



COMPARISON OF SWAT-BASED ECOHYDROLOGICAL MODELING IN THE RAWA PENING CATCHMENT AREA, INDONESIA

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ABSTRACT

The Soil and Water Assessment Tool (SWAT) is an ecohydrological model widely applied to assess water quality and watershed management. This tool also has the advantage of building watershed models even with limited monitoring data availability. The essential data required by this tool includes digital elevation models (DEM), land use maps, climate data, and soil data. Nonetheless, the availability of spatial data is still often a challenge in developing hydrological models, especially in developing countries such as Indonesia. This research will compare the accuracy of freely available data in Indonesia in facilitating the development of hydrological models from SWAT in the Rawa Pening catchment area. This research is crucial since Rawa Pening Lake is a priority lake for revitalization, so the research results will help provide suggestions regarding presenting data in SWAT modeling. This research compares SWAT models built from different land use and DEM (Digital Elevation Models) data. The land use data being compared is the result of processing from the Google Earth Engine (GEE) platform using machine learning with land use data from government agencies, namely the Ministry of Environment and Forestry, while the DEM data being compared is SRTM and DEMNAS data. The validation results using R, R², RMSE, and NSE show that, in general, the model built from land use from GEE is the best compared to the other models. In modeling SWAT in Indonesia, we recommend using good-quality land-use data. Utilizing supervised classification through Random Forest (RF) algorithms within GEE can facilitate the acquisition of this data. To reduce computation time, the DEM can be SRTM with a small sacrifice of accuracy.

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Keywords: DEM; Google Earth Engine; land use; SWAT; streamflow

INTRODUCTION

Water is a highly essential source of living on Earth. The importance of water resources is a primary human need and greatly influences food and energy security (Pasika & Gandla, 2020; Wulandari et al., 2021). However, current climate change is affecting the quantity and quality of water resources, requiring management and independent investigations into the mechanisms

of their availability (Chen et al., 2019; Saade et al., 2021). Managing water resources is a critical problem in the water security framework defined by the Sustainable Development Goals (SDGs) (UNEP, 2017). To unequivocally achieve the United Nations' SDGs, advanced techniques are required to intensify research in water and watershed management (Dekongmen et al., 2022; Djufry, 2012). Advanced techniques can take the form of eco-hydrological modeling tools such as the Soil and Water Assessment Tool (SWAT) (Ha et al., 2018).

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SWAT is an ecohydrological model created by the Agricultural Research Service of the United States Department of Agriculture (USDA) (Arnold et al., 1998; Sammartano et al., 2019; Cai et al., 2023). This is a physically based model with a spatially dispersed hydrologic model based on hydrologic response units (HRUs) created by a mix of land use, soil type, and slope (Poblete et al., 2020). SWAT's primary application is ecohydrology simulation in small watersheds, particularly concerning land use and climate change (Tan et al., 2019; Marin et al., 2020). These uses include research on water quality and the forecast of the effect of land-use changes and erosion (Anand et al., 2018; Sowah et al., 2020; Mapes & Pricope, 2020; Lei et al., 2021; Olaoye et al., 2021; Panda et al., 2021; Alitane et al., 2022; Hung et al., 2022).

The SWAT model simulates hydrological, sediment, pollutant processes, and vegetation management in the basin using a water balance method (Aloui et al., 2023). The SWAT tool can also be paired with a statistical downscaling model as a hydrological and climate change parameter (Eingrüber & Korres, 2022). The SWAT modeling method can be applied to rain and run-off factors, which will then be used to analyze farming dynamics (Dash et al., 2020). In some SWAT studies, it is also used to assess the effect of Ridging Across Slope (RAcS) and Ridge Along Slope (RAIS) on sedimentation results in basin areas (Kuti & Ewemoje, 2021). The SWAT model can be changed in various studies, including Soil Organic Carbon, where the algorithm is merged based on variables (Liang et al., 2022).

SWAT has the benefit of being able to construct a watershed model using less surveillance data. The data set contains a digital elevation model (DEM), land use map, climate data, and soil data (Kiros et al., 2015; Muthee et al., 2022). Nonetheless, the availability of spatial data is frequently a problem in creating hydrological models, particularly in emerging nations (Escamilla-Rivera et al., 2022). Particularly in Southeast Asian nations, such as Indonesia, SWAT applications are still limited due to the limited availability of land use maps (Tan et al., 2020). The lack of high spatial resolution (30 m) land use data with regular updates is due to the need for high-performance computing to keep, organize, and evaluate huge volumes of satellite data (Midekisa et al., 2017).

The problem of providing appropriate land use data for SWAT modeling in developing countries is not only caused by budget and human resources. The difficulty of supplying land

use statistics is also affected by geographical variables, such as Indonesia's heavy cloud cover (Dimiyati et al., 2022). However, Indonesia has a high rate of watershed harm and a decline in public water quality (Trisakti et al., 2017; Pambudi, 2019). The Rawa Pening Catchment Area is one example of a significant Environmental Disaster Risk (Mardiatno et al., 2021). It has a water body named Rawa Pening Lake, and the water condition is Highly Polluted, so it has become one of the national priority lakes in Central Java Province, Indonesia (Piranti et al., 2019; Mardiatno et al., 2023). In fact, one of the outlets from Rawa Pening Lake, namely the Tuntang River, is a polluted river prone to flooding (Danurrachman et al., 2023). This makes providing representative land use data in the Rawa Pening catchment area very urgent because this is related to SWAT modeling for policy formulation.

A platform that is very helpful in providing and analyzing representative land use is Google Earth Engine (GEE) (Kumar & Mutanga, 2018; Sidhu et al., 2018). This cloud-based platform provides datasets and facilitates the processing of geo-big data over a wide area for environmental monitoring over a long period (Amani et al., 2020). In the analysis process, GEE also has machine learning algorithms such as Classification and Regression Tree (CART), Support Vector Machine (SVM), and Random Forest (RF) (Shaharum et al., 2020; Gxokwe et al., 2022). Many studies, including Wang et al. (2018), Pande (2022), Magidi et al. (2021), and Kolli et al. (2020), have been using machine learning in GEE to track land use linked to watersheds and water resources. Studies that address machine learning selection and processing stages, on the other hand, are rarely conducted (Shih et al., 2019). The comparison of machine learning in providing land use data for SWAT modeling is one of the future SWAT research challenges (Aloui et al., 2023).

Based on the problems and facts described, this research uses machine learning in GEE to analyze land use, where land use data are used to create a hydrological model from SWAT in the Rawa Pening catchment area. In addition, this research compares the SWAT model from land use data from machine learning at GEE with data from the Indonesian Ministry of Environment and Forestry (KLHK). This research also compares SWAT models built from different DEM data, namely Shuttle Radar Topography Mission (SRTM) and DEMNAS. Each DEM used impacts the SWAT result (Nazari-Sharabian et al., 2020; Tran et al., 2022). Research related to com-

paring data in SWAT studies in developing countries has been widely carried out, such as Wiwoho et al. (2021), Aqnouy et al. (2023), Chathuranika et al. (2022), Dos Santos et al. (2022), and (Shekar et al., 2023) with climate and meteorological data, but research comparing land use and DEM data is still rarely carried out. The land use data and DEM data that we compare can be obtained for free to answer the problem of lack of data related to SWAT modeling. It is hoped that the results of this research can provide suggestions to help developing countries, especially Indonesia, generate an efficient SWAT model for managing water resources and watersheds, especially in priority areas such as the Rawa Pening Catchment Area.

METHODS

This research was specifically conducted in the Rawa Pening Catchment Area, an upstream part of the Tuntang sub-watershed. Administratively, the Rawapening catchment area is located in Semarang Regency, Central Java Province, Indonesia (Figure 1). Geomorphologically, Rawa Pening is surrounded by mountains that serve as water catchment areas (Sanjoto et al., 2020). This site was selected because it has a variety of hydrological activities, including lakes, irrigation, rivers, wetlands, and rain recharge.



Figure 1. Research Area

This research examined SWAT models derived from various land use and DEM data. Based on actual circumstances, the SWAT model was evaluated for accuracy. Due to the lack of

data, this research assessed the SWAT model in the Rawa Pening Catchment Area in 2019. The information used is freely accessible in Indonesia (Table 1). Land use KLHK data had been used, as well as GEE data coming from machine learning-based categorization. CART and RF were the Machine Learning technologies used.

Table 1. Data and Source

Parameter	Source
Land-use	Land-use mapping using machine learning in GEE KLHK (Indonesian Ministry of Environment and Forestry)
DEM (Digital Elevation Model)	SRTM DEMNAS
Soil	Indonesian Center for Agricultural Land Resources Research and Development
Weather	NASA POWER

The DEM data utilized in SWAT modeling are SRTM, which can be accessed via the following link <https://earthexplorer.usgs.gov/>, and DEMNAS can be accessed via the following link <https://tanahair.indonesia.go.id/demnas/#/> freely. DEMNAS is DEM data produced by Badan Informasi Geospasial (BIG) or the Indonesian Geospatial Information Agency, derived from the assimilation of IFSAR, TERRASAR-X, ALOS PALSAR, and mass point data (Zylshal et al., 2021). DEMNAS has a more precise spatial resolution of 0.27-arcsecond when compared to SRTM, which has a precision of 30-arcsecond (Mutaqin et al., 2021). DEMNAS is an Indonesian data product that can be extracted into data on the height of the Earth's surface and used for hydrological studies (Ihsan et al., 2023). The following are the steps of data handling and analysis:

Land use mapping had three major stages: selecting data sources, selecting classification techniques, and evaluating accuracy. The data source chosen were satellite images obtained from GEE, namely Landsat 8 OLI/TIRS Collection 2 atmospherically corrected surface reflectance. This research compared Machine Learning RF and CART for the classification technique, which is pixel-based Supervised Classification. The classification method employed input data, namely image pairs constructed from various bands and Spectral Indices; the Spectral Indices employed in this research are listed in Table 2. There were six

bands used: band 2, band 3, band 4, band 5, band 6, and band 7. These bands were selected because they have higher accuracy than a mix of all bands (Yu et al., 2019; Fariz et al., 2022). The six bands, along with DEM and spectral indices, were expected to improve the precision of the land use map. The spectral indices chosen were the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), and Bare Soil Index (BSI) (Table 2). NDVI was chosen to distinguish between vegetation and non-vegetation, while NDBI was chosen to discriminate between built-up areas and was proven to identify building density (Loukika et al., 2021; Fariz & Faniza, 2023). Water spectral indices such as NDWI and bare soil such as BSI were chosen to discriminate water bodies and bare soil objects, which are numerous in the research location.

Table 2. Spectral Indices Used in the Research

Spectral indices	Formula	Source
NDVI	$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$	Rouse Jr et al. (1974)
NDWI	$NDWI = (NIR - SWIR) / (NIR + SWIR)$	Gao (1996)
NDBI	$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$	Zha et al. (2003)
BSI	$BSI = \frac{(SWIR2 + RED) - (SWIR2 + BLUE)}{(SWIR2 + RED) + (SWIR2 + BLUE)}$	Roy et al. (1997)

The classification procedure began with training on the incoming data. Training samples were collected in batches of 50 for each land use type. This research charted land use with nine groups related to the Ministry of Environment and Forestry for a total of 450 marks in the Training Sample (Letsoin et al., 2020). Following the training data collection, the categorization procedure was carried out using CART and RF machine learning. The final step was to validate the mapping findings using a validation sample of 225 points.

The SWAT model in this research used the QSWAT3 model with an interface in Quantum GIS. The SWAT model could be constructed utilizing data from land use, DEM, sediment, and weather. The four SWAT models were compared with the configurations shown in Table 3. The SWAT models were then contrasted with the watershed boundaries and river flow values received

from BBWS Pemali Juana (Central River Region). The watershed factors contrasted were the area's size, form, and elevation, which influenced the hydrological reaction (Buakhao & Kangrang, 2016).

Table 3. SWAT Models Compared

Model	Land-use	DEM
Model A	GEE	DEMNAS
Model B	GEE	SRTM
Model C	KLHK	DEMNAS
Model D	KLHK	SRTM

The model evaluation used in this research was a comparison of the streamflow data produced by the SWAT model with the Automatic Water Level Recorder (AWLR) measurement data from BBWS Pemali Juana. The AWLR location is in Tuntang River at -7.2610, 110.4526 (Figure 2). Several formulas, such as R, were used in validation (Correlation coefficient), R² (Coefficient of determination), Root Mean Square Error (RMSE), and Nash-Sutcliffe efficiency (NSE). R and R² functioned to indicate the degree of connection between the observation and model, where the model was suggested to be more related and important the closer it got to 1. NSE indicated how well the observation versus model data plot matched the 1:1 line (Knoben et al., 2019). The RMSE number was used to calculate a model's error rate; the lower the RMSE value, the more accurate the model. These data were most commonly used for SWAT model validation. Therefore, they can be used for validation (Gao et al., 2019).

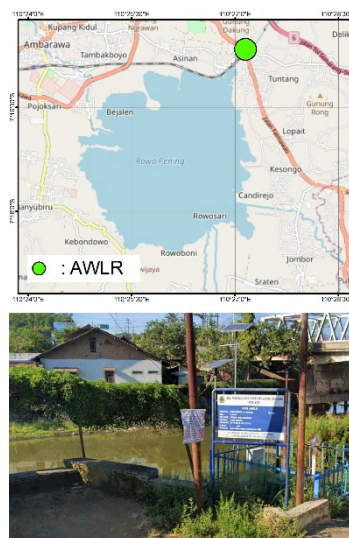


Figure 2. AWLR Location

RESULTS AND DISCUSSION

Land use mapping uses machine learning-based supervised classification on GEE. Using GEE in land use mapping in Indonesia is very helpful in reducing cloud cover because we get cloud-free satellite imagery using the BQA algorithm and median function (Fariz & Nurhidayati, 2020; Jamaluddin et al., 2022). The results of land use mapping produce land use classes, namely paddy field, forest plantation, forest, settlement, mixed garden, dry agriculture, mixed dry agriculture, dry shrub, and water bodies. The mapping results show that RF is the best machine learning for mapping land use in the Rawa Pening Catchment Area. Land use maps built from

CART have an accuracy value of 0.48, while land use maps built from RF have an accuracy value of 0.85.

The fact that RF is the best machine learning in this research is most likely due to its non-linear nature and noise-free classification results (Pelletier et al., 2016). Compared to other forms of Machine Learning, such as CART, Machine Learning that employs a set of decision trees has been shown to map land use with greater precision (Orieschnig et al., 2021; Zhang et al., 2022). This provides RF appropriate for study locations with a fragmented spatial distribution of land use, as opposed to CART, which is appropriate for areas with a uniform distribution (Pan et al., 2022).

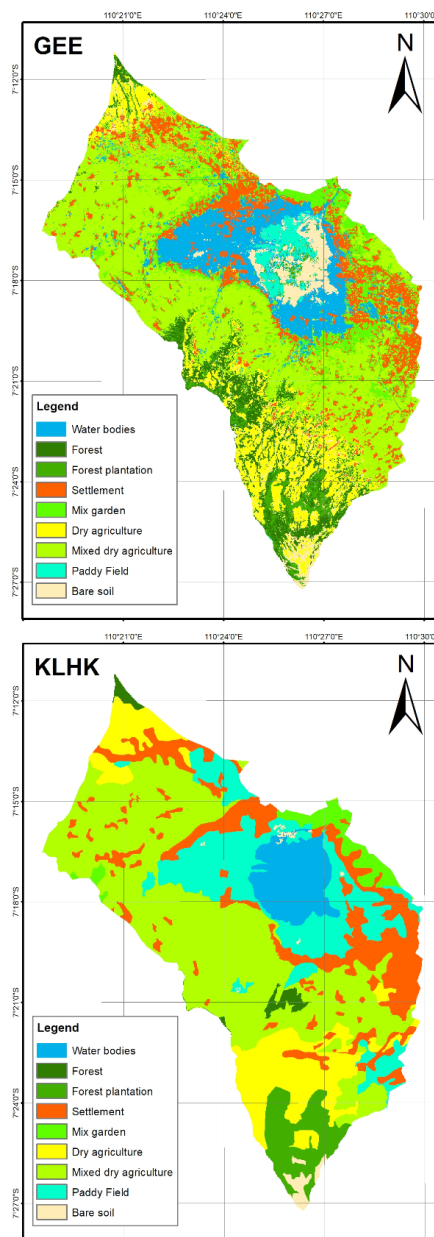


Figure 3. Comparison of Land Use Maps from GEE (RF classifier) with KLHK

In addition, the land use map from Machine Learning RF is used as input data for the SWAT model. Compared to land use data from KLHK, the GEE land use map appears coarser and more detailed (Figure 3). There are standardized land use classifications on the KLHK's Land Use map, such as settlements associated with mixed gardens.

DEM data is separated into two categories: the Digital Surface Model (DSM) and the Digital Terrain Model (DTM). DSM displays increased natural and built-up features on the Earth's surface. Meanwhile, DTM has bare Earth (Nemouli et al., 2019). Shawky et al. (2019) state that most global DEM datasets can be considered compromises between DSM and SRTM. DEMNAS is included in the DTM used in this research.

Table 4. SWAT Models Compared based on DEM Data

DEM	Basin (Km ²)	Sub-basin	HRU
SRTM DEM	246.96	51	1092
DEMNAS DEM	239.44	53	2123

In the Rawa Pening Catchment Area, catchment delineation has been accomplished using DEM (SRTM and DEMNAS) data. The delineation procedure generates watershed and sub-watershed boundaries and river networks (Table 4). When the SRTM DEM and DEMNAS DEM are used to delineate the basin area, the results are marginally different. According to Table 4, the SRTM-defined Rawa Pening Catchment Area has a larger area than the DEMNAS-defined basin. The difference in the area amounts to approximately 7,52 km² or 1.03%.

Compared to the watershed boundary derived from the Pemali Juana BBWS, the delineated watershed boundary of the SRTM DEM and DEMNAS DEM has a different size and shape. The watershed boundary sourced from BBWS Pemali Juana has an area of 273.29 Km², which is greater than the watershed boundary of SRTM DEM and DEMNAS DEM. The watershed boundary of the SRTM DEM has an intersected area of 89.8% against the watershed boundary of the BBWS Pemali Juana, while the DEMNAS DEM has an intersected area of 87.2%.

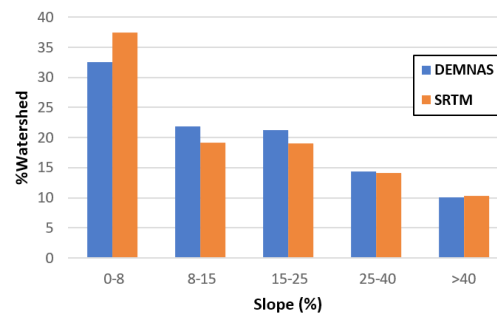


Figure 4. Comparison of the Percentage Slope Area of Watershed Delineation

HRU is the name given to the land unit created by the SWAT model, which represents an overlay of soil type, land use, and slope gradient in the Rawa Pening Catchment Area. The results of the HRU creation provide information regarding land use, land, slope, area, and proportion of the watershed. The quantity of HRU extracted differs between the two DEMs. SRTM DEM yielded 51 units of HRU, while DEMNAS DEM generated 53 units. It obviously depends on the river's morphology since the territory of each HRU is distinct. The broadest sub-basin in SRTM DEM is approximately 14,38 km², whereas the widest sub-basin in DEMNAS DEM is 18,56 km².

The slope product can be seen in Figure 4. There are variations between the DEMNAS and SRTM slope sectors. This difference is due to the size and configuration of the cells. Slope Area 0-8%, which is highly delicate, is mainly derived from SRTM, whereas Slope Area 8-25, a moderate and steep slope, is mainly derived from DEMNAS. In some hydrologic models, the slope derived from the DEM does not influence the output data (Buakhao & Kangrang, 2016).

To ascertain the level of validity of a model's results, every model must undergo a validation test. Comparisons are made between the SWAT model's discharge value and the AWLR discharge data to validate the model. The SWAT model's discharge data is broken down into four groups, including land use data from GEE and KLHK and DEM data from DEMNAS DEM and SRTM DEM.

The outcomes of model validation using R, R², RMSE, and NSE indicate that Model A and Model B are the best SWAT models (Table

5). Model A is constructed using GEE and DEM-NAS land use data, while Model B is constructed using GEE and SRTM DEM land use data. Model A performs exceptionally well compared to monthly data, while Model B performs exceptionally well compared to daily data.

Table 5. SWAT Model Validation Results

Model	Daily Discharge Data				Monthly Discharge Data			
	R	R2	RMSE	NSE	R	R2	RMSE	NSE
Model A	0.46	0.21	10.23	-2.44	0.86	0.73	3.35	0.59
Model B	0.49	0.24	9.75	-2.12	0.86	0.73	3.43	0.58
Model C	0.45	0.20	10.43	-2.57	0.84	0.71	3.47	0.56
Model D	0.47	0.23	10.12	-2.36	0.85	0.71	3.57	0.53

The high-precision land use map is created using Machine Learning RF. Previous studies by Oo et al. (2022), Sundar and Deka (2022), and Arjasakusuma et al. (2020) assert that RF land use map is preferable to CART. RF can map multi-class land use, like this research so that it can accommodate minor classification differences (Sundar & Deka, 2022). The RF land use map is contrasted with other data in Model A, Model B, Model C, and Model D for SWAT modeling. The validation results suggest that Model A and Model B outperform other models.

Compared to DEMNAS, the SRTM-derived model produces superior results compared to daily data. This may happen because SRTM, despite being a DSM, is derived from radar-derived data that can penetrate the surface, passing through the vegetation cover, allowing the collection of a more representative topography (Karabulut & Özdemir, 2019). DEMNAS is generated by the assimilation of IFSAR, TERRASAR-X, ALOS PALSAR, and MASS POINT data. Furthermore, DEMNAS in the study area, Central Java Province, is not in the form of DSM or DTM, although it appears to possess the same profile as DSM. In research about hydrological models, DTMs are more applicable than DSMs (Höfle et al., 2013; Shawky et al., 2019).

In contrast to the daily and monthly data, the model constructed from the land use data of GEE outperforms the KLHK data. This indicates that the quality of the land use map is more important than the quality of DEM in SWAT modeling (Fan et al., 2021). To make the SWAT model more accurate in Indonesia, we advise utilizing high-quality land use data by employing supervised classification following Machine Learning RF on GEE to obtain it. To decrease computation time, the DEM can be SRTM with a small loss of precision. This research has several limitations, such as not comparing the results of other SWATs, such as sediment yield, total nitrogen, and groundwater flow (Sukumaran &

Sahoo, 2020). Future work may be performed by enhancing the output compared. In addition, the data being compared are not limited to Land Use and DEM, as appropriate soil and meteorological data play a significant role in SWAT modeling (Tyagi et al., 2019; Krpec et al., 2020). Apart from that, further research also needs to compare the computation time of each SWAT model because not all developing countries have the hardware capable of carrying out spatial modeling, such as SWAT, for watershed management. Some of this future work is very useful for developing watershed management policies based on SWAT modeling that are more effective and efficient, especially for developing countries like Indonesia.

CONCLUSION

In this research, the comparison of SWAT models was centered on land use and DEM data. The utilized Land Use and DEM data are both Open-Source and Free Access. The used land use data comes from the supervised classification process that uses machine learning at the GEE and the Ministry of Environment and Forestry's Land Use Data. For DEM data, DEMNAS and SRTM are used. The following are the results of this research: (1) Land Use mapping on GEE utilizes Machine Learning RF and CART. The accuracy test results indicate that the land use map derived from RF is accurate. The RF land use map is then utilized for SWAT modeling; (2) The validation outcomes utilizing R, R2, RMSE, and NSE indicate that Model A (Land Use GEE and DEMNAS) and Model B (Land Use GEE and SRTM) are preferable to the other models in general. In Indonesia, we recommend utilizing high-quality data land use for SWAT modeling by employing supervised classification based on machine learning RF on GEE to acquire it. To decrease computation time, the DEM can be SRTM with a small loss of precision.

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