Comparisons of distributed and lumped rainfall-runoff model for soil moisture estimation

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Abstract. Soil moisture or soil water content is employed in a wide range of scientific and technical fields. In slope instability phenomena, soil moisture plays an important role since soil water lowers soil strength and raises stress [1]. Slope failure initiation involves several variables that affect the hydrologic behavior of a local catchment [2], including soil wetness. Rainfall as the primary component contributing to the landslide's occurrence has been explored in several studies [3][4]. The rainfall, soil moisture, and infiltration dynamic characterize the hydrological processes that influence the runoff generating process. The landslide is typically induced by severe rainfall after a prolonged period of wet conditions. Several landslide warning systems involve antecedent soil moisture and rainfall threshold [5][6]. Due to the high cost and difficulty in situ soil moisture measurements, large-area ground soil moisture monitoring at the high spatial and temporal resolution is rarely available. The soil water index has been monitored using a variety of operational satellites [7]. However, all satellite observations involve distortions caused by atmospheric conditions.

1. Introduction
Soil moisture or soil water content is employed in a wide range of scientific and technical fields. In slope instability phenomena, soil moisture plays an important role since soil water lowers soil strength and raises stress [1]. Slope failure initiation involves several variables that affect the hydrologic behavior of a local catchment [2], including soil wetness. Rainfall as the primary component contributing to the landslide's occurrence has been explored in several studies [3][4]. The rainfall, soil moisture, and infiltration dynamic characterize the hydrological processes that influence the runoff generating process. The landslide is typically induced by severe rainfall after a prolonged period of wet conditions. Several landslide warning systems involve antecedent soil moisture and rainfall threshold [5][6]. Due to the high cost and difficulty in situ soil moisture measurements, large-area ground soil moisture monitoring at the high spatial and temporal resolution is rarely available. The soil water index has been monitored using a variety of operational satellites [7]. However, all satellite observations involve distortions caused by atmospheric conditions.
Several types of research have analyzed the effect of water to reduce the shear strength in soil mechanic context. However, they suffer from several major drawbacks: ignorance relationship between landslides and the surrounding environment, neglect of precipitation, evaporation, vegetation, and topographical influence, and inability to accommodate the soil moisture dynamic [8] [9]. Several attempts have been made to use physically-based distributed models for estimating surface soil moisture [10][11]. Most of those studies have only been carried out using a land surface model, which is more suitable for larger-scale phenomena.

The major objective of this study is to investigate the performance of the hydrological model to derive the soil moisture distribution in a sub-catchment that varied temporally and spatially. This research aims to use the Tank Model as a lumped hydrological model to obtain soil water content as a comparison. To validate the accuracy of the model results, soil moisture content from the soil test is compared with the simulated moisture content. The challenges of using these approaches to derive the contributing factor for landslide occurrence prediction are discussed.

2. Materials and Method

2.1. Study Area

For this study, the upper Brantas river basin's catchment area is chosen as the study area (112.54 km2). The watershed is covered by forest in the upstream and dense dwellings downstream. With annual mean rainfall of 2000 mm, 85% of rain occurs during the rainy season due to rapid land-use change and prolonged precipitation in sloping terrain in the upstream (10% -25%). The upstream is primarily composed of Andosols soil types. In 2018, at least seven landslides occurred that killed 28 lives [12]. Figure 1 illustrates the upper Brantas River Basin.

2.2. Rainfall-Runoff Inundation Model

For this study, the Rainfall-Runoff-Inundation model (RRI Model) is used to simulate the catchment response to climatological data. RRI is a physically-based distributed hydrological model. That describes the water cycle process in a catchment discretized on a grid basis. The RRI Model is a two-dimensional numerical simulation that simulates rainfall-runoff and flood inundation [13]. The model distinguishes catchment slopes and river channels. This model simulates lateral subsurface flow, vertical infiltration, and surface flow to provide more accurate depictions of the raining to flooding process.

The parameter set in RRI is river Manning roughness coefficient (ns_river), land slope (ns_slope), soil depth (L, soil depth) in meter, porosity (η, φ, gamma), vertical hydraulic conductivity (K, kv) in m/s, soil suction head (∆Ψ, Sf) in meter, lateral hydraulic conductivity (ka) in m/s, unsaturated porosity (gamma). These parameters can be obtained from recommended range, soil texture database, or laboratory test.

2.3. Green-Ampt Infiltration Model

One advantage of the RRI Model is that it applies the Green-Ampt method for estimating vertical infiltration. It has an exact analytical solution based on approximate physical theory to include soil moisture content and soil properties. Moisture content θ (dimensionless) is the ratio of the volume of water in the soil pore to the total volume of the soil pore. The soil porosity η (dimensionless) is the ratio of non-solid volume to the total volume of soil. The moisture content is equal to the porosity when the soil is saturated. The infiltration process is simplified as Figure 2. The wetting front is a line that divides the soil profile into an upper saturated zone and a lower unsaturated zone [14]. Assuming the soil initially has moisture content as θi, the moisture content will increase from θi to η when the rainwater penetrates the ground.
Figure 1. Upper Brantas River Basin, topography (left), landuse (middle), soil (right). Triangle and circle are raingauge station and basin outlet.

Figure 2. Green-Ampt infiltration process.

The cumulative depth of infiltrated water $F$ (m) is:

$$F(t) = L \times (\eta - q_i)$$  \hspace{1cm} (1)

In the RRI Model, $L$ is the soil depth (m) specified in the parameter setting. Once $F$ is found, the infiltration rate $f$ (m/h) can be obtained by:

$$f = K \left( \frac{\Psi (\eta - q_i) + F}{F} \right)$$  \hspace{1cm} (2)

Where $\Psi$ is soil suction head (m) and $K$ are vertical hydraulic conductivity (m/h). The value of $(\eta - q_i)$ is defined as Gamma in RRI algorithm. An output, namely Gampt-ff, shows Green-Ampt cumulative water depth (m) or $F$ in Eq. 1. Once soil porosity, soil depth, and Gampt-ff are known, the soil water content can be calculated using Eq. 1.

2.4. Tank Model
Osanai et al. [15] proposed early warning for slope failures in Japan using rainfall indices and soil water index from the Tank Model. The Tank Model is a conceptual lumped model that depicts the rainfall-runoff transformation as a sequence of tanks [16]. Three tanks were used in this study since the river is soil water index by base flow, and the watershed is believed to be of medium size. The calibrated model
is used to derive the soil water index. Soil water index is defined by Vasconcellos et al. [17] as the sum of storage in the first and second tanks at each time step.

2.5. Data Preparation
The hydrological simulation is done daily with the same spatial resolution as the terrain map. Daily rainfall (mm/h) is obtained from Dau, Pendem, and Karangploso Rain gauge Stations (Figure 3). The runoff is evaluated in one outlet point at -7.913, 112.588 for the year 2016. Observed discharge data is needed to confirm the output of the hydrological model. Hourly observed water level at these outlets is acquired from the Bango Gedangan River Bureau. Topography data used here is Digital Elevation Model (DEM) obtained from SRTM, which was reanalyzed from HydroSHEDS global dataset with 30-sec resolution. Land use data is spatially distributed from GLCC-V2 (Global Land Cover Characterization) provided by USGS. FAO Digital Soil Map of the World (DSMW) is taken for gridded soil data. An example of the spatial distribution of rainfall over the basin is presented in Figure 1.

3. Results and Discussions

3.1. RRI Model Preprocessing
The preprocessing steps using DEM data in the target basin include basin delineation and confirming river stream agreement with real ground stream shape. Figure 4 displays the preprocessed topographical data and the basin delineation result. The data preparation related to land use is land use reclassification (Figure 5).

3.2. Results of Simulation using RRI and Tank Model
The hydrological model is run on an hourly basis for the year 2016. The parameters are tuned using rain and runoff observations in the same period. The resulted parameter is shown in Table 1. The result of the simulated hydrograph is shown in Figure 6 for Tank Model (top) and RRI Model (bottom). Using a visual comparison of the observed and simulated hydrograph, the rainfall-runoff simulation using Tank Model as a lump hydrological model could not simulate the discharge variation at basin outlet, such as those in May to November 2016. However, in terms of floods, the high events in the rainy season could be reproduced. Regarding RRI Model as a distributed hydrological model, the model can capture high rainfall cases, though the amount is somewhat high. Three runoff peaks resulted from the RRI Model, i.e., August, October, and November 2016.

A possible explanation for the imperfect results of the RRI Model might be the unrepresentativeness of spatial rainfall distribution. In this sense, spatially distributed rainfall observation from weather radar or satellite is necessary to improve the modeling performance. Figure 7 reports the advantage of using the RRI Model. The flood discharge variation along the river and distribution of inundation depth in the flood plain can be simulated for every step. This output would enhance the understanding of catchment response to the heavy rain, which will be beneficial for better comprehending local landslide phenomena [18][19].

3.3. Soil Water Content from RRI Model
Both RRI Model and Tank Model are used to retrieve the soil moisture value from the modeling. Figure 8 presents the Green-Ampt cumulative depth of infiltrated water from the RRI Model in the 2016 simulation in the meter unit. By dividing these values with 1 m soil depth and calculating the additional soil water content for every time step, the fulfillment of the soil porosity with infiltrated water could be extracted. In Figure 9, this parameter is presented in a dashed line by time variation within January to March 2016, taken from a point near the basin outlet. The chart shows that the cumulative infiltrated water rises with consecutive increases in the daily rainfall. It moves further to the stable value in the middle of February 2016. The soil water content reaches its maximum value with a soil porosity of 0.479 (silty clay), as the soil is saturated due to rainfall. The study finds that no significant differences are found for the soil moisture variation, which ranges from 0.458 to 0.479, as the dotted line shows in
Figure 9. This issue could be attributed to the parameter specification in the initial condition. With a
current parameter setting and limited calibration and validation period, caution must be applied as the
findings might not be directly transferable to the operational scheme.

Figure 3. Rainfall data

Figure 4. DEM preprocessing

Figure 5. Land use reclassification, soil map, and Thiessen Polygon preprocessing
Table 1. Parameter setting of RRI and Tank Model

| Parameter          | Value         |
|--------------------|---------------|
| **RRI Model**      |               |
| Ns_slope           | 0.03          |
| Ns_river           | 0.04          |
| Soil depth         | 1             |
| Gammaa             | 0.479         |
| Ksv                | 5.56          |
| Sf                 | 0.292         |
|                    | 2             |
| Gammam             | 0.068         |
| Kg0                | 0.000         |
|                    | 5             |
| Fpg                | 0.03          |
| rgl                | 0.5           |
| Riv_thresh         | 20            |
| Width_param_c      | 5             |
| Width_param_s      | 0.35          |
| Depth_param_c      | 0.95          |
| Depth_param_s      | 0.2           |
| Height_limit_param | 20            |
Figure 6. Hydrograph and hyetograph from RRI and Tank Models simulation

Figure 7. Flood discharge variation along the river stream (left) and distribution of inundation depth in the flood plain (right) from RRI Model for 2 February 2016

Figure 8. Green-Ampt cumulative depth of infiltrated water (m) for the condition of 25 January 2020 (left), 2 February 2020 (middle), and 6 February 2020 (right)
3.4. Soil Water Content from Hydrological Models
The present study is designed to derive the soil moisture value for landslide hazard assessment. The point moisture values from RRI Model and basin moisture values from Tank Model are compared with those from the ground and remote observations (Figure 10). Volumetric soil moisture observations from Soil Moisture Active Passive (SMAP) by NASA [20] and from Soil Moisture and Ocean Salinity (SMOS) mission by ESA [21] are shown along with soil test in some specific points near the basin outlet. This observation has been reported in [22]. The estimated soil water content from RRI Model provides a comparable value with SMOS remote observation in terms of the amount. Assuming the soil test is the actual value regarding the Tank Model, the Tank Model could serve a better result in terms of the temporal variation. Yet, the present results are significant in at least major two respects, i.e. well-calibrated RRI Model could be a potential method as it can provide spatial variation of soil moisture factor, rather than quantitative value, even in the small scale over the catchment; the bias correction of remote observation is significant for verification.

Figure 9. Time variation of infiltration parameter from RRI Model

Figure 10. Soil water content from the models, soil sample test, and remote sensors

4. Conclusions
The current study aims to obtain the soil moisture value from two hydrological models, namely RRI Model and Tank Model. This investigation shows that no significant differences are found for the soil moisture variation from RRI Model, which could be attributed to the parameter specification in the initial condition. It is also shown that Tank Model could show the moisture variation along the simulation period. These results suggest that RRI Model, which is calibrated well, could be a potential method as it can provide spatial variation of soil moisture on a small scale over the catchment. This research will serve as a base for future studies on landslide early warning systems when the rainfall-short term prediction is introduced to the model. The findings in this report are subject to at least two limitations, i.e., the calibration issue; the uncorrected satellite soil moisture for model verification. Further research is needed to account for the continuous soil sample testing in some representative points over the basin and improve the model calibration procedure.
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