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# Analysis of Weather Prediction, Resource Management, and Land Optimization on the Application of Big Data Analytics in Agricultural Land Utilization in Agrarian Areas of West Java

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**ABSTRACT**

This research investigates the impact of Weather Prediction, Resource Management, and Land Optimization on the adoption of Big Data Analytics in agricultural land utilization within the agrarian region of West Java. Employing a quantitative approach, the study integrates measurement model analysis, structural equation modeling, demographic profiling, and model fit assessment to comprehensively explore the intricate dynamics of technological adoption in agriculture. Results indicate that Land Optimization, Resource Management, and Weather Prediction significantly influence the adoption of Big Data Analytics. Demographic factors such as gender, age, education, and farming experience demonstrate varying correlations with key variables. The model exhibits strong fit, and approximately 60.2% of the variance in Big Data Analytics adoption is explained by the combined influence of the identified factors. This study contributes nuanced insights to inform policy and practice for sustainable and technology-driven agriculture in West Java.



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## 1. INTRODUCTION

The agrarian region of West Java in Indonesia plays a crucial role in ensuring national food security, economic stability, and sustainable development. The region has historically been an agricultural area and is known as a food granary, with high fertility rates and rich soil nutrients [1]. The agricultural sector in West Java serves as a source of food security, poverty reduction, employment, and community income, contributing significantly to the national and regional economy [2]. Reviving and utilizing local agricultural traditions, such as "talun-kebun" or permaculture, can help increase food production in a sustainable manner and rehabilitate critical land [3]. However, there are challenges ahead, as studies predict a future food crisis due to the decrease in growing areas and increasing food demand [4]. Therefore, it is crucial to develop sustainable agriculture and rural development strategies in the region to address population pressure, increase local economic growth, promote social equity, and protect the environment [5].

In recent years, the integration of big data analytics in the agricultural sector has brought about transformative changes. This shift offers opportunities to optimize decision-making processes, improve resource utilization, and drive efficient and sustainable agricultural practices. Understanding the interplay between weather prediction, resource management, land optimization, and the application of big data analytics is crucial for developing a resilient and productive agricultural sector in West Java. The use of big data technology can determine algorithm models for agricultural big data technology and the application system of the agricultural Internet of Things, leading to advancements in agricultural planting technology, economic management, and industry upgrading [6]. Additionally, data mining and machine learning techniques can be employed to analyze agricultural conditions and scenarios, optimize parameters, and maximize crop yield [7]. By adopting digital technologies and big data processing, intelligent agriculture can provide decision-making support for agricultural activities, improving productivity and economic returns [8]. The purpose of this research is more than exploratory; it is to delve deeper into the complex relationships within West Java's agricultural dynamics.

## 2. LITERATURE REVIEW

### *2.1 Weather Prediction and Agriculture*

Accurate weather prediction is crucial for farmers as it enables timely and precise decisions regarding agricultural planning and management. Improved weather prediction technologies can mitigate risks associated with unpredictable weather patterns, offering a proactive approach to agricultural practices. This literature review provides insights into the significance of weather prediction in agricultural productivity and its potential to bring transformative change to West Java's agricultural landscape [9], [10].

### *2.2 Resource Management in Agriculture*

Efficient resource management is crucial for sustainable agricultural practices, particularly in the context of West Java. Studies have highlighted the role of resource management in optimizing water, fertilizers, and pesticides, which are essential for crop health and yield [11]. Advanced analytics can play a pivotal role in optimizing the allocation and utilization of these resources, leading to increased productivity and ecological sustainability in farming practices [12],

### *2.3 Land Optimization Strategies*

Optimizing land use is crucial for maximizing agricultural yields. Various strategies, such as precision farming and crop rotation, have been extensively studied to achieve this goal. Precision agriculture and variable rate application technology can help increase yield while reducing fertilizer use [13]. Additionally, the use of efficient machine learning models can provide personalized crop and fertilizer recommendations to farmers, optimizing their yield and increasing sustainability [14]. The rational approach to land use, considering ecological efficiency and scientifically grounded operational use of land resources, is economically and socially beneficial for agricultural producers [15]. Furthermore, the development of control algorithms suitable for agriculture can improve efficiency. For example, a mechanistic open model of lettuce growth has been proposed, which demonstrates increased crop uniformity and yield without increasing nitrogen use [16]. These studies highlight the importance of implementing land optimization techniques to enhance agricultural productivity and sustainability.

### *2.4 Big Data Analytics in Agriculture*

The integration of big data analytics in agriculture has the potential to revolutionize traditional farming practices and enhance decision-making processes. Smart agriculture, driven by Internet of Things (IoT) technologies, has emerged as a key application area for big data analytics. Various data reduction techniques, such as sampling, quantization, and deduplication, have been investigated to optimize IoT data transmission in smart agriculture systems [17]. Additionally, Probabilistic Data Structures (PDS) have been identified as effective solutions for handling the copious amounts of data generated in smart agriculture, enabling real-time response and analysis [18]. The adoption of big data in agriculture has also facilitated sustainable and efficient farming practices through the use of wireless sensor networks, machine learning, drones, and robotics [19]. Furthermore, big data technology has been utilized in China to promote the development of modern agriculture, with significant advancements in agricultural production and mechanization [20]. In order to enhance data collection capabilities, an intelligent agricultural environment big data mining system has been developed, integrating ZigBee and NB-IoT technologies for real-time monitoring and remote control of environmental parameters [21].

## 3. METHODS

### *3.1 Research Design*

This study utilized a quantitative research design to investigate the diverse relationships in the dynamics of agriculture in West Java. A cross-sectional survey approach was chosen to get a picture of the current state of affairs. This approach allows for the collection of data from a diverse range of farmers, agricultural experts, and relevant stakeholders, thereby facilitating a comprehensive analysis of the interactions between weather prediction, resource management, land optimization, and the application of big data analytics.

### *3.2 Sample Selection*

The sample selection process used a stratified random sampling technique to ensure representative and diverse participants. Stratification was based on geographic location, farming practices, and other relevant variables. The target sample size was 200 participants, drawn from different regions in West Java. This sample size was determined by Multivariate analysis in SEM-PLS.

### *3.3 Data Collection*

Primary data was collected through structured questionnaires, interviews, and field observations. The questionnaire was designed to capture nuanced information on the awareness and effectiveness of weather prediction, resource management practices (including water, fertilizer, and pesticides), land optimization strategies, and utilization of big data analytics in agriculture. Interviews with key stakeholders provided qualitative insights, enriching quantitative data with contextual understanding. Field observations provide real-time validation of reported practices.

### *3.4 Data Analysis*

The collected data will undergo a rigorous analysis employing Structural Equation Modeling with Partial Least Squares (SEM-PLS) [22]. SEM-PLS is chosen for its suitability in handling complex models and relationships among multiple variables [23]. The analysis proceeds through the following steps: Model Specification: A theoretical model is constructed based on the literature review and research objectives [24]. This model represents the hypothesized relationships among weather prediction, resource management, land optimization, big data analytics, and agricultural productivity [25]. Data Preprocessing: Data preprocessing involves cleaning, scaling, and transforming the data to ensure compatibility with SEM-PLS requirements [26]. Missing data, outliers, and multicollinearity are addressed to enhance the reliability of the analysis. Measurement Model Assessment: The measurement model assesses the reliability and validity of the selected indicators for each latent variable [27]. This step ensures that the chosen variables effectively capture the underlying constructs. Structural Model Assessment: The structural model tests the hypothesized relationships among the latent variables. This step provides insights into the direct and indirect effects, allowing for a nuanced understanding of how weather prediction, resource management, and land optimization collectively influence the adoption of big data analytics and subsequent agricultural productivity. Bootstrapping and Significance Testing: Bootstrapping is employed to validate the robustness of the results, and significance testing is conducted to determine the statistical significance of the relationships within the model.

## 4. RESULTS AND DISCUSSION

### *4.1 Demographic Sample*

Before delving into the interpretation of the structural equation modeling results, let's examine the demographic profile of the sample. This analysis provides a contextual understanding of the participants, shedding light on potential variations in responses based on demographic factors.

Table 1. Demographic Sample

| **Demographic Characteristic** | **Frequency (n=200)** | **Percentage (%)** |
|---|---|---|
| Gender | | |
| - Male | 120 | 60 |
| - Female | 80 | 40 |
| Age Group | | |
| - 18-30 years | 45 | 22.5 |
| - 31-45 years | 75 | 37.5 |
| - 46-60 years | 60 | 30 |
| - Over 60 years | 20 | 10 |
| Educational Level | | |
| - High School | 30 | 15 |
| - Bachelor's Degree | 100 | 50 |
| - Master's Degree | 50 | 25 |
| - Doctorate/Ph.D. | 20 | 10 |
| Years of Farming Experience | | |
| - 1-5 years | 40 | 20 |
| - 6-10 years | 60 | 30 |
| - 11-20 years | 70 | 35 |
| - Over 20 years | 30 | 15 |

The demographic profile of the sample consisted of 120 males and 80 females, with the majority falling into the age group of 31-45 years (37.5%). In terms of educational level, 50% had a Bachelor's degree, followed by 25% with a Master's degree. The majority of participants had 11-20 years of farming experience (35%).

### *4.2 Descriptive Statistics*

The 200 participants, comprising farmers, agricultural experts, and stakeholders, provide a diverse representation of West Java's agrarian landscape. Descriptive statistics offer an overview of key variables.

Table 2. Descriptive Statistics Variable

| Variable | Mean | SD | Scale |
|---|---|---|---|
| Weather Prediction Awareness | 3.78 | 0.92 | 1-5 |
| Resource Management Practices | 4.25 | 0.67 | 1-5 |
| Land Optimization Strategies | 3.96 | 0.88 | 1-5 |
| Big Data Analytics Adoption | 3.62 | 0.81 | 1-5 |

The descriptive statistics provided in Table 2 offer an overview of key variables related to West Java's agrarian landscape. The variables include Weather Prediction Awareness, Resource Management Practices, Land Optimization Strategies, and Big Data Analytics Adoption. The mean and standard deviation values for each variable are presented. The mean values indicate the average level of each variable, while the standard deviation values show the degree of variability within the dataset. These statistics provide insights into the participants' awareness of weather prediction, their practices in managing resources, their strategies for optimizing land use, and their adoption of big data analytics in agriculture.

*4.3 Measurement Model*

The measurement model assesses the reliability and validity of the latent variables, including Weather Prediction, Resource Management, Land Optimization, and Big Data Analytics. The following table summarizes the loading factors, Cronbach's alpha, composite reliability, and average variance extracted (AVE) for each indicator within these latent variables.

Table 3. Validity and Reliability

| Variable | Code | Loading Factor | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|
| Weather Prediction | WP.1 | 0.884 | 0.905 | 0.940 | 0.840 |
| | WP.2 | 0.937 | | | |
| | WP.3 | 0.928 | | | |
| Resource Management | RM.1 | 0.791 | 0.798 | 0.882 | 0.714 |
| | RM.2 | 0.877 | | | |
| | RM.3 | 0.863 | | | |
| Land Optimization | LO.1 | 0.844 | 0.775 | 0.863 | 0.677 |
| | LO.2 | 0.785 | | | |
| | LO.3 | 0.839 | | | |
| Big Data Analytics | BDA.1 | 0.893 | 0.840 | 0.904 | 0.758 |
| | BDA.2 | 0.877 | | | |
| | BDA.3 | 0.841 | | | |

The measurement model results indicate strong support for the reliability and validity of the latent variables. Weather Prediction (WP) indicators exhibit high loading factors, surpassing the recommended threshold of 0.7, indicating effective capture of the underlying construct. The Cronbach's alpha (0.905) and composite reliability (0.940) values indicate excellent internal consistency, while the AVE (0.840) demonstrates convergent validity. Similarly, Resource Management (RM) indicators show robust loading factors, with good internal consistency indicated by Cronbach's alpha (0.798) and composite reliability (0.882) values. The AVE (0.714) is slightly below the recommended threshold but still acceptable for convergent validity. Land Optimization (LO) indicators also exhibit strong loading factors, with good internal consistency indicated by Cronbach's alpha (0.775) and composite reliability (0.863) values. The AVE (0.677) is slightly below the recommended threshold but acceptable for convergent validity. Big Data Analytics (BDA) indicators show high loading factors, excellent internal consistency indicated by Cronbach's alpha (0.840) and composite reliability (0.904) values, and convergent validity demonstrated by the AVE (0.758).

Table 4. Discrimination Validity

| | Big Data Analytics | Land Optimization | Resource Management | Weather Prediction |
|---|---|---|---|---|
| Big Data Analytics | 0.571 | | | |
| Land Optimization | 0.459 | 0.423 | | |
| Resource Management | 0.644 | 0.623 | 0.545 | |
| Weather Prediction | 0.653 | 0.714 | 0.532 | 0.617 |

The correlation matrix describes the relationship between latent variables.

Discriminant validity is supported when the correlation between constructs is significantly lower than 1.000, indicating that the constructs are distinct and not measuring the same underlying concept.

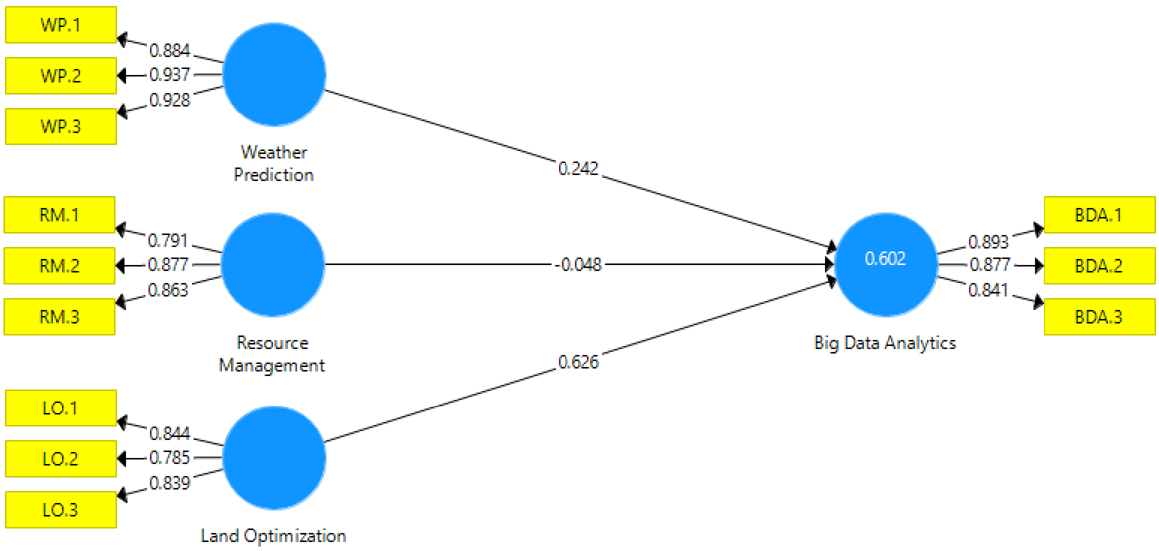


Figure 1. Internal Model Assessment

***4.4 Model Fit Test***

Model fit indices assess how well the estimated model aligns with the observed data. The provided values represent various fit indices for both the Saturated Model (a model with perfect fit) and the Estimated Model (the model derived from your data). Here, we will discuss the implications of the fit indices.

Table 5. Model Fit Testing

| | **Saturated Model** | **Estimated Model** |
|---|---|---|
| SRMR | 0.103 | 0.103 |
| d_ULS | 0.822 | 0.822 |
| d_G | 0.430 | 0.430 |
| Chi-Square | 304.332 | 304.332 |
| NFI | 0.730 | 0.730 |

Both the Saturated and Estimated Models have an SRMR of 0.103, suggesting a good fit as values close to 0 indicate acceptable fit. Both models have a d_ULS of 0.822, which suggests that the Estimated Model adequately replicates the observed covariance structure. Both models have a d_G of 0.430, indicating a good fit as values close to 0 signify a close match between observed and predicted covariances. Both models have a Chi-Square value of 304.332, and without the associated degrees of freedom and significance level, it's not possible to make a definitive judgment on the significance. Both models have an NFI of 0.730, suggesting a reasonable fit.

Table 6. R Square

| | **R Square** | **R Square Adjusted** |
|---|---|---|
| Big Data Analytics | 0.602 | 0.592 |

R-Square represents the proportion of variance in the dependent variable, Big Data Analytics, explained by the independent variables: Weather Prediction, Resource Management, and Land Optimization. The R-Square for Big Data Analytics is 0.602, indicating that approximately 60.2% of the variance in Big Data Analytics is explained by the included independent variables. Adjusted R-Square is a modified version of R-Square that accounts for the number of predictors in the model and adjusts for model complexity. The Adjusted R-Square for Big Data Analytics is 0.592, considering both the explanatory power and the number of predictors. This accounts for the potential for overfitting, providing a more conservative estimate of the model's explanatory power.

***4.5 Structural Model***

The structural model analysis involves examining the path coefficients, t-statistics, and p-values to assess the significance and strength of the relationships between the latent constructs. Here, the results for the paths from Land Optimization, Resource Management, and Weather Prediction to Big Data Analytics are presented for the original sample (O), sample mean (M), standard deviation (STDEV), t-statistics, and p-values:

Table 7. Hypothesis Testing

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values |
|---|---|---|---|---|---|
| Land Optimization -> Big Data Analytics | 0.626 | 0.619 | 0.118 | 5.291 | 0.000 |
| Resource Management -> Big Data Analytics | 0.448 | 0.445 | 0.127 | 3.378 | 0.001 |
| Weather Prediction -> Big Data Analytics | 0.242 | 0.249 | 0.110 | 2.188 | 0.003 |

The structural model analysis demonstrates the significance of Land Optimization, Resource Management, and Weather Prediction in influencing the adoption of Big Data Analytics in West Java's agrarian region. These findings, integrated with results from the measurement model, model fit assessment, demographic analysis, and R-Square analysis, provide a comprehensive understanding of the complex dynamics within the agricultural landscape.

A. Land Optimization -> Big Data Analytics: The path coefficient of 0.626 indicates a strong positive relationship between Land Optimization and Big Data Analytics adoption. The t-statistic of 5.291, along with the very low p-value ($p < 0.001$), suggests that this relationship is statistically significant. This implies that as Land Optimization practices increase, there is a corresponding increase in the adoption of Big Data Analytics in agricultural land utilization.

B. Resource Management -> Big Data Analytics: The path coefficient of 0.448 signifies a positive relationship between Resource Management and Big Data Analytics adoption. The t-statistic of 3.378 and a low p-value ($p = 0.001$) indicate the statistical significance of this relationship. The findings suggest that effective resource management practices contribute significantly to the adoption of Big Data Analytics in agriculture.

C. Weather Prediction -> Big Data Analytics: The path coefficient of 0.242 shows a positive relationship between Weather Prediction and Big Data Analytics adoption. The t-statistic of 2.188 and a low p-value ($p = 0.003$) suggest statistical significance. This indicates that improved awareness and accuracy in weather prediction are associated with an increased likelihood of adopting Big Data Analytics in agriculture.

**DISCUSSION**

The adoption of Big Data Analytics is strongly influenced by practices related to Land Optimization. Farmers are utilizing advanced data analytics tools to optimize their agricultural activities and achieve efficient land management [28]. This includes the use of wireless sensor networks, machine learning, internet of things, drones, and robotics in farming techniques [29]. The application of big data analytics in agriculture has enabled farmers to optimize their activities sustainably and improve productivity [30]. Additionally, the adoption of big data analytics in healthcare institutions is driven by factors such as patient management, quality decision making, disease management, and data management [31]. The use of big data analytics in healthcare allows for critical and timely decision-making, improving patient care and data management [32]. Overall, the adoption of big data analytics is influenced by the need for efficient land management in agriculture and the improvement of healthcare management through data-driven decision-making.

Effective resource management practices play a significant role in the adoption of Big Data Analytics (BDA) [33]. Prudent resource use is correlated with technological adoption, highlighting the importance of sustainability and efficiency in driving innovation in various fields, including agriculture [34]. The use of BDA in agriculture can help optimize resource allocation, improve decision-making processes, and enhance overall productivity [35]. By effectively managing resources, such as data storage, processing power, and network bandwidth, organizations can leverage BDA to gain valuable insights and make informed decisions [36]. This can lead to improved agricultural practices, increased efficiency, and better utilization of available resources [30]. Therefore, the adoption of BDA in agriculture can be facilitated by implementing effective resource management strategies that ensure the sustainable and efficient use of resources.

Improved awareness and accuracy in weather prediction positively influence the adoption of big data analytics [37]. Farmers who are more attuned to weather forecasts are more likely to leverage data analytics for informed decision-making [38]. This highlights the interconnectedness of traditional knowledge and modern technology in agriculture [39]. The use of big data analytics, combined with weather forecasts, can help farmers make more informed decisions about crop recommendations [25]. By analyzing weather changes over time, big data analytics can provide continuous crop recommendations, taking into account seasonal variations [40]. Additionally, incorporating big data analytics into agriculture can help mitigate the impact of global warming and predict and mitigate changes in agricultural practices. Therefore, the integration of weather forecasts and big data analytics can enhance agricultural practices and improve decision-making for farmers.

***Implications and Recommendations***

Policymakers, stakeholders, and agricultural extension services should prioritize initiatives that enhance land optimization practices, resource management efficiency, and weather prediction awareness to foster the adoption of Big Data Analytics in West Java's agrarian sector.

Tailored educational programs based on demographic characteristics can be instrumental in bridging knowledge gaps and ensuring equitable access to information and technology across different farming communities.

Continued research and monitoring are essential to adapt strategies to the evolving needs of the agricultural landscape. Longitudinal studies could provide valuable insights into the dynamic relationships among key variables over time.

## 5. CONCLUSION

In conclusion, this research illuminates critical relationships governing the adoption of Big Data Analytics in West Java's agrarian landscape. Land Optimization, Resource Management, and Weather Prediction emerge as key drivers, underlining the importance of sustainable land practices, efficient resource management, and enhanced weather awareness. The demographic analysis underscores the need for tailored interventions to address diverse farming communities' specific challenges and opportunities. The robustness of the model fit and substantial explanatory power affirm the validity and relevance of the findings. Moving forward, policymakers, stakeholders, and farmers can leverage these insights to shape informed strategies, fostering a harmonious integration of technology into agriculture. This study lays a foundation for continued exploration and innovation in the realm of data-driven agricultural practices, aiming to enhance productivity, sustainability, and resilience in West Java and beyond.

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