Comparison of FAO and SOILGRID Data Application on Streamflow and Sus-pended Sediment Study Using SWAT Model: A Case Study of Upper Yom Basin, Thailand

Leak Ngeang, Sarintip Tantanee*, and Ruediger Anlauf

Abstract— *Hydrologic models for river basins are important tools to describe water and sediment transport in watersheds. Important input data are soil related parameters, such as texture, water holding capacity, hydraulic conductivity, and others. However, good quality soil information is rarely available in Thailand, especially in mountainous areas. Therefore, two different open source global soil data were used in this study, i.e. FAO World Soil Map and the Soilgrids data. Aim of this research was to evaluate the performance of the SWAT hydrological model with respect to the simulation of streamflow and suspended sediments in a mountainous region in northern Thailand with special consideration of differences in the results based on the different soil data sets. After model calibration, streamflow and suspended sediments were simulated sufficiently well with both soil data. However, the low-resolution FAO data gave slightly better results than the high-resolution Soilgrids data, which generally was not expected. Mean clay, silt and sand content derived from FAO and Soilgrids data are very similar, while other soil parameters showed significant differences. The ranges of the soil information, i.e. the span between the lowest and highest value, were always much larger for the FAO data compared to those of the Soilgrids data. These differences are the possible reason for the difference in simulation quality using these soil data with SWAT.*

Keywords— **FAO, Sediment, Soilgrids, Streamflow, SWAT model.**

1. INTRODUCTION

Soil information is one of the crucial model inputs of any hydrological modelling. Soil information like soil texture and soil hydraulic conductivity have an effect on infiltra-tion, surface runoff, and pollutants processes [1]. How-ever, according to [2], detailed soil information is barely accessible, especially for a large watershed in Thailand. Therefore, the open source soil data, such as FAO [3] and Soilgrids [4], were used for this study.

Few researchers studied the effect of soil data with different quality and scale on hydrological process by using SWAT (Soil and Water Assessment Tool). Refer-ence [5] used SSURGO data with high spatial resolution and STATSGO data with very low resolution for a water-shed in Colorado, USA. High resolution soil data predict-ed more streamflow than low resolution data and less sediment and sediment attached nutrients. Another study [6] showed that the same two soil data sources caused a change in the position of critical sources areas for sedi-ments and differences in sediment yield (higher when simulated with low resolved data). However, no general statement could be derived.

Soilgrids [4] is a new source of soil information globally available since 2016, but few researchers used it so far to simulate hydrological processes with SWAT, e.g. [7].

Objective of this investigation was to test differences in streamflow and sediment yield simulated with SWAT based on FAO and Soilgrids soil information for the Upper Yom Basin in Thailand.

2. MATERIALS AND METHODS

2.1 SWAT model

SWAT (Soil and Water Assessment Tool) is a public domain model developed by the United States Department of Agriculture (USDA) and Agricultural Research Service (ARS) [8]. SWAT is a model on river basin level, constantly timing, spatial physically distributed, and developed to estimate the effect of land utilization on hydrology, sediment yield, and water quality. SWAT is generally used for huge complicated watersheds with variable soil, land use and management conditions over long time periods [8].

The SWAT model can simulate small as well as large watersheds by dividing the area into uniform sub regions. SWAT uses Hydrologic Response Units (HRUs) to take the spatial heterogeneity into account with respect to land use, soil properties, and slope in a basin. Fig. 1 shows a flowchart of SWAT processing. A SWAT extension integrated to a Geographic Information System (GIS) organizes input of different spatial data, such as soil, land use, and climate data model data. Presently, SWAT is integrated in an ArcGIS interface named ArcSWAT [9].

The simulation of the hydrology of a watershed is done in two separate divisions. One is the land phase of the hydrological cycle that controls the amount of water, sediment, nutrient and pesticide load to the main channel

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in each sub-basin. Hydrological components simulated in the land phase of the hydrological cycle are infiltration, redistribution, evapotranspiration, canopy storage, lateral subsurface flow, surface runoff, ponds, tributary channels and return flow. The second division is the routing phase of the hydrologic cycle that can be defined as the movement of water, sediments, nutrients and organic chemicals through the channel network of the watershed to the outlet [9]. In the land phase of hydrological cycle, SWAT simulates the hydrological cycle based on the water balance equation as shown in equation (1).

$$SW_t = SW_o + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - w_{seep} - Q_{qw})_i \quad (1)$$

where SW_t is the final soil water content (*mm*), SW_o is the initial soil water content on day *i* (*mm*), *t* is the time (days), R_{day} is the amount of precipitation on day *i* (*mm*), Q_{surf} is the amount of surface runoff on day *i* (*mm*), E_a is the amount of evapotranspiration on day *i* (*mm*), W_{seep} is the amount of water entering the vadose zone from the soil profile on day *i* (*mm*), and Q_{gw} is the amount of return flow on day *i* (*mm*) [9].

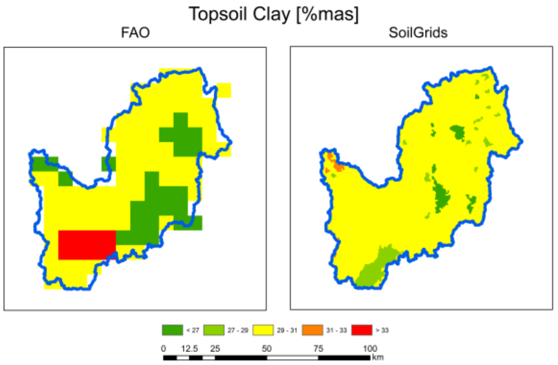

Fig.1. SWAT methodology flowchart.

Surface runoff occurs whenever the rate of precipitation exceeds the rate of infiltration. SWAT offers two methods for estimating surface runoff: the SCS curve number procedure [10] and the Green & Ampt infiltration method [11]. Using daily or sub daily rainfall, SWAT simulates surface runoff volumes and peak runoff rates for each HRU. In this study, the SCS curve number method was used to estimate surface runoff because of the unavailability of sub daily data for the Green & Ampt method. The runoff is calculated as shown in equation (2).

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \quad (2)$$

where Q_{surf} is the accumulated runoff or rainfall excess (*mm*), R_{day} is the rainfall depth for the day (*mm*), *S* is the retention parameter (mm).

Soil erosion and sediment yield are computed in the SWAT model using the Modified Universal Soil Loss Equations (MUSLE) [12] as shown in equation (3).

$$sed = 11.8 \times (Q_{surf} \times q_{peak} \times area_{hru})^{0.56} \times K_{USLE} \times C_{USLE} \times P_{USLE} \times LS_{USLE} \times CFRG \quad (3)$$

where *sed* is the sediment yield on a given day (metric tons), Q_{surf} is the surface runoff volume (mm ha^{-1}), q_{peak} is the peak runoff rate (m^{3}s^{-1}), $area_{hru}$ is the area of the HRU (ha), K_{USLE} is the soil erodibility factor, C_{USLE} is the cover and management factor, PUSLE is the support practice factor, LS_{USLE} is the topographic factor and *CFRG* is the coarse fragment factor.

2.2 Study area

The study area is in central northern Thailand between 18°27'N-19°24'N latitude and 99°44'E-100°41'E longitude, having a catchment area of 5321 km^2 (Fig. 2). The topography of the basin varies from hilly areas in the northern part, with a maximum elevation of about 1734 m above mean sea level to lowland flat areas in the center of the region, with minimum elevation of about 181 m above mean sea level.

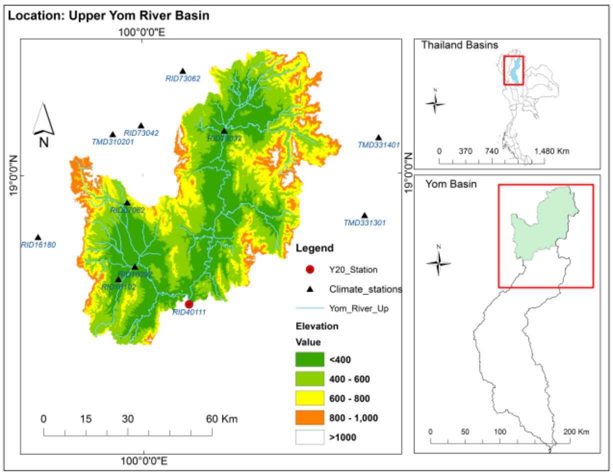

Fig.2. Location of study area, the Upper Yom River Basin, Thailand.

2.3 Datasets

The SWAT model requires meteorological data, digital elevation model (DEM), soil information, and land use as input data.

The meteorological data composed of rainfall, maximum and minimum temperature, wind speed, solar radiation, and relative humidity were obtained from the Royal Irrigation Department, Thai Meteorological Department [13], and Global Weather Data [14]. Daily meteorological data were used for the period 2000 to 2013.

The digital elevation data with 30 m resolution used in this study was taken from the Thai Land Development Department [15]. The catchment area of the upper Yom Basin was delineated, and the drainage pattern of the land surface analyzed by ArcSWAT based on the 30-m-resolution Digital Elevation Model (DEM) (Fig. 3).

Land use data with a resolution of 250 m was taken from Land Develop Department of Thailand [15]. The land use in the Upper Yom Basin characterized by forests (82.8%), agriculture (11.8%) and paddy fields (3.2%); the remaining 2.2% is represented by various land use types, such as orchards, villages, water bodies and rangeland (Fig. 4).

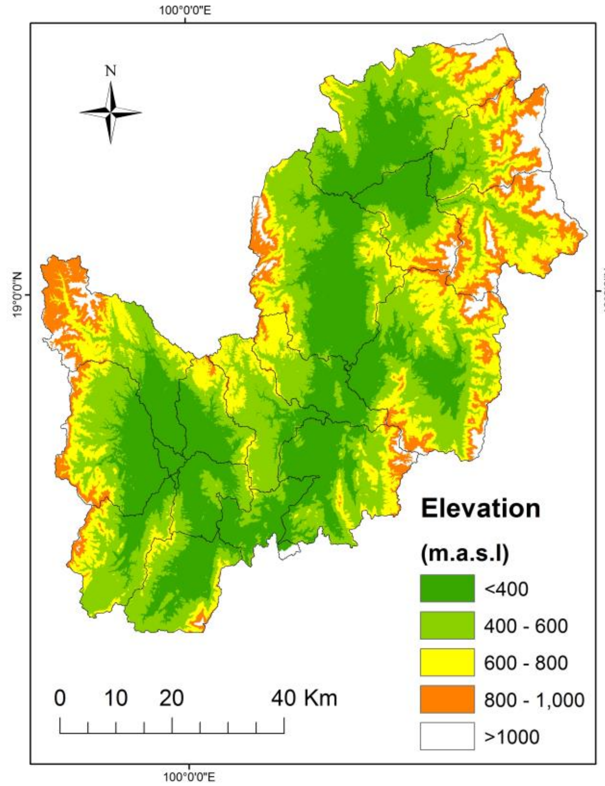

Fig. 3. Digital Elevation Model for the Upper Yom River Basin.

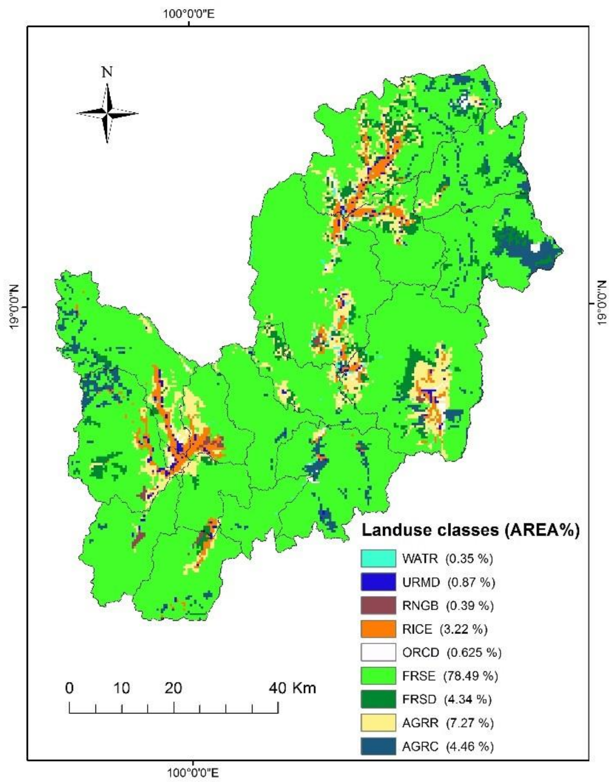

Fig.4. Land use classification for the Upper Yom Basin.
The codes used in the ArcSWAT database are: WATR (Water bodies), URMD (urban areas), RNGB (range-brush), RICE (paddy fields), ORCD (orchards), FRSE (evergreen forests), FRSD (deciduous forests), AGRR (agriculture row crops), AGRC (general agriculture).

Good quality soil information is rarely available in Thailand. Therefore, two different sources of soil data are used for this study: FAO World Soil Map and Soilgrid-250-m.

The FAO World Soil Map in the scale of 1:5.000.000 [3] was provided in digital form by [16]. The soil properties of the dominant soil type were processed and made directly useable with SWAT by [17]. Fig. 5 shows the FAO soil map of the Upper Yom Basin. Soils are classified as Orthic Acrisols with fine texture (60.93%), Ferric Acrisols (22.73%), Gleyic Luvisols (10.25%), Dystric Nitosols (6.07%) and Orthic Acrisols with medium texture (0.01%). Most of the soil units fall in the hydrological group D, some in hydrological group C.

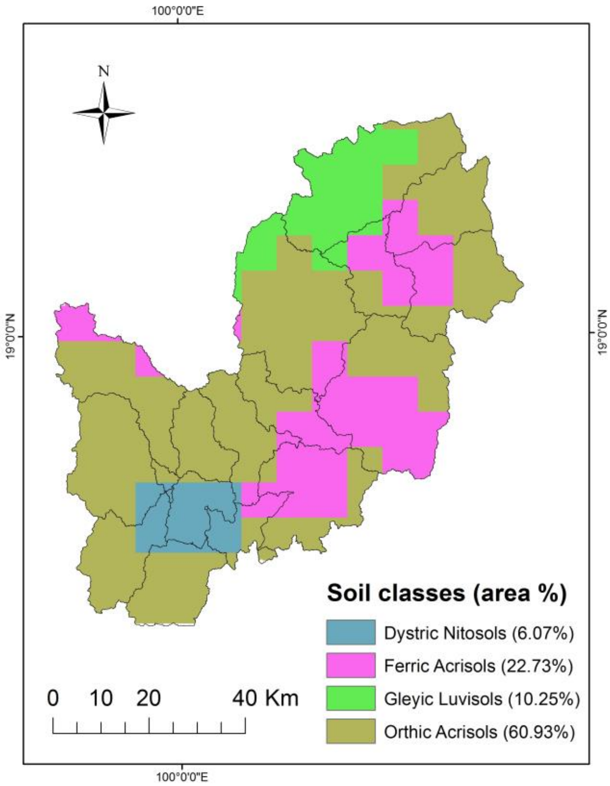

Fig.5. FAO Soil classes for Upper Yom Basin.

Soilgrids is a soil mapping system based on global soil data using machine learning algorithms [18]. Soilgrids data are available worldwide at 250 m spatial resolution in 7 depths from 0 to 200 cm. Gridded data for clay, silt and sand content, bulk density, organic carbon, soil depth and stone content were used. Due to limitations in calculation time, SWAT cannot run for every 250-m grid cell in larger regions. Therefore, the Soilgrids data must be aggregated to space units having homogeneous properties. As soil texture (particularly clay content) and soil depths are very important soil parameters for water and sediment flux, these parameters were used to group the data into new units. This was done with a python script in ArcGIS in the following sequence [19]:

- The clay content of the first 4 Soilgrids layers (0-30 cm depths) was averaged for each grid cell to get an average topsoil clay content;
- The topsoil clay content was reclassified into three

groups (lowest third, medium third, and highest third);

● The rooting depth was classified into three classes: shallow (<110 cm) medium (110-150 cm) and deep (>150 cm);

● The reclassified topsoil clay content and rooting depth were intersected in ArcGIS

● Zones of adjoining grid cells were constructed having the same reclassified topsoil clay content and rooting depth; these zones were considered as homogenous soil units

● For each of these homogeneous zones the average values of clay, silt, sand content, available water content and Ksat were calculated as averages for the topsoil (0-30 cm) and the subsoil (30 – 100 cm). Also, the depth was calculated for each soil unit.

The resulting map classifies soils in different soil entities, where the most dominant types are the units YOM0023 (75.76%), the YOM1024 (7.6%), and the YOM1149 (3.75%). The remaining soil units have a very small percentage (Fig. 6). Most of the soil units fall in the hydrological group D (about 85%) followed by group C (about 15%). The procedure to extract relevant data for ArcSWAT from the SOILGRID data is described by [19].

2.4 Model performance

Three statistical measures were employed to evaluate the performance of SWAT in terms of the accuracy and consistency on the prediction of discharge and sediment load: the coefficient of determination (R^2), Nash-Sutcliff efficiency (NSE), and Root Mean Squared Error (RMSE).

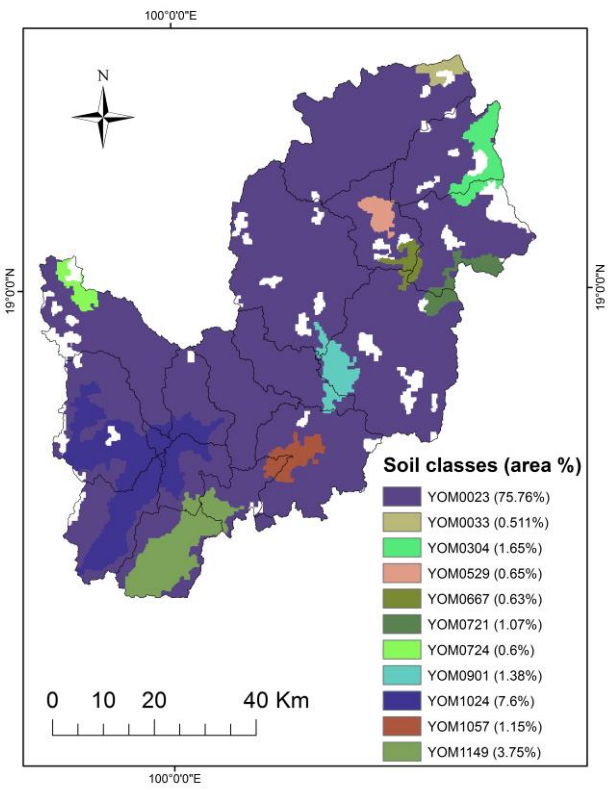

Fig. 6. Soilgrid classes for Upper Yom Basin.

The coefficient of determination (R^2) describes the degree of collinearity between simulated and measured data. R^2 has been widely used for model evaluation. R^2 ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable [20].

Nash-Sutcliffe coefficient (NSE) is a statistical measure that determines the relative magnitude of the residual variance compared to the measured data variance by [21]. NSE ranges between -∞ and 1.0, with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance [21].

The root mean square error (RMSE) has been used as a standard statistical metric to measure model prediction error in meteorology, air quality, and climate research studies; a smaller RMSE value indicates better model performance [22]. RMSE is one of the commonly used error index statistics according to [23].

3. RESULTS AND DISCUSSIONS

3.1 Sensitivity Analysis

A sensitivity analysis for the simulation period from 2003 to 2013 was conducted for streamflow and suspended sediments. Since streamflow is the main controlling variable, sensitivity analysis and calibration were done first [24] followed by suspended sediments.

13 parameters for streamflow and 9 parameters for sediment were selected based on studies of [25] and [26] using default simulations based on FAO and Soilgrids data. From the 13 parameters for streamflow, 8 and 10 parameters for FAO and Soilgrids data (Table 1), respectively, were identified as statistically significant and were finally used to calibrate and validate streamflow.

For suspended sediments, 4 parameters for FAO and Soilgrids were statistically significant and finally used to calibrate and validate suspended sediments (Table 2).

3.2 Model Calibration and Validation

The SWAT model was calibrated for streamflow for 7 years from 2003 to 2009 for both FAO and Soilgrids data separately. Validation was carried out for 4 years from 2010 to 2013. Monthly measured streamflow data at basin outlet was used for calibration and validation. Default values and calibration results for streamflow based on FAO and Soilgrids data are given in table 2.

Fig. 7 shows the calibration results for streamflow for the calibration period. Simulated streamflow after model agreed very well with the measured data based on the two soil datasets. However, statistical measures show that the streamflow simulated with FAO soil data were slightly better than those based on Soilgrids (equal R^2 and slightly better NSE and RMSE for FAO (Table 3). Fig. 8 shows the streamflow for the validation period. The statistical results show that R^2 is slightly better for Soilgrids data, but NSE and RMSE are again slightly better for FAO data. However, both data sources provide a satisfactory validation although FAO data generally give a slightly better results

Suspended sediments simulation show that the model predicted very similar monthly suspended sediments both soil data, both for the calibration period (Fig. 9) and the validation period (Fig. 10). Similar to streamflow simulation, the results for suspended sediments simulation were slightly better based on FAO data compared to Soilgrids data (Table 4). Similar to streamflow, the results for suspended sediments show that both data provide a satisfactory validation, although FAO data gave a slightly better results (NSE 0.87 for FAO and 0.77 for Soilgrids data for the validation period, Table 4).

Table 1. Sensitive parameters for streamflow for FAO (8) and Soilgrids (10) soil data with their default and calibrated values

No	Parameter	Default	Calibrated value	
			FAO	SoilGrid
1	CN2	77	79.54	68.24
2	ALPHA_BNK	0	0.28	0.48
3	ESCO	0.95	Not used	0.92
4	SOL_K	3.83	5.36	5.18
5	SOL_BD	1.34	1.30	0.96
6	SOL_AWC	0.2	0.66	0.11
7	GWQMN	1000	220.50	493.50
8	CH_K2	0	Not used	166.75
9	GW_REVAP	0.02	0.17	0.02
10	GW_DELAY	31	5.25	4.25

Table 2. The 4 sensitive parameters for suspended sediment with their default and calibrated value using FAO & Soilgrid

No	Parameter	Default	Calibrated value	
			FAO	Soilgrid
1	SPCON	0.0001	0.0001	0.0002
2	SPEXP	1.0000	1.0009	1.0016
3	CH_COV2	0.0000	0.0015	0.0024
4	CN2	77.0000	77.1444	81.5623

Table 3. The performance indexes for calibration and validation streamflow for both FAO and Soilgrid

	Calibration		Validation	
	FAO	Soilgrid	FAO	Soilgrid
R^2	0.90	0.90	0.87	0.91
NSE	0.83	0.72	0.78	0.69
RMSE	0.42	0.53	0.46	0.56

Table 4. The performance indexes for calibration and validation suspended sediment for both FAO and Soilgrid

	Calibration		Validation	
	FAO	Soilgrid	FAO	Soilgrid
R^2	0.90	0.86	0.87	0.77
NSE	0.88	0.81	0.87	0.74
RMSE	0.34	0.44	0.37	0.51

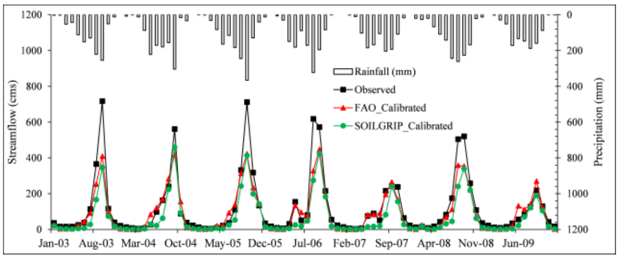

Fig. 7. Comparison of simulated monthly streamflow based on FAO and Soilgrid for calibration period.

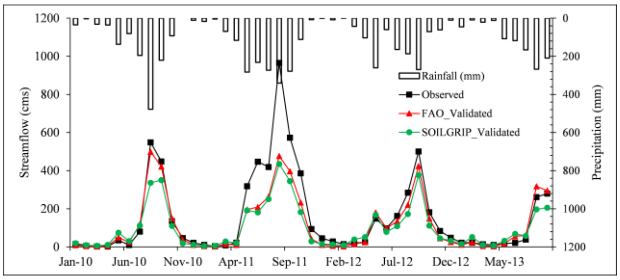

Fig. 8. Comparison of simulated monthly streamflow based on FAO and Soilgrid for validation period.

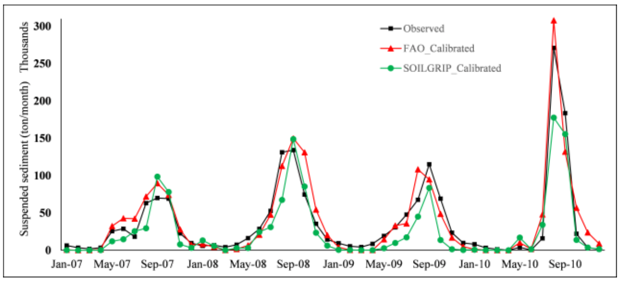

Fig. 9. Comparison of simulated monthly suspended sediment based on FAO and Soilgrid for calibration period.

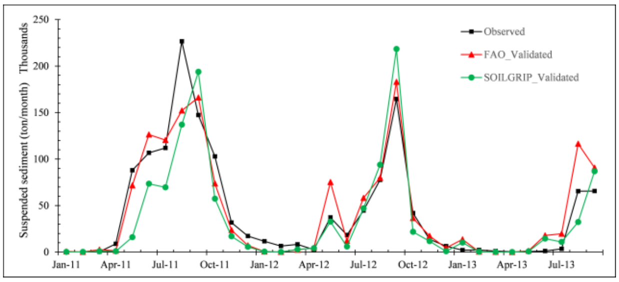

Fig. 10. Comparison of simulated monthly suspended sediment based on FAO and Soilgrid for validation period.

3.3 Differences between FAO and Soilgrids soil data

Generally, one would expect better results using soil information with a higher resolution. In this study, however, the low-resolution FAO data (about 7 km grid size) proved to give slightly better results with SWAT model than the high-resolution Soilgrids data (250 m grid size). The spatial delineation of the FAO soil data is based on FAO soil units, and the soil information used by SWAT is derived for these soil units by [17]. The FAO soil data have been used together with SWAT and the derived soil information has possibly been optimized for the use with SWAT. The Soilgrids data are relatively new, have rarely been used with SWAT and the spatial delineation of soil units to be used with SWAT must be done by the user. In this study, topsoil clay and soil depths were used as main factors to delineate soil units, and some filter procedure was used to eliminate very small soil units. The resulting maps of the soil 4 parameters clay, sand, available water capacity (AWC) and Ksat for the topsoil is shown in Fig. 11. Clay and sand maps for the Upper Yom basin derived fom FAO and Soilgrids data are similar, but the FAO maps show bigger differences for different parts of the basin. The AWC of the Soilgrids data is generally higher compared to the FAO data, and the Ksat is generally lower (Fig. 11). Comparing the mean values of bulk density (DB), AWC, Ksat and Rock fragments (> 2 mm size) for FAO and Soilgrids data for the Upper Yom Basin showed significant differences (Table. 5). Mean values for sand, silt and clay were very similar (Table. 5). The ranges of the soil information, i.e. the span between the lowest and highest value of the selected parameters, were always much larger for the FAO data compared to those of the Soilgrids data (Fig. 11). These differences are the possibly reason for the difference in simulation quality using these soil data with SWAT.

4. SUMMARY AND CONCLUSIONS

This investigation used soil data with different spatial resolutions, i.e. FAO soil data (7 km raster size) and the Soilgrids data (250 m raster size) as the inputs to the SWAT model for simulating streamflow and suspended sediment. After model calibration, streamflow and suspended sediments were simulated sufficiently well with both soil data. Thus, both soil data (FAO and Soilgrids) can be successfully used with SWAT for the Upper Yom Basin.

However, the low-resolution FAO data gave slightly better results than the high-resolution Soilgrids data, which generally was not expected and needs further investigations.

Two strategies for further investigations are proposed: It is necessary to compare FAO and Soilgrids parameters, especially those, which SWAT is sensitive to, with good quality measured soil information to show if there might be a general bias in one of the data sets. This should be done in different catchments with different land uses and different topographic conditions.

As mentioned before, we used clay content and soil depths as main parameters to delineate homogeneous soil units. Another way to optimize the use of Soilgrids data for SWAT is the test of different strategies to produce soil units for SWAT from the Soilgrids data. The basis for the delineation could be WRB soil units (also available in Soilgrids), available water capacity, slope, or other parameters which SWAT is sensitive to. This might result in possibly better results of the Soilgrids data due to its higher resolution.

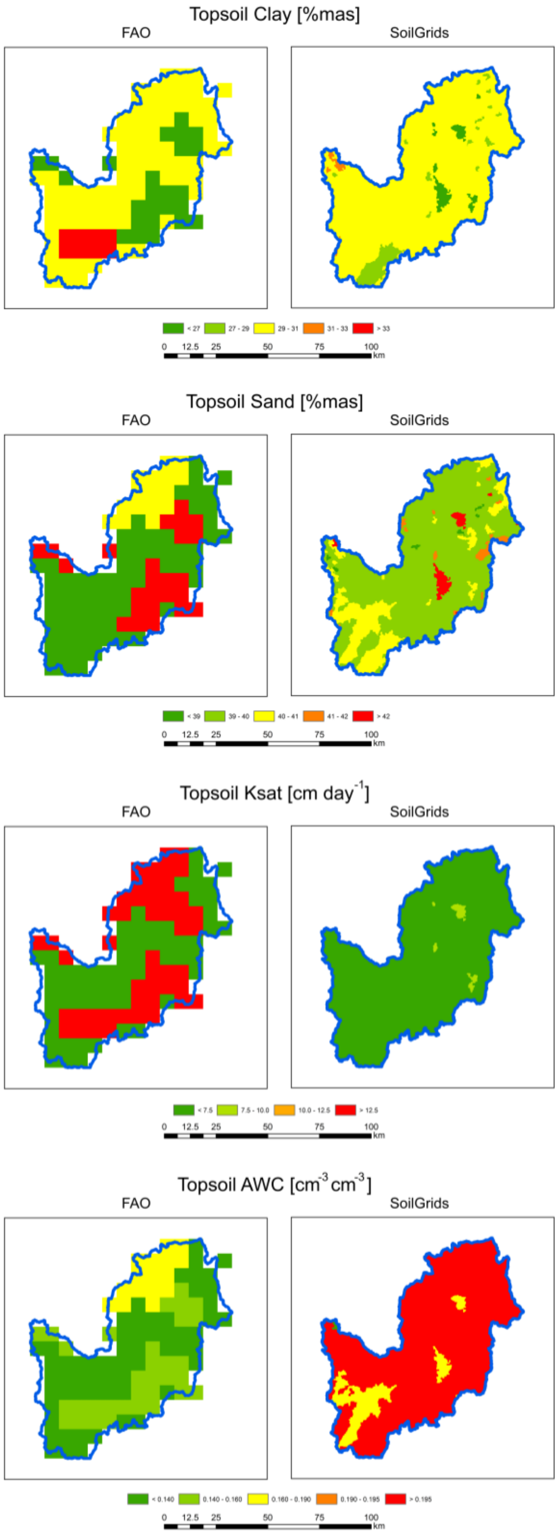

Fig. 11 a-b-c-d. Differences of the soil information derived from FAO and SoilGrids information for Upper Yom Basin.

Table 5. Mean and range of soil parameters of FAO and SoilGrids soil information

Para-meter	unit	FAO		SoilGrids	
		mean	range	mean	range
DB	g cm^{-3}	1.28	1.10-1.40	1.34	1.20-1.43
AWC	$cm^{-3}cm^{-3}$	0.11	0.07-0.18	0.20	0.19-0.20
Ksat	cm day^{-1}	12.57	7.3-23.5	3.90	2.6-9.2
Sand	%mas	43.8	27.0-63.0	40.9	38.9-63.0
Silt	%mas	27.4	19.0-32.0	29.8	26.2-33.2
Clay	%mas	28.2	18.0-41.0	29.4	25.4-31.9
Rock	%mas	0.000	0.000	23.2	10.2-32.4

Lack of good quality soil data is an important problem related to hydrologic modeling in many parts of the world. The availability of data, often downloadable from the internet, such as land use and weather data, is steadily increasing. The demand for hydrologic modeling also steadily increased in the last decades and will very possibly further increase in the fields of drought management and flood disaster control, also due to climate change effects. Good quality soil data are necessary for any simulation. Therefore, further investigations in this respect should be an important field of research.

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