QUALITY ASSESSMENT OF TIME SERIES MODIS DATA FOR LONG-TERM MONITORING

Dyah R. Panuju[1, 2], Amy L. Griffin [1], David J. Paull [1]

[1] School of Physical, Environmental and Mathematical Sciences, UNSW Canberra, Australia
[2] Department of Soil Science and Land Resource, Bogor Agricultural University, Indonesia
Email: dyah.panuju@student.adfa.edu.au; panuju@apps.ipb.ac.id

ABSTRACT

The role of remote sensing in long-term monitoring is essential to support the understanding of land surface dynamics. Serial monitoring requires periodical and frequent observations to allow discrimination between short- and long-term phenomena. High temporal frequency observations depend upon optical sensors. Moderate Resolution Imaging Spectro-Radiometer (MODIS) offers a higher frequency of temporal observation compared to Landsat and a better spatial resolution than Advanced Very High Resolution Radiometer (AVHRR), so provides a good source of hypertemporal observations. The assessment of spatial, radiometric, and atmospheric conditions is a pre-requisite for consistent hypertemporal observation to inform affecting factors in detecting a given change phenomenon. Satellite and sensor properties, algorithms for data generation, and climatic factors during image acquisition are known factors dictating the quality of images. In tropical areas where persistent cloud cover exists, atmospheric conditions may be the most important determinant of quality. Therefore, careful examination of the usability of the data is vital to reducing the likelihood of misleading interpretation of temporal change phenomena. Employing the Time Series Generator (TiSeG) and GeoDa to assess the distribution of time series data quality for the MODIS land product, this article examines the temporal and spatial pattern of invalid pixels generated based on targeted quality of the MODIS product for a 15-year period. This experiment was conducted in the Western part of Java, Indonesia, which is the most dynamically changing and topographically heterogeneous area in Indonesia. The distribution of invalid pixels in MODIS vegetation indices and their scientific data sets (SDS) varied spatially and temporally. Seasonal patterns within the annual span were clearly observed, while some noise was successfully detected. Noise clusters related to climatic or instrumental issues were clearly detected by using local association of statistical autocorrelation techniques. We also found clear relationships between invalid pixel generation and terrain factors.

KEYWORDS: usability, scientific data set, MODIS, data quality, West Java

1. INTRODUCTION

The detection of change has been explored from bi-temporal to trajectory analysis. Bi-temporal analysis focuses on the difference between two images, usually by categorising the spectral value through classification or focusing on the spectral differences. The methods have been shown useful for change detection, however their discrete nature and temporally limited observations constraint the identification trends for continuous monitoring. Change processes between observations may potentially escape observation. The capacity to identify trends by using frequent observations clearly differentiates trajectory from bi-temporal change analyses. The advantages provided by trajectory analyses are usually supported by statistical time series analysis techniques. The application of time series analysis can differentiate long-term from short-term variations and apprehend the entire seasonal cycle of vegetation phenology (Jönsson and Eklundh, 2002).

Concerns about sources of data and their quality emerge as frequent observations are necessary in time series analysis. Optical sensors have been the main data source for analysis since these products have been available for the longest (Batista et al., 1997; Townshend and Justice, 2002). With the availability of freely accessible images from several sensors such as AVHRR, MODIS, Satellite Pour l'Observation de la Terre vegetation (SPOT-VGT), and Landsat, the exploration of annual and decadal monitoring of regional and global scale areas of the Earth surface has become possible (Brink and Eva, 2009; Fensholt et al., 2009). In order to identify continuous valid changes (Huete et al., 2010) and to measure the change impacts on terrestrial ecosystems (Brown et al., 2006), consistent and continuous observations are required. Nonetheless, disturbances sourced from atmospheric conditions, acquisition, and product generation systems (Colditz et al., 2008) have affected the quality of optical images and their derived products. Correction or normalization are essential pre-processing steps to generate consistent quality of optical images. Quality checks may provide additional benefits to ensure the properties of images prior to their employment and interpretation for change analysis. They can do so by differentiating changes from data artefacts (Roy et al., 2002), which in turn result in better change interpretation and avoid misleading conclusions.

Despite the importance of assessing data quality, a survey of the relevant literature indicates a paucity of research on checking spatio-temporal quality of images for long-term monitoring. Temporal quality of MODIS was usually assessed by smoothing data supported by science data sets (SDS) in order to evaluate the usability of MODIS products. There has been little discussion of evaluation of the spatial dependence of potentially erroneous data and possible related causes of this dependence. Hence, this research addresses the aforementioned issues, and particularly focuses on the spatial dependence of erroneous data; and it explores the relationship between this parameter and possible related factors such as terrain attributes and land cover types.

Vegetation indices, in particular, have been broadly used as a proxy of the physical amount of green vegetation fraction (Huete et al., 2010) for the long-term monitoring of land surface dynamics (Huete et al., 2002). The indices have been defined as composite measures of vegetative properties such as chlorophyll content, leaf area, and canopy cover and structure (Huete et al. 2010). Vegetation indices may also represent vegetation vigor or the health of vegetation (Ji and Peters, 2003; Pena-Barragan et al., 2011). Long-term monitoring of land cover surfaces has used these indices particularly to scrutinise the sequential change of vegetation growth (Carrao et al., 2010; Julien et al., 2011). Various indices, for instance the Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), and land surface temperature have been used in multitemporal or continuous monitoring of change (Gallo and Tarpley, 1996; Lambin and Ehrlich, 1996; Zha et al., 2003). As a seamless product systematically generated for a global extent (Huete, 2012), NDVI is the most popular product for the task.

In temporal analysis, the value of the indices is supposed to indicate the environmental condition. Therefore the reliability of the time series indices should be assessed circumspectly to avoid biased interpretation and conclusions, particularly for tropical areas that likely suffer from persistent cloud cover (Ali et al., 2013).

Evaluating the temporal quality of the MODIS product has commonly been performed by using the accompanying quality information, which includes vegetation index (VI) quality, pixel reliability, snow and cloud cover, as well as the sun and view zenith and relative azimuth angles. All that information has been published as a science dataset (SDS) for MODIS products. The VI quality is a layer informing whether the VI is produced or not produced due to severe disturbances like cloud, while pixel reliability provides information about the quality of a pixel. The information indicates noise that affect the quality. The pixel reliability is labelled using numbers, i.e. no data (-1), good data (0), marginal data (1), snow/ice (2), or cloudy (3) (Solano et al., 2010). In this research, the quality information was used to establish the experiment settings.

A quality target is usually defined during quality assessment for filtering and further data refinement. For example an evaluation of the temporal quality of MODIS data in Africa (Ghana, Cote d'Ivore, and South Africa) was carried out by filtering data based on usability information in the SDS for time series smoothing; it was similarly performed for datasets of Germany (Colditz et al., 2008; Colditz et al., 2007). In fact, there are three types of information within the SDS, i.e. usability, reliability and general quality of data, each of which can be used to filter data for temporal analysis. In this research the assessment of MODIS quality was carried out based on usability information.

2. METHOD

2.1. Study Site

The research site is situated in Western Java, Indonesia (Figure 1), and is considered to be the most dynamically changing area in Java. A historical study based on pollen and sediment analysis in Banten, Western Java reported that anthropogenic factors were the predominant influence on the process of vegetative land cover change in the area over the last 135,000 years (van der Kaars and van den Bergh, 2004). Topography varies across the site; with an altitudinal span of 0 meter to about 2900 meter above sea level. Precipitation in the southwest of the area during the wet season is reasonably high. The wet season usually occurs between October and March with an annual rainfall about 3300 mm (average of 15-years of precipitation data, taken from the Gunung Mas meteorological station). During the dry seasons (April-September), on the other hand, some areas in the eastern part of the region suffer from drought. In this area, the annual precipitation is approximately 2400 mm (average of 15-years, 2001-2015, taken from the Jatiwangi meteorological station). This area is composed of three provinces, i.e. Jakarta, West Java and Banten provinces, and it includes cities, paddy fields, agricultural estates and national parks. Paddy fields are mainly distributed in the north coastal region while estates are mostly located near the mountainous regions, where commodities such as tea, oil palm, and rubber are cultivated.

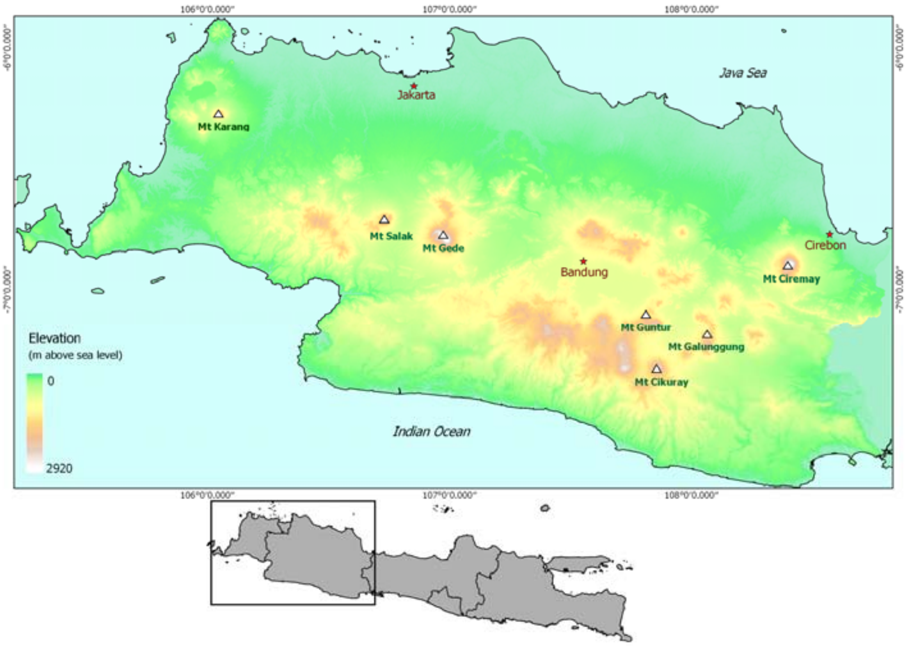

Figure 1. Research location. The Digital Elevation Model of Western Java is derived from Shuttle Radar Topography Mission (SRTM) 1 Arc Second Global.

2.2. Data Pre-Processing

We employed MODIS vegetation products (MOD13Q1) Collection 5 spanning from Julian day 1 of 2001 to 353 of 2015 to generate the experimental database. Collection 5 includes improved detection of clouds based on a new quality-based filtering scheme (Solano et al., 2010). All data granules (345) were downloaded from the Land Processes Distributed Active, Archive Center (LPDAAC, https://lpdaac.usgs.gov/data_access/data_pool). MOD13Q1 consists of 12 scientific data sets (SDS) including vegetation indices, vegetation indices quality, four reflectance bands (red, near infrared/NIR, blue, and medium infrared/MIR), view and sun zenith and relative azimuth angles, composite day of the year, and pixel reliability (Huete et al. 2010). This particular product was selected to obtain the best spatial resolution of MODIS data at 250 m to deal with small parcels of land use/cover and to obtain an acceptable composite image in an area that are severely affected by the presence of cloud. Prior to analysis, all the MODIS products were reprojected from sinusoidal to geographic using the World Geodetic System (WGS) 1984 system and cropped to the extent of Western Java (Upper Left latitude -5.80 and longitude 104.90; Lower Right at latitude -7.85 and longitude 108.64) by using the MODIS Reprojection Tool (MRT). The cropped images were subsequently exploited to assess the quality of time series MODIS data and to describe its usability.

2.3. Assessment of the Temporal Quality of MODIS Indices

A set of experiments for exploring fifteen years of the MODIS data was conducted based on three targeted qualities, i.e. acceptable, pixels without shadow/cloud/snow (SCS), and acceptable quality without SCS. This set was selected considering the previous set of assessment for German data (Colditz et al. 2008), which urged the avoidance of overly strict settings such as perfect or good quality, and which may have resulted in insufficient data for time series analysis. A detailed description is presented in Table 1.

Table 1. Quality settings used in the experiment

Code	Quality/ Explanation
A	Acceptable
O	Without Shadow/Cloud/Snow
AO	Acceptable without Shadow/Cloud/Snow

By using the time series generator (TiSeG), the datasets were processed to identify invalid pixels and maximum gaps within a series from the ingested datasets (Colditz et al. 2008).

2.5. Assessment of the Spatial Distribution of Invalid Pixels and Temporal Gaps

The evaluation of the spatial distribution of MODIS quality aimed to test the significance of spatial autocorrelation of invalid pixels and maximum temporal gaps within the 15-year observation period. Spatial autocorrelation has been discussed with respect to ecological phenomena captured by remote sensing imagery (Wulder and Boots, 1998).

Spatial autocorrelation deals with identifying the similarity of properties located nearby. Various statistics have been introduced to measure spatial autocorrelation, whilst it is recognised that semi-variance has been primarily employed in remote sensing areas (Wulder and Boots 1998). Two other spatial statistics used to measure spatial autocorrelation are Moran's I and the G* statistic. Moran's-*I* tests the null hypothesis that spatial autocorrelation among the invalid pixel distribution is zero. Any deviation to the hypothesis will result in a rejection of the null hypothesis, meaning that data are spatially auto-correlated. While Moran's *I* indicates a global pattern of spatial autocorrelation, the G* statistic demonstrates the local variation of spatial patterns (Getis and Ord, 1992). As recommended by Getis and Ord (1992), the *G** statistic and Moran's *I* should be used to obtain optimal interpretation of spatial properties. Hence, this research explored those two analyses to evaluate the spatial distribution of MODIS quality.

In this research, the G* statistic is used to describe the local spatial association of the invalid pixels and maximum gaps. The statistics may identify local dependence (Getis and Ord 1992) between the queen's case distance (*d*) of invalid pixels and maximum gaps. The probability statistic (p-value) was generated to test the significance of spatial association indicated by the G* statistic. It describes clustering of high or low frequencies of invalid pixels and maximum gaps. The clusters having probability values of less than 0.05 were flagged as statistically significant. The label differentiates clusters of high and low values and insignificant clusters for mapping. The spatial distributions of invalid pixels and maximum gaps were evaluated based on the 15 years of observations by using GeoDa.

2.4. Assessing Invalid Pixels and NDVI Values over Different Terrain and Land Cover Types

The distribution of invalid pixels was identified over different terrain morphometric attributes and land cover/use types. The Digital Elevation Model of Shuttle Radar Topography Mission (SRTM) 1 Arc Second Global (approximately 30 meters in GeoTiff format) was employed to derive aspect, elevation and slope. The data were obtained from the United States Geological Survey. The aspect and slope were estimated using 3rd order polynomial based on Haralick (1983) in SAGA. Sampling of locations for different land cover types was guided by high-resolution images from Google Earth, ground survey, and datasets provided by the Indonesian State Forest Corporation, PT Perhutani, and the regional watershed management institution (Badan Pengelolaan Daerah Aliran Sungai) of Ciliwung and Cisadane. The ground survey was conducted between 25 December 2015 and 10 February 2016. Four main land cover types were observed, including two vegetative covers (forest, crops), water, and built-up area. The assessment excluded water use since VI is irrelevant to water (Didan et al., 2015; Solano et al., 2010). Crops are temporally heterogeneous in use, and vary in type and stage of planting. Built-up covers were taken carefully to exclude industrial areas. The samples were selectively taken at 3x3 pixels at distributed locations for those land cover types. Land cover/use types were sampled from ten locations that varied by elevation and aspect. Samples were used to assess the relationship between the distribution of invalid pixels and terrain attributes as well as land cover types. Finally, the relationship between terrain attributes and the pixel-wise invalid pixels within the 15-year observation window for each land cover type was evaluated.

3. RESULTS AND DISCUSSION

3.1. General Patterns of Usability and Temporal Distribution of MODIS Land Product Collection 5 for Western Java for the 15-years Observation Period

In general, the three settings indicate that if more criteria are added, then more unusable data (invalid pixels) can be found. Figure 2 shows that a greater frequency of invalid pixels was generated by combining targeted quality. The acceptable quality (A) generated more invalid pixels and gaps than no shadow/cloud/snow cover (O). This means that properties other than shadow/cloud/snow cover such as geometric angles cause invalid pixels in the acceptable category. The maximum temporal gap provides a different trend from invalid pixels. The combined settings (AO) does not generate gaps in a proportional manner with the invalid pixels' generation at the same settings.

Figure 3 shows the temporal distribution of periods when the invalid pixels most likely to be generated by quality category. The proportion of area with invalid pixels fluctuated over the period of 2001-2015 (see the top of Figure 3). The percentage indicates the area with invalid pixels at any frequency from 1 to 345. It suggests that about 60% to 80% of the area has usable pixels for analysis depended upon targeted quality. The trend describes that worse quality disturbances possibly occurred in 2010, with almost 45% of the area comprised of unusable pixels. It was consistently shown that targeting data without shadow/cloud/snow (O) may generate more usable area while the combined quality category (AO) produced the highest percentage of area with invalid pixels.

The next assessment was performed by averaging the percentage area of invalid pixels on the same Julian date over fifteen years of observations (bottom of Figure 3). The result shows that a seasonal trend was clearly indicated. The highest percentage of invalid pixels is likely to be generated between days 1 and 129 (January to beginning of May) or between days 257 and 353 (September – December). These periods of high percentages of invalid pixels are coincident with the wet seasons, whereas more invalid pixels were likely to be generated in the wet season due to severe cloud cover. It indicated that MODIS data are likely to be more unreliable in the wet season than the dry season for Western Java. Moreover, the variance of invalid pixels in the rainy season is also higher than in the dry season.

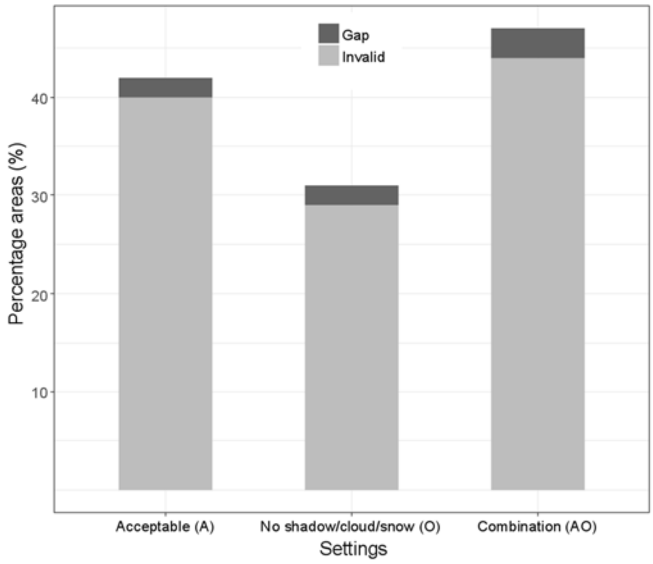

Figure 2. The average of percentage area with invalid pixels and gaps within the 15 year observation period based on three quality settings, i.e. Acceptable quality (A), no shadow, cloud and snow/SCS (O) and combination of acceptable and no SCS (AO).

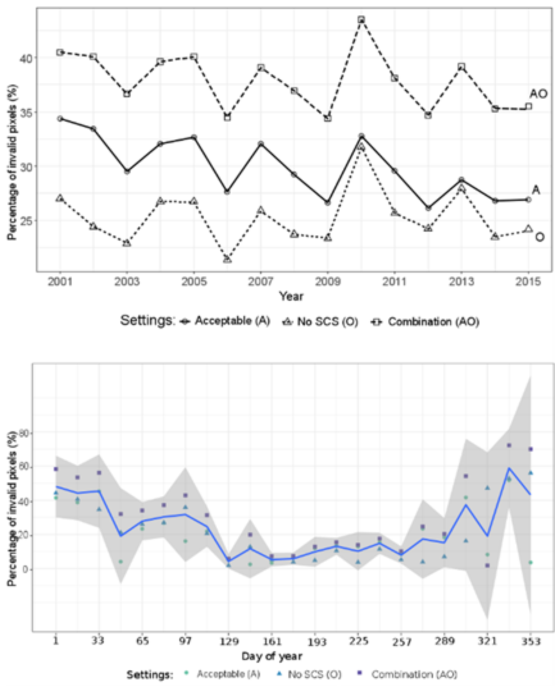

Figure 3. The temporal trend of percentage of area with invalid pixels (top) and the seasonal trend generated based on three quality settings, i.e. acceptable (A), no shadow/cloud/snow (No SCS/ O), and combination (AO), which derived from the yearly average of percentage area with invalid pixels over 15 year observation period (bottom)

3.2. The Spatial Distribution of Likely Invalid Pixels of MODIS Vegetation in the 15-years Observation Period

Moran's I statistics showed that a strong positive spatial autocorrelation was generally among invalid pixels and gaps (Figure 4). Moreover, the map of the frequency of invalid pixels and maximum gaps (Figure 5) and their test using the G* statistic clearly highlights the spatial distribution of invalid pixels for different quality categories (Figure 6).

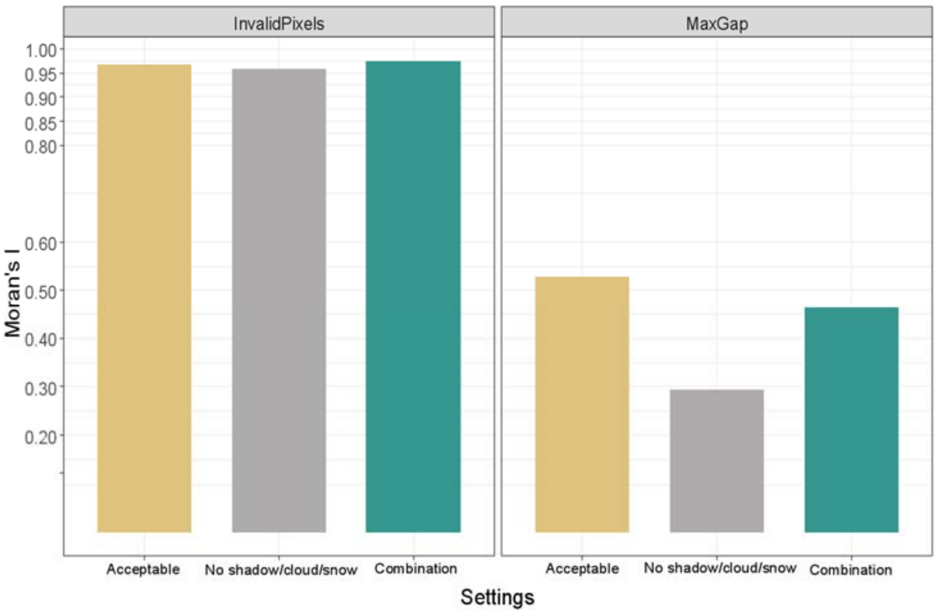

Figure 4. Moran's I of the frequency of invalid pixels and maximum gaps generated from 15-year observation to indicate the spatial distribution of those variables in three quality settings, i.e. acceptable, no shadow/cloud/snow, and combination

Figure 4 exhibits the difference of combining SCS and other single quality settings (AO) to the generation of invalid pixels and maximum gaps. The combination of quality settings increased the frequency of invalid pixels. However, combining O with another setting does not result in the increasing of estimated maximum gaps. Since acceptable settings consider not only shadow/cloud/snow contamination but also sun and view angle geometry, it indicates that the effect of sun or view angle geometry appear to be prevalent. The O category presents the lowest proportion of invalid pixels and temporal gaps within a series compared to other quality categories. This research found that spatial dependence of invalid pixels and maximum gaps notably differs when different settings were applied. The magnitude of Moran's I indicates that invalid pixels were evidently more clustered while the maximum gaps tend to be less strongly clustered. In contrast, the maximum gap seems to be more unique throughout the settings. The test elevates the importance of addressing data quality disturbances and making users more cautious when selecting samples for time series extraction.

The spatial distribution of the frequency of invalid pixels and maximum gaps over the study area identifies locations with severe data quality disturbances. As presented in Figure 5, the number of invalid pixels at a location generated from the 15-years of observation range between 23 and 340 while the maximum gaps range from 3 to 23. It indicates that the north coastal region, which includes Jakarta, and high altitude locations nearby Mount Ciremay were severely affected by data quality disturbances. As the capital city and the biggest metropolitan area in Indonesia, the Jakarta has been severely polluted by vehicles and industrial areas. Meanwhile, high amounts of invalid data along the coastline may be related to the difficulties in handling the interface between water and land. As asserted by Friedl et al. (2010), the algorithm to address artefacts along the coastline has been revised continuously in MODIS data generation from collection 1 to collection 5. The other location having high data quality disturbances at the south eastern end of Western Java is the Priangan region, covering some hilly and mountainous areas. There are several mountains near the region including Mt Ciremay, which is the highest in Western Java (about 2900 m asl), Mt Cikuray, Mt Galunggung, Mt Guntur and a few others. Nearby the location is covered with forests in which evaporation may generate clouds and thereby affect the quality of MODIS data.

The spatial distribution of the frequency of invalid pixels and the average proportion of area with gaps from the 15-year observation period as measured by using the G* statistic is presented in Figure 6. A significant clusters of high gaps was found in the Jakarta Metropolitan area, along the north coastline and in the mountainous regions of Priangan. The threshold of 23 refers to the number representing a whole year of invalid pixels observed consecutively. Some pixels along the coastline were found to have consecutive gaps larger than 23, which likely related to cutline of the border with the sea.

The G* statistic reveals the spatial dependence of the frequency of invalid pixels and gaps. The spatial distribution of the data quality may guide the identification of locations having more reliable data. It may indicate, for instance, the most suitable location for taking reliable samples for classification or change detection. The result may assist in selecting good pixels for training and testing areas for classification or image analysis, instead of relying merely on visual investigation or ground truth data. This analysis may substitute a probability analysis that was proposed by Asner (2001) to evaluate areas severely affected by cloud in the humid tropics.

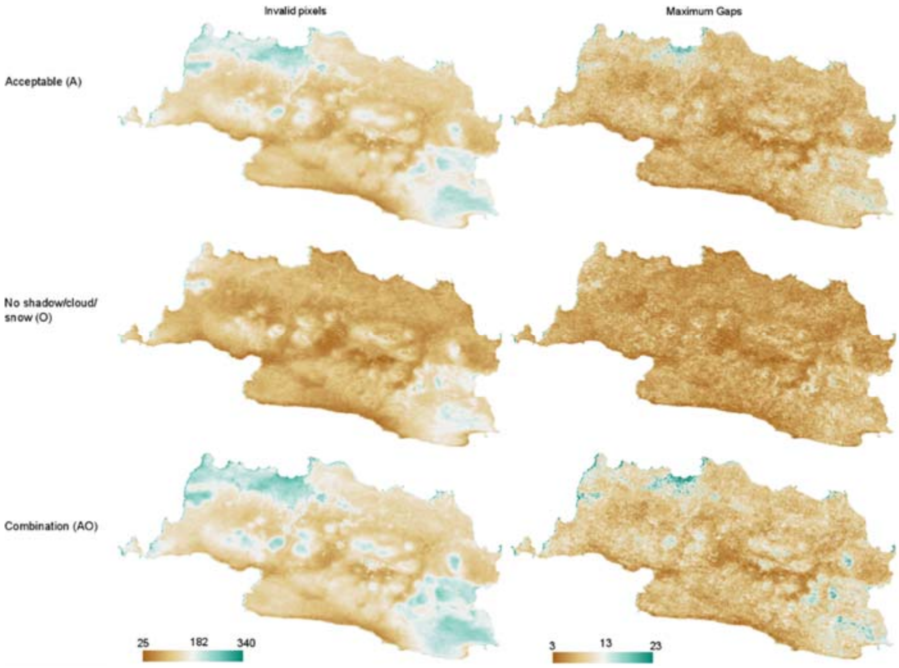

Figure 5. The distribution of invalid pixels and maximum gaps in generated from the 15-year observation period based on three data quality categories, i.e. acceptable (A), No shadow/cloud/snow (O) and their combination (AO)

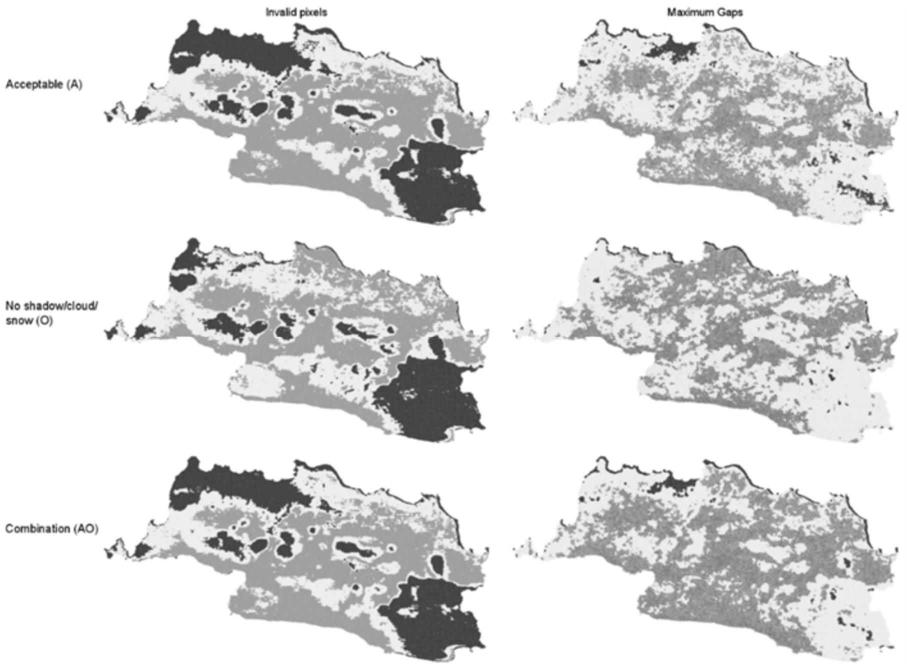

Figure 6. The distribution of G* statistic for the frequency of invalid pixels and maximum gaps derived from the three quality categories, i.e. acceptable (A), No shadow/cloud/snow (O) and their combination (AO). Darker areas indicate statistically significant clusters of high numbers of invalid pixels and large maximum gaps, grey shows cluster of low numbers of invalid pixels and maximum gaps, and light areas signify no significant clustering.

3.3. Generated Invalid Pixels over Various Land Cover Types and Terrain Attributes

Figure 7 shows the difference of percentages of invalid pixels for combinations of land cover types and terrain attributes. Built-up area was distributed at locations with slopes between 0% and 30%, crops were cultivated in areas with slopes spanning at 0%-25%, while forest was distributed across slopes ranging between 25% - 250%. The figure demonstrates the relationship between slope and elevation with the frequency of unusable pixels from the 15-year observation.

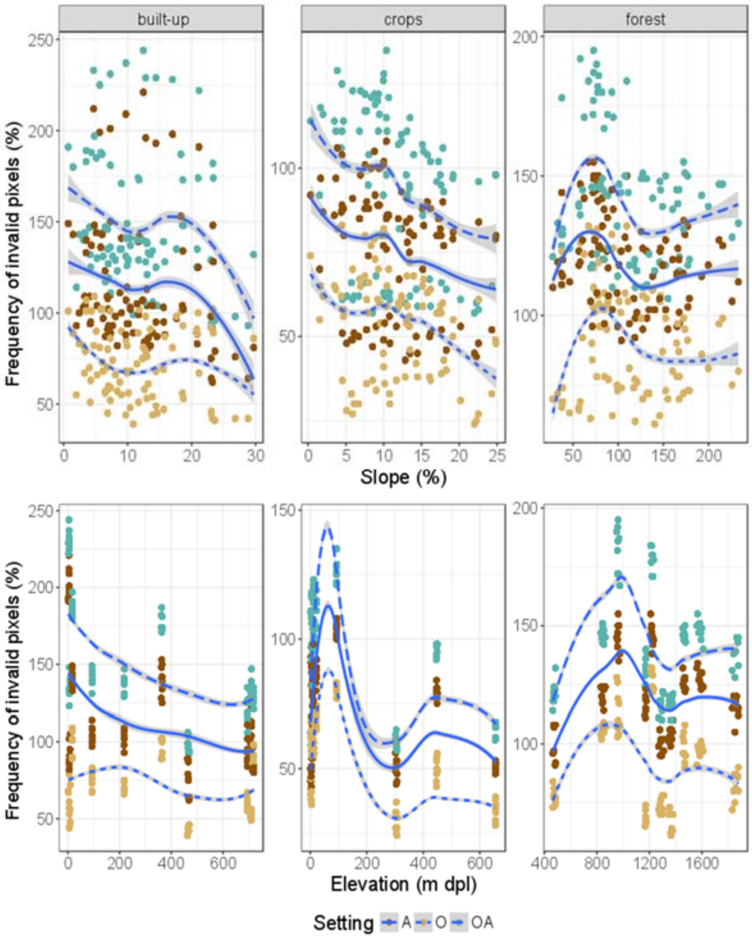

Figure 7. Scatterplot and smoothed model (blue line) based on locally weighted regression (loess) to relate the frequency of invalid pixels within 15-year MODIS observation period and slope (top) or elevation (bottom) for three land cover types generated for three data quality categories, i.e. acceptable (A), no shadow/cloud/snow (O), and their combination (OA)

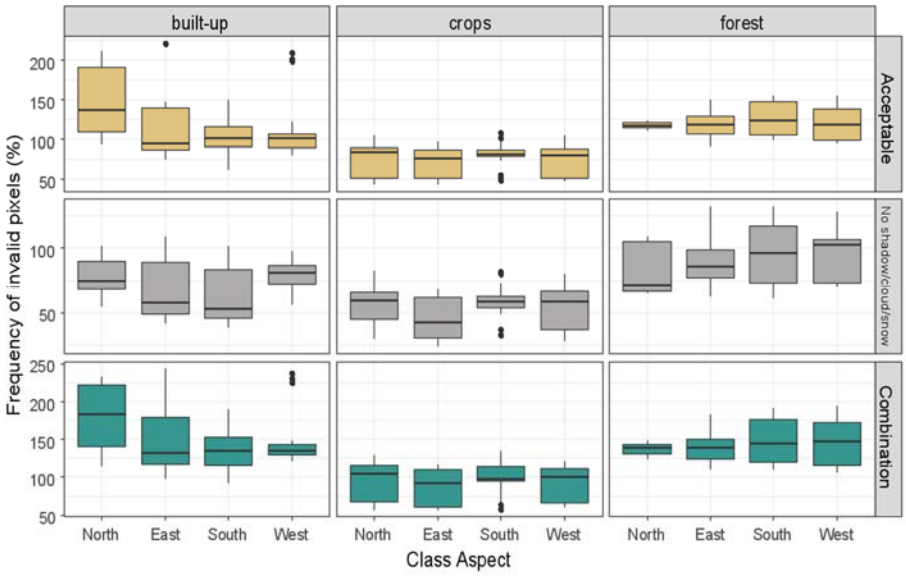

Figure 8. Frequency of invalid pixels over three land cover types (built-up, crops, and forest) and aspect and three data quality categories (acceptable, no shadow/cloud/snow, combination) from the 15-year observation period in Western Java

It appears that the relationship between the frequency of invalid pixels and terrain attributes may not be linear. By using locally weighted regression (loess) it seems that slope and elevation may negatively relate to the frequency of invalid pixels. This relationship was similar for built-up and crop land covers, but not for forest cover. As aspect was defined as “the compass direction of maximum rate of change” (Skidmore, 1989), the relationship between aspect and the distribution of invalid pixels differs by the position and orientation of samples to geographic directions. Built-up areas facing east and north were likely to have more invalid pixels than west and south-facing aspects. Meanwhile, there was a fairly similar relation for crops cultivated at location facing east, west and north having a somewhat higher frequency of invalid pixels than crops cultivated facing south. For built-up areas, the higher frequency of invalid pixels was clustered mostly at the north or east aspects, while the likelihood of invalid pixels was greater for west or south facing aspects for forest cover.

3. CONCLUSION

Global change studies have highlighted the necessity of long-term monitoring employing remote sensing technology. High temporal resolution images such as the MODIS land product have been analysed using time series approaches for this purpose in which requiring reliable data to avoid spurious results. The experiment with various data quality settings demonstrates that the evaluation of MODIS quality should consider shadow/cloud/snow flags provided as an additional layer of MODIS product to represent the usability of the data. Exploring temporal patterns provides information on possible change or periodical patterns which may relate to the dynamic phenomena. It appears that the peak months of the dry season (June-July) are the best months for image acquisition in this tropical region since more reliable data can likely be obtained. Cloud presence in the rainy season increases the number of invalid pixels and produces a greater variance. Seasonal assessment of estimated invalid pixels and temporal gaps based indicates that the dry season span from April to October may be the best period to collect data for land cover monitoring in Western Java.

While previous research paid more attention to time series smoothing, a lack of understanding of spatial variability of invalid pixels is evident in the literature. This research demonstrates that investigating the spatial distribution of data usability could assist in the identification of reliable locations and period for data selection in the tropical areas. The G* statistic highlighted the location severely affected by disturbances indicated by higher frequency of invalid pixels and maximum gaps. Mountainous areas and polluted urban areas would potentially be the places covered by cloud in the rainy season or affected by severe noise.

Relating morphometric attributes with data usability indicates that erroneous data would potentially be prevalent in steeper slope and elevated terrain. However, built-up land cover located in flat areas suffering from severe pollution also generate likely high numbers of invalid pixels. Invalid pixel generation related variably with the aspect over different land cover types. The result indicates that cloud effects may not be the only source of noises in the study area.

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