Dynamics pattern analysis of paddy fields in Indonesia for developing a near real-time monitoring system using MODIS satellite images

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Abstract

Accurate and up-to-date information of paddy fields over wide areas is essential to support sustainable agricultural and a food security program. It is an urgent need to develop near-real time paddy field monitoring, which can be used by policy maker for handling the food problems directly. This study explored the use of multi temporal MODIS EVI 16-day composite data, which provided the seasonal dynamics for the paddy field patterns from 2000 to 2014. We characterized seasonal vegetation dynamics from MODIS satellite datasets in order to analyze the dynamics change in paddy field. The results indicate that the methodology employed in this research distinguished many specific uses in paddy fields as means of their cropping intensity. Moreover, the seasons were the most important factor affected the dynamics change in the agricultural system. Indeed, characterizing the long-term vegetation dynamics provides information about the characteristic and trends in paddy field area, either caused by natural factors or human activities, also to be a guidance of water resources management due to improving its effectiveness.

Keywords: seasonal dynamics change; paddy field; MODIS EVI
1. Introduction

Understanding the potential production of paddy fields accurately including its future trends is necessary to improve the effectiveness and efficiencies of the agricultural land development programs in Indonesia. Moreover, an update and accurate database concerning the rice cropping intensity including its dynamics changes are essential. A new research on the paddy fields and the general relationships between environmental variability in water resources and crop production will improve to up-to-date information about the potential production of rice and developing a monitoring system of dynamic changes in the paddy fields.

Recently, most of available database of paddy field in Indonesia were determined by remote sensing data through applying single-date satellite imagery and/or aerial-photographs, which was necessarily coincident with temporarily cover types, either barren land or inundated (water). The conventional approach due to comparison imagery taken at different dates over the same locations for assessing the change might not be sufficient to identify the dynamic changes, because of insufficient documentation of change events, particularly in areas with very dynamic changes in paddy fields.

Moreover, the change in paddy fields is more complicated since it can be also categorized into three types and mechanisms: 1) seasonal change, driven by annual temperature and rainfall interactions on vegetation phenology; (2) gradual change, caused by inter-annual climate variability or land management; and (3) abrupt change, caused by disturbances such as land conversions [1]. In such a situation, simultaneous analysis of land surface attributes from long-term data sets and seasonal variation seems to be a way to deal with the above issue [2].

Monitoring seasonal changes in vegetation activity and identifying crop phenology stages from satellite remote sensing datasets may enable us to understand the dynamics changes in paddy fields, including cropping system changes under various climate conditions. For example, while extreme drought result in delayed heading and thus decreased rice yields [3]. The crop phenology is characteristic of biologically complex ecosystems reflecting the response of the earth’s biosphere to annual dynamics of the earth’s climate and hydrologic cycle [4].

This study will investigate the seasonal vegetation dynamics of long-term paddy field considering climatic variability, then, to provide sufficient information of the dynamics change in paddy fields. Moreover, through this pattern analysis, disturbance events on rice-crop growth either by natural processes (e.g. drought event) or land conversion could be recognized.

2. Methodology

2.1. Paddy field in Java

The island of Java has a long history of agriculture and settlement, and is characterized by high population density and high productive land [5]. According to Statistics Indonesia [6], about 70.62% of Java is considered to be agricultural land use as follows: paddy fields, mixed gardens, uplands/dry lands, open grass, fishponds, and plantations, with as much as 5.43% of the area covered by settlements.

2.2. Satellite images

The MODIS product used in this study is the MODIS EVI which is embedded in the MOD13Q1 product. The MOD13Q1 product is the Vegetation Indices (VI) Composite 16-day Global 250 m SIN Grid V005, and the MODIS Land Discipline Group has developed an algorithm of EVI for use with MODIS data [7]. It is computed by algebraic combination of three spectral bands (red, blue and NIR) and designed to enhance the contribution of vegetation properties [8].

Improving aerosol correction at the surface reflectance level (MOD09) and a new filtering scheme in the VI algorithm implemented in collection 5.0 has positively impacted the MODIS VI [9]. Moreover, to get a greater percentage of clear-sky data, the maximum value composited (MVC) method is applied to the MODIS VI and is combined with the MODIS BRDF (bidirectional reflectance distribution function) or MOD43 product to generate the 16-day composite MODIS VI (MOD13Q1 product) [10]. Nevertheless, if the composite period is too long, the land surface does not remain static; and if it is too short, the atmospheric disturbance cannot be removed effectively.
[11]; consequently, there are some residual errors. Such noise degrades the data quality and introduces considerable uncertainty in temporal sequences, confusing the analysis of temporal images sequences by introducing significant variations in the EVI time series data. Therefore, noise reduction or fitting a model to observe data is necessary before analysis of vegetation dynamics can be determined.

In this study, we used the MODIS EVI datasets which has been filtered by wavelet transforms for reducing the residual noise of image data [12]. The MODIS EVI datasets were acquired from January 2001 to December 2013 and captured 299 time series with the interval time 16 days. Then, to examine the details of the temporal pattern of the MODIS EVI and analyze the change of it, we used a finer spatial resolution Landsat TM and ETM+, a high resolution image (Google Earth) as well as reference data derived from the ground survey points.

2.3. Image transformation using wavelet function

The wavelet transform decomposes a signal into different scales by successively translating and convolving the elements of a high-pass and low-pass scaling filter associated with the mother wavelet. We used the coiflet mother wavelet because this wavelet shape is as similar as possible to the temporal vegetation dynamics of a crop phenology as pointed out by Sakamoto et al. [13].

In this processing, the order 2 of coiflet function was used since the trend of that order is similar to the trend of the original data. Order of the wavelet function is a measure of the wavelet’s smoothness, where a higher order produces a smoother wavelet. This analysis was performed using MATLAB through the 1-D multi-signal wavelet analysis function. The MODIS EVI data pre-processing was conducted to provide a filtered data set to support multi-temporal analysis.

The result of filtering pattern of one pixel and image transformation by using wavelet function is given in Fig. 2 and Fig. 3, respectively. Fig. 2 show that wavelet transform filters some noises (de-noise) of MODIS EVI time-series data; so that the planting, heading and harvesting dates in the agricultural land especially can be determined.
2.4. Change analysis of successive patterns

The change of vegetation dynamics was recognized using a distance of average EVI values for two successive three months (January-March → April-June → July-September → October-December), which computed for all pixels and included all consecutive study years during periods from 2001 to 2012 by a function shown in the equation below [14]:

\[
d_{k,l} = \frac{N_{k}}{N_{new}} |\mu_k - \mu_{new}|^2 + \frac{N_{l}}{N_{new}} |\mu_l - \mu_{new}|^2
\]

where \( k \) and \( l \) are two successive 3 months, and \( d_{k,l} \) is the distance between EVI values of the two successive patterns of \( k \) and \( l \) three months data, \( N_k, N_l \) is the number of observations in \( k \) and \( l \) three months data, \( N_{new} \) is the number of
observation of the two pattern of $k$ and $l$ three months data ($N_{\text{new}} = N_k + N_l$) and $\mu_k$, $\mu_k$ is the mean of EVI values in $k$ and $l$ three months data, $\mu_{\text{new}}$ is the mean of EVI values of the two pattern of $k$ and $l$ three months data.

Fig. 4. Identification of the change information from a change of temporal EVI profile.

2.5. Probability of change pattern threshold

The distance of the EVI values for two successive periods (January-March → April-June → July-September → October-December) was computed for all pixels and included all consecutive study years during the following periods 2001-2013. The difference in distance for those four periods in every year exhibited an approximately normal distribution about the mean ($\mu = 0$). Statistical analysis using a standard normal distribution was undertaken to identify pixels that had the greatest change in distance of EVI for each period. Three change thresholds (TH) were selected corresponding to a range of z-value probabilities: 2.0, 3.0, and 3.5, which was the limit to define a change or no-change in the temporal pattern. These value ranges were selected because they produced appropriate estimates of annual change values based on a previous change rate for the Java area [15].

In order to determine the threshold of change pattern probability, some pixels of the change and no-change events were randomly selected to correspond to the range of three z-value probabilities.

2.6. Accuracy assessment

The creation of a reference datasets in order to assess the accuracy for the result is one important step in this study. As explained earlier, assessing the accuracy of a map derived from 250 m image data was the disparity between the image pixel size and the average patch size of the landscape. In order to create a reference dataset to assess the accuracy, we used a finer spatial resolution Landsat 5 TM, 7 TM+, 8 OLI/TIRS as well as ground survey data.

3. Results and Discussion

3.1. Rice cropping intensity

Regarding to the previous study [16], the number of cultivation cycles (seedling to harvesting) in paddy fields that occur yearly depends on the availability of water. The rice paddy fields in Java could be sorted into several types of cropping systems. In the irrigated areas, paddy rice can grow during dry season, so that rice crops can be grown one to three times in this land within a year. From the clustering results of EVI, at least eight types of paddy-rice field were distinguished which broadly represent the rice cropping intensity in paddy fields of Java. Distribution of these paddy-rice field is given by Figure 5.
3.2. Threshold probability of change pattern

Standard normal distribution of statistical analysis was performed to identify the greatest changing of the distance of EVI value for each change period. The TH factors of 3.5 provided the best accuracy at 82.99%, meanwhile TH of 2.0 and TH of 3.0 are 77.98% and 80.53%, respectively. The TH of 3.5 was statistically significant at level 95% (p: 0.05) compared to the TH factors of 2.0; however, it was not significantly different from TH factors of 3.0. Alternatively, in application of change detection, the TH of 3.0 could be applied as a threshold since it was also statistically significant compared to the TH of 2.0. Figure 6 shows the distribution of pattern change in Java’s paddy fields, which can be detected by temporal pattern using the TH of 3.0.

3.3. Change pattern identification

In this study, simultaneous analysis of long-term vegetation dynamics allowed the change to be detected including some properties such as the location, area, time and change mechanisms. Moreover, seasonal variability (climatic regime) might also affect the change patterns of the temporal vegetation dynamics of many land use types including agricultural lands. Figure 7 shows several change patterns of agricultural land use which does not necessarily indicate a specific change of land use. Some of those temporary changes are: 1) a temporary change in cropping system, that is a triple cropping system changed to a double cropping system (B), 2) land in a plantation area is unplanted (barren land) for a long time because of a severe dry season (C), 3) intensive upland temporarily changed into barren land because of an extremely dry season, however, the land is then cropped just after the rainy season in following year (E), and 4) a pond temporarily changed into vegetated land when the water drained (F). This issue is similar to Lunetta et al. [17] who mentioned that the phenological issues associated with those land use types represent the temporal complexity of the change detection by a simultaneous analysis.
Fig. 6. Distribution of pattern change in Java’s paddy fields, which can be detected by temporal pattern.

Fig. 7. Several detected changes from a single MODIS pixel within agricultural lands that assigned as seasonal/gradual changes.
In addition, characterizing the vegetation dynamics as demonstrated in this article can also monitor even some locations that have the potential to change several times in the long term. Dynamic changes in paddy fields, from one cropping system to double cropping system and conversion into another type, could be identified as well as detected by the changing of temporal pattern more than once, as represented by Figure 8.

In Figure 8, pattern 1 indicates a conversion of forested land (bushes) into intensive agricultural land. Meanwhile, pattern 2 represents the changing of a temporal pattern that occurred many times in a rice paddy field. The severe dry season in 2001 and 2007 caused the cropping system changed. The climate variability was caused the cropping system was changed in several periods.

Due to our analysis, the agricultural lands with a double cropping system has a periodic component. Moreover, after the second cropping, e.g. in early 2006, it was postponed, because of the extreme dry season throughout the areas. Such paddy fields was classified into the paddy rice field with rain-fed system; consequently, the paddy rice is only planted during the rainy season, meanwhile, during the dry season the land remained fallow.

In many areas of the paddy-rice field with triple irrigated cropping system, this paddy fields has been improved as an irrigated land, therefore, there can be cropped three times a year (triple cropping system). The paddy – paddy pattern is the important cropping pattern in this land, as expressed by the first and second time patterns. Then, the third crop type is a secondary crop, since they are expressed by a different pattern. The dry season caused a vegetation pattern change in agricultural land. In many cases, the land has been idle or not cropped during the extreme dry season, even on intensive agricultural land, the farmer tried to crop the land with dryland crops (palawija). However, the extreme dry season as impacted by El-Nino during July – September 2006 caused many agricultural lands to become barren, and the cropping pattern was disturbed.

As mentioned above, the extreme climate variability caused many paddy fields, especially in non-irrigated land; to remain barren as well the planting time was postponed. Indeed, characterizing the long-term vegetation dynamics of paddy field provides information about the characteristic and trends in these land use types, either caused by natural factors or human activities.
4. Conclusion

This study used MODIS EVI to determine dynamics change in paddy fields due to the change in temporal vegetation patterns. The wavelet transform was applied to filter out some noises in 299 time series MODIS EVI. Consequently, the MODIS EVI wavelet-filtered could determine the vegetation phenology in agricultural lands.

The trend of dynamics change pattern in agricultural lands can be explained mainly by several characteristics: (1) in general, the area was influenced by annual rainfall, and the vegetation provided a negative response during the dry season and starts to emerge during the rainy season, then, (2) the rainy season tended to come early in several years, e.g. 2003, has affected the change pattern by earlier planting time, (3) there was a water crisis in Indonesia, especially in 2005, which the average EVI over this time also indicated a drought situation and (4) land conversion, paddy fields is converted into settlement or industrial areas.

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