Optimization and estimation framework of smart farm based on spatial data mining and geostatistics

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Abstract. The development of integrated information systems in the field of rice plant has become an urgent need for policy makers at both provincial and national levels, specialized in developing countries such as Indonesia. At this time, data related to rice availability is still spread across several agencies and difficult to access easily and quickly to support strategic and rapid decision making. This data is the level of fertility of rice plants, fertilizers and water content at certain locations and times. Fertilizers, new superior varieties and water content are production factors that are vital in supporting the efforts to increase national rice production. New superior varieties including hybrid rice are generally responsive to macro fertilizers NPC (Nitrogen-Phosphorus-Calcium), where fertilization efficiency and effectiveness is very dependent on local location. The use of fertilizers with excessive doses must be prevented by socializing the right dosage specifically for location and time. The use of fertilizers with high doses of nitrogen also results in plants being more susceptible to plant pests. Based on the consideration of efficiency and sustainability, the use of uniform recommended doses for large areas and not considering the specific conditions of the plant is no longer relevant to be applied. Therefore the distribution of the characteristics of rice and soil at specific locations and times is very important information.

Research objectives to develop technology that integrates operational information systems at farmer levels (SMS, GSM or IoT) and information systems in management levels with GIS, Spatial data mining, Kriging Interpolation and Artificial Intelligence systems that have prediction ability and optimization of food security problems, especially rice. Spatial data mining with approached geostatistics used to map the distribution of various factors, Nitrogen, Phosphorus, Calcium and Water content that influence the growth rate of rice plants. The results of this study are a smart farm framework that can estimate and optimize sustainability and availability of rice.

1. Introduction

The global food security challenge is straightforward: by 2050, the world must feed 9 billion people. The demand for food will be 60% greater than it is today. The problems of global food security is the availability and continuity of food in the future, where the level of food demand from the agricultural sector is expected to double to 2050 (Francisco Yandun, etc, 2017). Food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life. The absolute number of people in the world affected by chronic food deprivation began to rise in 2014 going from 775 million people to 777

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million by 2015, and is now expected to increase further, to 815 million by 2016. This is an important thing to eradicate hunger and poverty. Food is a primary necessity for people, with other needs that are urgently needed in order to live humanly.

The early use of precision agricultural terms in 1990 as the title of a workshop held in Great Falls, Montana, sponsored by Montana State University. Prior to this, the term 'site-specific management' or 'location-specific farming' was used. In fact, two international conferences on 'precision farming' refer to site-specific management in the title, but at the third conference in 1996 the term precision agriculture was used. By the mid-1990s, what we now regard as a new paradigm in agriculture is called precision agriculture.

Indonesia is one of the developing countries that once was still famous for its livelihood as farmers, but now Indonesia is facing serious problems in terms of food security. Strategic measures are needed in solving food security issues, such as land area, fertilization and superior seeds, quality and quantity of human resources and technology for the advancement agriculture of Indonesia.

Indonesia Directorate General of Food Crops (2014) stipulates an increase in rice production by 2.3% per year starting 2015, reaching 81,971,853 tons in 2019. The increase in rice production targets is based on the potential to increase rice productivity by more than 1 ton per hectare, so the target of 2015 is the achievement of national rice productivity 5,274 ton/ha. Efforts to increase rice production by increasing the area of planting is difficult to do, so that the increase of rice production is done by optimizing the application of rice farming technology to increase productivity. The applied technology is location specific technology based on Integrated Crop Management Concept.

The development of smart farm in the field of food security has become an urgent need for the effectiveness of food policy makers at both the provincial and national levels. At this time data related to food security is still scattered in some agencies and difficult to access easily and quickly let alone to support strategic and rapid decision making in the field of food.

Rice is the staple food of more than half of the world’s population – more than 3.5 billion people depend on rice for more than 20% of their daily calories. Rice provided 19% of global human per capita energy and 13% of per capita protein in 2009. Asia accounts for 90% of global rice consumption, and total rice demand there continues to rise.

Indonesia is famous for the agrarian country until now still can not get out of food problems in his own country. Countries that most of the people working in agriculture are still not able to develop sustainable food security. There is no proper optimization and prediction model in terms of future food security, so that local and national government policies are decidedly inappropriate. The controversy over rice imports during the harvest in some rice barns is an example of inappropriate government policy.

In Indonesia, the government has done many policies to overcome food problems. One example, Indonesia already has Government Regulation (PP) no. 25/2012 on Sustainable Land Agriculture Farm Information System. However, the regulation can not be applied yet, farmers in general still use conventional system. Farmers have no power to survive in the face of the ferocity of industrial progress and the modernization of urban life. There has been a lot of research about smart farm framework, with various technologies and also methodology. But the results of these studies have not helped solve the problem of food security. This research aims to develop an smart farm framework that can visualize (2D, 3D or 4D maps) of rice distribution parameters that will be used to monitor, optimize and predict the future.

2. Approach
Knowledge based artificial intelligence development, by testing the variation of NPC (Nitrogen, Phosphor and Calcium) from 20% to 180% fertilization and brown planthopper attack on various rice varieties to digital image of rice leaf in a series of age to rice plants, conducted hydroponically in the greenhouse. As for the treatment of pest attacks, rice is grown with optimum hydroponic media composition and given inoculation of planthopper pests with populations varying between 0-25 tails per clump of plants to cause variation in pest attack rates. Photographing of rice leaves to record digital
images of rice leaves from various variations of nutrient adequacy, variation of pest attack rate, and variation of plant age.

Analysis of digital image parameter of rice leaf. Digital image processing is done to obtain image parameters, namely: Red (R), green (G), and blue (B), Hue, Saturation, Intensity, Mean, Entropy, Energy, Contrast, and Homogeneity. Analysis of image parameter correlation with nutrient adequacy percentage and pest attack rate. Knowledge base Artificial Intelligence is used to predict the level of nitrogen adequacy in rice crops and the level of pest attacks. Implementation of IoT and SMS Gateway for control, monitor and capture growth rate parameters and pest attack status (Figure 1). Based on digital leaf image inputs that have been in the process of relying on knowledge base on the application of ANN (Figure 2) in obtaining recommendation of recommended fertilizer dosage and pest attack status (Figure 3).

By knowing the growth history and the level of pest attack on rice plants, frameworks can be made to recommend fertilization and pest prevention, prediction and optimization of sustainability and availability of rice crops in the future (Figure 4). The method used is spatial data mining and kriging interpolation, which will provide distribution maps of factors (NPC) that affect the growth of rice plants and predictions of the availability and sustainability of food in the future (Figure 5).

Figure 1. Autoreply Growth Up Monitoring

In Figure 1 shows the system architecture that monitors the growth rate and fertility of rice plants, by taking an image using a mobile phone, then forwarded through the GSM (Global System for Mobile communication) network and received by the server application via the SMS gateway. Intelligent system in Figure 2, processing images, extracting image data, training, testing and providing outputs in the form of recommendations for actions to be taken on the rice plant. The recommendation will be sent from the application server to the user (farmer). Examples of recommendations can be seen in Figure 3.
2.1. Geostatistics, Kriging Interpolation

Geostatistics is a technique used for surface mapping from limited sample data and approximate values in locations without samples. Geostatistics is used for spatial data modeling, spatial spatial characterization, spatial interpolation, simulation, sampling optimization and uncertainty characteristics. The idea of geostatistics is adjacent points each other in a field that tends to be near its values. Several mathematical interpolators and regression (trend surface analysis) have been used with varying success for making maps from sparse data. None, however provides sound estimates of the errors in its interpolations. Kriging, the geostatistical method of interpolation, does that. Further, it minimizes the errors and is best in that sense, and because its predictions are also unbiased it is often known as a best linear unbiased predictor (BLUP).

The term krigeage was coined by P. Carlier in recognition of D.G. Krige’s pioneering innovation for estimating concentrations of gold and other metals in ore bodies. Matheron (1963) later introduced it into the English language as ‘kriging’, and his doctoral thesis (Matheron 1965) placed the technique within the general framework of the theory of random processes. Matheron’s work was not in isolation; Kolmogorov (1939, 1941), Wold (1938) and Wiener (1949) had already come close to kriging, but in time rather than in space (Cressie 1990).

Kriging predicts values at unvisited sites from sparse sample data based on a stochastic model of continuous spatial variation. It does so by taking into account knowledge of the spatial variation as represented in the variogram or covariance function. Ordinary kriging requires no other information than that plus the measurements and their geographic coordinates. It is by far the most popular kind of kriging, and with good reason; it serves well in most situations with its assumptions easily satisfied. It is also robust with regard to moderate departures from those assumptions, and therefore we focus on it. More elaborate forms of kriging have been developed to tackle increasingly complex problems in petroleum engineering, mining and geology, meteorology, soil science, precision agriculture, pollution control, public health, fishery, plant and animal ecology, remote sensing and hydrology.

2.2. Kriging

Kriging is a method of analyzing geostatistical data used to estimate the value of a value that represents a point that is not sampled based on the sample points surrounding it by using a semivariogram structural model. Kriging is also a method used to highlight special methods that minimize variance from estimation results. When viewed in general, the Kriging method is a geostatistical analysis method to interpolate the value of content as an example of mineral content, based on sample data taken in an
irregular place. In general, kriging is a method for analyzing geostatistical data to interpolate the value of mineral content based on data. In other words, this method is used to estimate characteristic values (Frans Richard 2018).

At the non-sampled point, it is based on information from the characteristics of the sampled dots that surround it by considering the spatial correlation that exists in the data. The kriging estimator can be written as follows (Bohling, 2005):

\[ \hat{Z}(u) = \sum_{\alpha=1}^{n} \lambda_{\alpha} [Z(u_{\alpha}) - m(u_{\alpha})] \]  

Information:
- \( u, u_{\alpha} \): the location vector for the estimation and one of the adjacent data, is declared \( \alpha \).
- \( m(u) \): expectation value of \( Z(u) \)
- \( m(u_{\alpha}) \): the expected value of \( Z(u_{\alpha}) \)
- \( \lambda_{\alpha}(u) \): \( Z \) value \( (u_{\alpha}) \) for location estimation \( u \).

The same \( Z(u_{\alpha}) \) value will have different values for estimates at different locations.

\( n \): the number of sample data used for estimation.

\( Z(u) \) is treated as a random field with a trend component, \( m(u) \), and the remaining component or error, \( e(u) = Z(u) - m(u) \).

Remaining kriging estimates for \( u \) as a summation of the remainder in the surrounding data. The \( \lambda_{\alpha} \) value is obtained from the covariance or semivariogram, with the remaining characteristic components required. The purpose of kriging is to determine the value, \( \lambda_{\alpha} \) which minimizes the variance in the estimator, can be stated as follows:

\[ \hat{\sigma}_{e}^2 = \text{var} \{ \hat{Z}(u) - Z(u) \} \]  

Many methods can be used in the kriging method, but based on whether or not the mean is known, Kriging can be divided into three, namely Simple Kriging, Ordinary Kriging, and Universal Kriging.

**Simple Kriging**
Simple Kriging is a kriging method with the assumption that the average (mean) of the population is known and has constant value. The processing of the Simple kriging method is by means of the spatial data that is supposed to be partitioned into several parts.

**Ordinary Kriging**
Ordinary kriging is a method that is assumed that the average (mean) of the population is unknown, and that spatial data does not contain trends. Besides not containing trends, the data used also does not contain outliers.

**Universal Kriging**
Universal kriging is a kriging method that can be applied to spatial data containing trends or nonstationary data.

**Kriging Spatial Interpolation**
Spatial interpolation is the prediction of a variable at an unmeasured location based on a sample in a known location. Spatial interpolation method using GIS can be used when estimating wind speed for a location. There are various spatial interpolation methods such as IDW, Kriging, Natural neighbors, Spline, Topo to Raster, and Trend. Weather data is generally recorded at point locations, so some form of spatial interpolation is needed to estimate data values in other locations. Various deterministic and
geostatistical interpolation methods are available to estimate unmeasured locations but, depending on the spatial attributes of the data, accuracy varies greatly between methods. The final use of the surface of the interpolation variable must also be taken into account because different methods produce different results (Willmott et al. 1985). Spatial interpolation is more useful if adequate weather station densities are available throughout the study area. Wind speed, for example, is more varied in distance shorter than temperature or relative humidity, and is therefore expected to require a denser network of monitoring sites to achieve accurate and precise interpolation surfaces (Luo et al. 2008).

Spatial data play an important role in planning, risk assessment and decision making, especially in wind disaster management. However, it is usually not always available and is often expensive and difficult to obtain. Spatial data collected in the field usually comes from a coordinate point source, the processing requires continuity of spatial data of an area / region under study so that the interpretation obtained is accurate (Chinta, Agarwal, and Rao 2014)

Figure 4 is a complete framework of smart farm which consists of the bottom part is data capture, the middle part is spatial data mining process, GIS reaches the top in the form of food security dashboard.

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**Figure 4. Optimization and Estimation Smart Farm Framework**
3. Result

Research contribution is Developing Framework of Smart Farm Based on Spatial data mining and Geostatistics method in order to optimize and predict food security, especially rice. In addition it also helps farmers, local governments and central government to control, monitor, predict and optimize the growth rate of rice plants.

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