Performance evaluation of soil water content observation from satellite images in sediment disaster-prone area

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Abstract. Soil water content observations from remote sensing are growing for landslide disaster management due to the potential of wide coverage and fine resolution. Characteristic evaluation of various soil water content products is necessary for improving the accuracy. This study assesses soil water content products from Soil Moisture Active Passive from Global Modelling and Assimilation NASA, Soil Moisture and Ocean Salinity from ESA, and Soil Water Index (SWI) from Copernicus Global Land Service. Results are compared with soil test in terms of spatial and temporal distribution, time series, and quantitative performance indices. The study is conducted in Brantas River Basin Indonesia, where the upstream is vulnerable for landslide disaster. The investigation has shown that with correlation coefficient 0.81, SWI is suitable for further application in the study area. This finding has important implications for modelling the landslide hazard using quantitative soil water content product from satellite imagery.

1. Introduction
Landslide cases are highly triggered by rainfall. The rainfall intensity and the runoff influence the soil water content. Landslide in hilly regions around the world are often affected by high soil water content. Therefore, landslide early warning system should be more effective by tracking changes in the condition of the soil water content [1,2]. A variety of methods have been used, i.e. field sensor, direct test, remote sensors, and even hydrological or land surface model assimilation to estimate moisture [3-5]. Each has its own advantages and disadvantages. Every remote sensing imagery has geometrical distortions and some other errors due to atmospheric effects. However, it facilitates wide and long data coverage.

Soil water content observation from satellites has recently been advanced and widely used. Because most satellite observed data require similar long processed before being used, it is preferable to use higher level for operation purpose. The Soil Moisture Active Passive (SMAP) from Global Modeling and Assimilation NASA provides Level 4 Surface and Root Zone Soil Moisture Product [6]. The Soil Moisture and Ocean Salinity (SMOS) mission, which is one of ESA missions, observes variability in soil moisture globally in Level 2 and 3 product [7]. It also provides global Level 3 data for limited access and Level 4 data for European area. Soil Water Index (SWI) and Surface Soil Moisture from Copernicus Global Land Service is available at global scale for direct utilization as it has been verified with global Land Surface Models output and with in-situ measurements [8]. Several attempts have been made to make inter-comparison of soil water content estimates from satellite [9]. The accuracy is evaluated in
terms of data availability, spatial and temporal resolution, spatial and temporal variations, error, RMSD, MSE, bias, and correlation. However, few of them discuss the comparison with ground-truth data.

Brantas River in Indonesia is Java Island's second largest river. The upstream of this river is particularly vulnerable to landslide disasters because of its morphology and anthropogenic activities [10]. Until recently, there has been little attention paid into the landslide mitigation specifically in this area. Most studies in upper Brantas have only focused on soil water content ground measurement, erosion and sedimentation, and landslide disaster management efforts [10,11].

The study will review the benefit of soil water content measurement from SMOS, SMAP, and SWI imagery products. The major objective is to propose the recommended satellite image for operational purpose in upper Brantas Basin. Both qualitative and quantitative measures are used in investigating the performance of these images. By comparing the remote sensing data with the results of soil test, this study also attempts to validate the satellite imagery. The study offers some important insights into the use of continuous wide coverage of soil water content information for landslide disaster prediction.

2. Methods

2.1. Study area
To examine the remote sensing data, the catchment area of upper Brantas River Basin (Figure 1) is selected as a study area (112.54 km²). The area is covered by forest in the upstream and dense residential area in the downstream. With relatively high mean annual rainfall of 2000 mm/year, 85% of the rain falls in the rainy season. Due to rapid land use change and prolonged precipitation in a common occurrence on the sloping downhill in the upstream (10%-25%), this catchment is vulnerable for landslide. The upstream is formed mainly Andosols soil type. At least seven landslides in 2018 caused 28 deaths [10].

2.2. Soil water content satellite products
Different satellite mission have measured soil water content in different way and level. Recently, higher level of satellite soil water content measurement have been published. In Figure 2, we show the comparison of these data. The spatial data for this study are taken from one week in the rainy season of 2020 covering whole Brantas catchment area. A short sample is chosen because of the expected difficulty of obtaining the continuous data. This data are selected because during this period, there was observation campaign of soil testing. This period is chosen for its representativeness of rainy and not rainy days. In Figure 2 the availability of data during observation campaign is shown.

2.3. Comparison of the observation
Investigating the accuracy and availability is a continuing concern within the utilization of soil water content product form satellite. For this study, ground truth data from previous research is used to explore the advantage and drawback of each observation. Furthermore, the comparison of each satellite data in terms of spatial and temporal availability, spatial distribution, quantitative value.
Figure 1. Upper Brantas River Basin.

Table 1. Comparison of satellite products.

| Provider            | SMAP                     | SMOS L2                  | SWI                  |
|---------------------|--------------------------|--------------------------|----------------------|
| NASA, JPL CIT       | ESA                      | Copernicus GLS           |
| Level               | 4                        | 2                        | 2                    |
| Spatial resolution  | 10 km                    | 15 km                    | 11 km                |
| Temporal resolution | 3 hours                  | 1 day                    | 1 day                |
| Type                | Active passive           | Passive                  | Active               |
| Reference           | Kimball et al., [6]      | Bengoa et al., [7]       | Marschallinger et al., [8] |
| Temporal coverage   | 31 Mar 2015 - date       | 6 Jun 2010 - date        | 20 Feb 2007 - date   |
| Spatial coverage    | Global                   | Global                   | Global               |
| Unit                | %                        | %                        | %                    |
| Web                 | https://nsidc.org/data/SPL4 | https://smos-diss.eo.esa.int/socat/SMOS_Open/ | https://land.copernicus.us.eu/global/products/swi |

Figure 2. Data availability during observation campaign.

The performance indices i.e. mean absolute error, root mean square error, correlation coefficient, percent bias. In order to examine the trend significance, Mann Kendall analysis is used. This assessment
provides an important contribution to advance the understanding of the available soil water content observation over East Java area.

3. Results and discussion

3.1. Spatial and temporal distribution
The maps in Figure 3 presents the example of soil water content spatial distribution in Brantas River Basin from 2 observation time. From the map we can see that the SMOS data has some blank grids and the spatial resolution is rather rough. Regarding SMAP and SWI, both has similar finer spatial resolution. However, quantitative value of SMAP tends to be lower than SWI. In terms of temporal availability, from Figure, it is clear that SMAP is relatively continuous. Though SWI is missed in 1 day of observation, overall, this product is quite reliable. SMOS product is rather incomplete, which requires preprocessing as consequences. SMOS is found also to have high spatial variation of moisture value.

3.2. Soil water content quantitative estimate
The consistency of the observation to provide the accurate estimation of soil water content is evaluated by showing the time series chart. Figure 4 shows the temporal variation of soil water content observation spatially averaged over the upper catchment, middle catchment, and lower catchment. Interpolation is done to construct data points between the range of known values. It is apparent from the figure that the quantitative amount of soil water content from SWI is close to the true value. However, in terms of tendency, SMOS data provides a better trend visually compared to the true value.

Figure 3. Soil water content spatial distribution in whole Brantas River Basin.
Figure 4. Time series of soil water content observation in upstream, middle, and downstream.

All the observations indicate positive trend with true value with Z value ranges from 0.78 to 3.10. SWI is observed to have similar trend of the water content with true value indicated by Mann Kendall test that shows Z test and significance value which is close (Table 1). Contrary, the study does not find a similar trend of SMOS, though visually it shows a similarity with true value. SMOS has highly positive and significant tendency. It seems possible that this result is due to high variance of SMOS measurement, compared to other three measurements.

From the previous discussion, the analysis reveals the advantage of SWI in terms of qualitative assessment. It is now necessary to examine the quantitative estimates of soil moisture. The statistic of all data is summarized as box plot in Figure 5. Maximum, minimum, mean, standard deviation, 25% percentile, median, and 75% are set out. SMOS is obviously highly variable. Many grids are observed.

Table 2. Indices comparison of satellite products.

|                      | SMOS | SMAP | SWI  | Soil Test |
|----------------------|------|------|------|-----------|
| Mann-Kendall Z       | 1.65 | 3.1  | 1.45 | 0.78      |
| Trend significant at a | 0.1  | 0.01 | >0.1 | >0.1      |
| MAE                  | 0.40 | 0.31 | 0.11 |           |
| RMSE                 | 0.43 | 0.32 | 0.12 |           |
| P-Bias               | -57.69% | -48.18% | 17.41% |           |
| r                    | 0.46 | 0.66 | 0.81 |           |

Figure 5. Distribution of the data indicating data range, 25, 50, and 75 percentiles (black markers), mean, and standard deviation.
Similar values views at lower parts of the span, but in other grids values are more variable. Meanwhile,
SMAP has low variation indicated by small span. Although the range of data is a little higher, there
appears to be some agreement between that SWI central tendency and the true value. In addition, the
standard deviation is small, indicating that the values tend to be near to mean or expected value.

3.3. Performance evaluation
The performance indices show a good correspondence between the estimated soil water content from
SWI and observation. There is positive strong direction of a linear relationship between SWI and true
value indicated by correlation coefficient of 0.81. Although SMOS and SMAP have shown positive
correlation coefficient too, the values suggest a weak relationship exists. MAE, RMSE, and P-bias
indices reflect low accuracy of estimated soil moisture from SMOS and SMAP for direct application in
upper Brantas River Basin. On average, SWI is shown to have good performance indicated by MAE,
RMSE, and P-bias which are outperform others. The better performance in SWI could be attributed
to data fusion approach that is pre-processed to the data from sensors.

The discrepancy of performance of each satellite observation is associated with the characteristic of
the sensors and algorithm. As given in Figure 2, densely populated area tends to have high moisture value
and vegetated area tends to have low moisture value. This study supports the idea of Wang et al., that
vegetation characteristics are influencing the soil water content [4]. Interestingly, very high soil water
content is found in similar spots from SMOS observation, which is at middle south because there is large
reservoir at this area. Low moisture is found in some area that does not have water body, such as
mountain top. These finding is in agreement with Su et al., which states that SMOS is highly affected
by water bodies [9]. SMOS can capture the variation of water content as actual value. However, as with
common remote sensing data, the data therefore need to be processed by renormalization [9].

4. Concluding remarks
In this research soil water content products from Soil Moisture Active Passive from Global Modelling
and Assimilation NASA (SMAP), Soil Moisture and Ocean Salinity from ESA (SMOS), and Soil Water
Index (SWI) from Copernicus Global Land Service are compared with soil test in terms of qualitative
and quantitative assessments. Regarding the temporal availability, SMAP product is relatively
continuous. Both SMAP and SWI provides good availability spatially. SWI is observed to have similar
trend with true moisture value indicated by Mann Kendal Z value. SWI is suitable for further application
in the study area with 0.81 correlation coefficient. Although SMOS and SMAP have shown positive
correlation coefficient too, i.e. 0.46 and 0.66 respectively, the values show a weak relationship exists.
RMSE value of 0.43 and 0.32 for SMOS and SMAP respectively suggests bias correction procedure for
their application. This finding may contribute to the modeling of landslide phenomenon in slope hill by
introducing quantitative soil water content product from satellite imagery to hydrological model and
land surface model.

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