An early investigation of spatial correlation between Sentinel-2 based rice growth stages maps with satellite-based precipitation data to support digital agriculture development in Indonesia

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Abstract. Sustainability of rice production is a critical issue to ensure food security and needs to be monitored on time. Therefore, the online monitoring system using Sentinel-2 has been introduced to monitor rice fields in Indonesia. However, the system needs to be coupled with precipitation to improve user usage. In this study, the spatial correlation using Pearson’s correlation analysis and linear regression between the floods and the vegetative stages area of the rice monitoring maps and the precipitation data from CHIRPS was investigated. The analysis was conducted with the two datasets with 439 regencies in Indonesia on a monthly basis from December 2019 until May 2020. The result shows that 96 regencies have a highly positive correlation ($r>0.6$, $p>0.05$, $n=6$) with 57 regencies have a high $R^2$ ($R^2>0.6$). Also, there are 83 regencies has a profoundly negative correlation ($r<0.6$, $p<0.05$, $n=6$) with 32 regencies with high $R^2$ ($R^2>0.6$). On the other hand, there are 79 regencies have medium $R^2$ ($0.4\leq R^2<0.6$), and 271 regencies have the lowest $R^2$ value ($R^2<0.4$). These early-stage results show an opportunity to combine two datasets to produce early warning systems or recommended cropping calendar in a timely and accurate manner to the stakeholders or the farmers.

1. Introduction

Over the last decades, numerous studies on rice monitoring using remote sensing technologies have been studied extensively [1-9]. The monitoring application is heavily dependent on Moderate-Resolution Imaging Spectroradiometer (MODIS) vegetation indices such as normalised difference vegetation index and enhanced vegetation index [10-12]. In the cloud prone area, MODIS has less clean data, especially in the rainy season even for composite product. Many researchers have used some filtering to guess the missing values such as wavelet filtering or Savitzky-Golay filter [5, 13-16]. However, these methods are not favourable for detecting rice growth stages in near real-time monitoring especially for complex rice field which need better resolution of 10-50 m. Moreover, the existing MODIS model relied on the vegetation index need local knowledge due to the value of Enhanced Vegetative Index for vegetative stage and ripening stage is almost the same range (0.3-0.4) or temporal profiles which make it difficult to be applied to other area [17].

The radar-based sensor such as TerraSAR, ALOS Palsar, Radarsat or Sentinel-1 has been highly used to overcome the cloud problem [18-22]. Some studies have been reported has good accuracy in Asia.
and Europe region, especially for Sentinel-1, because it is available with no cost [23-25]. The backscatter of radar can detect flooding and vegetative stage very well but not for bare land area due to dry land can be confused with vegetative stage due to absorption of radar energy in some area [26]. Nevertheless, in our practical experience, the application of rice monitoring with Sentinel-1 is still revolving and only established in a small and specific area. Moreover, it needs much time to cultivate a stable model or methods that will apply at a national level.

Meantime, the Indonesian Agency for Agricultural Research and Development (IAARD) has solved these problems using Sentinel-2 imagery with more features than MODIS such as better resolution of 10 m and have more bands than MODIS with a resolution less than 500 m [27, 28] using machine learning approach with Support Vector Machine (SVM) as the classifier. The SVM was chosen because the previous study shows that SVM has better accuracy than other classifiers [29]. Also, the released time is more recent than the MODIS-based standing crop from 8-days to 5 days. The IAARD rice monitoring has been maintained by Integrated cropping calendar team since December 2019. The information is accessible on the interactive website (katam.litbang.pertanian.go.id/SC) and Android application with the title “Monitoring of Sentinel-2 Rice Growth Stages”.

On the other hand, rice cultivation has been dependent on water availability from surface irrigation. The global water footprint was calculated as 784 km³/year, and the water trading for rice trade is 31 km³ year⁻¹ [30]. The surface irrigation also depends on precipitation rate based on the hydrological cycle, which can be altered by climate change [31]. In some irrigation area, water availability is not a big obstacle, but in the rain-fed paddy field, the precipitation is crucial to rice productivity. Surmaini, Hadi, Subagyono and Puspito [32] reported that drought could bring less than one million ha. Thus, monitoring precipitation is also as vital as rice monitoring. BMKG has already have installed numerous rainfall stations to measure the precipitation. However, it is impossible to install rain gauge to all regions due to the high maintenance and labour cost even with automated weather stations. The global science community has been developed with a satellite-based model to overcome the missing data using a global climate model. There are a few climate models such as Integrated Multisatellite Retrievals (IMERG) [33], Global Satellite Mapping of Precipitation (GSMaP) [34], and Climate Hazards Group Infrared Precipitation with Station (CHIRPS) [35]. CHIRPS has been studied globally because it has higher spatial resolution of 0.5 degree than others and has data availability from daily to monthly data. Moreover, Liu, Aryastana, Liu and Huang [36] reported that CHIRPS is one of the global climate models that has a good correlation with ground rain gauge stations in Bali islands.

To date, there is no attempt to correlate between two datasets of rice monitoring and precipitation datasets at a national level. The correlation between the rice growth phases may give some information about how the precipitation rate gives some negative or positive effect on the planting area, particularly in the flooding and vegetative area. Thus, the objective of this study is to investigate the correlation between rice growth stages data with precipitation data monthly from December 2019 to May 2020. The information of the correlation can be used for a foundation to another following research to understand the lag effect and the effectiveness of both datasets to real application in regency decision making to secure food production.

2. Study area
Indonesia is the southernmost country in the Asia region and located between 6 degrees North and 11 degrees South latitude and between 94 and 141 degrees East longitude [37]. The climate in Indonesia is humid equatorial to the monsoonal equatorial climate according to the Köppen-Geiger classification [38]. Indonesia is administratively divided into 34 provinces, and each province is partitioned into regencies with a total of 439 regencies which have the official rice fields record. The total rice area based on the latest information from the Ministry of agriculture which has been coordinated with the Ministry of Agrarian Affairs and Spatial Planning/National Land Agency is 7.4 million ha at the end of 2019. The distribution of rice fields is Sumatra (1,752,308 ha), Java (3,472,864 ha), Bali & Nusa Tenggara (461,038 ha), Kalimantan (723,947 ha), Sulawesi (972,854 ha), Maluku (31,826 ha), and Papua (45,055 ha) (http://katam.litbang.pertanian.go.id).
3. Methods
This study attempted to establish the relationship between the rice growth phase area and precipitation in monthly data using Pearson's correlation formula and linear regression. The first step is to summarize the data from the rice monitoring application. The second step is to extraction of precipitation data from Google Earth Engine. The next step is to analyze the dataset with Pearson correlation and simple linear regression. The final step is to map the result of the correlation and $R^2$ to all regency.

3.1. Rice growth stages data compilation
The rice growth stages monitoring based on Sentinel-2 has been done by processing images from December 2019 until May 2020 based on more than 2,544 images from 353 unique path/row for all Indonesia rice area. The system automatically selects the only images with <30% cloud cover to minimize computation power. The pre-defined model of machine learning with >90% overall accuracy classified the satellite imagery on formal rice field area into five classes: 1) bare land, 2) flooding, 3) vegetative stage, 4) reproductive stage, and 5) ripening stage. The flooding area and the vegetative area were chosen due to the closest characteristic of rice growth stages which demonstrate water availability in the rice field. The average of flooding area and the vegetative area was collected every month based on 445 regencies. The sum of the two stages was divided with a total field area to get the monthly percentage. Figure 2 shows the map of the monthly proportion of flooding and vegetative stages. It shows that the variability of data availability is high due to the rainy season in December 2019, and it got more data until April 2020.

3.2. CHIRPS precipitation data collection
The collection of prescription data from CHIRPS has been done in Google Earth Engine (GEE). Many studies have reported GEE is the one of frontier regarding cloud computing in earth science research and development [39]. The dataset of GEE is abundant and easy to use for further analysis with its owned IDE and Python programming [40]. We used a custom script to extract the precipitation data from CHIRPS dataset based on each regency boundary. Figure 3 reveals the dynamic of rainfall in Indonesia area from December 2019 until May 2020. The rainfall rate was already high in December 2019 on Sumatra, Kalimantan, and Java island. The next month, the rainfall is well distributed in all area. However, from March 2020, the rainfall was dropped in East Nusa Tenggara until May 2020.
Figure 2. The monthly percentage of flooding and the vegetative area from December 2019 until May 2020.

Figure 3. The monthly precipitation rate from CHIRPS daily data from December 2019 until May 2020.
3.3. Correlation and linear regression

The relationship between the percentage of flooding and vegetative stage area and precipitation is analysed with Pearson's correlation coefficient (r) and p-value to determine the significance of the dataset with formula as follows:

\[
 r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt[n]{n \sum x^2 - (\Sigma x)^2} - [n \sum y^2 - (\Sigma y)^2]}
\]

where n: number of data, \(\Sigma x\): a total of the percentage of flooding and vegetative stage area, \(\Sigma y\): a total of the precipitation value, \(\Sigma xy\): a sum of the product of precipitation value, \(\Sigma x^2\): a sum of the squares of the percentage of flooding and vegetative stage area, and \(\Sigma y^2\): a sum of the squares of precipitation value.

The linear regression between parameters is also analysed to get the coefficient of determination (R²) and regression line equation using R statistics programming with ggplot2 and ggpubr package for plotting for each regency [41, 42]. Since the rice monitoring programme started in December 2019, there will be only maximum six-monthly data for each regency. It can be a limitation to the accuracy of the study.

4. Results and discussion

4.1. Data compilation

The compiled data shows that there is a low count of data for 51 regencies (11.6%) with only three data. The other regencies that have only four data are 152 (34.6%). Total regencies with five or six data are 236 (51.8%) regencies. Figure 4 shows that the distribution map of data availability of Sulawesi, middle of Sumatra, west of Kalimantan, east of Java, Nusa Tenggara, and Bali island has a useful dataset. Papua island has incomplete dataset since the rice area is only concentrated in a few regencies such as Merauke, Sorong, and Manokwari.

![Figure 4. The distribution of number of data availability.](image)

4.2. Monthly correlation analysis

Figure 5 shows the distribution of Pearson's correlation coefficient between the monthly percentage of flooding and vegetative stage and monthly precipitation rate. There are 96 regencies that have a highly positive correlation \((r>0.6, p>0.05, n=6)\), and there are 83 regencies that have a profoundly negative correlation \((r<0.6, p<0.05, n=6)\). Most of the positive correlations exist on Sulawesi and Sumatra island. On the other hand, negative correlations occur on Kalimantan and Java island.
The positive correlation means that Sentinel-2 imagery can provide clean data over six-month periods. The cropping calendar of these areas is sensitive to precipitation rate and mostly is a rain-fed area such as Pagar Alam, South Sumatra; Mamuju, West Sulawesi, and Poso, Central Sulawesi. However, the rice fields that support irrigation have a negative correlation such as Indramayu, Subang, Karawang and most regencies in Java island, except Lebak, Banten; Ciamis, West Java; and Malang, East Java. On the other hand, no or weak correlation can be interpreted as incomplete or missing data. These dynamic correlations can be implied that Sentinel-2 can capture the rice growth stages but not of all regencies in Indonesia, such as Papua and Maluku island.

In addition, the correlation can change over the years due to climate change. In this study, we acknowledged that the planting time in December 2019 was later than usual planting time. Since in 2019, Indonesia has had El-Nino which gives a long dry season. These findings also concur with other investigations that drought can change the planting time [43, 44].

4.3. Linear regression analysis

Figure 6 (a, b, e, f) gives the illustration of regencies which have a highly positive and negative correlation, and figure 6 (c, d, g, h) gives the examples of low $R^2$ values. Precipitation rate was believed as the main drive of rice cropping pattern in the field level. However, based on our result, it does not have a positive correlation over the Indonesia region. The variability of local climate, local knowledge, and limited resources can lead to a low $R^2$ value as reported by Wood, Jina, Jain, Kristjanson and DeFries [45] and [46]. The local market also can be a driving factor of choosing rice or other commodities such as shallot in Brebes. The farmer who has rice fields will tend to plant shallot other than rice even for first planting season because the price of shallot mostly increased in rainy season [47-49]. To be precise, we have generated a plot for each regency, and it can be accessed on https://github.com/FadhlullahRamadhani/Correlation-precipitation-Sentinel-2 for reader's exploration.
Figure 6. The examples of Pearson's correlation and linear regression for (a) Karang asem, Bali; (b) Magetan, East Java; (c) Ponorogo, East Java; (d) Brebes, Central Java; (e) Polewali Mandar, West Sulawesi; (f) Timor Tengah Selatan, East Nusa Tenggara; (g) Pesisir Barat, Lampung; and (h) Trenggalek, East Java.

Moreover, ArcGIS software has been used for mapping the number of available data, $r$ and $R^2$ for each regency. Those data were joined with the BPS-based administrative boundary. The next step, we classified the correlation to separate between high positive relationship (>0.6), low positive relationship (0.59-0.4), no relationship (0.39-(-0.39), low negative relationship (-0.59-(-0.4)), and high negative relationship (>0.6). On the other hand, the map of $R^2$ consists of four classes: <0.2, 0.21-0.4, 0.41-0.6, and >0.6.

Figure 7 demonstrates the map of distribution $R^2$ of two parameters. There are 89 regencies that have a high $R^2$ and average $R^2$ values exist in 79 regencies. Also, there are 166 regencies that have the lowest
R² value. The distribution of high R² is consistent with correlation results which spread to most regencies in Kalimantan, and Sulawesi island, while Sumatra and Java island have lower R² value.

The rice monitoring of Sentinel-2 is more accurate in field level (10 m spatial resolution) than MODIS-based rice monitoring, but cloud will always conceal the earth surface from the satellite sensor, causing lower R² than expected. The dataset was started in December 2019, which had more cloud cover for optical data, especially in Java island. Moreover, there is a possibility that the rice fields are not linear but have a polynomial relationship since the flooding and vegetative stages are less in the second rice planting, which occurred around April to May 2020. The Sentinel-2 failed to capture the dynamic growth in those rice fields.

![Figure 7. The distribution of R² in Indonesia.](image)

5. Conclusions
The results of this study demonstrated that there is a highly positive correlation between the precipitation and rice growth stages for 96 of 439 regencies in Indonesia. Since this study is an initial research of the integration of remote sensing information and recommended cropping calendar or an early warning system, the result can be enriched with the correlation between other rice growth stages with different sensors or with various other global climate models. Moreover, it would be a foundation of a more in-depth investigation after the rice monitoring in one year or more. Also, this study shows that rice field in Indonesia still has dependent on the precipitation rate on a larger scale. The government or the stakeholder can make better policy to increase the productivity and cropping index with this information. Moreover, a drought problem can be more manageable both using an agricultural insurance scheme with an online and a digital system.

Acknowledgments
The author would like to give a huge appreciation to Integrated cropping calendar team from IAHRI, especially Sentinel-2 standing crop team for the raw data of rice monitoring IAAAD’s scholarship provided funding of this paper through Sustainable Management of Agricultural Research and Technology Dissemination project. We also thank the R development team, GEE developers, and ESA Copernicus data hub for amazing technologies for public access freely. Fadhullah Ramadhani is the main contributor. Misnawati and Haris Syahbuddin are the supporting contributors.
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