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GEOSTATISTICS AND DIGITAL IMAGE ANALYSIS FOR OPTIMIZING RICE PRODUCTION

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ABSTRACT

Rice, as the staple food for a significant majority of the Indonesian population, plays a crucial role in food security and socio-economic stability. To address the strategic challenges associated with rice production, this study focuses on utilizing geostatistics and digital image analysis techniques to optimize rice production and enhance agricultural practices. The key factors influencing rice production, including land area, fertilization, seed varieties, human resources, and agricultural technology, are examined in relation to food security concerns. Fertilizers, high-yielding varieties, and water availability emerge as vital elements for increasing national rice production. However, the efficiency and effectiveness of fertilization practices are heavily influenced by localized conditions, and current approaches often lack rationality and balance. To achieve efficient production and rationalize fertilization practices, this research proposes the application of geostatistics and digital image analysis techniques. Geostatistical models, specifically the Kriging Method, are employed to predict the spatial distribution of key nutrients and fertilizers, such as Sodium, Phosphorus, and Potassium (NPK), required by rice plants in paddy fields. Additionally, digital image processing and computer vision technologies are utilized to automate the assessment of nutrient adequacy based on leaf color analysis. This advancement replaces the previous manual comparison method, providing a more accurate and efficient approach. The integration of geostatistics and digital image analysis offers a promising solution to optimize nutrient management, precision fertilization, and overall rice production. By harnessing advanced technologies and data-driven approaches, this study aims to contribute to the development of sustainable agricultural practices, ensuring improved food security and socio-economic well-being for the Indonesian population.

Keywords: *Geostatistics, Digital Image Analysis, Rice Production, Nutrient Management, Precision Fertilization, Food Security.*

1 INTRODUCTION

Rice production is of utmost importance for ensuring food security and socio-economic stability for the majority of the Indonesian population. However, several strategic challenges hinder the optimization of rice production and the enhancement of agricultural practices [1]. In this study, the focus is on utilizing geostatistics and digital image analysis techniques to address these challenges and optimize rice production. The title of this research article is "Geostatistics and Digital Image Analysis for Optimizing Rice Production."

Factors such as land area, fertilization, seed varieties, human resources, and agricultural technology have a significant impact on rice production and food security. Among these factors, fertilizers, high-yielding varieties, and water availability emerge as crucial elements for increasing national rice production [2]. However, the efficiency and effectiveness of fertilization practices are often hindered by localized conditions, and existing approaches lack rationality and balance.

To achieve efficient production and rationalize fertilization practices, this research proposes the application of geostatistics and digital image analysis techniques [3]. Geostatistical models, specifically the Kriging Method, are employed to predict the spatial distribution of key nutrients and fertilizers, such as Sodium, Phosphorus, and Potassium (NPK), required by rice plants in paddy fields. Additionally, digital image processing and computer vision technologies are utilized to automate the assessment of nutrient adequacy based on leaf color analysis. This advancement replaces the previous manual comparison method, providing a more accurate and efficient approach.

The integration of geostatistics and digital image analysis offers a promising solution to optimize nutrient management, enable precision fertilization, and enhance overall rice production. By harnessing advanced technologies and data-driven approaches, this study aims to contribute to the development of sustainable agricultural practices, ensuring improved food security and socio-economic well-being for the Indonesian population.

This research builds upon the identified problems in rice smart farms, such as the lack of smart farm technology to monitor and optimize fertilizer requirements and the growth rate of rice plants. Furthermore, the absence of a comprehensive framework utilizing geospatial data for smart farm implementation poses challenges. The research objectives encompass identifying NPK fertilization parameters related to rice plant growth rate, optimizing and predicting fertilization parameters, and developing a smart farm framework for future fertilizer optimization and availability. The study specifically focuses on rice crops and employs a combination of spatial data and geostatistical methods to optimize and predict based on parameters affecting rice plant growth rate and soil characteristics.

The global issue of food security emphasizes the need for sustainable and efficient agricultural practices, as the agricultural sector's food demand is projected to double by 2050 [4]. Countries such as India, Thailand, the Philippines, China, Japan, and the United States have already implemented smart farms to address factors affecting the growth rate of rice plants [5]–[7]. Precision Agriculture (PA) or Smart Agriculture serves as a systems approach to managing soil and crops, reducing decision uncertainty through better understanding and management of spatial and temporal variability [8]–[10]. Precision farming, which originated in the mid-1980s, aimed to increase fertilizer application efficiency by varying levels and mixes within fields based on available technology.

In Indonesia, where the government targets a grain surplus of 10 million tons, fertilizer plays a vital role in supporting national rice production [11]. However, existing fertilization recommendations have limitations, and the use of Ricefield Soil Test Equipment is limited by equipment availability in the field [12]. The efficiency of fertilization on paddy fields, as the largest fertilizer consumers, needs improvement to ensure even productivity distribution, especially considering the rising fertilizer prices.

By addressing these challenges and integrating geostatistics and digital image analysis, this research aims to contribute to the advancement of precision agriculture in rice production. The findings hold the potential to revolutionize fertilizer optimization, enhance productivity, and contribute to sustainable agricultural practices, ultimately ensuring improved food security and socio-economic well-being for the Indonesian.

2 LITERATURE STUDY

Based on an extensive review of scholarly journals, this literature review chapter explores the use of advanced technologies and methodologies in the implementation of Smart farms. The analysis covers various aspects, including the development of an experience-based food security scale adapted from the United States Household Food Security Survey Module, which assesses food security in Kolkata slum households. The results indicate that 15.4% of households in this context are food insecure. Additionally, statistical analysis techniques [13]–[15] are employed to examine study locations, survey details, typological construction, food security assessment, and scenario analysis [16].

The literature review also investigates the application areas of thermal Remote Sensing (RS) in agriculture, including irrigation scheduling, drought monitoring, plant disease detection, and the mapping of soil properties, residues, tillage, field tiles, crop maturity, and yield. Furthermore, a reporting system is proposed as a potential solution [17]. Challenges associated with the implementation of thermal RS are discussed, such as spatial and temporal resolution, atmospheric conditions, and plant growth stages [18].

To achieve scientific cultivation and reduce management costs, a wireless sensor network architecture specifically designed for vegetable greenhouses is proposed, with a focus on environmental monitoring [19]. Moreover, an Internet of Things (IoT) platform for agriculture is introduced, enabling seamless data collection from multiple sensors, cameras, and drones [16], [20]–[22]. In this project, the information gathered from input sensors is processed using a neural network

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algorithm and a correction factor for monitoring purposes. Soil monitoring is also incorporated, providing a series of assessments to track changes in soil conditions and properties over time [23].

The literature review discusses changes, potential, open issues, and future trends [24]. It explores the use of ontologies to combine data from heterogeneous databases and devices such as climate sensors and mobile phones. Shallow parsing is used to extract domain-specific concepts and their attributes from semi-structured texts, and production rules are employed to enable the formalized functional knowledge of dispersed language texts across the Web [25]. Geographic Information System (GIS) is utilized as a tool in this research, estimating rice yield of each soil group in a particular district [26]. A mathematical model is developed for estimating rice production in terms of harvested area and yield [27]. Soil sensing in precision agriculture, satellite remote sensing, plant proximal remote sensing for precision agriculture, and hyperspectral remote sensing in precision agriculture are also discussed [28]. The articles referenced in this literature review primarily come from international journals related to smart farms, data mining, prediction methods, IoT technology, and geostatistics [29].

Geostatistics is described as a suite of mathematical tools originally developed to study phenomena that vary in space, but it has evolved for application to various earth science problems. Geostatistics' strength lies in its stochastic approach to numerical modeling. While not all tools in the geostatistical toolbox are stochastic, most of them, or at least the workflows they describe, are. Geostatistics excels in inferring a population from sample data, in contrast to traditional statistics, which often dilutes sample information into summary statistics like mean and variance. Geostatistics focuses on natural phenomena that exhibit spatial correlation, which is a feature of all natural phenomena. Spatial continuity or variability, spatial anisotropy, and trends are typical features of importance.

Traditional soil mapping typically uses a representative soil property from a given location to describe a soil unit, vectorized using physiographic and landforms methods in the soil map. However, soil mappers acknowledge that the spatial variability of soil properties is not accurately represented as they are distorted by boundaries [30], [31]. In reality, soil properties exhibit spatial variability and form a continuum, which should be considered for accurate prediction. Traditional methods of soil analysis and interpretation are often tedious, time-consuming, and costly. Geostatistical methods, such as Kriging, Inverse Distance Weighting, and Spline, are widely accepted as important spatial interpolation techniques in soil mapping [17], [32]. Although various methods exist, studies have reported better interpolation results with Kriging than with other methods [30]. Geostatistics is commonly used as a predictive tool, incorporating expert knowledge to make accurate predictions of soil properties [31]. Geostatistical techniques estimate spatial variability using variogram models, which predict the values of soil properties at unsampled locations [33]. These methods assess spatial correlation in soils and ascertain the spatial variability in soil properties (physical, chemical, and biological) [33].

In Nigeria, the soil maps available were mostly prepared through conventional survey methods, with limited use of modern spatial mapping techniques [33]. Accurate prediction of soil property variability, such as particle size distribution, pH, organic carbon, CEC, and available phosphorus, is crucial for sustainable agriculture. The objective of this study is to map soil properties (Sand, Clay, pH, OC, P, N, and CEC) and predict their spatial variability using geostatistical techniques [34].

Geostatistics methods such as Kriging, Inverse Distance Weighting, and Spline are commonly used in soil mapping as spatial interpolation techniques [35], [36]. Kriging, in particular, has shown better interpolation results compared to other methods [37]. Geostatistics is also employed as a predictive tool, incorporating expert knowledge to accurately predict soil properties [38] [39].

These techniques utilize variogram models to estimate spatial variability and predict soil property values at unsampled locations. They are widely used to assess spatial correlation and variability in soil properties, including physical, chemical, and biological characteristics [40]. Kriging, specifically, employs the mean of known locations to estimate soil properties in unsampled areas [41].

Geostatistics deals with regionalized variables, which are variables that exhibit spatial variability and are often denoted as Z. These variables can be continuous (e.g., permeability and porosity) or categorical (e.g., lithofacies classification). Due to the complex and erratic nature of regionalized variables, they are considered random variables and modeled as random functions [42].

Kriging, one of the geostatistical methods, is an optimal interpolation technique that regresses against observed data points and weights them based on spatial covariance values. It involves estimating the value of a variable at an unmeasured location using observed values from surrounding locations.

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The kriging approach utilizes a linear regression estimator and assigns kriging weights to neighboring data points for estimation [43].

The review concludes by highlighting the comprehensive analysis of utilizing advanced technologies and methodologies in the implementation of Smart farms. The findings demonstrate the development of innovative approaches, including the experience-based food security scale, thermal Remote Sensing (RS) applications, wireless sensor network architecture, and the Internet of Things (IoT) platform. These advancements offer promising solutions for addressing food security challenges, optimizing agricultural practices, and enhancing farm management efficiency. The review acknowledges the challenges related to spatial and temporal resolution, atmospheric conditions, and plant growth stages, emphasizing the need for further research and technological advancements in these areas. Overall, the literature review provides a robust foundation for subsequent chapters and contributes valuable insights to the field of Smart farming.

The research presented in this literature review makes a significant contribution to the current literature on rice production and agricultural practices. By integrating geostatistics and digital image analysis, it offers a novel approach to optimizing rice production. The study focuses on predicting the spatial distribution of key nutrients and fertilizers using geostatistical models, enabling efficient nutrient management and precision fertilization. Furthermore, by incorporating digital image processing and computer vision technologies, the research automates the assessment of nutrient adequacy based on leaf color analysis, improving efficiency and accuracy. These advancements in precision agriculture contribute to sustainable farming practices and resource utilization. Overall, this research provides valuable insights and practical solutions to enhance food security, socio-economic stability, and sustainable agricultural practices not only in Indonesia but also in other regions.

3 METHODS

This chapter presents the methodology used in the research, which follows a quantitative approach to gather and analyze data. Additionally, a qualitative research approach is employed to gain detailed information on the physiological attributes (PA) of rice plants, factors influencing rice plant growth, the fertilization process, and the construction of a Distribution Map of NPK Fertilizer.

3.1 Research Approach

The research utilizes a quantitative approach to decompose and analyze the obtained PA information, identifying the key factors that are significant for the study. This approach allows for a comprehensive understanding of the relationship between rice plant growth, NPK fertilization, and the factors affecting growth rates.

3.2 Research Categories

The research is categorized into four major categories, each serving a specific purpose in the study:

(i) Laboratory Experiments: This category involves conducting experiments in controlled laboratory settings to investigate specific aspects related to rice plant growth and NPK fertilization. These experiments provide valuable insights into the physiological processes and responses of rice plants to different fertilization methods.

(ii) Experimental Research (Field Experiments): This category focuses on conducting experiments in actual field conditions to observe and measure the effects of different variables on rice plant growth and the application of NPK fertilizers. Field experiments provide practical data that simulates real-world scenarios.

(iii) Field Studies: This category involves direct observation and data collection in natural field environments to examine the relationship between rice plant growth, fertilization processes, and other relevant factors. Field studies help capture the complexities and interactions occurring in the natural ecosystem.

(iv) Survey Research: This category utilizes survey methods to gather information from a representative sample of respondents. Surveys will be used to obtain data on farmers' practices, perceptions, and experiences related to rice plant growth and NPK fertilizer usage. The information collected through surveys provides valuable insights into the practical aspects of fertilization practices.

3.3 Experimental Design

This section explores the various types of experimental research designs used in the study. Researchers will learn about the criteria for establishing a good experimental design, ensuring the reliability and validity of the experiments conducted. The selected experimental designs will align with the research objectives and allow for the collection of relevant and accurate data.

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3.4 Development of NPK Fertilizer Distribution Software

The development of NPK fertilizer distribution software will involve several stages, including analysis, design, implementation, and maintenance. These stages will ensure the successful creation of a software tool that facilitates the efficient distribution of NPK fertilizers based on the research findings. The software will assist in optimizing the use of fertilizers and promoting sustainable agriculture practices.

This chapter outlines the research methodology, which combines quantitative and qualitative approaches. It also presents the four main categories of research: laboratory experiments, experimental research (field experiments), field studies, and survey research. Additionally, the chapter discusses the importance of experimental design and the stages involved in developing NPK fertilizer distribution software. These methodological aspects form the foundation for conducting the research and achieving the study objectives.

4 RESULT AND DISCUSSION

Rice experiments in 2 locations in the field with variations in nitrogen nutrient adequacy. The research location is in Magelang, Central Java, and in the Laboratory/Greenhouse of the UPNVY Department of Agriculture. The variety grown is "Ciherang" with the consideration of being the most popular variety grown in the research area and showing obvious visual symptoms.

4.1 Planting hydroponic rice in a greenhouse with variations in nitrogen nutrient adequacy.

This phase begins with preparing plant media in the form of river sand, as shown in Figure 1 and Figure 2. Before used, the sand is cleansed with tap water until the water is clear. The aim is to remove materials except sand that are possible to carry nutrition.

Figure 1: Media Preparation at the Greenhouse

Figure 2: Media neutralization

Planting is done in plastic pots, Figure 3, consisting of several treatments performed repeatedly. The selected varieties are the most popular varieties grown in the study area, as done in the laboratory, seen in Figure 4.

Figure 3: Rice planting in pots

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Figure 4: Laboratory Nutrition Preparation

The liquid media of hydroponic is prepared with complete nutrient composition which is based on the need of rice crop according to IRRI (International Rice Research Institute, Japan), except for the nitrogen content, variations of sufficiency percentage are made with the value of 10%, 20%, 30%, 40%, 50%, 60%, 70110%,120%, 130%, 140%, 150%. The plant is kept until harvest age.

4.2 Observation of plant growth

During the course of the study, the growth of the rice plants was carefully observed and measured. Several key parameters were monitored to assess the overall development and performance of the plants. Plant height, which refers to the vertical growth of the rice plants, was regularly measured to track their progress. Additionally, the wet and dry weights of the plant biomass were recorded. The wet weight represented the total weight of the plants, including moisture, while the dry weight indicated the weight of the plants after the moisture was removed. These measurements provided insights into the biomass accumulation and overall growth of the rice plants.

In addition to height and biomass measurements, the number of tillers and panicles per pot were also observed. Tillers are secondary shoots that grow from the main stem of the rice plant, and their count serves as an important indicator of plant vigor and productivity. By recording the number of tillers, researchers were able to assess the plant's ability to produce additional shoots, which can contribute to higher yield potential. Similarly, the number of panicles, which are the reproductive structures that contain the rice grains, was documented. Panicles play a crucial role in determining the potential rice yield.

By monitoring these growth parameters, including plant height, wet and dry weights of biomass, tiller count, and panicle count, researchers were able to gain valuable insights into the growth and development of the rice plants. These observations provided essential data for evaluating the plants' response to different treatments, environmental conditions, and management practices.

4.3 Photography of hydroponic rice leaf in green house and Paddy Field

This photography is performed to record digital image of rice leaf from various treatments of nutrient sufficiency variation, pest attack level variation, and plant age variation.

Figure 5: Photography of rice leaf

In Figure 5, Photo shoots of rice leaves were also carried out in the laboratory, and paddy fields (Figure 6 and Figure 7) in Windusari village, Magelang Regency, Central Java, Indonesia, so that later in building knowledge based on intelligent systems, they could adjust to ideal conditions in rice fields on real agriculture. area. Taking pictures of rice leaf green (RGB) can be done using a camera installed around a rice field or using a drone, where the tool is connected to the IoT so that in real time the user can know the condition of rice growth and recommendations for maintenance fertilizers to be applied to the area.

Figure 6: rice leaf in Windusari villages, Magelang District, Central Java, Indonesia

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Figure 7: Rice leaf in Secang villages, Magelang District, Central Java, Indonesia

This photography is performed on selected leaf sample that has been completely developed (fully expanded leaf), starting from plant age of three weeks after transplanting in 10 days of interval. This photography is performed until it comes into bud, seen in Figure 8.

Figure 8: Monitoring rice leaf growth

Table 1: Results of measurement of greenish leaf levels (RGB) First Week

Age	No	date	Red	Green	Blue
01-1-10 %	1	21 Mei	161	218	95
01-2-10%	2	21 Mei	156	218	99
01-3-10%	3	21 Mei	79	139	51
02-1-20%	4	21 Mei	129	185	88
02-2-20%	5	21 Mei	158	234	102
02-3-20%	6	21 Mei	80	134	38
03-1-30%	7	21 Mei	126	176	41
03-2-30%	8	21 Mei	151	219	80
03-3-30%	9	21 Mei	129	206	74
04-1-40%	10	21 Mei	149	214	70
04-2-40%	11	21 Mei	156	216	84
04-3-40%	12	21 Mei	113	181	68
05-1-50%	13	21 Mei	143	178	74
05-2-50%	14	21 Mei	138	185	81
05-3-50%	15	21 Mei	153	234	93

In Table 1 above, it is the result of observing the growth of rice plants in the weekly period, and monitoring and observing the color of rice leaves (R, G, B).

4.4 Developed Konwledge Base for Artificial Intelegence

Based on the color of rice leaves from the results of taking green leaf levels (RGB) for each age of rice growth, the RGB obtained is adjusted to the Leaf Color Chart (LCC). The level of fertilizer sufficiency at each LCC level was also recorded, so that by using Artificial Intelligence, the knowledge base that linked the greenness of rice leaves with the recommendation of sufficient fertilizer was needed. LCC is a standard for rice fertility level used by farmers, the principle of reading the chart is seen from the level of greenness of the leaves, as shown in Figure 9.

Figure 9: Leaf Color Chart (LCC), Manual Standard

4.5 Parameter analysis of the digital image of rice leaf

The process of digital image processing is performed to obtain image parameters, which are: Red (R), Green (G), dan Blue (B).

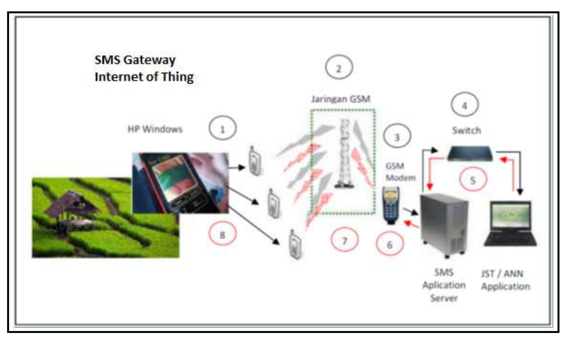

Figure 10: Real time system for monitoring and analysis rice growth

The development of digital image processing technology and artificial neural networks allows it to be used in agriculture. Such as the prediction of soil organic matter levels is carried out based on image parameters quantitatively with more accuracy. Previously, the measurement of nitrogen nutrient adequacy in rice plants has also been proven to be done by comparing leaf color with standard colors on the leaf color chart, although still manually. This study applies digital image parameters to estimate nitrogen adequacy based on leaf color so that it can be automated using computer assistance. The architecture of the Real time system for monitoring and analysis of rice growth can be seen in Figure 10.

Color models have been widely developed by experts including the Red, Green, Blue (RGB) color model and the Hue, Saturation, Intensity (HSI) color model. Color processing using RGB colors is easy and simple because the color information in the computer is already packaged in the same model. The thing that needs to be done is to read the values of red (R), green (G), and blue (B) on a pixel, then display and interpret the color of the calculation results so that it has the desired meaning.

To eliminate the influence of different lighting on the taking of objects, normalization is required, in the following way:

$$r = \frac{R}{R+G+B} \qquad g = \frac{G}{R+G+B} \qquad b = \frac{B}{R+G+B}$$

The HSI (Hue Saturation Intensity) color model is the model that best suits the sensing of the human eye. The Hue value represents the actual colors, such as red, purple, and yellow. Hue is used to distinguish colors and determine redness, greenness, and so on. The Saturation value expresses the degree of purity of the color of the light, that is, it identifies how much white is contained in the color. For example, if green is equated with 100% saturated color, then light green is a green color with a low degree of saturation because it contains white in it. While the Intensity value states the amount of light received by the eye regardless of color. The range of values is between dark (black) at low intensity and light (white) at high intensity.

Artificial neural network (ANN) is a computational structure developed based on the processes of biological neural network systems in the brain. Artificial neural networks are the elaboration of human brain functions (biological neurons) in the form of mathematical functions that carry out calculation processes in parallel. JST is flexible to data input and produces consistent responses. A multilayer network can demonstrate its perfect capabilities for solving problems. ANN can solve parallel calculations for complex tasks, such as prediction and modeling; classification and recognition patterns; clustering; and optimization.

The stage that has been achieved is the validation of the ANN program to test the work of the ANN program resulting in valid decisions about the nutrient adequacy status of nitrogen and the level of pest infestation. At this stage, rice planting has been carried out in 2 locations in Windusari and Secang Villages, Magelang Regency with a land area of ±1000 m 2 each. Nitrogen nutrient levels are made variations in the percentage of adequacy by 0%, 20%, 40%, 60%, 80%, 100%, 120%, 140%, 160%, 180%, and 200%. Nitrogen fertilizers are applied as a basic fertilizer and follow-up fertilizer. Plot size 5x5m with 2 replays x 2 locations. At each location: 1 test to be maintained until harvest, 1 more test as a sacrificial plant to take leaf samples. The variety planted is Ciherang with the consideration as the most popular variety grown in the research area and shows obvious visual symptoms against leafhopper pest attacks.

Observations of plant height, leaf color scores based on leaf color chart (LCC) and enhanced leaf color chart (enhance LCC) scales, as well as the dry weight of rice clumps were carried out every week as many as nine observations. Soil and rice leaf sampling for N grade analysis and rice leaf shooting to record digital images of rice leaves of various nutrient adequacy variations, variations in infestation rates/populations of brown stem leafhoppers, plant age variations, and location variations were also carried out at the time of observation. The results of shooting rice leaves are then analyzed by the parameters of the digital image. The digital image processing process is carried out to obtain image parameters, namely: Red (R), green (G), and blue (B).

The height of rice plants has a tendency that the plant gets higher with increasing nitrogen levels, then decreases again after exceeding the 100% nitrogen content. The same result was also obtained from the measurement of the dry weight of rice clumps. Observations of nitrogen adequacy using the leaf color chart scale (LCC) in Figure 10 and the enhanced leaf color chart scale (LCC) in Figure 12, showed an increase in scale although not so real. It is suspected that this is due to the presence of residues of nitrogen content present in the soil. So, a correction is needed from the results of the analysis of nitrogen levels in the soil. In Figure 13, you can see the influence of N content on plant height.

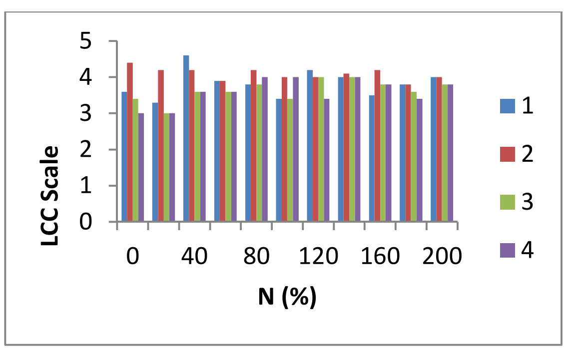

Figure 11: Leaf color scale on measurements with leaf color chart (LCC)

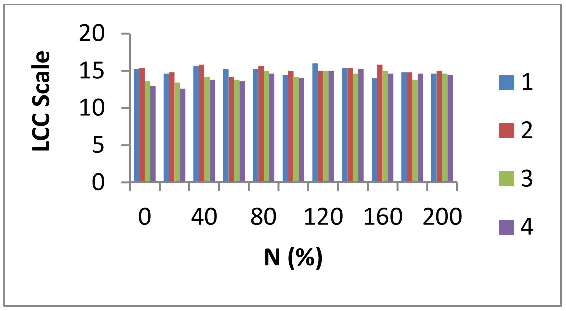

Figure 12: Leaf color scale on measurements with enhanced leaf color chart (LCC)

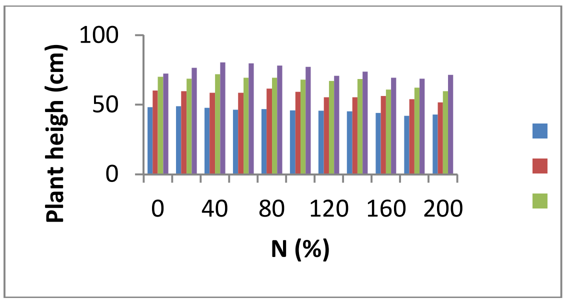

Figure 13: Rice plant height with variations in N levels

Designing nitrogen fertilizer dose directives (N) recommendations and directions for controlling brown stem leafhoppers based on leaf digital image input. After ANN can generate valid information on nitrogen adequacy levels based on digital images of observed rice leaf color with LCC.

In Figure 14 the growth of rice plants is shown in the variation of adequacy N based on the level of greenness of rice leaves in rice fields (C1, C2, to C9), and observed for the age of 1 to 9 weeks. From the image data of the greenness level of rice leaves is used as knowledge in ANN, so that a leaf greenness level standard can be developed, where this digital greenish gradation standard is different from manual LCC, in Figure 15.

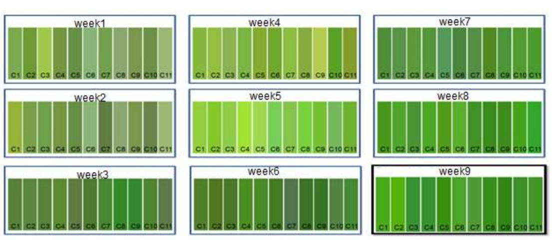

Figure 14: Digital image of rice leaf color on various variations of N adequacy in plants aged 1-9 weeks after planting

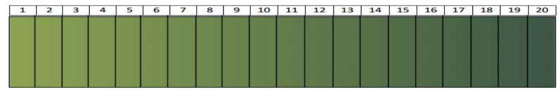

Figure 15: Enhanced leaf color chart (LCC) as Digital Grading Image Leaf Color Standard

Table 2: The value of digital imagery of leaf color compared to LCC color manual standard

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	
12	20	11	17	13	01	11	01	10	14	01	week1
20	03	11	17	13	01	18	01	10	13	01	week2
20	19	20	20	19	20	21	20	20	20	14	week3
17	15	01	12	20	20	13	18	01	21	20	week4
13	20	11	19	01	01	10	12	19	01	20	week5
19	12	18	17	01	18	13	20	17	20	20	week6
20	20	20	20	20	20	20	20	20	20	19	week7
20	20	20	20	20	20	20	20	20	20	20	week8
20	20	20	20	20	20	16	20	20	10	20	week9

Table 3: Recommended addition of urea (kg/ha) based on LCC measurement standards

No. Panel LCC	Availability N	Suggested additions Urea (kg/ha)
1	10%	270
2	20%	240
3	30%	210
4	40%	180
5	50%	150
6	60%	120
7	70%	90
8	80%	60
9	90%	30
10	100%	0
Nov-20	110-200%	No need to add

The recommended dosage direction of nitrogen fertilizers is prepared by making a calculation of plant needs based on the adequacy level and age of the plants produced by ANN Data for the determination of the need for nitrogen fertilizers and calibration of enchance LCC, as in Table 2 and Table 3. The design of the nitrogen fertilizer dose direction is adjusted to variations in soil fertility data according to the sender's location. As a pilot project,

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a map of the soil fertility of Magelang Regency was used.

Designing a prototype of data communication. Communication systems are designed for input-output automation in ANN systems. Automation is designed to allow the receipt of digital photo input from the field and answer responses can be carried out by the system interactively and independently through SMS-based services (short message system). Development of mobile applications to be installed to mobile phones. This application is used on the user side (farmer / user) so that the user's cellphone can send the necessary data correctly and well read to the ANN system. Improved database of soil fertility and nitrogen (N) fertilizer requirements as well as brown stem leafhopper attacks at the policymaker level. At this stage of the study, databases and servers. Currently, as a digital image recording tool, a cell phone with the ability to record images (digital camera facilities) is used. The phone used has a windows operational system (OS). In the tool, the digital image reader program is installed into units of values R (red), G (green), and B (blue). The results of the rice leaf image regam in the form of digital images that have been translated in the form of these numbers are then sent to the server via SMS line. The model is currently chosen considering that sending images requires greater costs (MMS lines). If it is sent through the internet route, it will be constrained by network limitations, and the ability of farmers to operate it.

4.6 IoT Accuisision Data

By using IoT online real time, data on NPK content in rice crop agricultural soil can be obtained. The IoT data component is seen in Figure 16: Real time for monitoring soil characteristic (NPK).

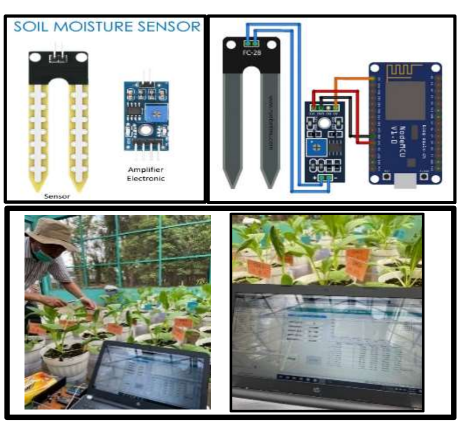

Figure 16: Real time for monitoring soil characteristic (NPK)

Results using IoT can in real time tell soil moisture and soil NPK levels. The resulting dataset can be seen in the table below. Dataset obtained both from greenhouses, Laboratories and in rice fields are processed using Machine Learning with Geostatistics in order to describe the distribution of NPK content of rice fields and fertility distribution of rice plants, so that from the beginning of planting to the harvest period can know the need for NPK fertilizers associated with rice fertility rates, As shown in Figure 17.

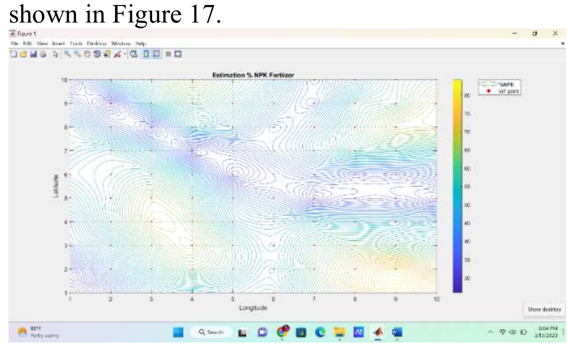

Figure 17: Map distribution of NPK content of rice fields

4.7 Analysis and Evaluation Criteria

This research encompasses various components, including the implementation of planting hydroponic rice in a greenhouse with variations in nitrogen nutrient adequacy, the observation of plant growth, the photography of hydroponic rice leaves in the greenhouse and paddy field, the development of a knowledge base for artificial intelligence, the creation of a map depicting the distribution of the greenish level of rice leaves and fertilizer recommendations in paddy fields, parameter analysis of digital images of rice leaves, and the acquisition of data through IoT devices.

By integrating geostatistics and digital image analysis techniques, this research aims to optimize rice production and overcome strategic challenges in agriculture. The utilization of geostatistical models, specifically the Kriging Method, enables the prediction of the spatial distribution of essential nutrients and fertilizers such as Sodium, Phosphorus, and Potassium (NPK) required by rice plants in paddy fields. This approach facilitates efficient nutrient management and precise fertilization practices. Furthermore, digital image processing and computer vision technologies are employed to automate the assessment of nutrient adequacy through leaf color analysis, providing a more accurate and efficient alternative to manual methods.

Through the integration of advanced technologies and data-driven approaches, this study aims to contribute to the development of sustainable agricultural practices, ultimately enhancing food security and socio-economic well-being in Indonesia. The research builds upon the challenges identified in rice smart farms, including the need for technology to monitor and optimize fertilizer requirements and the growth rate of rice plants. Additionally, a comprehensive smart farm framework is being developed, utilizing geospatial data to optimize and predict outcomes based on parameters influencing rice plant growth and soil characteristics.

Considering the global concern for food security and the projected increase in demand for agricultural products, sustainable and efficient agricultural practices are of paramount importance. Several countries, including India, Thailand, the Philippines, China, Japan, and the United States, have already implemented smart farming techniques to address factors affecting rice plant growth. Precision Agriculture (PA) or Smart Agriculture serves as a systems approach for managing soil and crops, reducing decision uncertainty by better understanding and managing spatial and temporal variability. This research aims to contribute to the advancement of precision agriculture specifically in rice production within Indonesia.

In conclusion, by addressing challenges and incorporating geostatistics and digital image analysis, this research endeavors to revolutionize fertilizer optimization, enhance productivity, and promote sustainable agricultural practices. The potential impact of the findings is significant, as they can revolutionize rice production, improve food security, and contribute to the socio-economic well-being of the Indonesian population.

5 CONCLUSIONS

In this study, efforts have been made to optimize rice production and address strategic challenges in agriculture through the implementation of Precision Agriculture. Geostatistics and digital image analysis techniques were used to obtain important information regarding the distribution of nutrients and NPK fertilizers required by rice plants in paddy fields. In this context, several layers of Precision Agriculture have been developed to achieve the objectives of this research.

Firstly, data was acquired from various input tools related to the growth rate of rice plants and the use of NPK fertilizers. This data formed the dataset that served as the basis for training, testing, optimizing, and estimating the use of NPK fertilizers. The processing of this dataset was a critical step in generating an effective and accurate model.

Secondly, the trained model from the dataset was utilized to perform estimation using geospatial/kriging methods. This estimation aimed to describe the distribution of rice fertility levels and NPK fertilizers in paddy fields. By understanding this distribution, agricultural practices can be precisely optimized according to the specific needs of each area of land.

However, it is important to acknowledge the limitations of this research. One limitation is that the study was conducted specifically in the context of rice production in Indonesia. The findings and conclusions drawn from this study may not be directly applicable to other regions or countries with different environmental conditions, agricultural practices, or socio-economic factors. Additionally, the utilization of the Kriging approach, while effective in predicting the spatial distribution of key nutrients and fertilizers, has its own limitations. The accuracy and reliability of Kriging estimates heavily depend on the quality and density of the available data. Limitations related to data availability, including potential data gaps or inconsistencies, may have influenced the precision of the predicted distribution of nutrients and fertilizers. Furthermore, the terminology and specific parameters used in this study may be context-specific to the Indonesian agricultural system, and their applicability to other regions may require adaptation and customization.

Lastly, a dashboard was developed to display visual information about the distribution of rice fields and NPK fertilizers. This dashboard facilitates farmers and relevant stakeholders in monitoring and managing agricultural practices more efficiently. The information presented through the dashboard provides a clear overview of land conditions, fertilizer requirements, and other important factors in rice production.

Thus, through the development of these layers of Precision Agriculture, this research strives to address challenges in rice agriculture and enhance efficiency and productivity. It is expected that this approach can make a positive contribution to achieving sustainable agricultural goals, improving food security, and enhancing the socio-economic well-being of the Indonesian population. Future studies should consider conducting similar research in different geographical locations and evaluating the effectiveness of the Kriging approach in diverse agricultural settings to enhance the generalizability and robustness of the findings.

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