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Competitiveness and Sustainability development in Agriculture Using Statistical Data Analytics Model

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ABSTRACT

Purpose: Agriculture is an evergreen and growing field that requires global efforts to improve sustainability and manage competitiveness in fast-growing, dynamic, resource-based environments. Agriculture is the foundation and common thread that interconnects and links all 17 Sustainable Development Goals. This paper examines the sustainable development of agriculture through the lens of Exploratory Data Analytics, a statistical model focused on competitiveness. Understanding the relationships among market dynamics, natural climate conditions and variations, and increasing resource limitations is crucial for achieving long-term environmental sustainability and seamless agricultural productivity. This problem is considered the most pressing and emerging issue, as agriculture is the primary source of human life. It aims to provide a statistical model for forecasting the public's support for agriculture, thereby increasing sustainable productivity and environmental protection.

Methodology: The proposed statistical model in this paper employs the EDA technique, which encompasses various internal mechanisms, including statistical and visualization methods, for analyzing and summarizing the dataset. EDA's main features are exploration, visualization, summarization, pattern recognition, and problem identification. The primary objectives of using EDA are to identify patterns, extract entity relationships, detect anomalies, and make informed decisions. It plays a key role in quantitative analytical research, helping researchers better understand the data and its behavior, and decide on a model before applying it to the application.

Findings: The corresponding food and climate dataset is analyzed using the EDA model in Python, and several key points are identified. The findings revealed that agricultural production is primarily dependent on several key factors, including climate, resource utilization, management, and resource allocation, as well as the adoption of advanced technological innovations, which contribute to high levels of competitiveness and improved sustainability. Although agriculture is one of the competitive industries, it is essential to focus on sustainability because it significantly impacts all the global Sustainable Development Goals. The proposed EDA model analyses multidimensional agricultural data, including agrarian output, economic factors, sustainability indicators, and temporal backgrounds. It also highlights the productivity of agriculture, which relies on utilizing modern resources to overcome competitive market values. The robustness of using modern, advanced technology-based resource management supports farmers, agricultural stakeholders, and stakeholders in fostering sustainable and competitive systems.

Keywords: Competitiveness Agriculture, Sustainable Agriculture, Agriculture Data Analytics, Competitiveness and Sustainability on Agriculture.

INTRODUCTION

Agriculture has always been the backbone of human civilization, forming the basis for producing food, fibre, and essential raw materials necessary for survival and economic growth. It has nourished billions of people and influenced societies, economies, and cultures worldwide. Over time, the agricultural sector has undergone significant changes in response to technological progress, shifting societal needs, and environmental challenges. From the basic methods of subsistence farming to the advanced stage of industrial agriculture, agriculture’s history highlights humanity's ability to innovate, adjust, and sustain itself. In recent years, sustainability has become a key focus of agricultural discussions. This change stems from the growing recognition of the environmental harm, resource depletion, and social inequalities associated with traditional farming methods. Sustainable agriculture is no longer considered optional or temporary but an essential approach. Its goal is to ensure that farming practices are environmentally friendly, economically practical, and socially fair, protecting future generations’ ability to meet their needs while addressing current demands.

At the same time, the concept of competitiveness has gained prominence in agriculture. Competitiveness refers to the ability of farming systems, regions, or nations to produce and market agricultural goods efficiently and profitably in an increasingly interconnected and globalized market. On the surface, sustainability and competitiveness may appear to be opposing forces. Pursuing higher profits and market share often leads to intensive farming practices that strain natural resources, degrade ecosystems, and exacerbate socioeconomic inequalities.

However, a deeper exploration reveals that sustainability and competitiveness can coexist, creating a synergistic relationship. When approached thoughtfully, sustainable practices can enhance long-term competitiveness by ensuring resource availability, improving soil health, reducing input costs, and responding to the growing consumer demand for environmentally friendly and ethically produced products. The integration of sustainability into agricultural competitiveness is critical due to the unprecedented global challenges. The world's population is expected to reach nearly 10 billion by 2050, resulting in increased demand for food, fiber, and fuel. At the same time, climate change poses significant risks to agricultural productivity, including rising temperatures, altered rainfall patterns, and more extreme weather events such as droughts and floods. Economic inequalities exacerbate the situation, as small-scale farmers, who produce the majority of the world's food, often lack access to the resources, technologies, and support necessary to adapt to these challenges. The combined challenge of improving agricultural competitiveness while ensuring sustainability is one of the key issues of our time.

Emerging trends and technological advancements are reshaping the agricultural landscape, offering innovative solutions to these interconnected challenges. Precision agriculture, for instance, utilizes technologies such as GPS sensors and drones to optimize resource use, reduce waste, and increase efficiency. Artificial intelligence (AI) and machine learning are being harnessed to analyze vast datasets, enabling farmers to make informed decisions about crop management, pest control, and irrigation. Genetically modified crops are being developed to resist pests, tolerate extreme weather conditions, and enhance nutritional content, thereby contributing to increased productivity and sustainability. Renewable energy sources, including solar-powered machinery and biogas, are being adopted to reduce the carbon footprint of agricultural operations. These advancements enhance competitiveness by improving efficiency and reducing costs, while also promoting sustainability by minimizing environmental impacts, supporting biodiversity, and increasing climate resilience. For example, precision agriculture helps reduce the excessive use of fertilizers and pesticides, which can harm soil and water systems. Renewable energy reduces reliance on fossil fuels, thereby decreasing greenhouse gas emissions. These innovations demonstrate how combining sustainability and competitiveness can drive agricultural development in a powerful way. However, achieving this balance presents its challenges. Small-scale farmers, essential to global agriculture, often encounter significant obstacles in adopting sustainable and competitive practices. These include limited access to modern technologies, financial resources, infrastructure, and market opportunities. Furthermore, policy frameworks and international trade regulations often favour large-scale industrial agriculture, overshadowing traditional and Indigenous farming systems. These conventional systems, based on local knowledge and ecological practices, typically employ sustainable methods that have been refined over generations. Disregarding these systems not only threatens biodiversity but also disrupts the cultural and social fabric of rural communities.

To overcome these challenges, inclusive and supportive agricultural policies are urgently needed. Governments, international organizations, and private sector stakeholders must work together to create enabling environments that empower smallholders, promote fair trade, and encourage investment in sustainable technologies. Financial incentives, capacity-building programs, and infrastructure development can help bridge the gap between small-scale and large-scale agricultural producers, ensuring that the benefits of competitiveness and sustainability are accessible to all. The relationship between sustainability and competitiveness has a significant impact on agricultural development at various levels. Competitive agricultural systems support economic growth, rural employment, and food security by consistently supplying affordable, high-quality products. At the same time, sustainability ensures that these benefits are long-lasting by protecting natural resources and strengthening resilience to environmental shocks. The connection between these two goals emphasizes the need to incorporate sustainability into agricultural competitiveness strategies. By doing so, agriculture can address critical issues such as food insecurity, rural poverty, and climate change, while contributing to global economic stability and ecological preservation.

New sustainable and competitive agriculture methods are sparking innovation and changing traditional practices. Approaches such as agroecology, permaculture, and organic farming are gaining popularity, offering ways to maintain productivity while protecting biodiversity and enhancing soil health. These practices mitigate the effects of climate change by capturing carbon, reducing greenhouse gas emissions, and conserving water. At the same time, advanced technologies like blockchain are enhancing transparency and traceability in agricultural supply chains, fostering trust and promoting fair trade practices. Smart irrigation systems enhance water use efficiency, and renewable energy solutions make farming operations more eco-friendly. The effects of these developments go beyond individual farms, impacting entire food systems, rural economies, and global trade. Sustainable and competitive farming practices can reduce food loss and waste, enhance nutrition, and strengthen supply chains, making them more resilient to market disruptions. They also open up new economic opportunities for rural communities, such as eco-tourism, organic certifications, and value-added processing. Consumer demand for sustainably and ethically produced food is changing market trends, motivating agricultural producers to adopt environmentally friendly practices as a means of gaining a competitive edge.

CONTRIBUTION

This paper contributes an effective data analytical method for agriculture fields by integrating competitiveness and sustainability analysis to identify patterns and trends in large datasets and provide actionable insights for policymakers. It offers a scalable framework for regional analysis, promotes innovative, resource-efficient, and climate-resilient practices, and advances data analytics in agriculture to support global challenges. It highlights the trade-offs and synergies between economic growth and environmental care, aiming to enhance productivity while ensuring long-term sustainability.

LITERATURE SURVEY

This section presents a comprehensive literature review on various methods for analyzing agricultural data, encompassing production, profit, and sustainability. For example, Syed Amir Ashraf et al. (2021) have presented an investigation into the recent development of nanomaterials in the agricultural industry. Nanotechnologies offer a range of essential features for various sectors. These features can broadly support food solutions for farms, functional foods, and nutraceuticals, thereby improving nutritional status, bioavailability, and the quality of food in terms of colour, texture, taste, and packaging. Nanotechnology is also utilized in agricultural products, including nano-pesticides, nano-fertilizers, and nano-growth promoters.

Arun V. Baskar et al. (2022) have presented an investigation into spent absorbent techniques that could provide recovery, regeneration, and safe disposal of spent absorbent from water resources. Various recovery and regeneration techniques are available to recover spent absorbent, including filtration, decomposition, separation, thermal desorption, supercritical fluid desorption, chemical desorption, and absorbent regeneration using microbial materials. Finally, this investigation highlights the current challenges in recovering spent absorbent and outlines the future direction for overcoming these challenges in the years to come, aiming to achieve sustainability. Syed Bilawal Bukhari (2024) has presented a crop recommendation system designed to improve sustainability in the agricultural sector, utilizing machine learning techniques. The proposed system helps to suggest a suitable crop for a particular area by analysing the environmental factors of the region, which include humidity, soil pH value, temperature, and rainfall. It utilizes a random forest classifier to analyze ecological factors and recommend suitable crops for cultivation. Ultimately, this crop recommendation system serves as a powerful technology in the agricultural field, enhancing the sustainability of agriculture.

According to research from the UN and many others, the world population is expected to reach around 9 billion by 2050, resulting in an increasing number of people facing hunger and famine. So, it creates a need for increasing agricultural production. It is the only solution to the hunger problem. So, Fatmanur Varlik et al. (2023) have presented a suitable plan for plant production based on agricultural lands located in cities. It will increase production and the growth of the plant. Ultimately, this method will enhance food production and improve food quality. Ammar Chouchane et al. (2024) have presented a deep learning (DL) based prediction for tomato plant disease by analysing the plant's leaf image, which helps avoid spreading and improve production. It employs a hybrid model that combines the Exponential Discriminant Analysis (EDA) method with the transfer learning (TL) approach. It also developed deep neural networks, such as Darknet-53, EfficientNet-B0, and ResNet-50, to analyze the leaf images. Two tomato leaf datasets, the Plant Village and Taiwan datasets, are used to evaluate the efficiency of this hybrid model. Finally, the simulation results show that the proposed hybrid model achieves a mean accuracy of 98.29% in predicting tomato leaf disease using leaf images. It helps to improve tomato production and also leads to sustainable agriculture. Christine Musanase et al. (2023) have presented an ML and Internet of Things (IoT) algorithm for improving crop production by optimising cultivating practices. It utilizes an ML model to recommend crops based on environmental factors, including soil type, rainfall, and levels of nitrogen, potassium, and phosphorus. A rule-based model helps recommend suitable fertilizers by analyzing the specific crops. These models were trained and tested on Rwandan crops to evaluate the model's efficiency. The estimated result shows that these proposed models have attained 97% accuracy in fertiliser recommendation systems, which helps to increase agricultural production. Chouaib El Hachimi et al. (2022) have presented an innovative weather data management (WDM) system that provides weather updates by analyzing meteorological station data, thereby helping to maintain crop growth and yields, and creating an irrigation schedule based on weather conditions. It uses both ML and DL models to analyse the raw data. This process consists of four steps: data acquisition, data storage, data processing, and data transmission to the application layer. This SWDM system helps to improve the sustainability of agricultural production in Morocco.

The agricultural sector makes significant contributions to the Sustainable Development Goals (SDGs) by ensuring food security, achieving zero hunger, improving access to nutritious food, and promoting sustainable agricultural practices. Nurul Izza Afkharinah et al. (2023) have presented an ML model for predicting crop growth phases more efficiently than manual methods. It utilizes the ML boosting classifier method to classify rice growth phases by evaluating various metrics, including precision, F1 score, recall, accuracy, cross-validation, Kappa score, and execution time. By analyzing these results, the proposed model has efficiently improved crop production by examining the growth phases. It has also suggested some steps and fertilizers to enhance the growth of the crops. Saltanat Sharipova et al. (2024) have presented the Exploratory Data Analysis (EDA) method to identify the effects of phosphorus on wheat yield. It uses various datasets to analyse the effects, such as precipitation, soil surface temperature, annual phosphorus application data from 2000 to 2022, and humidity range from April to September. The main motive of this model is to perform EDA on the given dataset to predict the impact of phosphorus on the wheat yield. The results indicate that precipitation and soil surface temperature exhibit a weak negative correlation. Humidity helps identify weak positive correlations, which in turn improve the sustainability of agriculture. Hafiyya R. M. et al. (2024) presented a crop rotation management (CRM) method to enhance and modernize agricultural practices. It combines a cutting-edge approach with AI techniques. By analyzing historical crop performance data and real-time weather forecasts, AI techniques can help suggest optimal crop rotations, leading to improved production by planting the right crops at the right time. The result shows that this crop rotation method maximises crop yields, enhances farming techniques by modernising them, and achieves sustainable farming.

LIMITATIONS AND MOTIVATIONS

It is understood that earlier research focused on whether sustainability and competitiveness, when combined, failed to address the issues and challenges. Strategies focusing on food production and profit cannot address sustainability issues. Similarly, resources, technical devices, and technological advances used to improve sustainability cannot address the problems of enhancing production and profit. Whereas, in the modern agriculture field, it is essential to focus on both competitiveness and sustainability to fulfil global needs and achieve SDG-2030 successfully because agriculture is the primary field that behind supports most of the SDGs, such as SDG-2, 6, 8, 9, 11, 12, 14, 15, and SDG-17. Thus, this paper aims to explore a statistical method for analyzing agricultural data to forecast the importance of simultaneously focusing on competitiveness and sustainability. The earlier methods used in the farm management field did not employ statistical analysis and relied solely on region-based data. Few applications use machine learning techniques for cloud-based agricultural data analysis and are inflexible in adaptation. Hence, this paper aims to utilize the EDA model to develop a data analytical framework for analyzing both competitiveness and sustainability in the agricultural sector.

PROBLEM STATEMENT

Improving competitiveness and promoting sustainable development are two key challenges that the agricultural sector faces. High production, easy access to the market, and more economic profit are the factors that classify competitiveness. Several strategies have been developed to mitigate greenhouse gas emissions, reduce biodiversity loss, and prevent resource depletion, which are key factors in determining the sustainability level in agriculture. However, creating strategies for improving sustainability compromises short-term production and profit, creating a conflict between environmental and economic objectives. Several earlier research methods have examined sustainability and competitiveness in the agriculture field. Still, they are poorly integrated and lack data-driven approaches for comprehensively indicating the relationship. The earlier methods depended on traditional statistical methods for quantitative analysis. They focused on narrowly solving problems, and thus, they found difficulties in complex data processing, multi-dimensional data relationships, and actionable perceptions. This research gap restricts stakeholders and policymakers from simultaneously promoting competitive and sustainable methods. Hence, this paper aims to utilize the EDA method in addressing the aforementioned problem, as it can handle complex and diverse datasets to recognize data patterns. It can correlate the data entities and trends. However, balancing competitiveness and sustainability in agriculture remains an area of ongoing exploration.

RESEARCH METHODOLOGY

The EDA method is widely used in data mining and analysis to identify patterns in input data and visualize the extracted essential features. It simplifies the data analysis process, producing more accurate and quicker results. This method is more useful for anomaly detection, pattern identification, and hypothesis evaluation, among other applications. Initially, the EDA method is applied to understand the relationship between the data points in the input dataset. Some major aspects of EDA techniques are evaluating distributed data, outlier detection, graphical representation, testing assumptions, handling missing values, correlation analysis, and visualization. The EDA technique can handle distributed data types and find their range, metrics, and dispersion. The correlation and variation between the data points are predicted and represent errors in the data entry. Through this, the missing values in the data are identified and removed or replaced with valid data. Various statistical calculations are performed to classify different classes of input data. The results are graphically presented as a bar, pie chart, box plot, and histogram [1]. Based on the input data, various types of EDA methods are analyzed. Generally, three EDA methods are utilized: univariate, bivariate, and multivariate analysis. The univariate analysis method is applied to understand the features or patterns in a single variable. Bivariate and multivariate analysis techniques are used to identify the relationship between two or more data points. In addition, spatial analysis, textual analysis, and time-series analysis methods are employed to analyze variations in geographically distributed data, cloud data frequency distribution, and real-time data. Using the following equations, the variance, correlation between data points, outlier detection, and dimensionality reduction are performed to yield the predicted output.

$$Variance\ (\sigma^2) = \frac{1}{n}\sum_{i=1}^{n} (x_i - \mu)^2$$

$$correlation\ (C_{xy}) = \frac{\sum_{i=1}^{n} \quad (x_i - \mu_x)(y_i - \mu_y)}{\sqrt{\sum_{i=1}^{n} \quad (x_i - \mu_x)^2 (y_i - \mu_y)^2}}$$

In EDA, the most common method used for outlier detection is Interquartile Range (IQR), and PCA is used for dimensionality reduction, which is expressed as;

$$IQR = \ Q_3 - Q_1$$

PCA,

$$\sum \quad = \frac{1}{n-1} X^T X$$

$$\Sigma v = \lambda v$$

In the above equations, x and y represent the input data, n represents the total number of data μ represents the mean value, X^T denotes the transpose of X, Q_1 indicates that the first 25% of the data Q_3 indicates the remaining 75% of the data, Σ represents the covariance matrix, v denotes eigenvector, and λ represents eigenvalues.

EDA model-based applications

In recent years, EDA-based models have been applied in various real-time industries, including hospitals, education, sports, agriculture, marketing, space travel, retail, and fraud detection. The primary function of EDA in these applications is to analyze the input data, make informed decisions, and produce an outcome. For example, the EDA method in a hospital analyzes real-time patient data, including admission, discharge, health conditions, health records, healthcare demand, and healthcare service data. similarly, in agriculture, the EDA method is applied to improve the competitiveness and sustainability of crop production. The steps involved in EDA-based data analysis include (i) analyzing user demand, query, or question. (ii) Load the facts in the model. (iii) analyzing the missing value, (iv) detecting data characteristics (variance, outliers, anomalies, etc). (v) Data transformation (data normalization, data encoding, mathematical evaluation, ratio calculation, and combining unique variables), (Vi) data visualization (graphs and tables), (Vii) outlier detection and handling, and (vii) generating the final prediction output. The overall workflow of the EDA model for data analysis is shown in Figure 1.

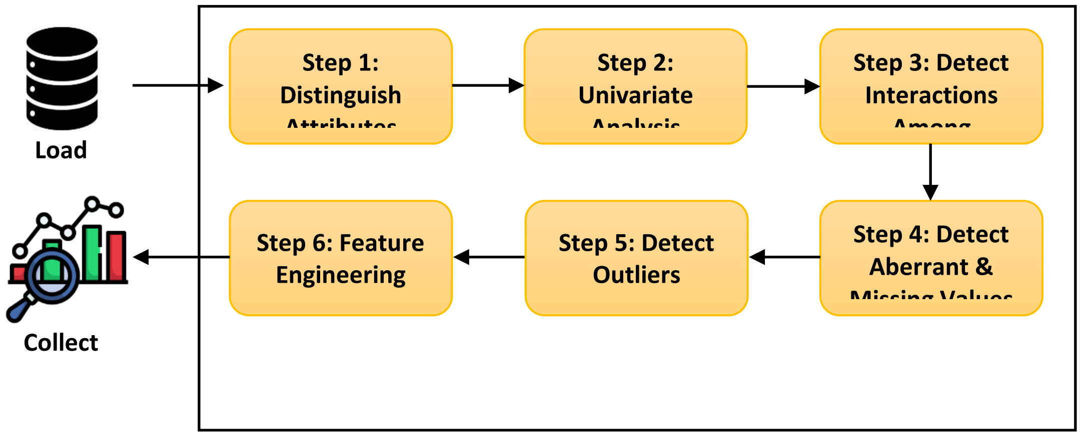

Figure-1. Statistical Data Analytics Model: EDA

EDA-based agricultural data analysis

The EDA technique is widely applied for data analysis and visualization. Similarly, this paper uses the EDA model in agricultural data to analyze and visualize crop production ratios. This is achieved by analyzing yield production, the relationship between input and output crops, sustainability, and emission level. The main goal of this paper is to analyze the competitiveness of crop production based on factors such as crop yield per hectare, cost per unit, market share, and export ratio. The crop production sustainability is evaluated based on water usage, CO2 emission, soil fertility, and crop diversification index (CDI) value. The input crop field data on different states, districts, seasons, crop types, total area harvested, and total crop production ratio-wise results are analyzed and visualized using these factors. The common equation applied to find and visualize the result of these factors is expressed as,

$$TCP_i = \sum \quad Production_i$$

Here, TCP represents the total cost of production, $\sum \quad Production_i$ represents the sum of production and i represents production of (state, district, crop type, or field).

Quantitative Analytics

A global dataset is used to analyze and obtain key points regarding agricultural competitiveness and sustainability. The data is collected from various sources, such as the Food and Agriculture Organization, the World Bank, market reports, and UNEP. Food production, crop yield, market access index, productivity in terms of workers, and competitiveness score are estimated to understand the production, yield, and profit. The efficiency of water use, fertilizer use, GHG emission, and sustainability scores are estimated to understand sustainability in agriculture. This section provides a quantitative analysis to understand the interconnection between competitiveness and sustainability in agriculture. It provides a way of identifying the opportunities to solve the issues and challenges in competitiveness and sustainability.

Analytics Outputs and Discussion

Figure-1 depicts the various performance evaluations in terms of the mean, median, standard deviation, Minimum, and maximum score of the crop yield per hectare, fertilizer used per hectare, water usage level (%), and GHG emission per hectare. Offering an understanding of both efficiency and environmental influence. The crop yield is shown in the blue bar, displaying consistently lows score across all metrics. pointing to potential challenges in productivity. The orange illustrates Water use efficiency, which shows moderate values with notable peaks in the maximum category, indicating differences in water management strategies. Fertilizer usage is represented in green, which reveals the highest score, particularly in the maximum range, highlighting its significant influence in agricultural methods but raising concerns about excessive usage. In contrast, greenhouse gas emissions are displayed in light blue, which remains a minimal score across all statistical measures. The standard deviation indicates substantial variation in fertilizer use and water efficiency, which emphasizes the need for more sustainable and consistent approaches.

Figure 2 presents the correlation factor score of crop yield. water use efficiency. fertilizer use. and greenhouse gas emissions. scaled between -1 and 1 for comparison. Crop yield and water use evaluation show strong positive normalized results, which indicates high performance and optimal resource utilization. Fertilizer use displays moderate positive results, which reflects its role in productivity but suggests room for balanced application. Despite their positive value, greenhouse gas emissions highlight environmental challenges as higher emissions represent sustainability trade-offs. The result obtained below 0 in specific metrics highlights inefficiencies or issues in balancing productivity and environmental concerns and requiring enhancements in agricultural methods.

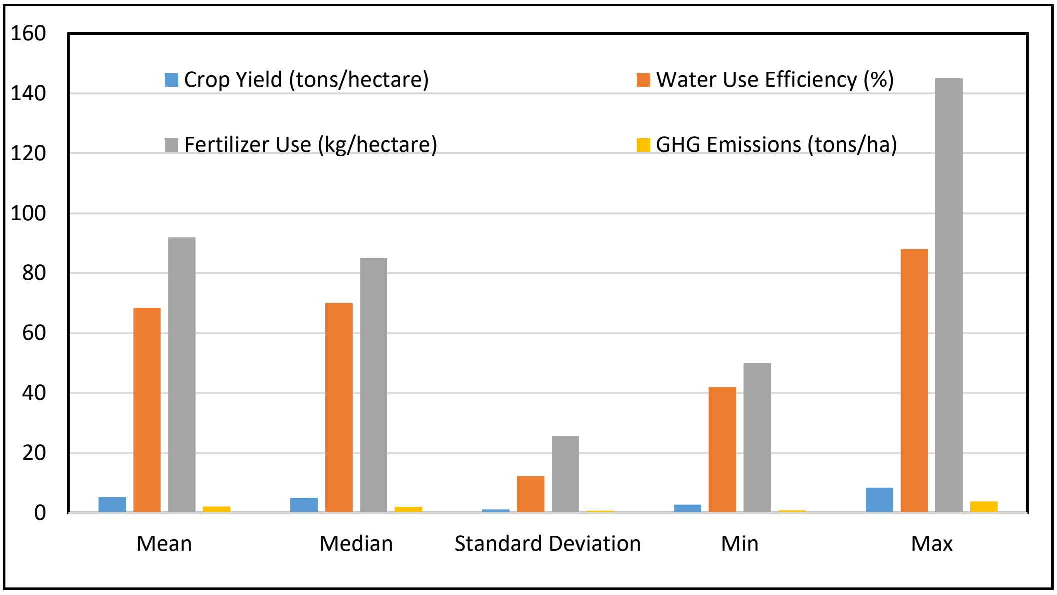

Figure-1. Key Indicators

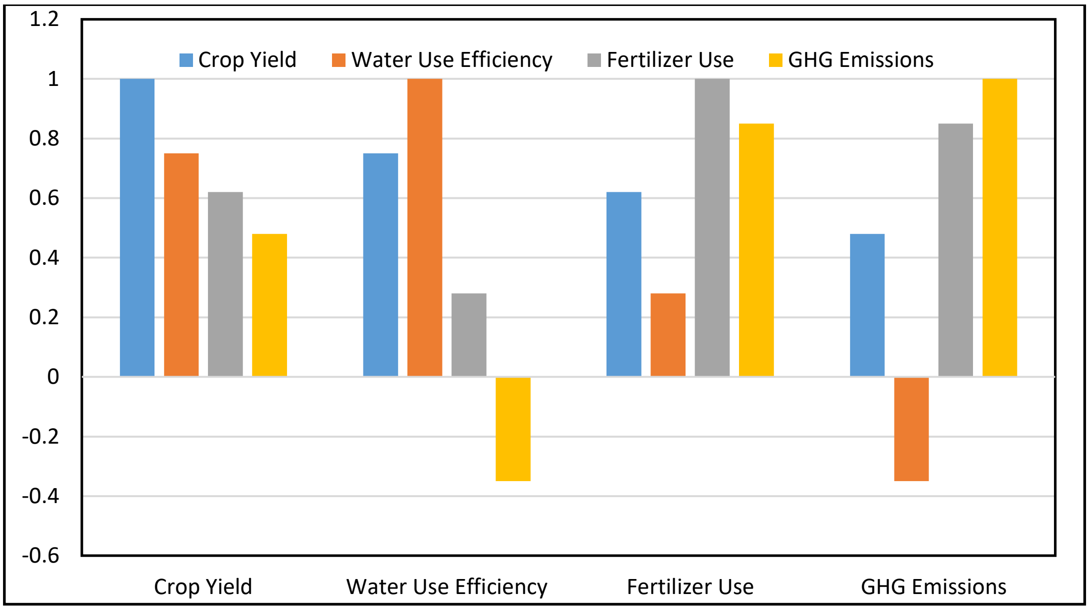

Figure-2. Correlation Factors

Figure 3 illustrates various strategies, including fertilizer subsidies, water conservation initiatives, and investments in research and development, for promoting sustainable agriculture. The analysis evaluates changes in crop yield and sustainability index in percentage. The prediction result is achieved with either a positive or a negative value. Farming subsidies lead to a moderate increase in crop yield but negatively impact the sustainability index, suggesting potential environmental concerns. Water conservation initiatives result in a more minor increase in crop yield while significantly enhancing the sustainability index and reflecting their role in promoting long-term resource efficiency. Investments in research and development provide balanced improvements in crop yield and sustainability. showing their potential to align productivity and environmental objectives effectively.

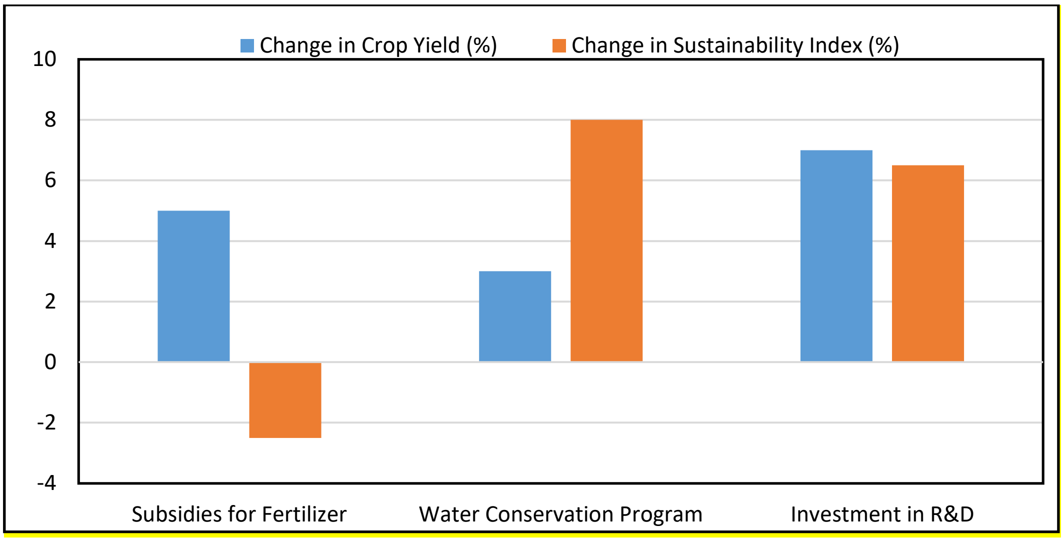

Figure-3. Strategies For Sustainable Agriculture

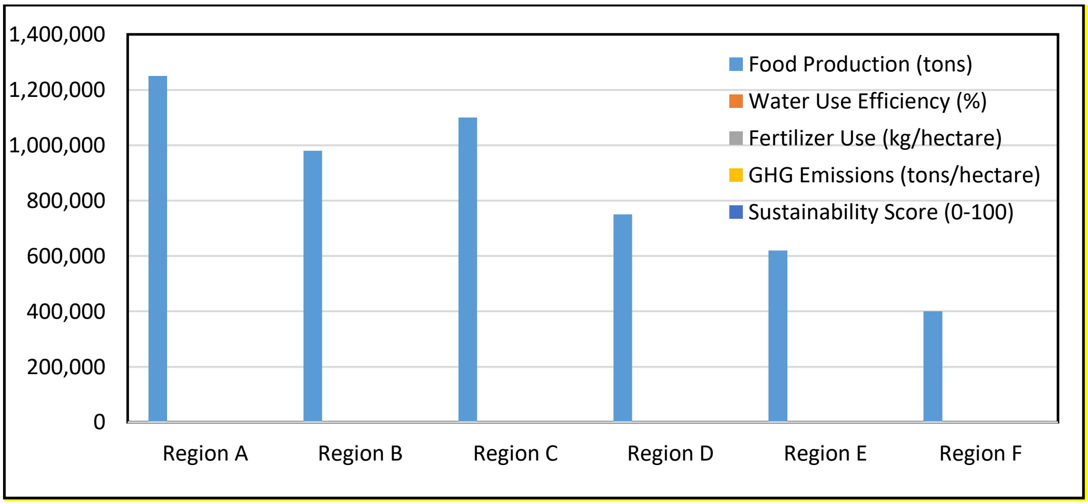

Figure-5. Sustainability Of Agriculture

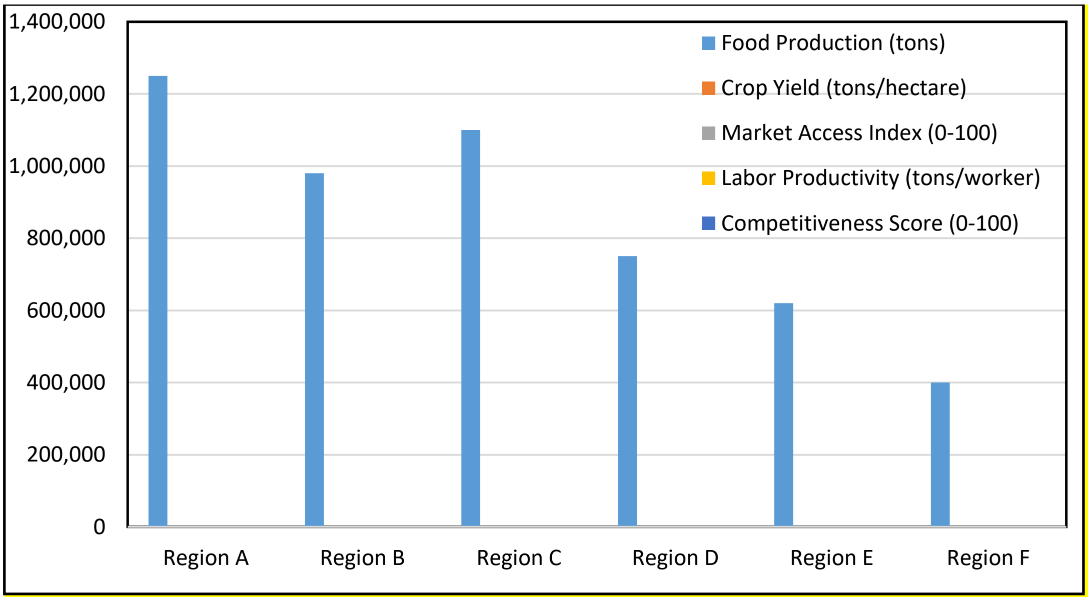

Figure-5. Competitiveness Of Agriculture

Figure 4 presents a comparative analysis of six regions, assessing food production, water use efficiency, fertilizer use, greenhouse gas emissions, and sustainability scores. Region A achieves the highest food production, but this comes at the cost of notable greenhouse gas emissions and moderate sustainability. Region C exhibits significant production, characterized by improved water use efficiency and reduced greenhouse gas emissions, reflecting balanced resource utilization. Region B achieves high output but with increased fertilizer consumption, which raises sustainability concerns. Regions D, E, and F exhibit lower production levels, particularly Region F, which has the lowest output and sustainability score.

This analysis highlights the trade-offs between productivity and environmental impact, underscoring the importance of sustainable practices. Figure 5 compares the comparison results of the top six regions in Tamil Nadu (Region A- Thanjavur, Region B- Erode, Region C- Salem, Region D- Madurai, Region E- Coimbatore, and Region F- Tiruchirappalli based on food production, crop yield, market access index, labour productivity, and competitiveness score. Region A exhibits the highest food production, indicating advanced agricultural practices and superior efficiency. Region C and Region B follow closely, contributing notably to crop yield and labour productivity. Regions D, E, and F have lower production levels, with Region F being the least productive. The market access index and competitiveness score reveal disparities in infrastructure and economic advantages across regions. This technical analysis underscores the need for targeted strategies to enhance productivity and market connectivity.

The EDA model enables policymakers, both private and government, to develop data-driven agricultural policies for monitoring and predicting climate change, resource limitations, and economic competition. It also helps to analyze, find, and guide equitable distribution of subsidies, fertilizers, water, and other agricultural inputs to the most climate-impacted and resource-limited regions.

Agro-tech startup companies and NGOs are also using EDA-based policy-making and analysis. The paper's output is organized into key statistical indicators, correlation and interrelationships, strategy analysis, and regional comparisons. A detailed comparison with the other existing studies is given in Table-1.

Table-1. Comparative Study

Author(s) & Year	Focus Area	Methodology	Scope	Key Findings	Comparison with the Present Study
Sharipova et al. (2024)	Phosphorus impact on wheat yield	Exploratory Data Analysis (EDA)	Specific crop (wheat), regional dataset	Identified a weak correlation between phosphorus use and wheat yield	The current study extends EDA across **multiple sustainability indicators** and **competitive metrics** (e.g., crop yield, emissions).
Musanase et al. (2023)	Fertilizer recommendation using ML & IoT	ML with rule-based models	Rwandan regional crops	Achieved 97% accuracy in recommending fertilizers based on soil and crop types	Your study emphasizes **statistical visualization** and **macro-level agricultural competitiveness**, not limited to a recommend-dation engine.
Bukhari (2024)	Crop recommendation based on environmental factors	Random Forest classifier	Area-specific crop suitability	Supports sustainability by selecting crops with suitable conditions	Your EDA framework explores **resource allocation, sustainability trade-offs, and competitiveness** on a broader scale.
Chouchane et al. (2024)	Tomato disease prediction using hybrid DL models	Exponential Discriminant Analysis + Transfer Learning	Tomato leaf image datasets	Achieved 98.29% accuracy in disease prediction for yield improvement	Your work avoids DL complexity and focuses on **interpretable data patterns** for decision-making.
Afkharinah et al. (2023)	Paddy growth classification	Boosting classifier	Paddy crop in Indonesia	Improved classification of crop growth phases using oversampling techniques	Your paper contributes a **generalized EDA model** that can apply to multiple crops and indicators.

Hachimi et al. (2022)	Smart weather data management for irrigation scheduling	ML and DL-based meteorological data processing	Morocco – weather station datasets	Improved irrigation efficiency using weather-based planning	Your study utilizes climate data, focusing on productivity and sustainability rather than scheduling.
Varlik et al. (2023)	Urban agricultural planning decision support	System-level modeling	City-based agri land use optimization	Proposed efficient land use for urban crop production	Your study emphasizes **rural and regional data**, integrating **economic competitiveness.**

A comparison of EDA with ML and DL is presented in the following table, examining cost, scalability, and real-world applications.

Table-2. EDA Comparison with ML/DL Models

Criterion	**EDA (Exploratory Data Analytics)**	**ML (Machine Learning)**	**DL (Deep Learning)**
Cost	Low (open-source, low computation)	Moderate (needs labeled data & tuning)	High (requires large datasets & GPUs)
Scalability	Medium (suitable for medium-large datasets)	High (but depends on model complexity)	High (but resource-intensive and less interpretable)
Interpretability	High (statistical graphs, clear patterns)	Moderate (some models like decision trees)	Low (black-box models)
Real-World Use	Ideal for initial analysis, policy design, and rural use	Useful for prediction and recommendation systems	Suitable for precision agri-tech and automation
Suitability	Best for **policy planning, research insight**	Best for **forecasting and optimization tasks**	Best for **image processing and sensor data**

The integration of agricultural competitiveness and sustainability using the EDA model provides valuable insights. However, it has some limitations, like the availability and completeness of agricultural datasets across various regions. Utilizing the data from multiple countries introduces data gaps, which can skew the analysis. The policies and practices used in one area cannot be directly applied to other regions. Therefore, it is crucial to prioritize the development of global agricultural schemes. Finally, EDA can only provide exploring, visualizing, and discovering patterns, and cannot establish causality. These limitations can provide opportunities for future work scope.

CONCLUSIONS

This research examines the relationship between competitiveness and sustainability in farming using Exploratory Data Analytics (EDA) to elucidate the complex connection between agricultural productivity, economic growth, and environmental conservation. It is discovered that increased productivity and improved market opportunities often lead to resource depletion and pollution. These challenges can be mitigated through the efficient management of assets, the use of advanced tools, and the implementation of targeted strategies. The research reveals local differences and highlights the need for methods to fit specific conditions. It presents a framework for analyzing farming information, identifies key factors affecting efficiency and durability, and proposes actionable remedies. The findings highlight EDA as a valuable approach for addressing global farming issues and promoting sustainable choices. Future research may utilize predictive analytics and larger datasets, incorporating social and climate aspects, to refine strategies and enhance agriculture's adaptability and sustainability in a rapidly changing environment.

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