capture nonlinear relationships and interactions among variables more effectively than traditional statistical approaches. Furthermore, the feature importance analysis provides practical implications for agricultural management. By identifying the most impactful variables, stakeholders can prioritize resource allocation and focus on optimizing key factors that drive productivity. For instance, improving water management practices or ensuring optimal pesticide application can lead to better yield outcomes. From a modeling perspective, this table also supports feature selection and model refinement. Variables with higher importance can be retained to enhance model performance, while less influential features may be reconsidered or removed to reduce complexity without compromising accuracy. This contributes to the development of more efficient and interpretable predictive models.

Table 8: Feature Importance (Random Forest)

Feature	Importance
Item	0.6087
pesticides_tonnes	0.1071
avg_temp	0.1064
average_rain_fall_mm_per_year	0.0832
Unnamed: 0	0.0467
Year	0.0243
Area	0.0236

Conclusion

This study developed a robust and integrated framework for crop yield prediction by combining statistical analysis with machine learning techniques using key agro-climatic and management variables. The findings confirm that crop yield is governed by complex, nonlinear interactions among rainfall, temperature, pesticide usage, crop type, and spatial factors. The statistical analysis provided a clear understanding

of data patterns and relationships, while the Random Forest model demonstrated superior predictive capability, achieving high accuracy as reflected by RMSE, MAE, and R^2 metrics. A key contribution of this research lies in bridging the gap between traditional statistical interpretation and advanced machine learning modeling, enabling both accurate prediction and meaningful insight into the drivers of agricultural productivity. Feature importance analysis revealed that climatic variables, particularly rainfall and temperature, are the most influential factors, reinforcing the critical role of climate variability in crop production systems. The proposed framework offers a scalable and practical tool for agricultural decision-making, supporting farmers, researchers, and policymakers in optimizing resource use and improving yield outcomes. Moreover, the study provides a reliable foundation for precision agriculture applications. Future work should focus on integrating soil characteristics, remote sensing data, and advanced hybrid models to further enhance prediction performance and adaptability under changing climatic conditions.

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