Increasing rice productivity in presence of climate change using Internet of Things (IoT)

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Abstract. Climate change is becoming increasingly unpredictable. This also has an impact on agriculture, such as the increase in rice productivity. The internet of things is one of the latest technologies that can help increase land productivity. One of the uses of the Internet of things is to identify the temperature and rainfall. The problems currently faced by farmers are determining planting schedules and pest control that caused the decline in rice production. In this study, IoT will be designed to develop smart agriculture using system thinking to increase agricultural dryland productivity where agriculture in Madura is classified as dryland agriculture with rainfall amounts falling into the low-medium category of 50 -150 mm/day, this also affects the temperature in rice cultivation, so the use of IoT will focus on controlling the temperature, pest and stability of the rice paddy soaking water while planting rice until the harvest process for maximum results. The result of this study is a causal loop diagram of internet-based system thinking that can be used as a recommendation to increase agricultural land productivity with temperature, pest and irrigation control using IoT, especially in the form of sensor technology.

Keywords: Agricultural productivity; Internet of Things; Rice; Sensor Technology; System dynamics.

1 Introduction

Rice cultivation is a key aspect in preserving Indonesia's national food security. As a vital meal of civilization, rice plays a strategic function in addressing people's food needs [1-3]. According to the Indonesian Bureau of Statistics (Badan Pusat Statistik), rice production in Indonesia reached 54.65 million tons of dry milled grains, equivalent to 34.3 million tons of rice in 2020 [4]. Compared to the expanding demand for rice in Indonesia, the country's yield is constantly declining. According to data from the US Department of Agriculture, Indonesia's milled rice production declined from 38.31 million tons in 2008 to 33.5 million tons in 2019. At the same time, the “regional sampling frame” approach (Kerangka sampling area /KSA)” conducted by Statistics Indonesia in 2018 and 2019 said that in 2018, the total national rice production was 59.2 million tons, decreasing to 54.6 million tons in 2019 [6].

Keeping an eye on the matter of rice consumption and ensuring its fulfillment will continue to be a significant subject of discussion. Continued development of the agricultural sector is vital in order to uphold its pivotal role in ensuring food security [5], boosting the earnings of farmers and rural residents, mitigating poverty, providing skilled workforce for non-agricultural industries, igniting economic growth, and fostering a robust economy [3]. Increasing rice production faces many challenges such as land convection which is weakened every year, decline in soil fertility over time, farmers' ignorance of agricultural technology, irrigation and other capital problems. In addition, the agricultural sector is threatened by climate change, such as changes in precipitation patterns, increasing extreme climatic events (floods and droughts), rising air temperature and sea level, cause changes in planting season, crop failure, reduce productivity and production, damage agricultural land resources, increase drought frequency, area and weight/intensity, increase humidity and increased intensity of plant pests (OPT) [7-10].

Precision agriculture refers to the utilization of technology in managing farms, where in the specific requirements of each field and crop are carefully observed, measured, and analyzed [11,12]. Smart farming refers to the utilization of information and data technology in order to enhance and maximize the efficiency of intricate agricultural systems [13]. Rice farming is considered a form of smart farming due to its significant role as a staple food in the Asia Pacific region and other parts of the world. Furthermore, the decrease in rice yields is caused by unpredictable weather conditions and the use of inefficient techniques for predicting them. Widespread losses among farmers

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occur due to heavy rainfalls during the rice-growing season, causing crop damage and yield losses. The productivity of rice farmers can be greatly enhanced by accurately predicting climate trends and environmental factors like soil nutrients [14]

The knowledge to forecast climate trends and environmental factors, such as soil nutrients, holds great significance for enhancing the productivity of rice farmers [15]. The current trend of heavily depending on fertilizers and pesticides to boost productivity is counterproductive to achieving sustainable rice yields due to its non-environmentally friendly nature [16]. The timing of the rice harvest has a direct impact on rice yields as the optimal time for harvesting rice is closely linked to grain loss [17].

In order to address the aforementioned challenges, it is crucial to implement a range of measures and tactics to ensure the fulfillment of food requirements. By controlling temperature and irrigation using sensor applications A dynamic systems approach offers an effective means to achieve optimum decision-making. A tool called dynamic system framework can be utilized for analyzing models and creating scenarios to enhance system performance [18]. Smart Agriculture encompasses the utilization of Internet of Things (IoT), sensors, and other advanced technologies to enhance agricultural productivity. Smart Agriculture tackles the interconnected predicaments of food security and climate change, meanwhile providing advantages to small-scale farmers through improved efficiency in the use of labor, seeds, and fertilizers. This ultimately leads to an increase in food security [19]. The adoption of new technologies, improvement and development of irrigation systems, and the availability of fertilizers at affordable prices can potentially lead to an increase in farm profits. The main key to enhancing production is by increasing productivity. It is crucial to enhance productivity, lower production costs, and ultimately boost farm income by improving the efficiency of production inputs and implementing effective post-harvest practices. In this research endeavor, our primary focus is to enhance the productivity of rice farming in East Java through the utilization of Internet of Things (IoT) for efficient planning of rice planting schedules and effective management. We will conduct a comprehensive study to develop a dynamic system model that can effectively contribute to the advancement of rice cultivation with the use of temperature control, pests, and irrigation using sensor applications, where sensors are one of the internet of things. With the help of the use of IoT for agriculture can increase productivity by progressively increasing the level of technology.

2 Research methods

2.1 System thinking methods

Systems thinking has its roots in mental models and has evolved and is increasingly used to understand complex dynamic systems (CDS) [20]. Framework energetic modeling is commonly used for its effective problem-solving capabilities. To further enhance its effectiveness, the introduction of energetic frameworks provides a deeper understanding of emerging issues and behaviors [20].

2.2 Internet of things

The use of internet devices is expanding rapidly in today's fast-paced world. The industry underwent a revolutionary transformation with the advent of the Internet, which enabled the interconnectivity of devices, commonly referred to as the Internet of Things (IoT). Kevin Ashton is credited with inventing the IoT in 1999. Each connected object has a unique identifier. The Internet of Things includes devices, sensors, animals, and more. Objects are assigned IP addresses for communication and data transmission. Smart agriculture benefits from IoT by using low-power sensors to collect and transmit environmental data. Data can be analyzed for quick answers or stored for future research. IoT is widely used in precision agriculture to create smart devices such as smart tractors and robots for labor-intensive tasks. These devices can adapt to different environments and manage agricultural systems. To tackle issues using big data and artificial intelligence, an IoT framework can be established. This framework will enable us to analyze continuous data streams and unveil patterns that traditional measurements fail to disclose [21-25]. Pesticides are used to kill pests and control weeds using chemicals [35]. With the help of the Internet of things (IoT) we can control the use of pesticides that are more scheduled and the amount of pesticide liquid given is more controlled than manual use by farmers. Just like the use of IoT to control pests and weeds, in temperature regulation too IoT also provides accurate temperature prediction done 24 hours in advance with an error of 1 ◦C so with this the IoT framework will make it easier for farmers to monitor crops and enable increased productivity by progressively increasing the level of technology [36].

2.3 Data collection

In the data collection phase, this is done in several ways, for example: information is extracted from various sources related to the subject, such as articles or magazines, websites and databases of previous studies, online news platforms, e.g. [26,27]. And the media are now ready to compete for the development of rice plants. Data from the literature are used as important variables and additional variables influencing each other in modeling the simulation system. This study contains two types of data namely primary data and secondary data. The raw data used for reference in this study include data on rice production (tons), rice production (tons/ha), harvested area (ha) and population (people) in Madura District as secondary data. Primary data is used to model the system which is derived from secondary data that is processed based on expert explanations in the field of agriculture. Raw data is used as material to validate and compare real system models. Secondary data used in these studies include data on pests, weather and climate, data on rice prices at the producer level, data on industrial and feed demand for rice, data on per capita consumption and other related food data (rice) and research. Previously associated with the use of dynamic systems and improving the production and implementation of environmentally friendly and drought-resistant rice technology. This information is used as modeling material and to clarify comparative research needs.

2.4 Behavior, stuctural, and model validation

There are two test methods to ensure that the model created represents the real system. The first test involves checking the warehouse structure and organisational chart of the identified model. Structural testing is used to determine the reliability of a model built and operated by experts to evaluate the correct ordering and equating of variables [28].

Perform structural testing to ensure all variables are related and nothing is static [29-32]. Additionally, structural testing should clarify the relationship between each response variable and the appropriate unit. Structural testing is performed by checking for errors in the generated model. If there are no errors in the model, the model has been validated. When simulating, the model works correctly and the message "model is ok" appears, it can be said that the model used in the research is accurate. Furthermore, unit testing is needed to ensure all variables in the model have the correct units. The generated stock and flow profile model is then validated to check whether the constructed model is consistent with the simulation model real system.

The second test is behavioral validity testing, which is used in model verification to test the nature of the model based on the goals it wants to achieve. In line with [28], the verification process is performed by two test methods, model verification by comparison test (mean comparison) or model verification by amplitude change comparison test (% variance error) [29-32]. The model is considered valid if in the mean comparison test E1 5% and in the amplitude variation comparison test (% variance error) if E2 30%. The system validation process is performed in two experimental ways, which are model validation with mean comparison or mean comparison test statistics [29-32].

3 Result and disscussion

3.1 Boundary adequacy

A table describing the internal and external factors, both supporting factors and factors that play an important role in modeling rice productivity and production system dynamics which affects controllable variables and uncontrollable variables that affect the increase in rice production with the use of IoT, which in turn can provide significant rice yield increases, as shown in Table 1 below.

Table. 1 Boundary adequacy of rice cultivation.

Sub Model	Endogenous	Exogenous	References
Rice production	• Land Harvest Area • Paddy Productivity		**[3], [29], [33], [34]**
Rice demand and Fullfilment Ratio	• Rice Production	• Land Extensification • Total Consumption • Population • Consumption per capita • Rice price in real term	**[3], [29], [33], [34]**
Land Productivity	• Fertilizer Effect • Harvest Control • Iot/Sensor Probe • Irrigation • Quality Rice Seeds	• Humidity • Rainfall • Temperature • Soil pH • pest	**[3], [29], [33], [34]**
Land area		• Land Use Change	**[3], [29], [33], [34]**
Population		• Birth Rate • Death Rate	**[3], [29], [33], [34]**

3.2 Sub model ratio of rice demand and fulfillment

A causal process between rice production and rice demand is shown in which demand is influenced by high population, so that per capita rice consumption will automatically increase if rice demand increases. The population itself is influenced by several factors, namely birth rate (R1) and death rate (B1), related to the land sub-model where changes in land use from agriculture to settlements can affect the increase in productivity of rice yields, and as shown in Fig.1 below.

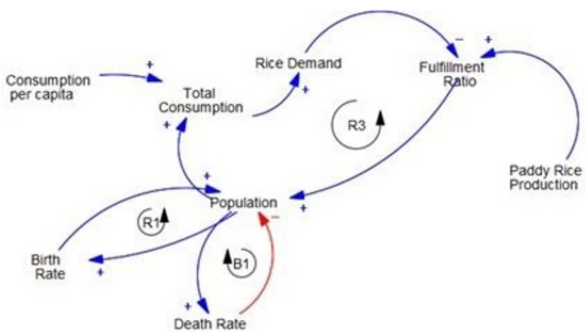

Fig. 1. Rice demand and fullfilment ratio sub model.

3.3 Sub model of rice productivity.

Fig. 2 describes some factors that affect rice productivity. Some key factors are important, which are (1) rainfall, seed quality, fertilizer and another factor, (2) IoT. Variables are used in IoT for monitoring applications that use temperature sensors so that this information data is processed and generated which is then used for decision making and is related to the land and rice production sub-model itself, where the productivity sub-model itself is very important in the overall process of the model for increasing rice yield.

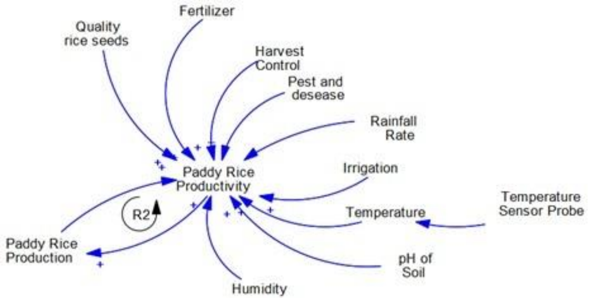

Fig. 2. Paddy rice productivity sub model.

3.4 Sub model of rice production.

An explanation of the problems that occur in rice production that persist to this day. Where the first is the area of harvested land, if the area of harvested land increases due to the release of existing land, then the area of planting will also increase so that rice production will also increase and vice versa if the area of harvested land decreases, then rice production will also decrease. And also how efforts to increase rice production by increasing the dry grain of rice rather than the weight of raw materials, where this can be increased by the process of rendement. This is shown in Fig. 3 below.

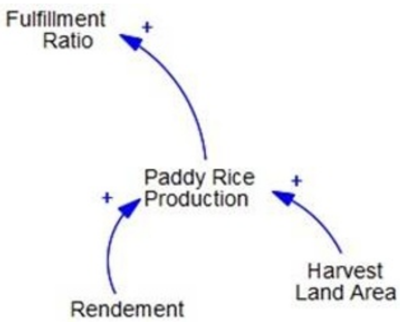

Fig. 3. Paddy Rice Production Sub Model.

3.5 Sub model of land area.

This illustrates the general structure of the rice field problem. Some of the influencing factors are the increase in land expansion, in which unproductive land is converted into productive land, as well as government and government conversion of forest land into rice fields. These two main factors can affect rice production and productivity. And as shown in Fig.4 below.

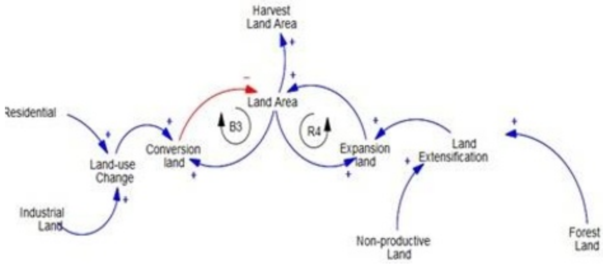

Fig. 4. Land area sub model.

3.6 Model validation of rice production.

The validation results showing that the model is valid are shown in Table 2. This graph shows the comparison between the original data and the simulated data in Fig. 5.

Table. 2 Model validation rice production.

Year	Real Data	Simulation Model
2007	498760	724777
2008	623549	522707
2009	745874	535817
2010	732035	548927
2011	790921	562037
2012	844563	575147
2013	867432	588257
2014	896265	601367
2015	924988	614477
2016	623338	627587
2017	1007665	647323
2018	462523	709491
2019	364913	1020320
2020	729838	1018520
2021	709627	893366
2022	708847	979241
2023	684962	773441
2024	661882	729362
Means	734730	714043
Standar Deviation	163732	172156
E1		2.90%
E2		4.89%

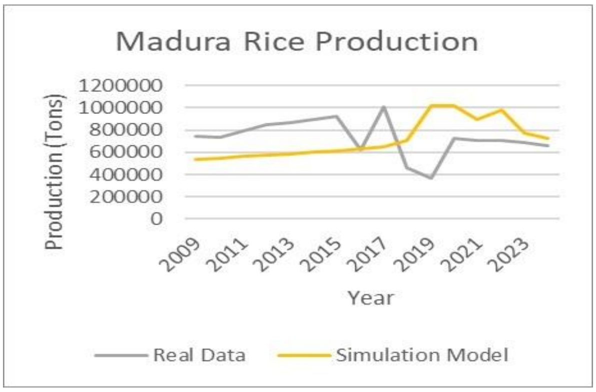

Fig. 5. Validation base model paddy rice production.

The validation results show a valid model with an E1 value of 2.9% and an E2 of 4.89% as shown in Table.2. With the results of data validation showing that the model is valid then to do the next process can be done so that the process of increasing rice production with IoT is successfully increased. This chart shows a comparison between the original data and the simulated data in Fig.5.

4 Conclusion

Therefore, a scenario model is created using the role of system dynamics with current rice farming conditions, which can become a description of new strategies for rice farmers. With the role of the Internet of Things in applying the dynamic systems model, it is hoped that stakeholders and governments will be able to make the right decisions and predict undesirable future possibilities. According to the simulation results, it is considered valid with an E1 value of 2.9% and an E2 value of 4.89%, where the model validation process uses a comparison of real data taken from secondary data and simulation data carried out using dynamic system calculations. Based on the potential, limitations and opportunities for success, a reasonable scenario that can be used as a policy decision to improve the quality of rice production is to apply GAP practices in pest and weed control and temperature control, and applying smart agriculture to improve farmers' productivity awareness of the problems. The application of information technology in agriculture by adopting IoT applications such as temperature sensors and sensors for spraying pest and weed control liquid is very helpful for farmers to increase rice production. As for the development of future research, it is hoped that this research can add other control sensors and the cost burden that must be borne by farmers in using the Internet of Things application in dryland agriculture.

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