# MULTI-SENSOR FOR DEBRIS FLOW MONITORING AND WARNING

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## ABSTRACT

Debris flow disaster is one of the most destructive events arising from volcanic eruptions. For disaster prediction systems, continuous rain and soil moisture monitoring is needed. This study aims to evaluate the performance of remote sensing technique and wireless sensor-based system to detect soil water content by comparing with direct soil testing and water budget modeling. The potential of Soil Water Index (SWI) product from Copernicus Global Land Service for providing continuous real time observation is evaluated. The study are conducted in upper Brantas River basin Indonesia. The analysis shows that performance of remote sensing and ground device installed on the river slope of upper Brantas is proven. The Pearson correlation coefficients when the observations are evaluated each other range from 0.59 to 0.75. The spatial autocorrelation for SWI gives Moran's I index of 0.20 to 0.50 which indicates positive correlation. The amount of moisture in the soil from laboratory test has shown the reliability of ground sensor monitoring as well as remote sensing product. This work is expected to contribute to debris flow hazard mitigation in volcanic regions.

*Keywords*: Soil water index, debris flow, satellite, ground sensors, rainfall

## 1. INTRODUCTION

Volcanic activities are associated with many direct and indirect hazards. Lahar flow occurs as a secondary results of a volcanic eruption. Lahar is known as mixture of rock debris with great solid fractions and water that flows rapidly from a volcano (Lavigne et al., 1988). Many lahar events report serious damages in the environment, people, and property, e.g. in Mount Pinatubo Philippine and Mount Merapi Indonesia (Belizal at al., 2013). The debris flow in volcano flank is generated by high rainfall and high soil moisture on a steep slope of volcanic ash deposits (Volentik et al., 2009; Capra et al., 2010). Soil properties of deposit material is considered as a variable in the debris flow modeling (Mead and Magill, 2017; Mead et al., 2016). Therefore, estimation of soil moisture in high temporal and spatial resolution is essential for mitigating lahar disaster.

In the areas with limited access to direct observation of soil properties, the use of remote sensing technic is beneficial. Monitoring of soil water index have been made through various operational satellite (Wagner et al., 2007). However, all satellite observation contains distortion due to atmospheric condition. Therefore, verification with other observation or analysis is necessary for calibration and interpretation. Past studies compared soil moisture observation from satellites with in-situ test using probe (Sherlock and Donnel 2003; Paulik et al., 2014). Osanai et al. (2010) proposed early-warning for slope failures in Japan using rainfall indices and soil water index from tank model. Soil test in laboratory represents the true condition of the soil water content in a catchment. However, there are very limited studies about calibration of in-situ measurement and satellite observation through laboratory procedure (Holzman et al., 2017). Furthermore, there is a lack of study regarding soil moisture as parameter in the context of lahar disaster modeling.

In this study, the performance of Copernicus Global Land Services and wireless in-situ system for providing continuous real-time observation of soil water index (SWI) is evaluated against soil laboratory procedure. The reliability of the sensors is also assessed in terms of hydrological process through tank model by introducing observed meteorological data. This work is intended to establish the monitoring system of soil moisture needed to develop more accurate lahar modeling for warning system.

## 2. METHODOLOGY

### 2.1 Study Area

The study site is upper Brantas River Basin (Figure 1). Brantas River (112.54 km$^2$) is the second longest river in Java Island, Indonesia which passes through Surabaya metropolitan city. This river is prone to debris flow because Kelud volcano that erupts in every 10 to 15 years is located in the center of the stream. Upstream of the catchment is landslide-prone region because it has steep slope (10%-25%) and dominated by Andosols soil type. During 2018, there were at least 7 landslide events that caused 28 fatalities (Sugiarto et al., 2019).

### 2.2 Remote Observation

Soil water index is obtained from Copernicus Global Land Services satellite imagery. The unit is $m^3/m^3$ that represents the volumetric ratio of soil water content. The data is available with 0.1◦ spatial resolution in every 12.00 GMT. Rainfall intensity from Global Rainfall Map (GSMaP) from JAXA Global Rainfall Watch System with 0.1◦ spatial resolution is employed as observed meteorological forcing data for Tank Model calculation. The example of the data is shown in Figure 1.

### 2.3 Field Data

One in-situ ground observation device is installed on the slope of Brantas River in the point of basin outlet. The ground sensor system consists of soil moisture module, wireless module, microcontroller board, radio module, and computer. The data is collected daily during observation campaign, i.e. 10 days during rainy season in February 2020. Ground truth of soil water content monitoring is performed by soil sampling and testing in geotechnical laboratory. The experiment measures the gravimetric water content and bulk density which are used to calculate volumetric soil water content. In order to evaluate the spatial distribution of the SWI, soil test is also conducted in five dispersed locations.

### 2.4 Modeling Soil Water Index

Tank Model is a conceptual lumped model that formulate the rainfall-runoff transformation analogized as a flow through a series of tanks (Sugawara et al., 1985). Three tanks are applied in this study because the river is influenced by base flow and the catchment is considered as medium size. The model is tuned by using observed discharge during rainy season and dry season in 2016. Afterward, the calibrated model is applied to analyze the SWI. According to Vasconellos et al. (2020), SWI is the summation of storage in first and second tank in every time step. The accuracy of SWI data from remote and in-situ point observations as well as the modeled SWI are evaluated against soil laboratory test by assessing the Pearson correlation coefficient. The spatial autocorrelation of the spatial SWI data is also discussed by verifying Moran's I index.

## 3. RESULTS AND DISCUSSIONS

### 3.1 Multi-Sensors Detection

The wireless sensor system detects the soil water content and delivers the data to the computer. The probe gives analog output that is converted into percentage. The number of received data is larger than sent data indicating good transmission rate. The measurement from the sensor is transmitted up to 20 m with 90.1% success rate. Other functionality assessment is delay test. In average, 2.3 minutes is required for the probe to update the water fraction change and transfer data to the receiver.

### 3.2 Correlation of Observation

Figure 2 shows the spatial SWI. A pixel of the SWI satellite image is compared to soil laboratory test as a ground-truth. The results of sampled soil SWIs is depicted in the left panel of Figure 2. This scattered set of points SWI value is processed using geostatistical procedure to generate an estimated spatial SWI using Kriging method (right panel of Figure 2). Figure 3 (a) and (b) is the scatterplot of ground-truth against ground sensors and remote sensors. At a glance, there is a positive relationship between the sensors and soil test results indicated by Pearson correlation coefficient of 0.75 and 0.59 respectively. However, imperfect relationship can be seen in the case of remote sensing because the satellite product tends to produce higher and smoother SWI value than the true water content.

At a specific area, such as at the downstream, there is a range of water content value from satellite imagery that is associated with true value. Both images show similar tendency where the SWI is higher in the downstream and lower in the upstream. The correlation is positive which is shown by correlation of 0.68 as demonstrated in Figure 3(c). Moran‘s I analysis finds significant patterns of spatial association of SWI of Copernicus satellite data product. The index ranges from 0.20 to 0.50 for all data in the observation campaign period.

### 3.3 Reliability of the System

Tank model is then applied to evaluate the relationship of the water budget components in the watershed. The results of the rainfall-runoff simulation is demonstrated in Figure 4. This figure indicated that the model can reproduce the runoff well. The good performance of calibration procedure is confirmed with RMSE and percent bias of 14.0 $m^3/s$ and 3.5% respectively. Calculated SWI from calibrated model is drawn in scatter plot (Figure3 (d)). With correlation coefficient of 0.73, the analysis demonstrated that multi-sensors system is quite reliable

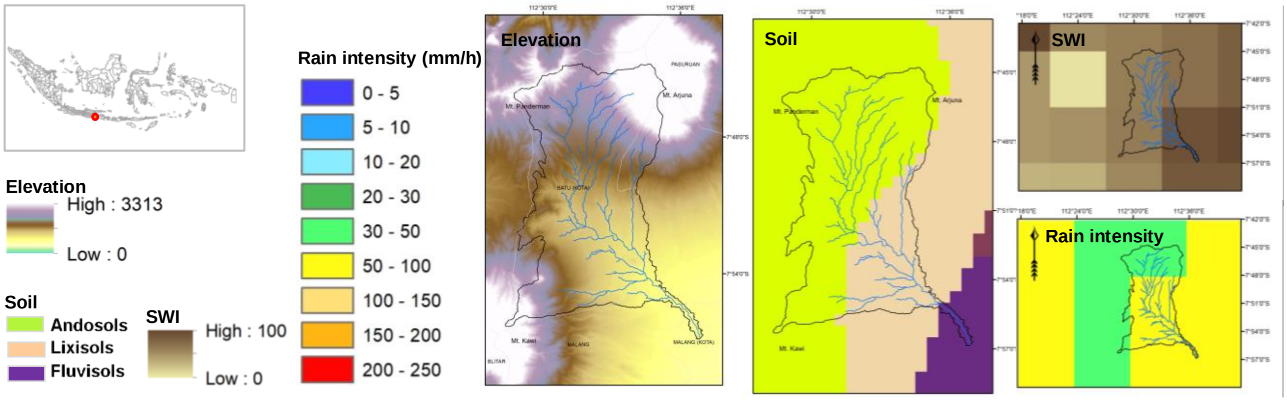


**Figure 1 Study area, topography, soil map, SWI from Copernicus, and rainfall intensity from GSMaP of 22 February 2020 case**

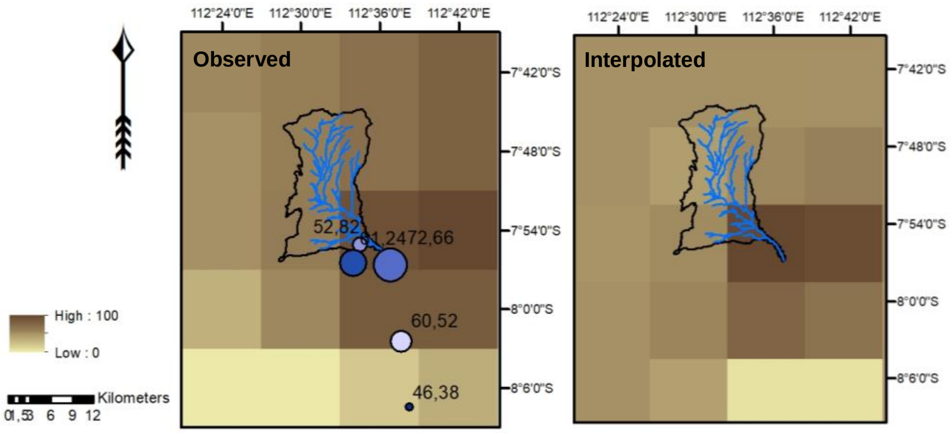


**Figure 2 Spatial SWI from remote sensing (left), point SWI from soil sample test (dots), and Kriging interpolation from point SWI (right)**

in estimating the value of soil water index in a catchment. Vasconellos et al. (2020) stated tank model gave satisfying performance and was applied to derive spatial SWI. The result also suggests that the satellite imagery is a great source for quick monitoring of SWI true value, though the data requires bias correction procedures. Results of the presented study is inline with research from Paulik et al. (2014) and Holzman et al. (2017) that reported also a good agreement between satellite and ground observations.

Lahar mechanism can be modeled through process-based approach, which is driven by the physical law of the phenomenon. There are also numerous studies that used statistical-based approach where empirical historical data is applied to predict the event through data-generating process. In process-driven model, soil moisture data will improve the calculation of rainfall-runoff transformation necessary for lahar generation model. In statistical model, the SWI parameter will increase the model performance because it depends strongly on the input accuracy (Sitterson et al., 2017). Furthermore, the information of antecedent soil moisture is also useful for predicting the initiation of debris flow through rainfall threshold method.

## 4. CONCLUSIONS

The performance of remote sensing technique and wireless sensor-based system to detect soil water content through direct soil testing and water budget modeling have been studied. The analysis shows satisfactory performance of remote sensing and ground device in detecting volumetric water content. The spatial autocorrelation for SWI from satellite gives Moran's I index of 0.20 to 0.50 indicating positive spatial correlation. When compared with soil test as ground-truth, ground and remote sensing products observe the amount of moisture in the soil reliably. Calibrated tank modeling in analyzing SWI value using empirical approach also presents the multi-sensors reliability. Good performance is shown by Pearson correlation of 0.59 to 0.75 among the measurement methods. Knowing the true value of SWI will be beneficial for increasing the skill of lahar flow model with physical as well as statistical approaches in volcanic basins. To improve the overall robustness of multi-sensors system, studying the soil depth of in-situ measurement, increasing the number of observation points, evaluating probe sensitivity, and bias correction are recommended.

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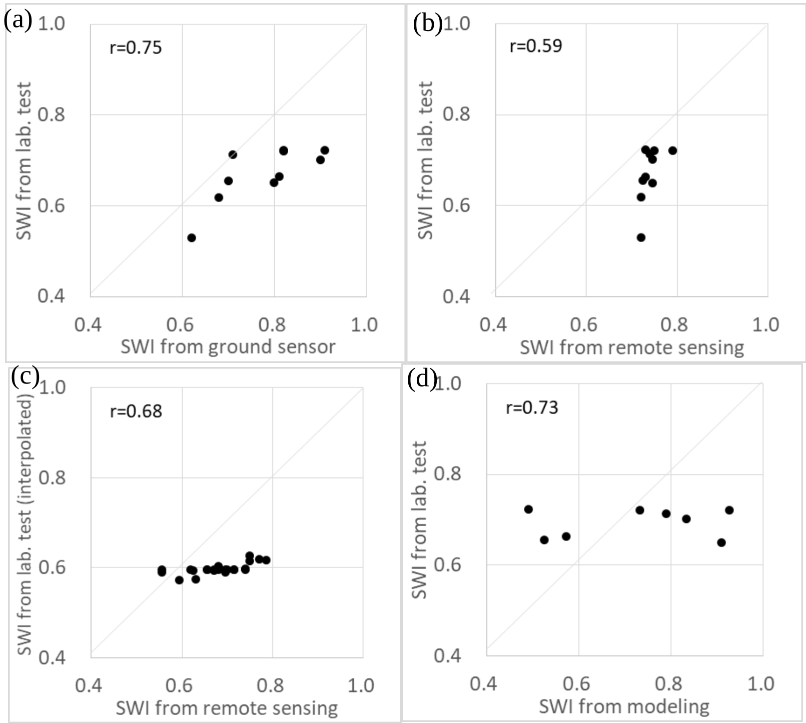


**Figure 3 (a) Correlation of SWI from soil sample test with in-situ sensor, (b) soil sample test with remote sensor, (c) interpolate soil sample test with remote sensor, (d) soil sample test with modeling**

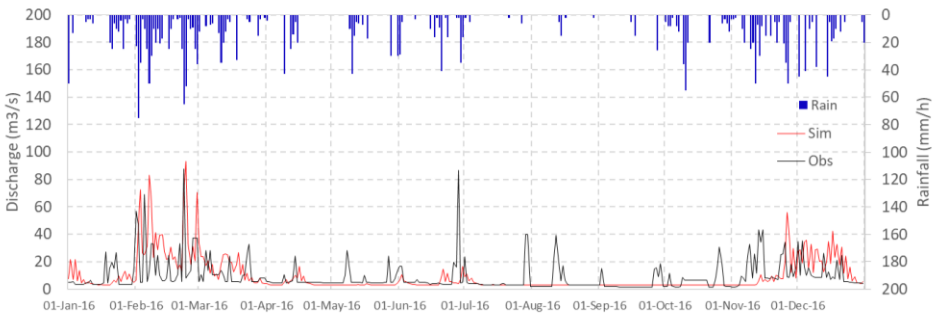


**Figure 4 Tank model simulation**

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