Mapping cropping patterns in irrigated rice fields in West Java: Towards mapping vulnerability to flooding using time-series MODIS imageries

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ABSTRACT

Information on the vulnerability to flooding is vital to understand the potential damages from flood events. A method to determine the vulnerability to flooding in irrigated rice fields using the Enhanced Vegetation Index (EVI) was proposed in this study. In doing so, the time-series EVI derived from time-series 8 day 500 m spatial resolution MODIS imageries (MOD09A1) was used to generate cropping patterns in irrigated rice fields in West Java. Cropping patterns were derived from the spatial distribution and phenology metrics so that it is possible to show the variation of vulnerability in space and time. Vulnerability curves and cropping patterns were used to determine the vulnerability to flooding in irrigated rice fields. Cropping patterns capture the shift in the vulnerability, which may lead to either an increase or decrease of the degree of damage in rice fields of origin and other rice fields. The comparison of rice field areas between MOD09A1 and ALOS PALSAR and MOD09A1 and Agricultural Statistics showed consistent results with R² = 0.81 and R² = 0.93, respectively. The estimated and observed DOYs showed RMSE = 9.21, 9.29, and 9.69 days for the Start of Season (SOS), heading stage, and End of Season (EOS), respectively. Using the method, one can estimate the relative damage provided available information on the flood depth and velocity. The results of the study may support the efforts to reduce the potential damages from flooding in irrigated rice fields.

1. Introduction

1.1. Background

Despite the growing rice demand, many rice-producing regions increasingly suffer from flood hazard occurrences worldwide (Okazumi et al., 2014; Gumma et al., 2015; List and Coomes, 2017). For example, USDA (2011) reported that heavy monsoon rainfall and typhoons et al., 2014; Gumma et al., 2015; List and Coomes, 2017). For example, as physical, economic, social, and environmental, and the dimensions (UNISDR, 2009). Vulnerability encompasses different dimensions, such as physical, economic, social, and environmental, and the dimensions vary accordingly depending on the exposed elements-at-risk (Cardona et al., 2012; van Westen and Woldai, 2012)). In irrigated rice fields (hereafter referred to as rice fields), the vulnerability to flooding may be determined by the interactions among environmental conditions (e.g., weather, locations), socioeconomic settings of farming communities (e.g., irrigation schedules, farming group decisions), and rice growth stages (e.g. seedling, flowering) during flood events. These conditions also indicate that the vulnerability to flooding in rice fields varies in space and time. Due to its complexity, the vulnerability assessment often focuses on a particular elements-at-risk and emphasizes on the physical aspect. In this regard, the vulnerability is defined as the degree of damage to an object (e.g., irrigated rice fields) exposed to a given level of hazard intensity (e.g., flood depth or duration) and often expressed using vulnerability curves (van Westen and Woldai, 2012). Additional datasets, such as the damaged yields and market price of yields, are required to derive the potential damages or losses in monetary values (Okazumi et al., 2014; Kwak et al., 2015).

Two challenges arise to exemplify the physical vulnerability to flooding in irrigated rice fields (hereafter referred to as ‘vulnerability’): the growth stages of rice fields in space and time and the availability of

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spatial and temporal data. The first is related to the spatial and temporal variations of rice growth stages. Irrigated rice fields are not only regulated by irrigation schedules or cropping calendars but also highly influenced by socioeconomic and environmental processes, causing simultaneous variations in growth stages at the irrigation system level. For example, rice fields belong to farmers located near primary irrigation channels may already be at the harvesting stage while those located at the tail end of irrigation channels may still be at the transplanting stage, or often the latter experiences delays in planting dates because of irregularities in the irrigation distribution. The second challenge is about the availability of data for deriving the vulnerability. The vulnerability can be derived from various data sources from the local to national level. At the national level, the agricultural statistical data may be widely available and can provide an overview of the general condition of a rice cropping system. However, the data may differ in quality between government agencies (Knapp and Kruk, 2010) and offer low-resolution vulnerability information, potentially obscuring significant variations at the local level. At the sub-national level, the elements-at-risk data, such as farming assets or rice field maps, may not be readily available, and the concern about the consistency and quality of data exists (Nicholls, 1995). Additionally, the available data about rice fields are also often lack of spatial and temporal dimensions (Bie, 2004), raising difficulties for the integration with hazard data. Thus, field observations are frequently needed to collect data on rice fields, which often require enormous financial, time, and human resources (Dalal-Clayton and Dent, 1990). The aforementioned challenges for mapping the vulnerability may be addressed by generating cropping patterns. A cropping pattern is a spatial and temporal arrangement of crops in rice fields (Manjunath et al., 2015). Cropping patterns result from the decision of farmers to optimize the use of resources (e.g., irrigation schedules, weather) (Serra and Pons, 2008). Cropping patterns possess spatial and temporal information that captures the responses of rice fields to a range of environmental and socioeconomic processes, including natural hazard occurrences (Xiao et al., 2005; Sakamoto et al., 2007; Boschetti et al., 2009; Sun et al., 2009; Gumma et al., 2011). Information on cropping patterns, generated by combining a rice field distribution and phenology metrics (Nguyen et al., 2011), offers insights about the vulnerability and can be used to monitor flood impacts in irrigated rice fields (Sakamoto et al., 2005; Sakamoto et al., 2007; Kotera et al., 2014). The rice field distribution provides spatial information and can be utilized as a baseline to monitor the increase or decrease in rice field areas. The phenology metrics deliver insights about growth stages and are beneficial for obtaining temporal information on irrigated rice fields. Additionally, because of its spatial and temporal characteristics, cropping patterns can also capture disruptions or anomalies in rice fields, that is, when the ongoing cropping pattern deviates from the historical cropping pattern (Patel et al., 2012; Zhang et al., 2014; Kuenzer et al., 2015). For example, the occurrences of natural hazards in irrigated rice fields, such as flooding or drought, may delay ‘normal’ cropping schedules (Naylor et al., 2001), decrease cropping intensities (Hoque et al., 1982), and reduce the available planting time (Kotera et al., 2014). 

Hyper-temporal remote sensing offers potential as a useful tool for monitoring changes and deriving cropping patterns in irrigated rice fields (Ehrlich and Tenerelli, 2013). Hyper-temporal-remote sensing refers to a continuous long-term earth observation using high temporal resolution remote sensing imageries (Picowar et al., 1998). The advantage is provided by the extensive areal coverage and the frequent visit of coarse-moderate spatial resolution passive remote sensors, such as MODIS (250m–1 km), which enable the continuous monitoring of vegetation’s physiological and biochemical states (Huete et al., 1997; Huete et al., 2002). Previous studies have increasingly proven the usefulness of hyper-temporal remote sensing data for monitoring rice agriculture areas, including mapping the spatial distribution (Xiao et al., 2005; Xiao et al., 2006; Zhao et al., 2015), extracting phenology metrics (Lieth 1974; Sakamoto et al., 2005; Boschetti et al., 2009; Motohka et al., 2009), mapping cropping patterns (Uchida, 2010; Nguyen et al., 2011; Peng et al., 2011; Manjunath et al., 2015), and detecting anomalies (Verbesselt et al., 2010; Atzberger, 2013; Rembold et al., 2013). Researchers frequently use vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI), to monitor the condition of vegetation on the earth’s surface (Evrendilek and Gurbeyaz, 2008; Qiu et al., 2013; Son et al., 2014). However, the use of EVI is often preferred than that of NDVI because the former is more responsive to biophysical variables, such as the leaf area and canopy coverage (Gao et al., 2000; Huete et al., 2002).

This study aims to generate a method to determine the vulnerability to flooding in irrigated rice fields using EVI derived from hyper-temporal 8 day 500 m spatial resolution remote sensing imageries (Fig. 1). This study is part of a broader research in which the socioeconomic aspects are also investigated. This study is limited to physical vulnerability. In this study, we do not use any flood model to simulate flood hazards but only provide a method for estimating the vulnerability to flooding. The vulnerability can be coupled with flood hazards using hydraulic parameters, such as depth and velocity. This study emphasizes the use of cropping patterns as one of the inputs for mapping vulnerability and does not focus on the comprehensive interpretation of conditions when rice fields are most vulnerable. The susceptibility of rice fields to flood events is different from that of other natural hazards, such as water-deficit events or strong winds. In doing so, EVI is used to produce the spatial distribution and phenology metrics of irrigated rice fields. The former and latter can be used to derive cropping patterns. Thus, cropping patterns can illustrate the spatial and temporal variations of vulnerability for a specific year. Previous studies estimating vulnerability frequently neglect the spatial and temporal components of rice fields (Kwak et al., 2015). In reality, cropping patterns vary in space and time, influenced by physical and socioeconomic factors. Furthermore, it is worth mentioning that cropping patterns were

Fig. 1. Framework for estimating the vulnerability to flooding in irrigated rice fields (slightly modified from Van Westen and Woldai (2012)). Vulnerability curves are derived from the relative damage of rice growth stages at varying hazard intensities. Focus of the present study is in the gray rectangle.
derived from time-series 8 day 500 m spatial resolution MODIS imageries (MOD09A1) in this study. The use of the moderate spatial resolution suggests that this study cannot provide a detail field recognition of an individual parcel of irrigated rice fields. Thus, the elements-at-risk of the present study is a group of irrigated rice fields (approximately 25 ha). It is expected that the results of the study can be used by rice agricultural stakeholders, such as water managers, extension, and disaster risk reduction officers to timely monitor changes and design effective strategies to reduce the potential damages and losses from flood hazards in irrigated rice fields.

1.2. Study area

1.2.1. Geographic location

West Java is a province of Indonesia located between 5°50′–7°50′ South Latitude and 104°48′–108°48′ East Longitude. It is bounded by the Java Sea and the Special Province of Jakarta to the North, the Central Java province to the East, the Indian Ocean to the South, and the Banten province to the West. Rice yields produced from this province contribute about 17% to the national rice production (Gustoni, 2013). Four northern districts of West Java, including Karawang, Subang, Bekasi, and Indramayu, are well known as Indonesia’s national rice production regions (van Valkenburg, 1936; Panuju et al., 2013). The topography is dominantly flat (Bernsten and Rachim 1982), and the dominant land use is irrigated rice fields. The irrigated rice fields in the four main rice-producing districts of West Java were selected as the study area (Fig. 2). The areas of irrigated rice fields in the districts are approximately 37% of the total area of rice fields in West Java (Statistik, 2012).

The study area experiences two seasons: wet and dry seasons and is situated in the humid tropical climate zone (Yulianto et al., 2015; Yanto et al., 2016). This seasonal variation is directly related to the geographic location of Indonesia, between the Pacific and Indian oceans and Asian and Australian continents. Average rainfall is approximately 2000 mm per year (Juwana et al., 2016). Irrigated rice fields in the study area are at risk of flooding during wet planting seasons and water-deficit events during dry planting seasons. For example, at least 20,000 ha irrigated rice fields in Karawang district were flooded during the flood event in March 2010 (Yulianto et al., 2015). The peaks of flooding and water-deficit events are usually from the beginning of January to the end of February and from the beginning of August to the end of September, respectively (As-syakur et al., 2013; Schollaen et al., 2013; Siswanto et al., 2016). Furthermore, irrigated rice fields are sensitive to the recurring pattern of ENSO (El Niño-Southern Oscillation) (Amien et al., 1996; Naylor et al., 2001; Surmaini et al., 2014). ENSO is characterized by anomalies in the sea-surface temperature and sea-level pressure (Southern Oscillation). El-Niño and La-Niña refer to warming and cooling periods, respectively. The extent of flooding and water-deficit events is partly associated with the severity of these climatic variabilities.

1.2.2. Irrigation management and cropping pattern

Several irrigation systems exist to serve the massive demand of water for irrigated rice fields in the study area for the whole year (Ravesteijn, 2002). Although average annual rainfall (2000 mm) is quite high (Juwana et al., 2016), it is mainly distributed from December to March and tends to spread over the middle and southern regions of West Java (Qian et al., 2010; Nuryanto et al., 2016). A large area of irrigated rice fields is served by a state company (Perusahaan Umum Jasa Tirta II – PJT II) where water flows from a multi-purpose Ir. Djuanda (Jatiluhur) reservoir in the Purwakarta district to a vast area of irrigated rice fields (approximately 240,000 ha) (Loebis and Syariman, 2016). Other irrigated rice fields are served by local water sources (e.g., reservoirs, rivers, deep wells).
The production and price risks. It is worth repeating that the delays in Table 1

### Table 1

<table>
<thead>
<tr>
<th>Rice field class</th>
<th>Wet planting season (rendang)</th>
<th>Dry planting season (gadu)</th>
</tr>
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<tr>
<td></td>
<td>Oct</td>
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</tbody>
</table>

Other rice fields are served by local water resources, such as smaller reservoirs, rivers, or deep wells. Although these rice fields are not obliged to follow official planting schedules like those served by the Jagtialhu reservoir, the national agricultural office suggests cropping calendars as a reference for rice cultivation (http://katam.itbang.pertanian.go.id/). In this regard, the complexity of irrigation management partly depends on the type of and access to water sources.

The arrangement of irrigation management in rice fields served by the Ir. Djumua reservoir reservoir command area are served by a complex irrigation system regulated by a cropping calendar and scheduled irrigation distribution (Husin et al., 1995; Uchida, 2010). Other rice fields are served by local water resources, such as smaller reservoirs, rivers, or deep wells. Although these rice fields are not obliged to follow official planting schedules like those served by the Jagtialhu reservoir, the national agricultural office suggests cropping calendars as a reference for rice cultivation (http://katam.itbang.pertanian.go.id/). In this regard, the complexity of irrigation management partly depends on the type of and access to water sources.

### 1.2.3. Farming practice, growth stages, flood events

Farmers generally adopt similar farming practices although variations in planting dates exist. In practice, tillage marks the start of planting seasons. Rice seedlings are commonly sowed in a nursery bed. Then, rice paddy is usually transplanted into puddled rice fields after reaching 20–25 days in the sowing bed. Farmers frequently outsource the tillage, transplanting, and harvesting activities to labor farmers. It is common to use the services of labor farmers from other sub-districts (organized by the middlemen) if there is a shortage in local labor farmers. Most farmers still use manual hand transplanting and harvesting methods. Farmers leave rice fields fallow after harvesting. The fallow duration differs in space and time, depending on various physical (e.g., extreme weather) and socioeconomic (e.g., farming group decision) factors. Also, the selection of rice varieties influences the duration of growing seasons. Most smallholder farmers plant the rice variety of Cihersang because of the taste and high demand as staple food. Large holder farmers may plant other varieties, such as Oryza sativa glutinosa, because of their higher selling prices or local inbred rice varieties due to their potential high yields. Furthermore, farmers perform different means to manage pests or diseases in rice fields, including the intensive uses of pesticides and traditional methods and tools, both individually and in a group (e.g., synchronize planting).

The growth stages of rice paddy can be divided into three main parts, including the vegetative, generative, and ripening phases (Datta, 1981; GRiSP, 2013). The vegetative phase starts from the germination to panicle initiation stage, taking 50–60 days after sowing. The generative phase runs from the panicle initiation to flowering stage, taking approximately 35 days, and the ripening phase begins from the flowering to mature grain stage, taking about 30 days.

Furthermore, flooding events are frequently reported in the study area due to the variabilities in extreme and non-extreme weather, especially for swampland (deep or semi-deep, locally known as sawah lebak) rice fields located near coastal areas (Amien et al., 1996; Naylor et al., 2001; Boer and Subbiah, 2005; Marulanda et al., 2011; Daruati et al., 2013; Darmawan et al., 2014; Yulianto et al., 2015; Setiawan et al., 2016). The impacts of flooding are partly determined by the rice growth stages during flood events, characteristics of flood hazards (e.g., depth, duration), and coping capacity of farmers. The impacts of flooding may range from a small reduction in yield quality or quantity to a complete harvest failure if flooding occurs during vegetative and generative phases, respectively. During flooding, the transport of oxygen from leaves to the roots ceases, and plants stop growing (Bailey-Serres et al., 2012). Studies have been continuously conducted to improve the flooding tolerance of rice crops (Miro and Ismail, 2013). Nowadays, several flood tolerance rice varieties (e.g., SUBIA, SORKELE) are claimed to be able to survive for approximately two weeks during complete submergence, using strategies such as...
yielding rice varieties and adapt to farmers in the irrigated rice especially those owning fields in coastal areas, cope with flooding events by delaying wet season planting dates, waiting for the rainfall intensity to weaken or ponding water to subside.

2. Materials and methods

2.1. Datasets and pre-processing

Fig. 3 shows the flowchart employed to achieve the research objective. This study specifically uses one of the land products of MODIS Terra. MODIS is one of the key instruments aboard the Terra and Aqua satellites. MODIS sensors provide a daily wide swath range (2330-km) observation, allowing for the monitoring of changes on the earth’s surface with a high temporal resolution (1-2 days) in 36 discrete spectral bands ranging in wavelengths from 0.4 µm to 14.4 µm. Hyper-temporal Surface Reflectance L3 8 day 500 m spatial resolution MODIS imagery (MOD09A1) were downloaded from February 2000 (DOY 49) to August 2014 (DOY 153) over the study area from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/). The MOD09A1 products are derived from the Level 2G MOD09GHK data with the highest observation score, lowest view angle, absence of clouds or cloud shadow and aerosol loading during an 8 day, and the data have been corrected in terms of radiometric and geometric (Vermote et al., 2011). The default sinusoidal projection was retained to avoid the misalignment of pixels due to re-projection. Next, the MOD09A1 data were stacked to produce time-series data (658 images). Then, the subset of the study area (Bekasi, Karawang, Subang, and Indramayu districts) was derived from the time-series MOD09A1. Next, the time-series Enhanced Vegetation Index (EVI) dataset was generated from the time-series MOD09A1 (Huete et al., 2002; Peng et al., 2011). EVI values range from −1 to 1 and a low EVI value indicates the lack of vegetation on the land surface. The equation to generate the EVI for this study is as follows (Huete et al., 1997; Huete et al., 2002; Sakamoto et al., 2007):

$$EVI = 2.5x \frac{NIR - RED}{NIR + 6xRED - 7.5xBLUE + 1}$$

where NIR is the near-infrared band (841–875 nm, Band 2); RED is the red band (621–670 nm, Band 1); and BLUE is the blue band (459–479 nm, Band 3). The Adaptive Savitzky-Golay filter that focuses on the upper envelope was applied to reduce the remaining noise components (e.g. aerosol or bi-directional reflectance) from the EVI dataset, resulting in the smooth temporal profiles of EVI (Jonsson and Eklundh, 2002; Chen et al., 2004; Wei et al., 2012; Ali et al., 2013a, 2013b; Ali et al., 2014), as shown in Fig. 4.

The time-series EVI dataset (2000–2014) was classified using an Iterative Self-Organizing DATA (ISODATA) unsupervised classification technique (maximum iteration of 50; convergence of 0.99; diagonal axis means) with ERDAS Imagine 2013 (Pan et al., 2003; Khan et al., 2010; Singh et al., 2011a; Bie et al., 2012). The unsupervised classification method was selected because of an incomplete knowledge of the distribution of land uses in the study area. The use of the clustering method is also justified by the nature of the growing seasons in the research area. The cropping schedules are partly influenced by the cropping calendar and farmers’ decisions. The latter is also related to the efforts of farmers to perform a synchronized planting to spread the risk of crop damages from rice pest and disease outbreaks (e.g., rat attacks). The ISODATA uses the minimum distance rule to calculate the class means and iteratively reclassifies pixels to new means until the threshold parameters or the maximum iteration numbers are satisfied (Tao and Gonzalez, 1974; Nguyen et al., 2011). A batch of unsupervised classifications was conducted from 10 to 100 clusters, and the divergence statistics was used to select the optimal number of classes (Swain 1973). The number of clusters is selected based on separability scores, a measure of the difference between cluster centers. The average separability score maximizes the global value of separations between clusters (Chuvieco and Huete, 2009). However, the average may still include clusters that are very close together and inseparable. Therefore, the minimum separability has to be regarded as well. In practice, the optimal number of clusters occurs when the average and minimum separability scores coincide. In the study area, this condition happens at the number of 88 clusters, as shown in Fig. 5. Thus, the eighty-eight cluster was selected to represent the land uses (e.g., settlements, rice fields, water bodies) (Swain, 1973; Khan et al., 2010; Nguyen et al., 2011). The selection of 88 clusters is also preferable to avoid the loss of essential information because of the under-estimation of the number of classes while maintaining the relatively low number of clusters (under 100) (Nguyen et al., 2011; Bie et al., 2012).
2.2. Cropping patterns

2.2.1. Mapping irrigated rice fields

Thirty-five out of 88 clusters were manually selected to represent the spatial distribution of irrigated rice fields in the study area. The rice clusters were identified by investigating the EVI profiles that represent the growing phases of rice fields. Rice fields have distinctive characteristics of growing rapidly after transplanting (vegetative phase), as shown by the increase of EVI; reaching the heading stage or maturity (generative phase), signified by the peak of EVI; entering the senescence phase, marked by the decrease of EVI; entering the fallow phase; and eventually restarting the whole growing process from the vegetative phase (see Fig. 4) (Toan et al., 1997; Xiao et al., 2005; Xiao et al., 2006; Zhang et al., 2015b). Furthermore, the small patches of rice clusters that are adjacent to or located in the middle of settlement areas were not included in the further analyses as the EVI profiles are likely to be influenced by the buildings’ presence. Next, the thirty-five rice clusters were grouped into eleven general units using a hierarchical cluster analysis method to represent the gradient of cropping schedules. The agglomeration of rice clusters into the smaller groups may add understandings about the interaction among rice clusters. The Ward method and Euclidian distance interval measure were used in the hierarchical cluster analysis (Ward, 1963; Gauch and Whittaker, 1981; Ali et al., 2013b). The hierarchical cluster analysis was performed using SPSS (Statistical Package for the Social Science).

2.2.2. Extracting phenology metrics

Phenology metrics, including the Start of Season (SOS), heading stage (PEAK), and End of Season (EOS), were extracted from the rice clusters to obtain the time component of rice fields. In practice, the SOS and EOS are the transplanting and the harvesting periods, respectively. The heading stage is the period 55–60 days after transplanting. Firstly, the median values (50 percentile) of the time-series EVI (658 imageries) were derived for each rice cluster (35 clusters). Next, the 14-year time-series median values were pooled and averaged per DOYs, resulting in the historical data. The 8 day historical average data (46 imageries, 1 image is an 8 day period) were linearly interpolated to generate a daily time-series EVI (365 imageries). Next, the DOYs for SOS, PEAK, and EOS were manually extracted from the daily time-series EVI by visually investigating thresholds. The following criteria were used to determine the phenology metrics. The SOS is the DOY when the EVI value is 0.1. If the EVI profiles do not have values lower than 0.1 throughout a cropping season, the DOY when the EVI is at the minimum value is used as the SOS. The heading stage is the DOY when the EVI is at the maximum value. The growing season is considered a failure if the maximum EVI value during a cropping season is not higher than 0.35. The EOS is the DOY when the EVI value reaches 0.3 during a senescent phase. The selection of the thresholds was performed using a trial and error approach based on the prior information on the dates of growth phases in the study area, gained after the fieldwork.

2.3. Mapping vulnerability to flooding

The vulnerability to flooding in irrigated rice fields is the degree of damage during varying rice growth stages given various flood hazard intensities. The vulnerability assessment thus requires information on
the hazard intensity, degree of damage, and rice growth stages. This study uses the results of Ganji et al. (2012) to support the attempt of utilizing rice cropping patterns for mapping the vulnerability to flooding. Ganji et al. (2012) performed laboratory tests on a rectangular flume (length = 10m; width = 0.3m; height = 0.45m) to investigate several hydraulic parameters for flood loss estimations at various rice growth stages, including the periods of after transplanting, shooting, clustering, and harvesting. They were able to derive vulnerability curves for varying intensities of hydraulic parameters at different growth stages. This study mainly focuses on the Reynolds number because the authors concluded that the Reynolds number, a dimensionless parameter, is the most effective parameter for simulating the flood physical-factor loss function (Fig. 6). Ganji et al. (2012): "In fluid dynamics, the combination of the effects of inertia force and viscosity is used for the analysis of submerged bodies. [...] the Reynolds number could be considered as the most effective hydraulic parameter for deriving the loss function. In fact, the Reynolds number is a dimensionless form of [height*velocity] in open channels." The higher the Reynolds number, the stronger the force of flooding to damage rice plants. Also, they suggested the use of a logarithmic function to represent the Reynolds number versus loss (Table 2).

The rice growth stages and their spatial distribution are generated in the present study. The rice growth stages (fallow-harvesting) are classified into five classes, namely the transplanting, shooting, clustering, harvesting, and fallow. Fallow is the periods after rice harvesting and before rice sowing and transplanting. Farmers do not cultivate rice fields during fallow periods, so there is no elements-at-risk (therefore no vulnerability) in rice fields during this stage. The number of farmers that plant cash crops is often negligible. The ‘fallow’ class is when 0.3 < EVI (senescent) and EVI < 0.1 (growing). The transplanting periods, with 0.1 ≤ EVI ≤ 0.3, belong to the 'transplanting' class. The 'shooting' class is when 0.3 < EVI ≤ 0.4. The periods from the stem elongation to milk stages, with the EVI > 0.4 from the growing to senescent phase, are grouped into the "clustering" class. Finally, the periods when 0.3 ≤ EVI ≤ 0.4 during the senescent phase, mostly during the ripening phase, are categorized into the ‘harvesting’ class. The present study assumes that there is no difference in the rice variety, and the whole study area is exposed similarly to flood hazards.

Fig. 6 exhibits the vulnerability curves derived from the Reynolds number at the transplanting, shooting, clustering, and harvesting stages. To interpret Fig. 6, one can assume a kinematic viscosity of $10^{-4}$ m$^2$/s, which means that the Reynolds number translate into velocity*depth by dividing the X-axis value by 10,000. For instance, for a depth of 1 m, the transplanted rice crops will suffer damages from the velocity between around 2.4 m/s and 4 m/s. It can be seen that the onset of damages at the shooting and harvesting stages is around the Reynolds number 23,000. The rice fields with transplanting and harvesting stages are completely damaged at the Reynolds numbers around 42,000 and 90,000, respectively. The clustering stage starts to suffer from damage at the Reynolds number around 57,000, suggesting that the more mature and clustered the rice fields, the lower the vulnerability level. It is plausible since the more mature or the more grouped the rice plants, the stronger the stem and the more resistance exerted by rice plants against the flood flow. Fig. 6 also displays that, after being plotted in the relative damage-hazard intensity graph, the transplanting, shooting, harvesting, and clustering stages show very high, high, moderate, and low vulnerability levels, respectively. The growth stages do not have equal growing lengths, suggesting that rice fields experience certain vulnerability levels for different periods of time. As an example, these levels are depicted on the vulnerability maps in the years 2013 and 2014. The spatial distribution and phenology metrics derived from time-series MODIS imagery enable the demonstration of the vulnerability in space and time. For example, rice fields may experience a very high vulnerability level for around 30 days in accordance with the length for growing from the transplanting to shooting stage.

2.4. Accuracy assessment

The accuracy of rice field areas and phenology metrics derived from MODIS imagery was assessed using secondary and primary data, respectively. Fieldworks were conducted from October to November 2014 and from December 2014 to January 2015 to obtain the data. The primary data are the dates of rice growth stages obtained from interviews with farmers. The secondary data, such as the maps of official administrative boundaries, rivers, irrigation channels, roads, and rice fields were collected from local government, agricultural, and irrigation management offices.

The areas of rice fields generated from MOD09A1 were compared with the areas of rice fields derived from the reference maps at the sub-district level. Two reference maps were used (Fig. 7). One is a rice field map (vector format) obtained from the Ministry of Agriculture of Republic of Indonesia (hereafter referred to as Agricultural Statistics). The other one is a land use map of Java (raster format) derived from ALOS PALSAR in 2010 (hereafter referred to as ALOS PALSAR) obtained from the Ministry of Public Works of Republic of Indonesia. The areas of rice fields were extracted from the ALOS PALSAR. Both reference maps were resampled into a 500 m spatial resolution using the nearest
neighborhood operation. All rice field maps are converted into the Geographic projection for the comparison. The accuracy of the rice field distribution was assessed using the coefficient of determination ($R^2$).

The observed phenology metrics were assessed using the ground truth data at the pixel level. The locations and dates of rice growth stages, including the transplanting (1–7 days after transplanting, number of rice pixels or $n = 61$), heading (55–65 days after transplanting, $n = 46$), and harvesting (85–95 days after transplanting, $n = 49$), were recorded using a hand-held Global Position System (GPS) and are used as the reference data for the SOS, heading stage (PEAK),

### Table 3

Generalized phenology metrics (Mean ± Stdv, in DOY ± days) for rice clusters in irrigated rice fields in the northern districts of West Java. Table 3 corresponds to Fig. 8.

<table>
<thead>
<tr>
<th>Map Unit</th>
<th>Rice Cluster</th>
<th>Area (km²)</th>
<th>Phenology Metrics (MODIS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>47</td>
<td>139.25</td>
<td>309±21 41±15 89±16 93±14 143±13 194±19</td>
</tr>
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<td></td>
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<td>115.5</td>
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</table>

$^a$ SOS = Start of Season; $^b$ PEAK = heading stage; $^c$ EOS = End of Season; $^d$ X = no planting or harvest failure. Periods from EOS to SOS in wet and dry planting seasons are fallow. Style of Table 3 was adopted from Nguyen et al. (2011).

### Table 4

Duration (Mean ± Stdv, in days) between phenology metrics. Variation is the average of all rice clusters (rounded).

<table>
<thead>
<tr>
<th>Wet planting season (WPS)</th>
<th>Dry planting season (DPS)</th>
<th>Fallow</th>
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<td>DPS-WPS</td>
<td>WPS-DPS</td>
<td>DPS-WPS</td>
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<tr>
<td>SOS$^c$-EOS$^d$</td>
<td>110 ± 16</td>
<td>71 ± 15</td>
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</table>

$^a$ SOS = Start of Season. $^b$ PEAK = heading stage. $^c$ EOS = End of Season.
and EOS, respectively. The accuracy of the estimated phenology metrics was assessed using the Root Mean Square Error (RMSE). The equation for deriving the RMSE is as follows:

$$RMSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2$$

where \(y_i\) and \(x_i\) are the observed and estimated values, respectively.

3. Results and discussion

3.1. Cropping pattern

Cropping patterns were generated from the rice spatial distribution and phenology metrics. Fig. 8 shows the spatial distribution of irrigated rice fields in West Java. The irrigated rice fields are the mosaics of thirty-five rice clusters derived from the time-series EVI collected over 14 years. The high temporal resolution enables the identification of irrigated rice fields despite the moderate 500 m spatial resolution of MODIS imageries. It can be seen that the pattern of rice clusters seems not to follow any particular administrative boundaries. Furthermore, Table 3 shows the phenology metrics derived from the time-series EVI.
from 2000 to 2014. For the past 14 years, the SOS ranges from the first week of November to the third week of March for wet planting seasons and from the end of March to the second week of August for dry planting seasons. The EOS ranges from the first week of March to the second week of June and from the last week of May to the first week of November for wet and dry planting seasons, respectively. The duration of rice growth during dry planting seasons is approximately 97 ± 8 days (after transplanting), fewer days shorter than that of wet planting seasons (110 ± 16 days after transplanting). This condition is associated with the variations in the solar radiation and temperature between dry and wet seasons (GRISP 2013; Deng et al., 2015; Huang et al., 2016; Wang et al., 2016). The fallow durations from the end of dry planting season (EOSdry) to the start of wet planting season (SOSwet) and from the end of wet planting season (EOSwet) to start of dry planting season (SOSdry) are 116 ± 25 and 42 ± 19 days, respectively (Table 4). Grouped using the Hierarchical Cluster Analysis, the rice clusters depict elongated horizontal shapes that show the gradient of wet season planting dates. The planting dates increase from south to north and from west to east as rice fields located farther from the Ir. Djuanda reservoir. The closer the rice clusters to the coastal areas, the later the planting dates, partly reflecting the influence of irrigation schedules on cropping patterns. However, the patterns of wet season planting dates may not be similar to those of dry planting seasons, perhaps because of the irregularities in the implementation of cropping calendars.

The cropping patterns generated in this study offer more detail information on rice planting schedules compared to those of official cropping calendars (see Table 1). These cropping patterns can be served as a baseline to monitor variations in cropping schedules. The comparison between the cropping patterns and official irrigation schedules for rice fields served by Ir. Djuanda (Jatiluhur) reservoir revealed that the ongoing cropping schedules performed by most farmers deviate from the official cropping calendar. For example, the official cropping calendar suggests that two cropping seasons should be completed by the end of September. In practice, farmers whose rice fields served by the PJT II start dry planting seasons later than the stipulated cropping calendar. Another example can be observed from the duration of fallow. Farmers performed longer fallow periods during both wet and dry planting seasons compared to those of the official cropping calendar (see Table 4). The differences between the actual and official planting dates are greater as rice clusters located closer to coastal areas. It is likely that the discrepancies are partly associated with flooding events and coping strategies to flood hazards.

3.2. Vulnerability to flooding

Fig. 9 shows the maps of vulnerability to flooding in irrigated rice fields in West Java derived from the cropping patterns and vulnerability curves. The transplanting, shooting, harvesting, and clustering stages are classified into very high, high, moderate, and low vulnerability classes, respectively (see Fig. 6). As an example, the maps are generated for different DOYs in the years 2013 and 2014 to illustrate the influence of irrigation schedules on the vulnerability. The maps show that rice fields were mostly in the transplanting and fallow periods at the beginning of January (DOY 1) in 2013 and 2014, having very high and no vulnerability levels, respectively (Fig. 9A and B). Most rice fields located in the southern and middle parts of the study area were at the clustering and transplanting classes, with the low and very high vulnerability levels, respectively during the DOY 41 in 2013 and 2014 (Fig. 9C-D). During the DOY 73, rice fields situated in the southern part grew from the clustering class to the harvesting and fallow classes, changing the vulnerability level from low to moderate and no vulnerability levels (Fig. 9E and F). Later, rice fields in the southern region were in the fallow period during the DOY 105 in 2013 and 2014, consequently having no vulnerability. It is worth repeating that the present study used the Reynolds number as the hazard intensity parameter to exemplify the vulnerability levels. The degree of damage at different growth stages results from the resistance of rice plants to the flow of flood water. The uses of other flood parameters, such as the depth, duration, velocity, may generate different vulnerability maps since each hydraulic parameter affects rice plants in various ways.

Fig. 9 reveals that cropping patterns are also able to provide information on the shift in the vulnerability to flooding. Rice fields, especially those located near coastal areas often suffer from recurrent flood events due to the accumulation of surface runoff from the upper regions during wet seasons. The extent of flood impacts is greater during strong La-Niña years (Naylor et al., 2001). Farmers who own rice fields in these flood-prone areas frequently resort to delaying planting dates until the end of February, waiting for rainfall intensity to weaken or flooding to subside before attempting wet planting seasons. Recently, these rice fields suffered from an extreme flooding event in the January 2014, causing delays in the wet season planting date. Farmers were not able to perform rice sowing or transplanting activities due to prolonged flood events. The events cause a shift in planting dates in the affected rice fields during the wet planting season 2013/2014. The shift changed the ‘normal’ vulnerability level, leading to either an increase or decrease in the vulnerability to flooding in the areas of origin and other rice fields. It can be seen that the vulnerability in rice fields located in the northern part of the study area differs between the year 2013 and 2014. Since farmers delay the wet season planting dates, the areas of rice fields with no vulnerability were higher during DOY 41 in 2014 compared to that in 2013. Consequently, the areas of rice fields...
with very-high high and moderate vulnerability classes were higher during the DOYs 73 and 105 in 2014 compared to those in 2013, respectively (Fig. 9E–H). This illustration suggests the importance of spatial and temporal perspectives to understand the vulnerability to flooding in irrigated rice fields.

3.3. Accuracy assessment

The areas of irrigated rice fields between MOD09A1 and ALOS PALSAR and MOD09A1 and Agricultural Statistics were compared to validate the spatial distribution of rice fields. The comparisons showed consistent results with \( R^2 = 0.81 \) and 0.93 for MOD09A1 and ALOS PALSAR and MOD09A1 and Agricultural Statistics, respectively, as demonstrated in Fig. 10. Furthermore, Fig. 11 shows a one-to-one comparison between the estimated and observed DOYs of phenology metrics. The estimated RMSEs for SOS (n = 61), PEAK (n = 46), and EOS (n = 49) are 9.21, 9.29, and 9.69 days, respectively. Since the RMSE values are almost similar to the MODIS data source (8 day interval), it can be concluded that the estimated phenology metrics were sufficient to represent rice growth stages in irrigated rice fields in the study area.

4. Conclusion

This study has successfully generated a method to determine the vulnerability to flooding in irrigated rice fields using the Enhanced Vegetation Index (EVI) derived from time-series 8 day 500 m spatial resolution MODIS images (MOD09A1) in irrigated rice fields in West Java. Coupling the vulnerability curves and cropping patterns, this paper has demonstrated that the vulnerability varies in space and time. Cropping patterns were generated by combining the spatial distribution and the phenology metrics, where the former and the latter provide spatial and temporal information, respectively. Cropping patterns can also capture the shift in the vulnerability that may lead to either an increase or decrease in the degree of damage in the rice fields of origin and other rice fields. Furthermore, the comparisons of rice field areas between MOD09A1 and ALOS PALSAR and MOD09A1 and Agricultural Statistics showed consistent results with \( R^2 = 0.81 \) and \( R^2 = 0.93 \), respectively. The estimated and observed DOYs of phenology metrics produced sufficient results, with RMSEs of 9.21, 9.29, and 9.69 days, for SOS, heading stage, and EOS, respectively. Using the method presented in this study, one can estimate relative damages provided available information on flood depth and velocity, for instance from a flood model. Water managers and extension and disaster risk officers can use the cropping patterns and vulnerability maps for in-depth discussions of designing effective planting dates, irrigation water management, flood risk reduction strategies.

Some further studies are proposed. This study used moderate 500 m spatial resolution MODIS imageries to determine the vulnerability to flooding in irrigated rice fields. The use of time-series remote sensing datasets with a higher spatial resolution (e.g., Proba-V or combinations of Sentinel-2 and Landsat series) may improve the results of the study. Furthermore, some reasons for variations in cropping patterns, such as the irrigation management and flooding events, have partly been identified; however, other socioeconomic and environmental factors that influence cropping schedules and potentially disrupt the continuation of farming practices remain to be explored.

Author contributions

Riswan Sianturi collected and processed the data, and wrote the paper. V.G. Jetten and Junun Sartohadi contributed important considerations and ideas.

Conflicts of interest

The authors declare no conflict of interest.

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Qian, Robertson, Muro, 2010. Interactions among ENSO, the monsoon, and diurnal cycle in rainfall variability over Java, Indonesia. J. Atmos. Sci. 67 (11), 3509–3524.


