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Rice Monitoring and Yield Estimation in Dumangas, Iloilo, Philippines Using Satellite Imagery

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ABSTRACT

An agricultural monitoring procedure utilizing the combination of remotely sensed data, vegetation indices, ground truth information, and local knowledge on the phenology and development of rice, which is the staple crop produced in Dumangas, Iloilo, Philippines, was established and analyzed in this study. The areas with standing crops and their corresponding growth stage were reported for the 2nd and 3rd cropping of 2020. The spatio-temporal analysis determined that NDVI is directly correlated with the photosynthetic activity and development of the crop. Dry season cropping lasted from October to January, while the 3rd cropping lasted from February to April. The percentage of the rice areas planted per month were also studied and observed that the area spatially and numerically increased as farmers planted during the start of the season. The ground data from the 20 GCPs were compared with the Sentinel 2 NDVI. The phenological metrics for each point characterized the development of the crop. From the investigation, the municipality commonly used hybrid varieties, which have a growth duration of 85 to 100 days. The NDVI ranges were 0.163 to 0.309, 0.35 to 0.682, 0.535 to 0.671, and 0.235 to 0.533 for seedling, vegetative, reproductive, and ripening. APSIM was used for yield modeling of the cropping season 2019 and observed to have a good correlation during the wet season. Underestimation was detected for cropping seasons during times with limited rainfall. This study was beneficial for the LGU in crop estimation as it produced highly reliable spatial and temporal results.

Keywords: rice monitoring, NDVI, GIS, remote sensing, yield estimation

INTRODUCTION

The production of rice, the main staple crop in the Philippines, is essential for food security in the country. Although most of the country is dedicated to agriculture, the Philippines still import rice from neighboring countries like Vietnam and Thailand. The country was determined to be the world's biggest rice importer in 2019, amounting to 2.9 million metric tons of imports (Bangkok Post, 2020). It exceeded China which requires a considerable import due to its large population. China only exported 2.5 million metric tons in 2019 (PhilStar, 2019). About 2.3 and 2.6 million metric tons were rice were imported in 2020 and 2021, respectively (Lagare, 2021). Impact on rice production is a great need for agricultural improvement and poverty reduction (Tibao, n.d). Interventions in rice technology are being studied by researchers in order to produce good quality rice with high yield.

It is important to monitor the status of the agricultural lands to determine how much crop will be harvested for a particular season. Traditionally, interview is conducted up to the smallest unit or per farm basis. The data collected are farm size, location, tenure status, irrigation system, crops planted, and type and number of farm equipment present (PSA-Region XII, 2020). From this survey, a summary is prepared per barangay, municipality, and province. However, surveying is quite a tedious and expensive process.

The country needs a decision support system that can gather information on the status and development of the agricultural areas. This will aid in the judgment and decision-making of policymakers and those in charge of agricultural planning and development. According to Dadhwal (2004), coalescing crop simulation models, satellite data, and geographic information system (GIS) is necessary for an improved and outstanding agricultural monitoring process. In addition, Dunaieva et al. (2019) mentioned that "combining GIS technology and remote sensing monitoring data is one of the cornerstones of a modern system of control and food security."

Lapada (2019) created of an automated rice monitoring system in Borongan City, Samar, Philippines using a Rapid Application Diagram (RAD). According to his study, the city data accumulation is done manually. He assessed the applicability of the software in terms of ISO 9126 Quality Model and determined that it followed the standards based on functionality, reliability, usability, efficiency, and maintainability with a Strongly Acceptable rating according to software expert testing. He recommended the Agriculture Office to use the said software.

Philippine Rice Information System (PRiSM), a collaborative project by the Philippine Rice Research Institute (PhilRice) and Department of Agriculture (DA), is the first satellite-based rice monitoring system in Asia. It generates rice area, yield estimation, and damage assessment maps in the country on a provincial level through processing Synthetic Aperture Radar (SAR) data in MAPscape-Rice software. The project conducts site visit and interview with the help of the local agricultural extension workers (PRiSM, n.d.).

Another program which makes use of smart technologies is Project SARAI or Smarter Approaches to Reinvigorate Agriculture as an Industry in the Philippines, It is a Department of Science and Technology – Philippine Council for Agriculture, Aquatic, and Natural Resources Research and Development (DOST-PCAARRD) funded project which aims to aid the agriculture sector in terms of the risks brought about by climate change. It is composed of various components for crop characterization, irrigation management, precision farming, agricultural monitoring, weather forecasting, and soil profiling (SARAI, n.d).

Regional agricultural monitoring is necessary to determine and analyze crop productivity, assess its behavior for future estimation, and notice changes caused by nutrient deficiency and pest infestation (Dunaieva et al., 2019). However, agricultural assessment requires a lot of resources if done traditionally. In addition, incomplete historical data is also a problem (Perez and Comiso, 2014). Remote sensing is a helpful and fast tool for delineating actual areas planted for a specific species.

One way of maximizing remotely sensed data for agricultural monitoring is through the use of Normalized Difference Vegetation Index or NDVI, one of the common vegetation indices used to monitor crop health. It shows the photosynthetic behavior of the plant and the change through time due to physiological development of the crop (Junges et al., 2017). The value ranges from -1 to 1, where lower than 0.1 depicts water and snow, moderate values from 0.2 to 0.5 show sparse vegetation and senescing plants, and high values above 0.6 are highly vegetative with peak and healthy vegetation (USGS, 2020). NDVI is greatly correlated to green biomass yield according to Rasmussen (1997) as cited by Noureldin et al. (2013).

NDVI can be computed using two bands – near infrared (NIR) and red. Different wavelengths have certain effects in the plant pigments. The visible light spectrum (red, green and blue) is absorbed by the plant while the near infrared light is reflected by the leaves (USGS, 2020). The equation for NDVI is given below:

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \text{Equation 1}$$

Dadhwal (2004) defined crop models as a "simple representation of a crop and explanatory nature". He noted that crop cultivar, soil, weather, biotic stress, cultivation, and management practices influence crop growth. In addition, the performance of a crop is simulated through mathematical models and computer programs to predict the production, which also includes the development of different plant parts, including leaves, roots, stems, and fruits (Oteng-Darko et al., 2013).

Agricultural Production Systems Simulator (APSIM) is a crop model that is widely used. It models crop phenology, leaf area development, biomass production, yield, and nitrogen accumulation and how they are affected by different weather variables. International Rice Research Institute (IRRI), Wageningen University, and Agricultural Production Systems Research Unit (APSRU) collaborated to create a crop model for rice which was called APSIM-ORYZA. This model's input variables include meteorological data, extinction coefficients for visible light and nitrogen distribution, light use efficiency, potential evapotranspiration, and water availability (Zhang et al., 2004). Simulation can be done using the APSIM User Interface or the command line (APSIM, 2021). Radanielson et al. (2018) mentioned that APSIM is a simplified model that incorporates farmers' management practices, decision trees, soil-water interaction, and weather information to estimate production. According to Gaydon et al. (2017), the soil is the "central simulation component" of APSIM. It means that the model simulates the interaction of the crop and the soil (Keating et al., 2003).

Gaydon et al. (2017) evaluated the use of APSIM in cropping systems in Asia. According to them, APSIM is widely used and accepted in Australia and Africa; however, for Asia, there was limited data and applicability of this simulation model, especially for rice-based cropping systems. They aimed to assess the model's capability in crop development and yield simulation of different crops.

The main problem is the need for a near-real time and site-specific agricultural monitoring and yield forecasting techniques that will be beneficial to the decision makers in the local government unit in terms of estimates in production. The results of this study will be an important tool that can be integrated to the traditional methods of monitoring since currently there is no means of yield estimation techniques before the harvest season in Dumangas, Spatial information can be incorporated in yield modeling since the output was on a barangay level. This study is also timely since during the pandemic there are unwanted restrictions that prevent agricultural technicians from going directly to the field to monitor the growth of the crops.

The general objective of this study is to monitor the growth of rice in Dumangas, Iloilo using free and open source satellite data. It also aims to assess the status of the standing crops in the area by utilizing existing SARAI-Enhanced Agricultural Monitoring System (SEAMS) methodology, determine the threshold for NDVI per crop stage using the Ground Control Points (GCP) and Sentinel 2 data, and conduct rice yield simulation by integrating RS data into a crop simulation model. This study integrates different kinds of data to characterize the relationship of NDVI with what is really happening in the field. By correlating high resolution and bird's eye view of the satellite with the local knowledge in terms planting, a barangay level analysis can be done.

MATERIALS AND METHODS

Study Area

The municipality of Dumangas, located in the province of Iloilo, a part of the Panay Island, is situated at the end of the Jalaur River with 12,788 hectares. It has bountiful agricultural resources composing of about 11,355,50 hectares (Decastillo, 2007). The map of the municipality can be seen in Figure 1.

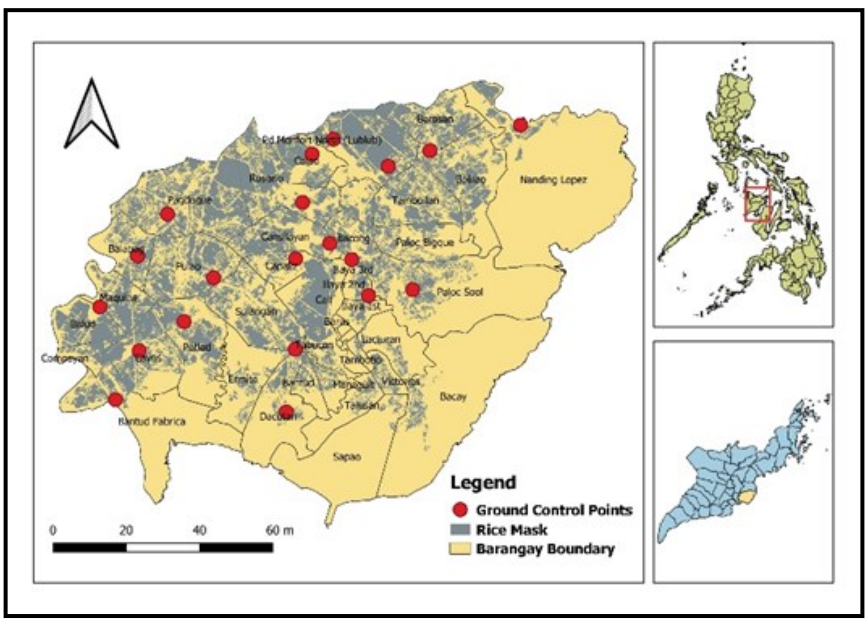

Figure 1. Map of Dumangas, Iloilo

Scope and Limitation

The study covered the rice areas of Dumangas, Iloilo during the cropping seasons in 2019 to 2021 because of data availability with respect to the deployment of SICApp. The limitations of this study were mainly due to the satellite's properties such as its spatial resolution, temporal resolution, and the effect of severe weather conditions. Moreover, the crop simulation was only applicable to Dumangas since the parameters used were site specific. Soil properties and weather inputs were derived from remotely sensed data. Fertilizer application and type of irrigation were determined by the agricultural technicians. Potassium was not included in the simulation because it was not included in the fertilizer types available in APSIM. Moreover, the sowing date was assumed and generalized for the barangay, which can be a source of discrepancy.

SARAI-Enhanced Agricultural Monitoring System (SEAMS)

It was developed to give the agricultural stakeholders site-specific crop advisories to reduce the impact of the changing climate. One of its components is the SARAI-Enhanced Agricultural Monitoring System or SEAMS, which maximizes free and open-source satellite technology in developing efficient agricultural monitoring techniques, weather forecasts, and disaster risk management methods.

By utilizing remotely sensed data, crop masks, the estimated area with standing crops, growth stage, flooded areas, and weather maps can be generated. In terms of agricultural monitoring, thresholding of NDVI is used to determine the areas planted with a specific crop. SEAMS uses the threshold of NDVI greater than or equal to 0.3. The project has a partnership with various state universities and colleges, provinces, and local government units (LGUs) across the country. The SEAMS methodology is also being used in a municipal level specifically the partners from the LGUs including Dumangas, Iloilo, and Muñoz and Lupao, Nueva Ecija.

The rice area of Dumangas, Iloilo was the pilot site of the project. Based on SEAMS' findings, the rice area being reported by the municipality was outdated with a difference of about 2,000 hectares difference. According to the Mr. Eugenio Decastillo, the municipal agricultural officer, they have been using this data since 1990s. A huge part of rice areas was converted to residential and commercial areas which was the reason of the discrepancy (Brusola et al., 2022). SEAMS also gathered ground based information to verify the rice mask developed using object-based image analysis (OBIA). This method is widely used for crop area and vegetation cover determination (Kavzoglu et al., 2019; De Luca et al., 2019; Frison et al., 2020).

Rice Mask

The rice mask per barangay was developed by SEAMS using the Orfeo Toolbox in QGIS. The corresponding area for each mask was determined. Only the barangays composing the top 90% of the rice area of the municipality were identified.

Ground Control Points

Twenty ground control points (GCP) were determined around Dumangas. All the areas were planted with rice and monitored using the SEAMS Image Capturing App (SICApp). It is an android application developed by the SARAI team in order to gather GPS and image data of a farm. It also includes information such as the crop planted and growth stage. Monitoring was done for two cropping seasons, then compared and correlated with the satellite information in order to determine the possible range of NDVI per stage.

NDVI Processing

Sentinel 2 data was used for this study. NDVI curves for the past five (5) years and the two (2) seasons were derived for the twenty ground control points. Recent images from Sentinel 2 were gathered for visualization and spatial analysis. Monthly monitoring of the vegetation, including the growth stage and standing crops of the top 90% rice-producing barangays, were noted. Since Sentinel 2 is affected by clouds, there is a slim chance of observing a cloudless image for the whole municipality. In this case, the least cloudy data for each barangay was determined and extracted. The process flow for NDVI processing can be seen in Figure 2.

Threshold Determination

The phenological metrics from NDVI (Figure 3) for each GCP were determined. These include Start of

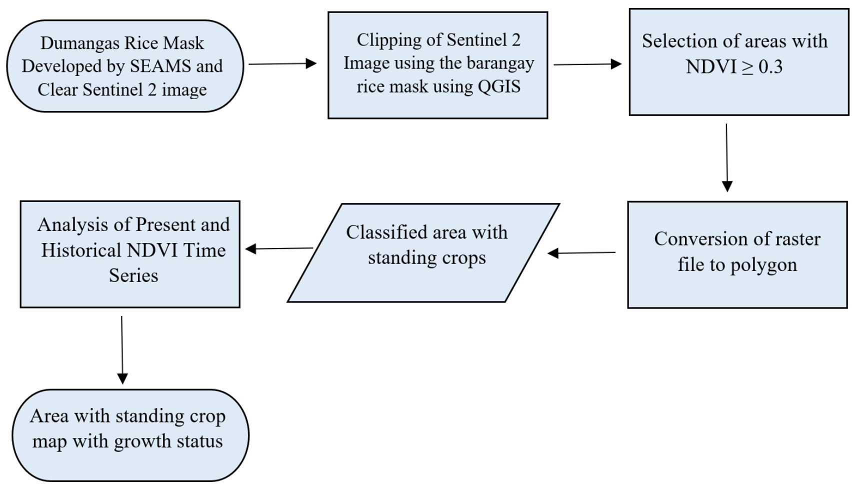

Figure 2. Process flow for NDVI processing

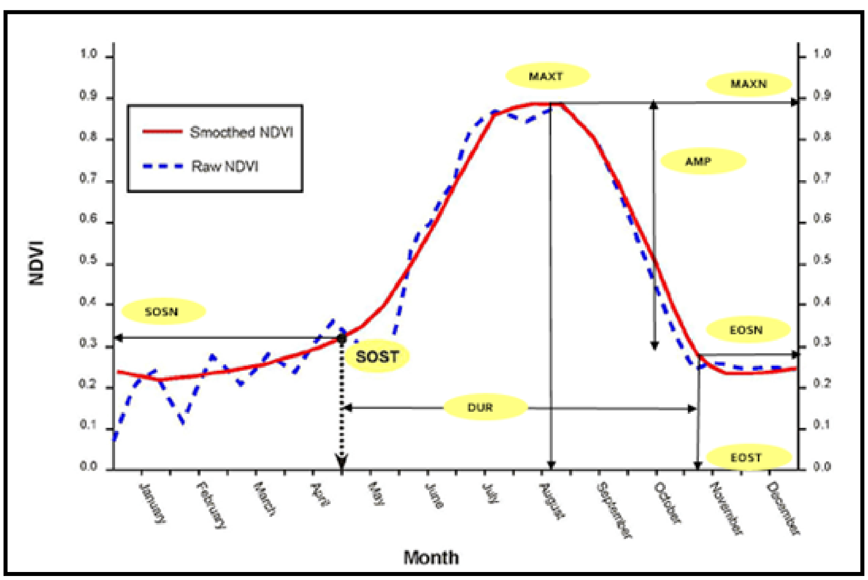

Figure 3. Phenological metrics from NDVI

Season-Time (SOST), Start of Season-NDVI (SOSN), End of Season-Time (EOST), End of Season-NDVI (EOSN), Time of Maximum (MAXT), Maximum NDVI (MAXN), Duration (DUR), and Amplitude (AMP) (USGS, 2020).

The ground data for all the ground control points showing the actual growth status taken at a specific time was compared with the nearest image taken by the satellite. Cloudy images were not included in the analysis. The NDVI value taken on the nearest date with the ground data was used as a basis for determining the threshold per growth stage. The upper and lower limit of the range were identified using the distribution in the box and whisker plot. The workflow of this methodology can be seen in Figure 4.

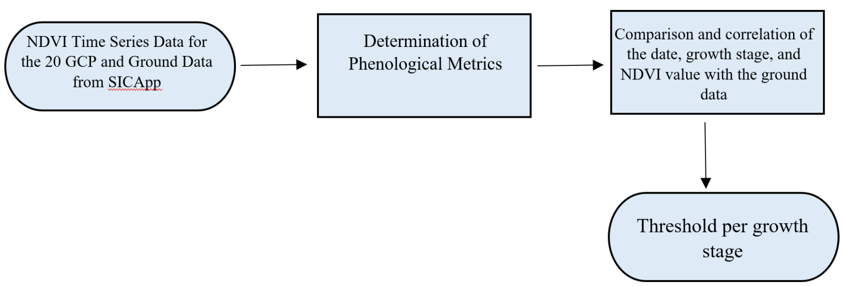

Figure 4. Process flow for threshold determination

Table 1. Data sources of the input parameters

Parameter	Source	Spatial Resolution	Temporal Resolution
Rainfall (mm)	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)	5 km	1 day
Minimum and Maximum Temperature (°C) Solar Radiation (W/m2)	National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS)	2.2 km	6 hours
Bulk Density Volumetric Water Content Permanent Wilting Point Field Capacity Saturated Water Content pH Organic Carbon Content	World Soil Information	-	250 m

Yield Modeling

Weather parameters such as rainfall, minimum temperature, and maximum temperature were gathered from different satellites to study the spatial variation in the municipality. Other input parameters needed for the simulation, such as soils data, fertilizer application, and crop information, were also collected. In terms of soil and water information, the necessary parameters are soil type, initial water information, irrigation information, and soil-water interaction data. Inputs for soil-water interaction include bulk density, volumetric water content, permanent wilting point (PWP), field capacity (FC), saturated water content, pH, and organic carbon content at various depths. Table 1 shows the details of the data inputs. The resolution of the remotely sensed data used was the highest and best to use for free satellite images. The available yield data for the 2019 cropping season was collected and tabulated per barangay.

Rice yield estimation was done using the APSIM crop simulation model and the collected input parameters. Rice yield data during the 2019 cropping season per barangay were used for testing the validity of APSIM. Rice yield was determined for the selected simulation duration. The original unit from the simulation is in kg/ha, converted to tons/ ha for consistency with the observed yield data. Estimated rice yields were plotted against the observed yield. The process flow for yield modeling can be seen in Figure 5.

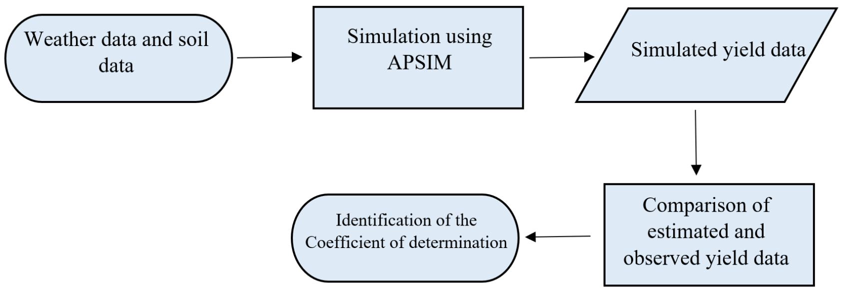

Figure 5. Process flow for yield modeling

RESULTS AND DISCUSSION

Rice Growth Status Using NDVI

The status of rice areas for 2nd and 3rd cropping during the year 2020 cropping season per barangay was mapped to determine the spatial distribution of the growing crop. Supposedly, 2nd cropping or dry season should begin in September but was moved to October because the farmers were still harvesting rice for the wet season in September. The generated agricultural monitoring maps for the dry season can be seen in Figure 6 and summarized in Table 2. In October, it can be noted that the status of crops per barangay was already at seedling or vegetative stage. As per the agricultural technicians of the municipality, the areas were divided according to their method of sowing: by transplanting or direct seeding. For those areas which used direct seeding method, rice crop status was at seedling stage by October. On the other hand,

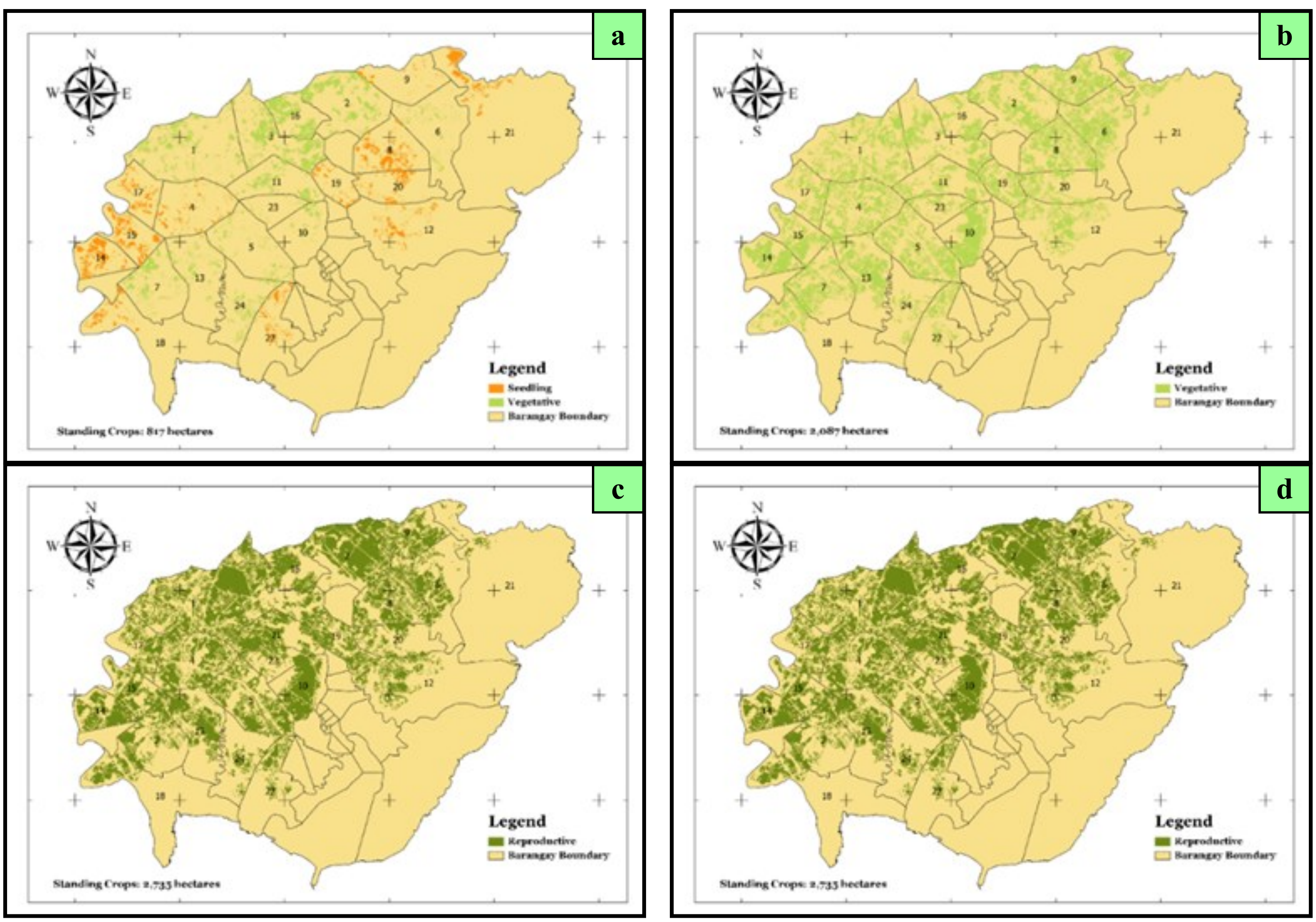

Figure 6. Status of standing crops for 2nd cropping in Dumangas, Iloilo in (a) October 2020, (b) November 2020, (c) December 2020, and (d) January 2021

those areas which used transplanting method, rice crop status was already at its vegetative stage from the beginning. It was observed that the percentage of standing crops increased as more areas began to plant. This was reduced upon reaching the ripening stage.

Table 2. Monthly status of standing crops per barangay in Dumangas, Iloilo for 2nd cropping

Month	Status	Standing Crops (ha)	Standing Crops (%)
October 2020	Seedling/ Vegetative	817	25.6
November 2020	Vegetative	2087	65.4
December 2020	Reproductive	2735	85.7
January 2021	Ripening	2351	73.6

Using various satellite images, the total area with standing crops was determined based on the properties of optical satellites. However, the quality of Sentinel 2 data is affected by weather disturbances where clouds cover some areas. In these areas, obtaining accurate information became a challenge and limitation. This was evident in the reported data in January. Most barangays in Dumangas were obscured with thick clouds during this month, leaving only one (1) image on January 24 with clear data. This was used for all barangays. This problem can be considered one of the limitations of using optical data.

For the 3rd cropping which usually falls during the summer season, three barangays were determined to plant mung bean instead of rice in the majority of their agricultural area. These barangays included Bolilao, Nanding Lopez, and Dacutan. The third season also showed that there was a synchronous planting across the whole municipality as presented by the maps in Figure 7. The monthly data can be seen in Table 3. The barangays planted mung beans were not counted and considered in the analysis. The result of this monitoring was coordinated with the SEAMS partners from Dumangas. They mentioned that farmers did not plant rice during this season because of the inadequate water supply for irrigation in their corresponding barangays. Rice growth relies during this cropping season on rainwater. Early maturing rice varieties were usually used during the 3rd cropping. When not planted with rice, mung bean, watermelon, vegetables, and other short-duration crops were cultivated (Decastillo, 2007).

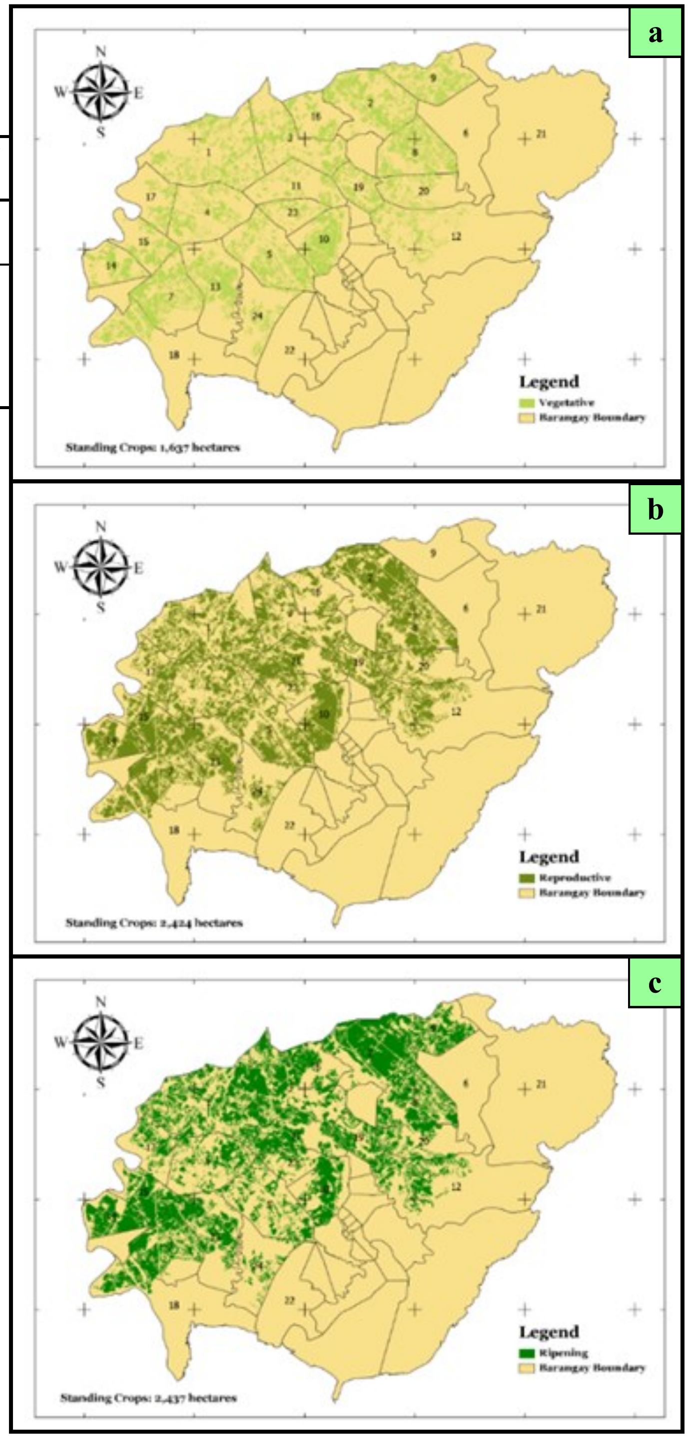

Figure 7. Status of standing crops for 3rd cropping in Dumangas, Iloilo in (a) February 2021, (b) March 2021, and (c) April 2021

Table 3. Monthly status of standing crops per barangay in Dumangas, Iloilo for 3rd cropping

Month	Status	Standing Crops (ha)	Standing Crops (%)
February 2021	Vegetative	1637	51.3
March 2021	Reproductive	2424	75.9
April 2021	Ripening	2437	76.3

Mapping the areas with standing crops provides good information on the spatial distribution of the locations with rice areas planted in the municipality. It also visualizes the standing crops and the status of the vegetation in the barangays. In addition, it helps in counter-checking the reported values and areas from interviews conducted by the agricultural technicians. Ali et al. (2020) highlighted the importance of using high resolution and multi-temporal satellite information in the analysis of crop growth and masking the regions that were not production areas to control the analysis derived from locations with NDVI less than 0.2.

Aside from the spatial distribution, it can be noticed that there was an increase in the area being planted during the start of the season. This reflects that the farmers begin to plant rice in their fields. The areas which planted early can also be determined in the maps. The vegetation's development status can be determined using the NDVI values.

NDVI Threshold Determination

For the threshold determination, the ground data of the GCP was plotted against the equivalent NDVI derived from Sentinel 2. The phenological metrics for each point was derived and summarized in Table 4. Most of the ground control points only planted rice for the 2nd cropping. For this season, the range of the SOSN was from 0.104 to 0.531. On the other hand, for the 3rd cropping, the value ranges from 0.131 to 0.309. The identified mean for the data was 0.252 while the standard deviation was 0.112. From the SEAMS methodology, the threshold used to determine standing crops was 0.3. From the GCP and NDVI data gathered and analyzed, it was found out that only five of the identified SOSN were greater than 0.3. For the EOSN, the range for the 2nd and 3rd cropping varied from 0.11 to 0.514 and 0.103 to 0.241, respectively. The computed mean and standard deviation for EOSN were 0.26 and 0.103, respectively. The maximum NDVI and the number of days when it was observed were also determined. From the results, the highest value was 0.765. Meanwhile, the range was 0.535 to 0.765. On the average, the maximum NDVI was 0.663 ± 0.079.

Table 4. Summarized phenological metrics of the different GCP points

GCP	SOSN		EOSN		Maximum NDVI		Duration	
	2nd Cropping	3rd Cropping	2nd Cropping	3rd Cropping	2nd Cropping	3rd Cropping	2nd Cropping	3rd Cropping
1	0.207	0.309	0.309	0.213	0.712	0.438	90 days	69 days
2	0.263	-	0.263	-	0.717	-	90 days	-
3	0.282	-	0.238	-	0.623	-	85 days	-
4	0.473	-	0.316	-	0.601	-	119 days	-
5	0.163	-	0.226	-	0.631	-	95 days	-
6	0.252	0.28	0.423	0.187	0.535	0.491	90 days	89 days
7	0.283	-	0.324	-	0.671	-	90 days	-
8	0.198	-	0.23	-	0.636	-	95 days	-
9	0.324	-	0.228	-	0.765	-	90 days	-
10	0.136	-	0.481	-	0.671	-	95 days	-
11	0.261	-	0.207	-	0.695	-	90 days	-
12	0.106	0.241	0.391	0.103	0.687	0.703	90 days	89 days
13	0.531	-	0.291	-	0.751		95 days	-
14	0.12	0.17	0.170	0.208	0.736	0.743	85 days	94 days
15	0.234	0.131	0.217	0.241	0.692	0.61	85 days	89 days
16	0.473	-	0.206	-	0.701	-	90 days	-
17	0.193	-	0.195	-	0.704	-	110 days	-
18	0.206	-	0.311	-	0.73	-	130 days	-
19	0.104	0.239	0.11	0.145	0.702	0.63	90 days	89 days
20	0.365	-	0.514	-	0.661	-	110 days	-

Based on the NDVI data generated, the threshold of greater than or equal to 0.3 derived from the methodology of SEAMS was determined to be an acceptable value as it was within the range of vegetative and ripening. Most of the areas which underwent land preparation and harvesting were lower than the 0.3 thresholds set for Sentinel 2. According to NASA (2021), threshold identification can be based on two methods, namely absolute or expert-based opinion, and relative, which can be grounded on about 10-20% of the observed NDVI amplitude.

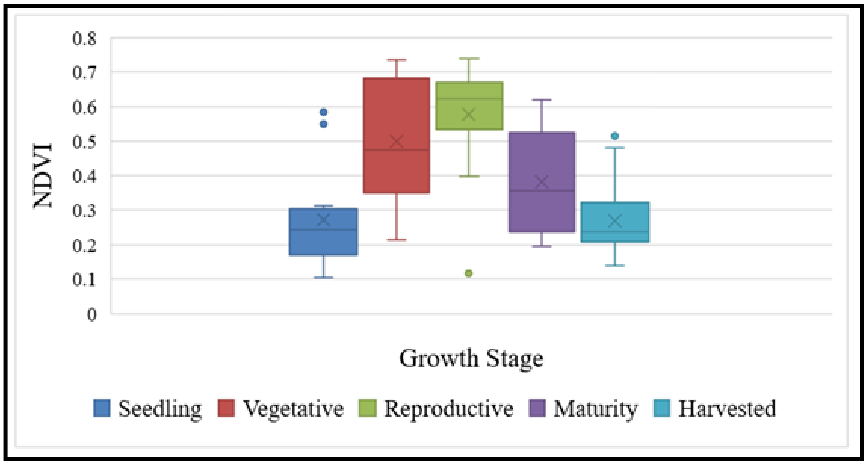

Figure 8. Range of NDVI per stage derived from the ground and Sentinel 2 data

In addition, looking into the information from the ground as taken using SICApp, the respective NDVI values for various stages were gathered from the Sentinel 2 data. The comparison correlated the NDVI value for these growth stages. The box and whisker plot presented in Figure 8 shows the range of corresponding NDVI.

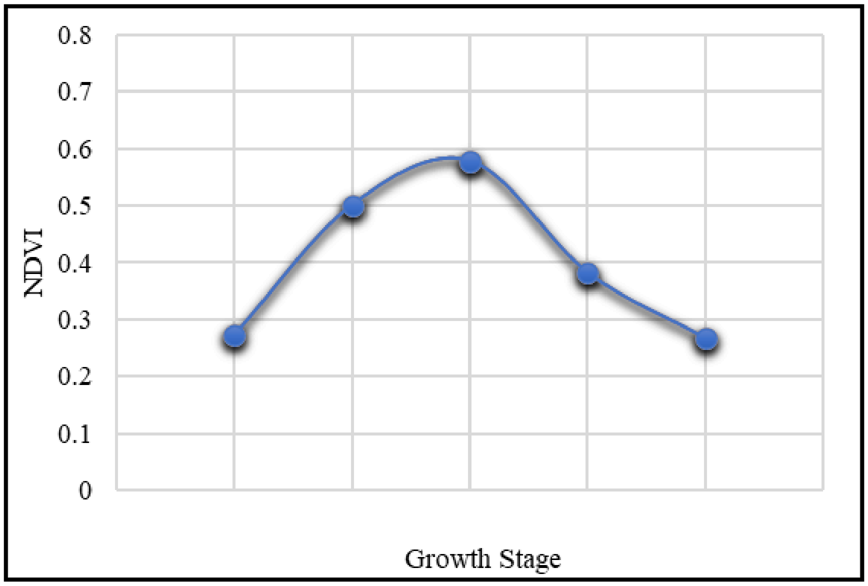

Figure 9. NDVI trend

From Figure 8, the NDVI range for each growth stage was determined. The seedling stage ranged from 0.163 to 0.309. The vegetative stage varied from 0.35 to 0.682. The reproductive stage has values from 0.535 to 0.671. The maturity or ripening stage went from 0.235 to 0.533. Lastly, harvested areas observed values from 0.2075 to 0.237. It can also be noticed that there was an overlap between the vegetative and reproductive stages which can be explained that the peak NDVI was observed during the end of the vegetative stage. The value lowered as it underwent the reproductive stage. The dots in the figure show the outliers. Meanwhile, Figure 9 shows NDVI trend based on the mean value per growth stage. However, in this presentation, it can be seen that the maximum NDVI was reached during the reproductive stage. Table 5 presents the raw data of the images collected for threshold determination.

The trend did not follow the result of the study of Lin et al. (2014) that the maximum value was achieved during the heading and flowering stage, and upon maturity, NDVI drastically decreased. A similar remark was observed by Ali et al. (2020) as they used the peak greenness in their multi-temporal research in predicting yield through NDVI and leaf area index (LAI). LAI is defined as “the ratio of the total area of all leaves on a plant to the ground area represented by the plant”. This relates to the available amount of biomass. However, the results showed the same information from the studies of Madigan et al. (2018), which explained that photosynthesis slows down as the crop undergoes the reproductive stage, and the moisture lowers. In addition, the research of Liu et al. (2015) mentioned that NDVI might also change depending on the

Table 5. Actual range of data collected

Growth Stage	Number of Data Collected	Upper Limit	Lower Limit	Median	Upper Quartile	Lower Quartile
Seedling	20	0.595	0.106	0.2445	0.309	0.1630
Vegetative	15	0.736	0.216	0.4730	0.682	0.3500
Reproductive	19	0.740	0.117	0.6230	0.671	0.5350
Maturity	14	0.619	0.196	0.3560	0.533	0.6385
Harvested	34	0.514	0.140	0.2370	0.237	0.2075

amount of fertilizer applied. Increasing nitrogen increases NDVI but remains constant for nitrogen of more than 120 kg/ha. The assumption was that there is a synchronous planting in a barangay level to simplify the result. Also, the growth stage of the majority of the barangay was reported for the result.

In the beginning, only bare soil is visible because it is just the start of sowing or transplanting. In this case, the red band value is relatively higher than the NIR. Next, there is an increase in the NDVI as the crop starts to grow, and high photosynthetic activity can be observed. It also shows the fastest vegetation growth until it reaches the maximum NDVI. In this stage, there is maximum green biomass during the heading or flowering stage. As it ages and begins to senesce, a rapid decrease in vegetation is observed, causing a maximum negative slope. Lastly, NDVI drops to its minimum value (NASA, 2021).

From the phenological metrices, it was found out that most of the varieties used for planting in Dumangas were hybrid varieties with a duration ranging from around 85 to 100 days. The common hybrid varieties grown in the municipality include SL 8, SL 19, SL 20, SL 22, Pioneer, and Longping. Meanwhile, some GCP showed a duration higher than 100 days. These areas were determined to plant inbred varieties such as NSIC Rc 222, Rc 216, and Rc 210. The difference in variety used also affected the range of NDVI and the maximum NDVI attained in the points selected. Verification of the study regarding the variety was challenging since the data on seed distribution since 2018 was not accessible to the staff of MAO and had already submitted to the DA Regional Field Office. As per Agriculturist Mr. Kim Dumdumaya (2021), it can only be assumed that those areas with irrigation plant hybrid seeds while the rainfed areas cultivate inbred seeds. NDVI trend for each GCP was derived and the duration of planting was identified based on the trend. Looking into the duration and the assumption, 16 out of 20 points or approximately 80%, had the correctly identified the variety. Only the points in Bantud Fabrica, Pulao, Nanding Lopez, and Ilaya 1st had the incorrect classification. It was also found out that hybrid varieties can reach a maximum NDVI of around 0.75, while the inbred varieties can be up to 0.7. Hybrid varieties technically can produce higher yield compared to inbred varieties because they are genetically manipulated. It has higher vigor which can be related to high NDVI.

Yield Estimation Using APSIM

Simulation of the planting for the 1st, 2nd, and 3rd cropping of 2019 was done using APSIM. The assumptions for the modeling were based on the information given by the staff from the MAO. Since the available yield data was per barangay, the assumptions were based on the practice of the majority in the area. The areas with irrigation were also identified. According to Mr. Dumdumaya (2021), old cropping practices were being done in the area, but the farmers started converting to mechanized farming. Type of planting differs per barangay. The summary can be seen in Table 6.

The amount of fertilizer being applied to the farm was also determined for both direct seeding and transplanting. For direct seeding, from 12 to 16 days after seeding, three bags of Triple 14 or Complete fertilizer (14-14-14) is applied. From 29 to 32 days after seeding, 1 to 1.5 bags of urea (46-0-0) are put in the soil. Lastly, 1.5 bags of urea are given 43 to 47 days after seeding. This practice is done for all seasons.

On the other hand, for transplanting, three bags of complete fertilizer along with one bag of urea and three bags of complete fertilizer with two bags of urea are applied 4 to 6 days after transplanting during the wet and dry season respectively. During the 14 to 16 days after transplanting, two bags of

Table 6. Irrigation and planting practices used for yield simulation

Barangay	Type of Irrigation	Type of Planting		
		1st Cropping	2nd Cropping	3rd Cropping
Pagdugue	Irrigated	Transplanting	Direct Seeding	-
PDMN	Irrigated	Transplanting	Direct Seeding	-
Rosario	Irrigated	Direct Seeding	Direct Seeding	Direct Seeding
Pulao	Irrigated	Direct Seeding	Direct Seeding	-
Sulangan	Irrigated	Direct Seeding	Direct Seeding	-
Bolilao	Irrigated	Direct Seeding	Direct Seeding	-
Cayos	Irrigated	Direct Seeding	Direct Seeding	Direct Seeding
Tamboilan	Irrigated	Direct Seeding	Direct Seeding	Direct Seeding
Barasan	Irrigated	Direct Seeding	Direct Seeding	-
Cali	Irrigated	Transplanting	Direct Seeding	-
Cansilayan	Irrigated	Transplanting	Direct Seeding	Direct Seeding
Paloc Sool	Rainfed	Direct Seeding	Direct Seeding	-
Patlad	Irrigated	Direct Seeding	Direct Seeding	-
Balud	Rainfed	Direct Seeding	Direct Seeding	-
Maquina	Irrigated	Direct Seeding	Direct Seeding	-
Calao	Irrigated	Transplanting	Direct Seeding	Direct Seeding
Balabag	Irrigated	Direct Seeding	Direct Seeding	Direct Seeding
Bantud Fabrica	Rainfed	Direct Seeding	Direct Seeding	Direct Seeding
Bacong	Irrigated	Transplanting	Direct Seeding	Direct Seeding
Paloc Bigque	Rainfed	Direct Seeding	Direct Seeding	-
Nanding Lopez	Rainfed	Direct Seeding	Direct Seeding	-
Dacutan	Rainfed	Transplanting	Direct Seeding	-
Capaliz	Irrigated	Transplanting	Direct Seeding	-
Ermita	Rainfed	Transplanting	Direct Seeding	-

complete fertilizer with 0.5 bags of urea are added to the soil for the wet season, while two bags of complete fertilizer with one bag of urea for the dry season. Lastly, an additional 0.5 bag of urea and one bag of muriate of potash (0-0-60) and one bag of urea and one bag of muriate of potash are applied for the wet and dry season, respectively. For the third cropping, the same application method is done with the dry season.

Irrigation and the planting practices being done in the area for the cropping seasons seen in Table 6. Irrigation and fertilizer application were also included in the simulation. The simulated yield result was presented in Table 7. The computed statistical parameters such as coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) for yield simulation were summarized in Table 8. Yield simulation for the wet season showed a good result and R^2 = 0.9529. In terms of MAE, the simulated yield is ± 0.98 which is an acceptable value. However, it can be noticed that there were barangays that predicted a relatively lower yield compared to the actual yield. It can also be seen that this result was consistent with the other cropping seasons. These barangays included Pagdugue, Pulao, Sulangan, Cayos, Barasan, Patlad, Maquina, and Balabag. These areas were close to each other. One of the factors related to this was the soil properties derived from World Soil Information with 250 meters spatial resolution due to the lack of ground data. According to Waldo Tobler, the first law in Geography is that "Everything is related to everything else but near things are more related than distant things" (University of Sheffield, 2012). This indicated that, possibly, the soil inputs for this neighborhood had a similar range of values that affected the simulated yield. Nevertheless, the other barangays predicted near yield values for the 1st cropping.

On the other hand, for the 2nd and 3rd cropping, the model produced a low yield. These particular cropping seasons happened to be dry and summer, causing the area to receive minimal rainfall. However, 8 out of 17 irrigated areas predicted a yield greater than 5 tons/ha, which was considered under the range of actual yield for the 2nd cropping. The rest of the irrigated barangays were included in the list with consistent low simulated yield. Meanwhile, few areas planted rice for the 3rd cropping, and underestimation was observed when the actual and simulated yields were compared. Compared to the first season, the MAE and RMSE were relatively higher while R^2 was lower. There was a discrepancy of ± 1.71 and ± 1.58 tons/ha from simulated yield for 2nd and 3rd cropping, respectively. The MSE being closer to 2 made the difference significant. In terms of RMSE, 1st cropping still had the best fit of data compared to other cropping seasons.

It was also found out that the model was more sensitive to nitrogen application than the addition of

Table 7. Observed and simulated rice yield per barangay

Barangay	1st Cropping		2nd Cropping		3rd Cropping	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
Pagdugue	6.10	4.65	5.89	4.01	-	-
PDMN	6.18	5.95	5.97	5.65	-	-
Rosario	5.96	5.65	5.02	5.11	4.40	3.3614
Pulao	6.19	3.78	5.27	3.24	-	-
Sulangan	6.05	2.96	5.31	2.59	-	-
Bolilao	6.25	5.58	6.10	4.26	-	-
Cayos	5.72	3.27	5.83	2.82	3.95	2.6745
Tamboilan	6.00	5.95	5.15	5.26	4.14	3.4589
Barasan	6.28	4.44	5.89	3.69	-	-
Cali	5.90	5.90	5.54	5.14	-	-
Cansilayan	6.01	6.37	4.80	5.69	4.01	3.5274
Paloc Sool	6.01	6.24	5.90	3.73	-	-
Patlad	6.29	3.76	6.02	3.22	-	-
Balud	5.88	5.84	5.49	3.05	-	-
Maquina	6.02	4.02	5.82	3.44	-	-
Calao	5.96	5.51	5.76	5.43	4.24	2.3633
Balabag	5.99	3.42	5.86	2.97	4.21	2.5221
Bantud Fabrica	5.84	5.60	5.73	2.98	4.31	0.1523
Bacong	6.02	5.87	4.76	5.61	4.01	2.5592
Paloc Bigque	5.96	6.68	5.75	2.49	-	-
Nanding Lopez	5.65	6.71	6.03	4.29	-	-
Dacutan	5.67	5.60	5.67	3.65	-	-
Capaliz	5.85	5.35	5.65	5.65	-	-
Ermita	5.69	5.89	5.96	3.99	-	-

Table 8. Statistical parameters computed for yield modeling

Cropping Season	R^2	MAE	RMSE
1st	0.95	0.98	1.40
2nd	0.14	1.71	2.00
3rd	0.09	1.58	1.91

phosphorus (Table 9). Nitrogen is an essential macronutrient that affects yield variation, grain quality, and fast plant development. Even though the soil already has nitrogen content, fertilizer application is necessary as it is considered a limiting factor in rice development. Fertilizers with nitrogen include urea, ammonium sulfate, and diammonium phosphate. To increase yield by 1 ton, about 40−50 kg N/ha of inorganic fertilizer should be applied (IRRI, n.d.). The optimal nitrogen amount for rice in China was determined to be 135 to 180 kg/ha based on the study of Liu et al. (2015). The simulation was tested wherein no fertilizer was applied and showed that it significantly decreased the predicted yield by at least 0.8 ton/ha.

From the results obtained, it can be concluded that the use of APSIM to quantify and predict rice yield in Dumangas can be promising as it gave close yield values for the wet season. However, underestimation and low yields were simulated for the cropping seasons with limited water availability. Consistent low predicted yield values were observed for some barangays, which may be due to the inaccuracy of the soil inputs. Furthermore, generalization of the management practices was made in this model; thus, the accuracy of the yield modeling procedure was compromised. In addition, fertilizer in terms of potassium inputs was not recognized in this model. It is suggested to apply the process at a farm level with precise integration of the actual field practices, including tillage practices, weed management, and pest control.

Moreover, the challenges encountered while using APSIM in an area-wide coverage included its requirement of intensive input parameters, limited data availability, asynchronous planting per farm, farmers opting to use traditional practices, and different variety used. The study area was determined to be lacking the necessary ground observation that can be used as input for the model. Consequently, there was no historical data for model calibration. Furthermore, according to Defiesta and Rapera (2012), the average farm size of rice areas in the study area is about 1.65 hectares. There were approximately 80 farms per barangay with different owners and management practices. With this, there may be a variation in planting date and variety per farm lot which can affect the predicted yield for the whole area. Mr. Dumdumaya (2021) also mentioned that there were farmers who do not use the recommended practices like fertilizer application because they tend to rely on the traditional way of doing so since about 95% of farmers in Dumangas were focused on rice cultivation with an average of 26 years of experience (Defiesta and Rapera, 2012).

Table 9. Fertilizer sensitivity analysis results

Barangay	Actual Yield	With Fertilizer	Without Fertilizer	Nitrogen Only	Phosphorus Only
PDMN	6.18	5.9469	4.5889	5.9469	4.5889
Rosario	5.96	5.6459	5.4607	5.4727	5.4607
Tamboilan	6.00	5.9541	4.7131	5.9541	4.7131
Cali	5.90	5.8952	5.8595	5.8952	5.8595
Cansilayan	6.01	6.3700	4.9952	6.3700	4.9952
Paloc Sool	6.01	6.2432	5.1058	6.2432	5.1058
Balud	5.88	5.8363	4.9810	5.8363	4.9810
Calao	5.96	5.5110	4.5214	5.5110	4.5214
Bacong	6.02	5.8674	4.7902	5.8467	4.7902
Bantud Fabrica	5.84	5.6000	4.5644	5.5991	4.5644

Gaps in the simulated yield results were observed in this study for the 2nd and 3rd cropping. Rice production is prone to weather-related risks such as drought spells during these cropping seasons. Many rice areas redo planting due to the lack of rainfall. In addition, the most common irrigation type in Dumangas was the shallow tube well, followed by the dam from the National Irrigation Administration (NIA). The damages incurred by drought and shallow tube well irrigation systems were not modeled and reflected in the methodology.

To improve the applicability of the model for the cropping seasons with limited water, it is best to initially conduct sampling in farms to determine crucial inputs, including the soil properties at different depths, irrigation measures, and management methods. This will establish the basis of the inputs that can be assessed for calibration. In addition, calibration should be done in a multi-temporal manner to evaluate and illustrate the simulation for normal and extreme weather, including El Niño and La Niña years. Wind speed can also be incorporated to model evapotranspiration. Lastly, to determine how the weather parameters alone affect yield, an empirical or regression model can be employed (Murthy, 2019).

With a well-calibrated and accurate crop yield model, valuable information such as the best variety to use, optimum sowing date, weather hazards, potential crops, and optimum input analysis can be derived (Murthy, 2019). Additionally, the effectiveness of a calibrated model ensures the correct characterization of the study area that can help in maximizing resources and promoting sustainable agriculture (Kephe et al., 2021). With these recommendations, a more accurate yield model for a barangay-level analysis can be developed.

CONCLUSION

Satellite remote sensing can be employed in agricultural monitoring. It provides accurate and valuable information for estimating areas planted without directly going to the field. The methodology established by SEAMS was analyzed to be a functional and easy way of investigating the characteristics of the vegetation in the area as well as its spatial distribution. Field validation was necessary to determine the actual status in the field and the accuracy and efficiency of the resulting maps derived from the satellite. NDVI showed a clear characterization of the crop phenology. The NDVI range for the growth stage can also be determined when the ground data and nearest observed satellite data are available. In addition, remotely sensed data can be used as inputs for crop models, given a lack of ground observation. Lastly, the analysis was site-specific; therefore, the guidance of the experts from the area should be considered.

RECOMMENDATION

Based on the results from this study, it is best recommended to have sufficient ground truth data of at least twice a month and possibly synchronous with the satellite's revisit time. A longer historical yield data may be used to test the accuracy of the model. Aside from using the NDVI threshold, other vegetation indices can be utilized and incorporated for a similar study. Unmanned aerial vehicle (UAV), which is a low altitude remote sensing, can also be considered. Actual soil data, planting date, and other model inputs should also be used to increase the accuracy of the crop model. It is a convention to prefer and use ground data whenever available. Also, analysis can be separated for irrigated and rainfed rice areas to have a clearer understanding of yield variation. Since the analysis is site-specific, it is suggested that the users who will adopt this methodology should be capacitated and knowledgeable about the actual field practices and conditions.

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