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SHAPING A BETTER PRIMARY INDUSTRY THROUGH SMART TECHNOLOGIES

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ABSTRACT

This paper presents the development of smart technologies application for shaping a better primary industry (agriculture and fishery) with several study cases in Asia, namely Japan and Indonesia. In the next decades, increasing the productivity of small-scale crop, livestock, fishery and forestry production systems will be key to achieving global food security. Smart technologies in the primary industry certainly help farmers and fishermen to monitor many aspects of the production part which can lead to better decision making, management, efficiency and eventually productivity. In order to shape a better primary industry, we applied smart technologies combined with data science for the agriculture and fishery sector in several case studies. Specifically, (1) application of a low-cost sensor network and data science to analyze the variables influencing fruit tomato sweetness in a Japanese greenhouse farm; (2) fish finder and data science utilization to evaluate catch amount and fish kind classification within set-net in Japan; (3) application of smart technologies for better mariculture in Indonesia. In light of the evidence, smart technologies can enhance the primary industry.

Key words: Smart technologies, Data science, Primary industry,

INTRODUCTION

The United Nation estimated that the world population will reach 8.5 billion people in 2030, 9.7 billion people in 2050 and will eventually reach 11 billion people in 2100 (UN 2019). The estimated growth of the population means a big challenge to provide food for the people in the future. Several reports have strategized how to provide and distribute food for the world in the future 2050 (FAO 2009; Searchinger et al. 2019) and 2100 (IARFR PAS 2021). At the same time, as the world economy rises compared to several last decades, people tend to increase the consumption of higher quality foods and more resource-intensive, animal-based foods (Sans and Combris 2015; Ranganathan et al. 2018; Andreoli et al. 2021). On the other hand, cutting greenhouse emissions from every aspect including agriculture and fishery as the main source of food is needed to ensure sustainability (Garnett 2011). Therefore, a strategy is crucial to fulfilling the want and need for food production in the future sustainably and effectively.

Primary industry is generally defined as an industry that involves in extraction and production of raw materials and natural resources, including forestry, mining, agriculture and fishery. Primary industry is very essential for our basic needs, as it included agriculture and fishery, the major producer of food for humans and feed for animals. Agriculture itself is broadly defined in Oxford English Dictionary (1971) as "The science and art of cultivating the soil, including the allied pursuits of gathering in the crops and rearing livestock (sic); tillage, husbandry, farming (in the widest sense)." While fishery is defined as "A part of the sea or a river where fish are caught in large quantities and also a place where fish are bred (kept in order to produce young) as a business (Oxford English Dictionary 1971)." As the definition stated above, the fishery can be divided into wild or capture and culture (Edwards and Demaine 1998; Lam 2013). Several institutions and previous studies considered fishery as agriculture in a broader sense (Scannes 2018; USDA 2020). Several institutions such as the

United States Department of Labor (2020) and the United States Bureau of Labor Statistics (2022) suggested that agriculture and fishery belong to the same category, food-related producers.

It simply means, straining agriculture and fishery is essential for not only present but also future sustainable, effective and efficient food production. In the last decade the term "smart agriculture" and "smart fishery" are widely used in both academic and mass media (Aqeel and Shaikh 2009; Ray 2017; Rose and Chilvers 2018; Honarmand-Ebrahimi 2021). This study defines smart agriculture as the combination of agriculture and the application of smart technologies. Similarly, the smart fishery is the combination of fishery and the application of smart technologies. The "smart" in smart technologies was initially an acronym of "Self-Monitoring, Analysis, and Reporting Technology" and was used in computer hardware in the early 1990s (IBM 2019). Yet, nowadays smart technologies are defined as innovative or new technologies that can integrate computing and telecommunication technology into other technologies that did not previously have such capabilities, such as the Internet of Things (IoT), Artificial Intelligence (AI), robot, remote sensing and so on (Kozlova 2021). It is necessary to investigate the application of smart technologies in the actual site in the agriculture and fishery sector. This study aims to enrich the discussion of shaping a better primary industry through smart technologies' application in the actual site, namely in several study cases of our research projects in the agriculture and fishery sector as the major food producer. Specifically, (1) application of a low-cost sensor network and data science to analyze the variables influencing fruit tomato sweetness in a Japanese greenhouse farm; (2) fish finder and data science utilization to evaluate catch amount and fish kind classification within set-net in Japan; (3) application of smart technologies for better mariculture in Indonesia.

Application of smart technologies for greenhouse fruit tomato. This section discusses the application of smart technologies, namely a sensor network, farming record, cloud system, database and data science for investigating factors that affect the sweetness degree of tomato (Saville et al. 2020). Tomato is one of the most consumed food vegetables in Japan, with a value of 224 billion JPY (approximately 2 billion USD) in 2020 even though it is categorized as fruit (MAFF 2022). Several previous studies showed that Japanese consumers seek quality (high sweetness degree) over quantity when purchasing tomatoes, they are even willing to pay a decent price for the high-quality tomato (Higashide et al. 2012; Amano and Hatanaka 2019). Japanese farmers are reportedly aware of the demand of Japanese consumers and put effort to provide high quality (Amano 2020). Several farmers screen every single tomato using a refractometer to sort tomato grade based on sweetness degree before shipping it to the market. One of the most popular tomato types is the fruit tomato, which is generally known as a type of tomato with a sweetness degree of more than 7 (Yabe et al. 2009; MAFF 2022). According to Amano and Hatanaka (2019), the price of tomato with unmeasured sweetness degree per 250g was 86 JPY, the price of sweetness degree between 7.0 to 8.4 was 500 JPY, 8.5 to 9.9 was 600 and for sweetness degree more than 10.0 was 700 JPY. No wonder why tomato farmers would like to produce sustainable high-quality fruit tomatoes. While some farmers with tens of years of expertise or large industrialized farms can produce sustainable high-quality fruit tomato, small-scale farmers still find it difficult to do so. Farmers would like to know what factors affect the sweetness degree of tomatoes. Therefore, in this section, a study was conducted to investigate the application of a sensor network and data science for determining factors affecting the sweetness degree of tomatoes in actual site operated by fruit tomato farmers (Saville et al. 2020).

This study was conducted in a greenhouse hydroponic tomato farm in Nara Prefecture, Western Japan. The data gathering was conducted from June 2017 to January 2020. This study used two types of data, namely, greenhouse microclimate environment and production data. The microclimate data was automatically acquired from the sensor network (Netatmo) installed inside the greenhouse (Fig. 1), while production data is manually input by the farmer. The data transference scheme in this study is shown in Fig. 2. The sensor network automatically recorded temperature, humidity, air pressure and CO_2 and send the data to the Netatmo cloud server. On the other hand, farmer recorded fertilizer input (NO_3 and Ca), pH, electrical conductivity (EC), water stress, cropping calendar, the daily amount of harvest and average daily sweetness degree into Google Drive. These two data are then combined in one database server in order to be analyzed. The analysis result is shared with farmer in order to support the decision making of the farmer.

Fig. 1. Sensor network used in fruit tomato greenhouse.

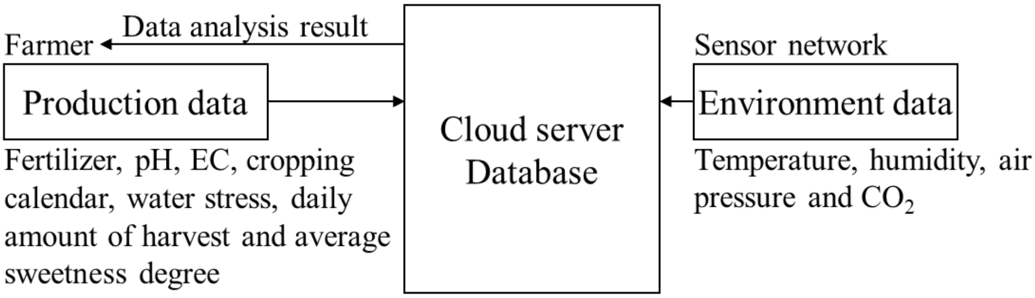

Fig. 2. Data transference scheme used in this section.

EC record through production cycles resemble an S-shaped curve as shown in Fig. 3. The first day of the production cycle is transplanting tomatoes from nursery. After several days, the tomato plant starts growing through the phase of growing time until it produces a flower and eventually tomato. Then, the tomato plant will reach maturity and farmer will start harvesting until the end of the production cycle. The cultivation time during the monitoring period of this research project range between 85 days to 150 days. With this in mind, this study extracted several independent variables from EC record, namely, growing time, growing time slope derivative, average, maximum, minimum and standard deviation of EC value both in growing time and cultivation time.

The gathered data were analyzed by using multiple regression analysis (MRA) in order to determine the factors affecting sweetness degree. Independent variable selection is needed to avoid multicollinearity before conducting MRA (Farrar and Glauber 1967). One of the ways is to check the correlation of independent variables. This study used the extracted EC variables and exclude fertilizer (both Ca and NO_3) as well as pH due to the high correlation between them. The independent variables. This study also considered maximum, minimum, average, cumulative as well as standard deviation of temperature and humidity as independent variables. Besides, this study also considered cumulative of

CO_2 and water stress. The dependent variable was the sweetness degree of fruit tomato. Next, a pre-processing standardization using z-score was conducted in order to make the variables at the same level of value. Subsequently, MRA was conducted several times to get the best model possible in this study. The MRA was evaluated using AIC and R-squared values (Akaike 1974). When AIC was comparatively high and R-value was comparatively small, this study omitted the independent variable with high P-value as well as changed the combination.

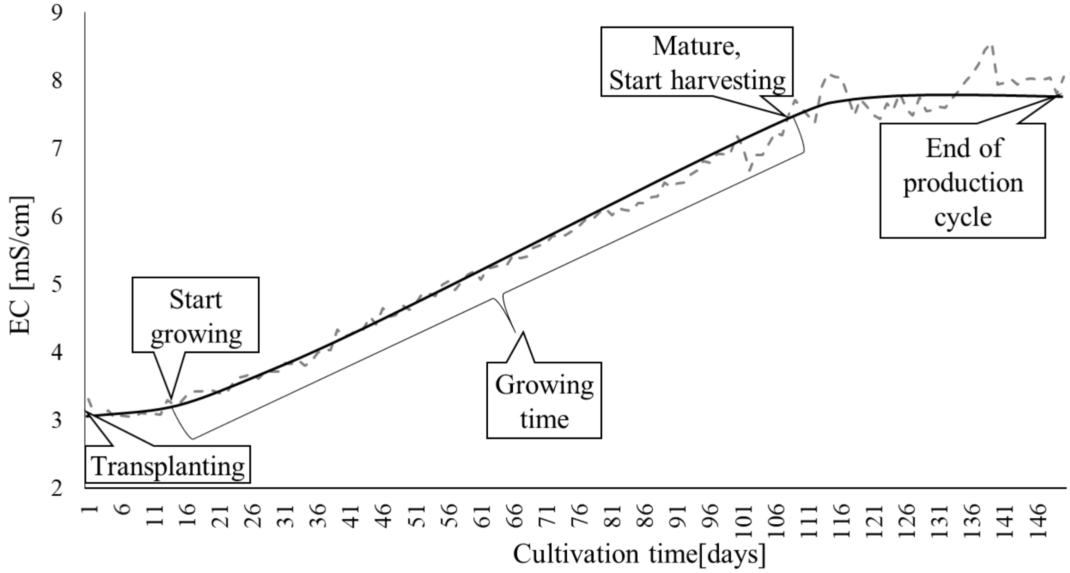

Fig. 3. EC record in one production cycle of tomato fruit.

After conducting several MRA, the best result was gained when the R-value was 0.91 and AIC was 13.11. The summary of the best MRA model is shown in table 1. The most significant independent for sweetness degree was growing time as indicated by the smallest P-value. This study then investigated the relationship between growing time and sweetness degree. The relationship between growing time and sweetness degree is shown in Fig. 4. The longer the growing time, the sweeter the fruit tomato will be. Yet, the sweetness degree of a fruit tomato will have its peak because the tomato will rot at a certain degree. Due to that reason, this study decided to use a three-degree polynomial curve as a trendline. In light of the evidence, smart technologies are useful to investigate factors affecting the quality of fruit tomato. The result was then shared with farmer as a decision support system for decision-making in production.

Table 1. MRA summary of sweetness degree of fruit tomato production

Variables	Estimate	Std. Error	T-value	P-value	α
Intercept	7.5329	0.07553	9.739	< 2e-16	
Growing time	0.61848	0.12402	4.987	0.00041	***
Cultivation time	0.65096	0.18156	3.585	0.00428	**
CO_2 cumulative	-0.3109	0.1653	-1.881	0.08674	.
Water stress cumulative	-0.0805	0.08979	-0.897	0.38913	

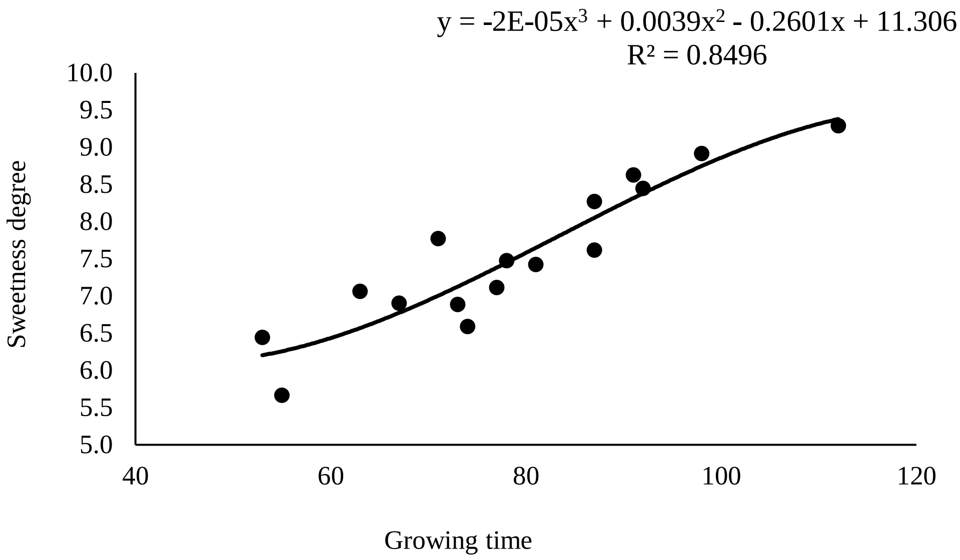

Fig. 4. The relationship between growing time and sweetness degree of fruit tomato.

Application of smart technologies for set-net fishing. This section discusses the application of smart technologies, namely ubiquitous buoy (Wada et al. 2008), catch fishing records, cloud system, database and data science for predicting fish catch in set-net (Saville et al. 2015). Set-net is one of the most popular fishing methods in Japan and across Asia. The fact that fishermen do not know the catch quantity in advance and will only be aware of the harvest situation once they arrive at the set-net region is one of the challenges with set-net fishing. When the amount of fish trapped in the set-net is particularly large and the fishermen are not ready for such a significant number of catches, they must load the fish and travel to the port, then return to the set-net to load the rest. The fishermen must do more effort, lose time and pay more for labor and gasoline. It is necessary to create a more effective and efficient set-net fishery monitoring system in order to address the issue. Thus, fishermen need a real-time monitoring system of fish trapped in set-net.

This study was conducted in set-net sites in Hokkaido, Toyama, Shizuoka and Mie Prefecture, Japan. The data gathering was conducted from June 2013 to July 2015. This study used two types of data, namely, ultrasonic wave monitoring data and catch data. The ultrasonic wave monitoring data was automatically acquired from a ubiquitous buoy installed on the final trap of the set-net, while production data is manually input by the fishermen (Fig. 5). All of the data was compiled in one cloud database. Next, the data was analyzed and visualized in website, therefore, the fishermen can monitor the fish trapped in the set-net in real-time. The ubiquitous buoy in this study is a modification of a fish finder that can transmit data (ultrasonic wave ping data) to the cloud in real-time. The ubiquitous buoy was installed in the final trap of the set-net because the fish most probably cannot get out of the final trap and the trapped fish is the catch of the fishermen. Fish finder is generally known for the ability to detect based on swim bladder. The intensity of ping data is highly dependent on the amount of fish below the water. In Fig. 6, body of the water is colored blue, when the buoy detects fish, the monitor indicates in green, yellow and red brownish color. The more the number of fish, the higher the ping value is with the darker color.

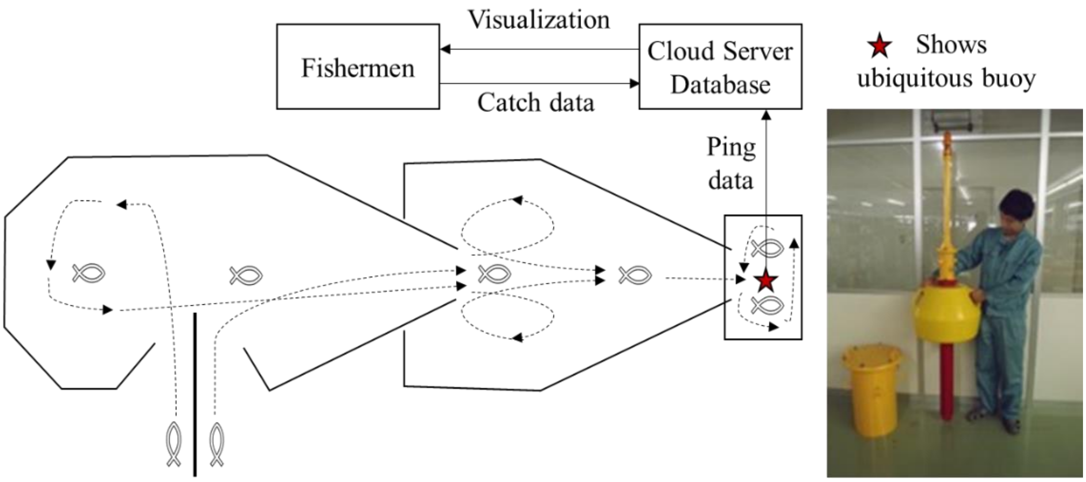

Fig. 5. Sketch of set-net and data transference.

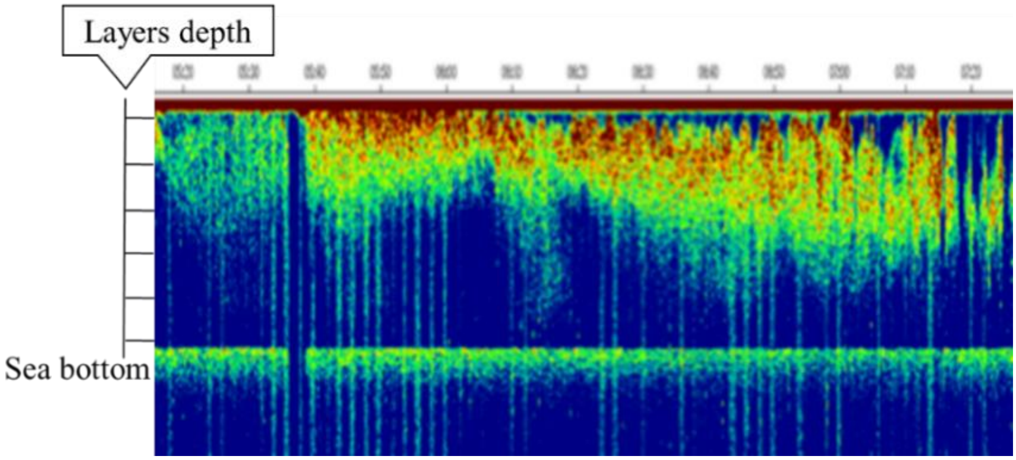

Fig. 6. Screenshot of ping data from ubiquitous buoy.

This study used MRA in order to predict the amount of fish trapped in a set-net. The independent variables were ping data. Yet, this study divided the water into 5 depth levels because fish usually move in different level depth at different time. In particular, the independent variables were the maximum, minimum, and average of ping values of each layer and sea bottom. The dependent variable was the catch amount. However, the amount of catch varies greatly, ranging from tens of kilograms to several tons. To minimize this variability, the study applied the Box-Cox Transform pre-processing, which scales the data values to fall at the same level. After the preprocessing, the data is used for MRA. As also discussed in the previous section, MRA was conducted several times to get the best model possible in this study. Next, the estimation results are converted into the same unit of catch by reverse transformation.

The best result in this study was obtained by using the maximum value of each layer and the minimum value of the sea bottom with the R-value was 0.97. The comparison of catch estimation and the real catch is shown in Fig. 7. Relative Absolute Error (RAE) is employed in this study to quantify the discrepancies between the algorithmic catch estimation and the real catch. The RAE of catch estimation in Toyama was 22% compared to the real catch record. The fishermen stated, besides fish catch estimation, real-time monitoring to show the situation in the set-net was already useful for fishermen. The fishermen can check the set-net condition anytime anywhere as long as they have an internet connection. Finally, it is important to note that smart technologies are useful for supporting set-net fishermen.

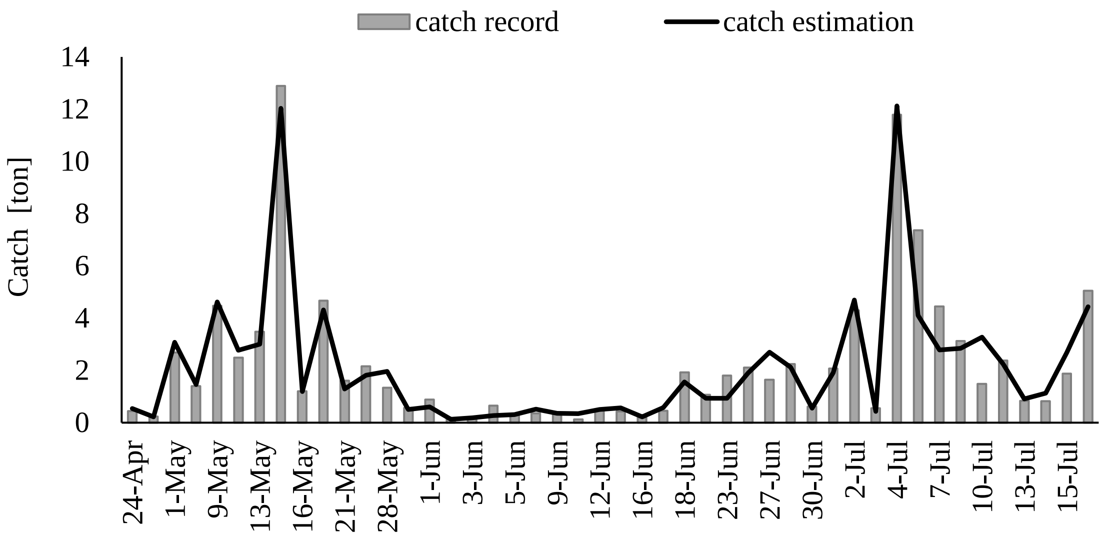

Fig. 7. Comparison of estimated catch amount and real catch data in Toyama site.

Application of smart technologies for Indonesian mariculture. This section discusses the application of smart technologies to face issues in Indonesian mariculture. Indonesia's unique geography, with over 17,000 islands and 81,000 km of coastline, provides an ideal environment for the development of the fishery sector, including both capture fishery and aquaculture. In 2020, Indonesia's production of capture fishery amounted to 7 million tons, while the production of aquaculture reached over 14 million tons, according to FAO (2022). The most commonly farmed species in Indonesia include shrimp, pelagic fish and seaweed as reported by the Indonesian Ministry of Marine Affairs and Fisheries (MMAF 2022). The MMAF has been actively promoting aquaculture activities among coastal communities, with a particular emphasis on mariculture, which involves the cultivation of aquatic animals and plants in marine environments (MMAF 2021).

Indonesia is one of the largest producers of aquaculture in the world. Indonesian aquaculture produced a massive 14.8 million metric tons in 2020, second to China (World Bank 2023). Yet, many issues occur in Indonesian mariculture. For example, grouper fish mass mortality in mariculture sites, Harmful algal blooms (HABs) caused some people to stop running aquaculture or investigate the suitability index for seaweed aquaculture. Indonesia is one of the largest exporters of grouper globally, yet sustainable production and day-to-day operation in mariculture site is affected by mass mortality. Therefore, a mortality monitoring system, as well as prediction, is necessary for grouper fish farmers' decision-making. On the other hand, HABs that periodically occur cause negative effects on marine biotas including fish, including mariculture sites. Hence, the investigation of the trigger of periodic HABs is necessary in order to prevent the occurrence in the future. Factors affecting seaweed production need to be clarified for better production and day-to-day operation planning. A seaweed suitability index in a form of a visualization map is important to clarify factors affecting seaweed production.

Gondol, Northwestern Bali Island is one of the largest grouper mariculture centers in Indonesia. However, Gondol also has the same problem as grouper mariculture elsewhere, high mortality rates. In general mortality rate of grouper in mariculture is 50%. When the number of groupers today is 10,000 but tomorrow 100 die, day-to-day operations, for example, the feed that must be prepared and given to the fish is also different for today and tomorrow. That's why a system is needed to monitor the number of groupers in the mariculture site, including a prediction system for the number of fishes. Data transference to monitor and predict fish mortality is shown in Fig. 8. The water quality sensor network (Wada et al. 2019) on grouper mariculture site automatically transmits temperature, current, salinity, conductivity, chlorophyll, turbidity and DO (dissolved oxygen) once in 30 minutes. While fish farmer input daily fish mortality records to the same cloud server database. Those data were then combined to develop the fish mortality prediction using the Random Forest algorithm (Saville et al. 2022). The result is shared to fish farmer on the website.

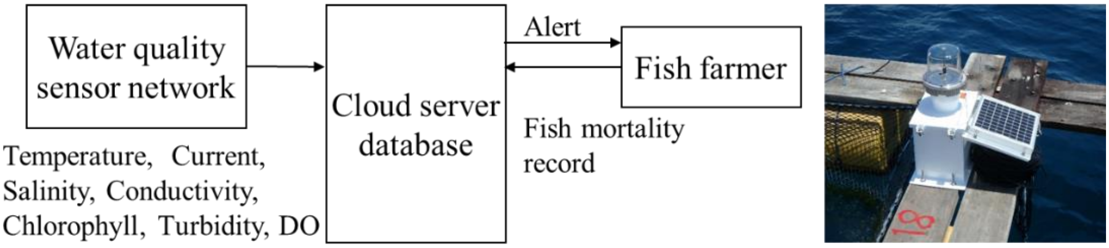

Fig. 8. Data transference scheme used in this section. The water quality sensor network is pictured in the right side.

Periodic HABs in Lampung Bay, Indonesia have caused a huge economic loss for the area surrounding the Bay. The HABs occurred every year, especially during the rainy season since its massive outbreak in 2012. The occurrence of HABs affected mariculture, in 2010 150 mariculture sites existed in the Bay, but, in 2018 only 26 survived (Saville et al. 2019). Therefore, an investigation of the trigger effect of HABs in the Bay is crucial. This study combined spatial analysis and *in situ* water quality monitoring in order to investigate the trigger of periodic HABs (Saville et al. 2022). The spatial analysis was conducted to investigate land use surrounding the Bay. While *in situ* quality monitoring was conducted to measure the nutrient upstream and downstream of the watershed.

The data used for spatial analysis was the 2018 high-resolution satellite (WorldView-3) and the 2011 Digital Elevation Model (DEM) obtained from NASA. Besides, a five-day extensive land use ground truth survey was also conducted in February 2020. The spatial analysis was divided to land use classification to map the land use and hydrologic characteristics analysis to map the watershed and water flow toward Lampung Bay. The spatial analysis was conducted using ArcGIS. Meanwhile, for *in situ* water quality, this study monitored pH, EC (electric conductivity), NO_2 and NH_3 in four sampling stations (two upstream and two downstream) from February 2020 to March 2021. NO_2 and NH_3 were monitored to represent Nitrogen (N) in the water, as N is known as one of the triggers of HABs. N is also generally known as one of the main compositions of fertilizer as this study suspects fertilizer run-off to be one of the triggers of HABs. The samplings were conducted after rain to test the run-off hypothesis. The analysis results are shown in Fig. 9. This study found that agricultural land in the target area was 1,200 ha with numerous sloppy hills and water streams toward the sea. The water stream passes through residential and urban areas. Moreover, the concentration of nutrients downstream was statistically significantly higher than upstream. The results indicated that fertilizer run-off might be one of the triggers for HABs occurrence. Besides, anthropogenic activities from residential and urban areas might also be one of the triggers.

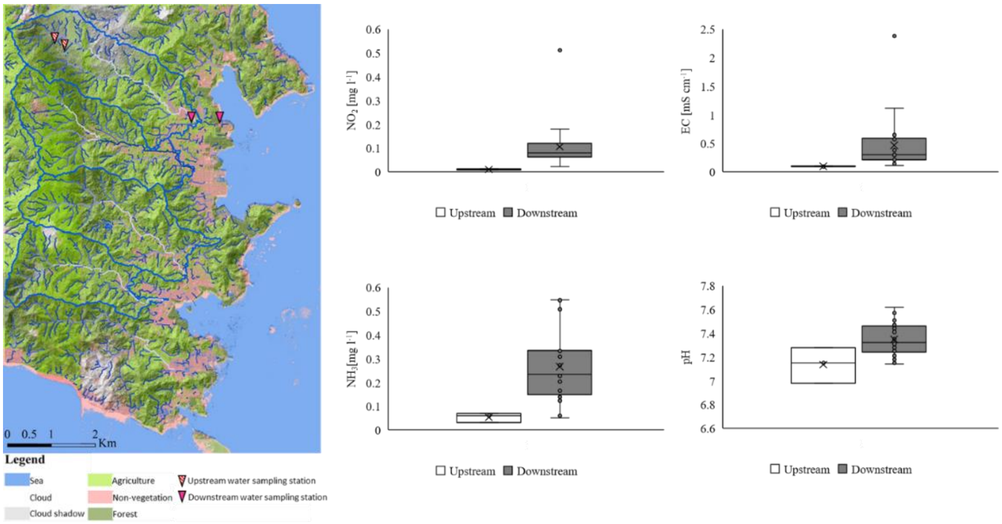

Fig. 9. Map of the spatial analysis result on the left. Boxplot of nutrients in upstream and downstream sampling stations.

Indonesia ranks second in the world in seaweed production at 10 million tons (FAO 2022). Seaweed farming has been a focus of the Indonesian government since 2016 (MMAF 2020). Needless to say, seaweed farming is an important source of income for Indonesian coastal communities. One of the pilot areas for seaweed farming promoted by the Indonesian MMAF is in Seriwe Bay, West Nusa Tenggara Province. However, according to the government of West Nusa Tenggara Province (2018), seaweed production in Seriwe Bay decreased from 14,000 tons in 2012 to 7,000 tons in 2017. Factors affecting seaweed production in Seriwe Bay are necessary to be examined. In order to understand the variables influencing seaweed production, it is necessary to visualize the seaweed suitability index on a map.

To realize the development of the seaweed suitability index, the same water quality sensor network as in Gondol was installed in the Bay. Meanwhile, seaweed farmers input their production data into a cloud server database. However, because there is only one sensor network, it cannot be used for the entire bay. Therefore, this study used the Landsat8 satellite image data series from January 2019 to December 2020 to obtain the sea surface temperature of the whole Bay. The temperature data from the sensor network was used for calibration of sea surface temperature obtained from the satellite. Other than that, this study also used the data of water depth and water circulation flow rate obtained from bathymetry in September 2018. The area of the bay was divided into several rectangular grids size 500×500m. The suitability index was formulated using MRA. The dependent variable was seaweed yield. The result of the suitability index is shown in Fig. 10, where this study divided the index into two seasons in Indonesia, rainy and dry. The P-value of Sea surface temperature and water depth were less than 5%, while, the water circulation flow rate was less than 0.1%. The results indicated that all of the independent variables were significant. Yet, the R-value was 0.13, which means, there is still a remaining unknown independent of 87% for the seaweed suitability index.

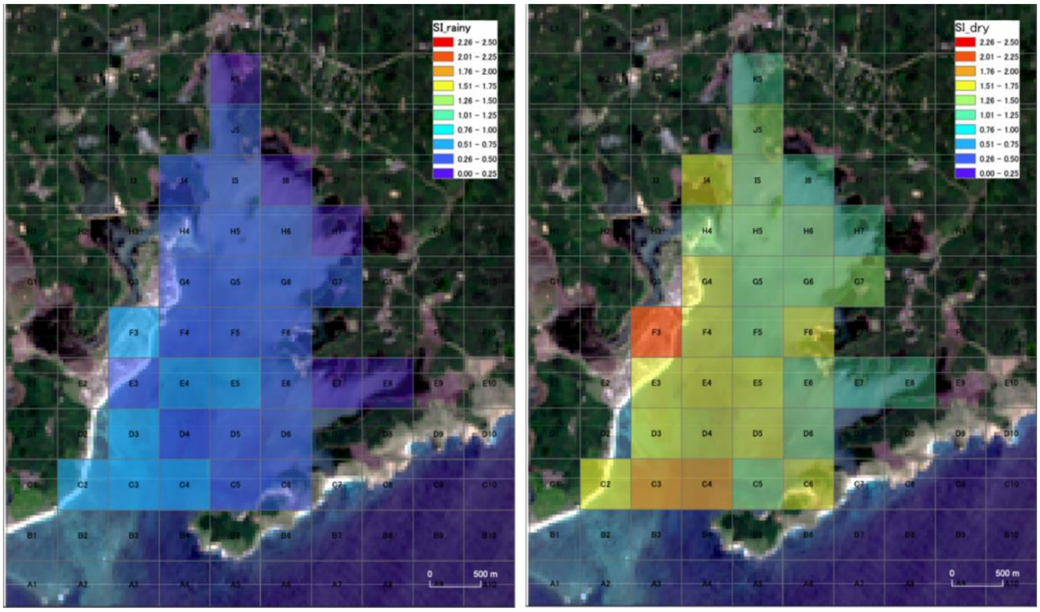

Fig. 10. Map of suitability index of seaweed production for rainy and dry season in target area.

CONCLUSION

This study discussed the application of smart technologies to enhance the agriculture and fishery sector as the primary industry with three study case research projects. The application of sensor networks, cloud database server and data science enable to examine factors affecting sustainable production, provide visualization for both agricultural as well as farmers and ultimately can enable farmers to make informed decisions about resource allocation for day-to-day operations. It should be evident that the research projects are pilot projects and should be continued to gain more stakeholder engagement in this industry. Because if more and more stakeholders apply smart technologies, most probably it will advance the primary industry as a whole, which in turn will be able to produce food more effectively, efficiently and sustainably.

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