App. Envi. Res. 41(3) (2019): 1-13

Applied Environmental Research

Journal homepage : http://www.tci-thaijo.org/index.php/aer

Estimation of Streamflow with Incomplete Soil Dataset in Krasioa Basin Using Soil-Landscape Evaluation Approach and SWAT Model

Isared Kakarndee[1,2], Ekasit Kositsakulchai[1,3,*]

[1] Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng Saen, Kasetsart University, Nakhon Pathom, Thailand
[2] Department of Civil Engineering Technology, Faculty of Industrial Technology, Valaya Alongkorn Rajabhat University, Pathum Thani, Thailand
[3] Water Engineering and Management Program, Asian Institute of Technology, Pathum Thani, Thailand
[*] Corresponding author: Email: ekasit.k@ku.th

Article History
Submitted: 8 June 2019/ Revision received: 22 July 2019/ Accepted: 30 July 2019/ Published online: 12 September 2019

Abstract

Data on soil properties are indispensable for process-based hydrological modeling. Soil information of Thailand is primarily provided by the Land Development Department (LDD), nevertheless soil property data are available only in arable land whose slope is less than 35%. The steep-slope land was generally labeled as Slope Complex (SC), there is no information available. This paper demonstrated the application of soil-landscape evaluation approach for predicting the missing properties of soil which resulted on enhancement of model performance in streamflow estimation in Krasioa Basin by the Soil and Water Assessment Tool (SWAT) model. The physical properties of soil-soil thickness, fraction of soil particles (clay, sand, organic matter) were predicted using the Soil-Landscape Estimation and Evaluation Program (SLEEP). The additional properties of soil including bulk density, hydraulic conductivity, and available water content were estimated using the pedo-transfer functions (ROSETTA). It was found that SLEEP model could provide consistent information on physical properties of soil. The SWAT model performance in streamflow simulation at the Krasioa Reservoir was improved using the proposed approach. Appropriate model inputs can generate reasonable output. Model performance can further be improved by calibration.

Keywords: Hydrology; Streamflow; Soil-landscape modeling; Pedo-transfer function; SWAT

Introduction

In order to get accurate and close-to-reality in hydrological assessment, spatial input data will determine the parameters that indicate the characteristics of the watershed. Since the soil properties affect hydrological response of the watershed relative to the amount of rainfall, details about them are necessary to examine

https://doi.org/10.35762/AER.2019.41.3.1

with data from the field or methods which are acceptable, before handling the hydrological model of watershed [1]. Physical soil properties are an important factor in controlling the hydrological process and are the key to controlling the parameters used to improve results [2-3]. The accuracy of the soil data determines the likelihood level [4-5]. Therefore, choosing the right soil properties to suit the size and condition of the watershed will result in a reliable streamflow assessment at the desired accuracy level [6].

Currently, geographic information system (GIS) is widely used to increase the spatial ease of field work and analysis in the laboratory [7-8], to distribute spatial soil data, to see the overall picture. These lead to the improved results in the creation of models for watershed management [9]. Statistical models developed by using the relationship between topographic and soil characteristics in areas with similar geological and geographical history, seem to be the right approach for predicting the spatial and understanding the landscape of the earth [10]. In addition, the use of digital elevation model (DEM) combined with satellite image in multiple linear regression models can analyze the spatial distribution of appropriate classification derived from the features [11]. The predicted soil shows a more realistic pattern using the characteristics of the soil obtained from the prediction model as an alternative to soil data [12-13]. The idea behind the Soil-Landscape Estimation and Evaluation Program (SLEEP) tool is to divide the watershed or area into zones or facets according to the average slope parameters and then take a model for each aspect related to soil characteristics to the terrain and environment [14].

The predictive accuracy of the SWAT model depends on whether the input factors describe the spatial characteristics of the watershed [15-18]. Fundamentally, a watershed model aims at minimizing errors in the streamflow estimation comparing with the observation. The estimation errors could be mitigated by defining an appropriate size of sub-watershed which represents the heterogeneous terrain and rainfall pattern [19]. Although reliable results were reported on a yearly and monthly time-step but it is likely that SWAT would be successful in the daily time-step only with GIS technology. The development in techniques and methods for digital soil resource dataset, resulted in the accurate calculation of rainfall-runoff in the basin [20].

In Thailand, the Land Development Department (LDD) conducts soil surveying only in cultivable area where the land slope is less than 35%. The land with slope greater than 35% has not yet been studied or classified because the steep-slope lands are difficult to manage for agriculture. The slope area greater than 35% is generally defined as slope complex (SC), there is no information available. The objectives of this study were, therefore, to apply the SLEEP for predicting the missing soil properties, and to evaluate the performance of SWAT model in estimating streamflow using the predicted soil properties in the Krasioa Basin, Thailand.

Materials and methods

1) Study area

The Krasioa River is a tributary of the Tha Chin River. Its drainage area about 1,327 km^2, lies between latitude 14°41'N and 15°17'N, and longitude 99°20'E and 100°6'E, in 3 provinces including Suphanburi, Kanchanaburi and Uthai Thani (Figure 1). The Krasioa River starts from the mountainous area in Ban Rai, Uthai Thani. The river flows south-eastward to Dan Chang, Suphan Buri and then eastward to join the Tha Chin River at Sam Chuk, Suphanburi, with the total length of 140 km. The altitude of the basin ranges from 6 meters above mean sea level (AMSL) to 1,414 AMSL.

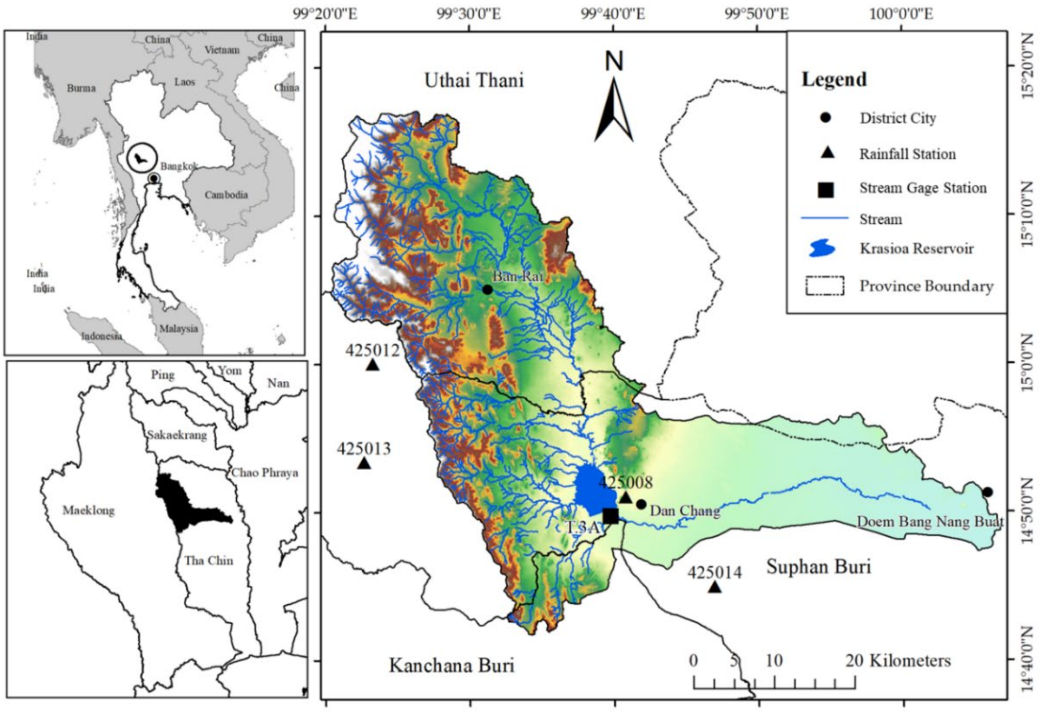


Figure 1 Study area (Krasioa basin, Thailand).

The Krasioa basin is located in the tropical climate region with a clear distinction between wet period from May to October and dry period from November to April. The mean daily temperature varies between 19.5°C and 36.4°C with the lowest in December and the highest in April. The mean daily relative humidity varies between 75.9% and 94.5%. The annual evaporation is about 1,704 mm. The annual rainfall is about 988.1 mm and the annual discharge of the basin is about 95.82 Mm^3.

2) Soil-landscape approach for estimation of soil properties

The SLEEP is a tool designed for helping SWAT users to generate a soil database at sub-catchment level from point field observations, or legacy soil maps. Spatial interpolation of the measured soil attribute is used to provide continuous representation of soil but there are some limitations owing to the non-uniform distribution of soils over an area. It is impractical to measure the soil attributes at each and every point on the earth surface [14]. The SLEEP uses measured soil properties e.g. soil depth, fraction of soil particle (sand, silt, clay), or percentage of organic matter, at different locations in a watershed along with the geographical coordinates of the measurement locations, to produce the spatially distributed soil properties for the whole watershed in the form of raster data [12]. The SLEEP utilizes the DEM and available soil observations to generate spatially continuous layers of soil attributes [11, 13].

ROSETTA model [21] was developed for estimation soil properties based on pedo-transfer functions (PTFs) [22-23] by the Agricultural Research Service (ARS) of the U.S. Department of Agriculture (USDA). ROSETTA uses the following hierarchical sequence of input data: soil texture, fraction of soil particle (sand, silt, clay), and bulk density. The hierarchy in PTFs allows the estimation of van Genuchten's water retention parameters [24] and the saturated hydraulic conductivity using limited input data (textural classes only) to more extended input data, e.g. fraction of soil particle, bulk density, and water retention points (field capacity, permanent wilting point) [21].

3) SWAT model

SWAT is a public domain model developed by a group of scientists from the USDA-Agricultural Research Service; USDA-Natural Resources Conservation Service, and Texas A&M University. SWAT model is a conceptual, time continuous and physically-based simulation model with GIS software as an extension to assist water resource managers in assessing the impact of management and climate on water supplies and non-point source pollution problems for a wide range of scales and environmental conditions across the globe. SWAT divides the watershed into sub-watersheds which are further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics [25]. SWAT is a comprehensive model that requires a diversity of information in order to run [26] and developed in a semi-distributed way, where the catchment is sub-divided into sub-catchments and further sub-divided into hHRUs, and land use, soil and slope can be accounted for by the model [27]. The SWAT model uses a daily time step and is able to conduct continuous simulations over long time periods [28]. SWAT is based on the principle that the water balance equation as shown in Eq. 1.

$$SW_t = SW_0 + \sum_{t=i}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \quad \text{(Eq. 1)}$$

where SW_t is the final soil water content (mm), SW_0 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).

The surface runoff is predicted by SCS Curve Number (CN) equation (Eq. 2).

$$Q_{surf} = \frac{\left(R_{day} - I_a\right)^2}{R_{day} - I_a - S}, \mathrm{R}_{day} > I_a \quad \text{(Eq. 2)}$$

where Q_{surf} is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm) S is the initial obstructions (surface storage, interception, and infiltration prior to runoff) (mm), I_a is the retention parameter (mm).

The retention parameter varies spatially due to soil, land use, management and slope changes (Eq. 3), and varies temporally due to changes in soil water content.

$$S = \frac{25400}{CN} - 254 \quad \text{(Eq. 3)}$$

where CN is the curve number corresponding to soil type, land use and land management conditions [29].

4) Model performance evaluation

The performance of the model was evaluated in order to assess how the model simulated values fitted with the observed values. Several statistical measures are available for evaluating the performance of a hydrological model such as percentage bias (PBIAS, Eq. 4), coefficient of determination (R^2, Eq. 5) and the Nash-Sutcliff efficiency coefficient (NSE, Eq. 6). PBIAS, R^2 and NSE can be used to determine how well the model simulates the average magnitudes for the output response of interest, is useful for continuous long-term simulations, can help identify average model simulation bias (over prediction vs. under prediction), and can incorporate measurement uncertainty [30]. R^2 widely used in hydrological modeling studies, thus serving as a benchmark for performance evaluation. R^2 over sensitive to high extreme values and insensitive to additive and proportional differences between model predictions and measured data. For a good agreement, the intercept should be close to zero and the gradient should be close to one [31]. NSE values can range between negative infinite and one [32].

$$PBIAS = \left(\frac{\sum_{i=1}^{n} O_{(i)} - \sum_{i=1}^{n} P_{(i)}}{\sum_{i=1}^{n} O_{(i)}} \right) \times 100 \qquad \text{(Eq. 4)}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(O_{(i)} - \bar{O}_{(i)}\right)\left(P_{(i)} - \bar{P}_{(i)}\right)}{\sqrt{\sum_{i=1}^{n} \left(O_{(i)} - \bar{O}_{(i)}\right)^2} \sqrt{\sum_{i=1}^{n} \left(P_{(i)} - \bar{P}_{(i)}\right)^2}} \right)^2 \qquad \text{(Eq. 5)}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} \left(O_i - P_i\right)^2}{\sum_{i=1}^{n} \left(O_i - \bar{O}_i\right)^2} \qquad \text{(Eq. 6)}$$

where $P_{(i)}$ is the simulated flow (m^3 s^{-1}), is the observed flow (m^3 s^{-1}) and is the number of data.

5) Data used

Climatic data were necessary to simulate runoff processes in the watershed. The available data from the Thai Meteorological Department (TMD) included relative humidity, maximum and minimum temperature, wind speed and solar radiation (sunshine hours). Rainfall and streamflow from 1982 to 2000 can be retrieved from the Royal Irrigation Department (RID). Rainfall stations close to the study area were selected.

The spatial data are also required for SWAT model setup. DEM with a spatial resolution of 90 m, was downloaded from http://www.srtm.csi.cgiar.org. It was used to delineate the watershed boundary, to define the drainage patterns, and to calculate slopes of the study area and channels. Soil and land use maps were obtained from the LDD. Satellite images can be downloaded from https://earthexplorer.usgs.gov/; band 4 (Red) and band 5 (NIR) of Landsat-8 were used in this study.

6) Methodology

The methodology included: (1) the development of regression model based on soil-landscape approach by SLEEP model and pedo-transfer functions by ROSETTA for predicting the missing data on soil properties; (2) the set-up of SWAT-based hydrological model for streamflow simulation; and (3) the evaluation of model performance on streamflow estimation at Krasioa Reservoir. The overall methodology was shown in Figure 2.

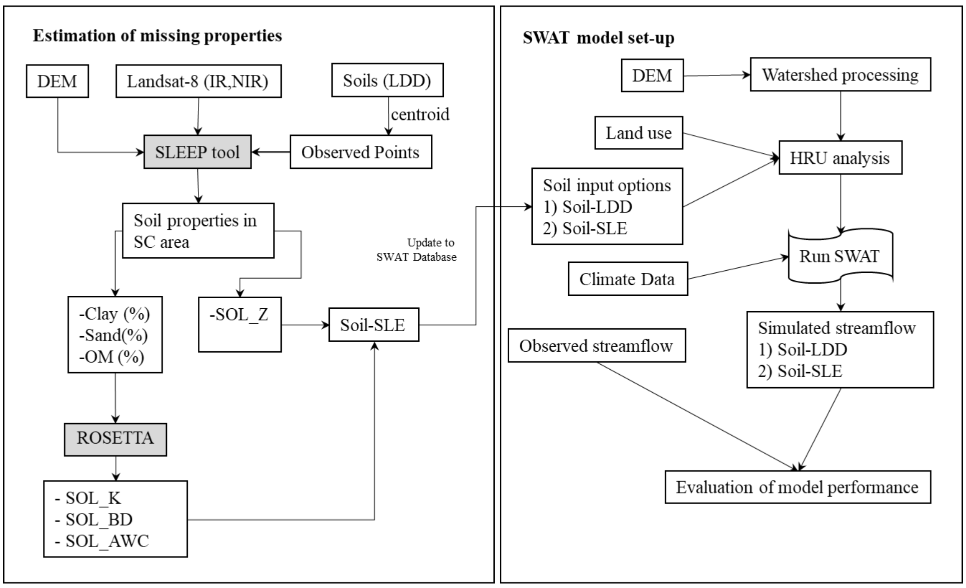


Figure 2 The overall methodology.

6.1) Estimation of missing soil properties

The first step was to develop a spatial regression model based on soil-landscape evaluation approach using SLEEP tool. The regression model was applied for prediction of soil physical properties of the SC in Krasioa basin. The required data for SLEEP including DEM, NDVI, and observed soil properties. DEM was used to delineate the watershed, to define the drainage patterns, and to estimate slopes of watershed and of channels. NDVI was calculated from band 4 (Red) and band 5 (NIR) of Landsat-8. The observed soil properties were extracted from attributes of the LDD soil map. The centroids of polygon were selected as the point location of observation with the total of 4,056 points. Next, the data points were divided into 2 sets: one for parameter estimation and another for validation. With the utilities of SLEEP tool, one regression equation was generated for predicting one desired soil property. In this study, we developed equations for the thickness of soil layer, the fraction of sand particle, the fraction of clay particle, and the percentage of organic matter.

In the next step, the others required soil-water properties for SWAT model were estimated by the ROSETTA model based on pedo-transfer functions (PTFs) using soil particle fraction (sand, silt, clay) and organic matter [23]. The required soil-water properties included the saturated hydraulic conductivity (SOL_K), the bulk density (SOL_BD), and the available water content (SOL_AWC). At this step, the soil map, fulfilled with the predicted data from soil-landscape evaluation (SOIL-SLE) was prepared.

6.2) SWAT model setup

In order to evaluate the SWAT model performance in estimating streamflow from the predicted soil properties. SWAT model was set up into 2 input options: Soil-LDD and Soil-SLE. The first option assumed the missing properties of Slope Complex to be those of medium texture (Soil-LDD), while the spatial soil properties predicted from soil-landscape evaluation and PTFs were used in the second option (Soil-SLE).

The SWAT model set-up comprised several steps, i.e. data preparation, watershed delineation, HRU definition, definition of weather stations, and edition of model database. The DEM, land use and soil maps of the study area were prepared. DEM was used in the watershed delineation. The study selected the threshold for stream definition of 25 km^2. This process resulted 39 sub-basins in the upstream of Krasioa Reservoir (Supplementary material (SM) 1). In this study, the multiple HRUs with the threshold of 5% land use, 5% soil, and 10% slope were selected. After the HRUs definition, the Soil-LDD option possessed 264 HRUs, while the Soil-SLE option 587 HRUs. The increasing in number of HRUs may be due to more soil classes in the Soil-SLE map.

Time series covering the period from January 1982 to December 2000 were selected at 3 climatic stations: Suphanburi, Uthai Thani and Kanchanaburi. Daily rainfall and others climate data (wind speed, maximum and minimum temperature, relative humidity and sunshine hours) were available. The estimated inflow into Krasioa Reservoir from 1982 to 2000 was used as the observed streamflow in Krasioa River. The observed data were used for evaluating performance indicators, i.e. PBIAS, R^2 and NSE. SWAT model run on daily time step from January 1982 to December 2000. The results were aggregated into monthly time step and evaluated with monthly observed data in this study.

Results and discussion

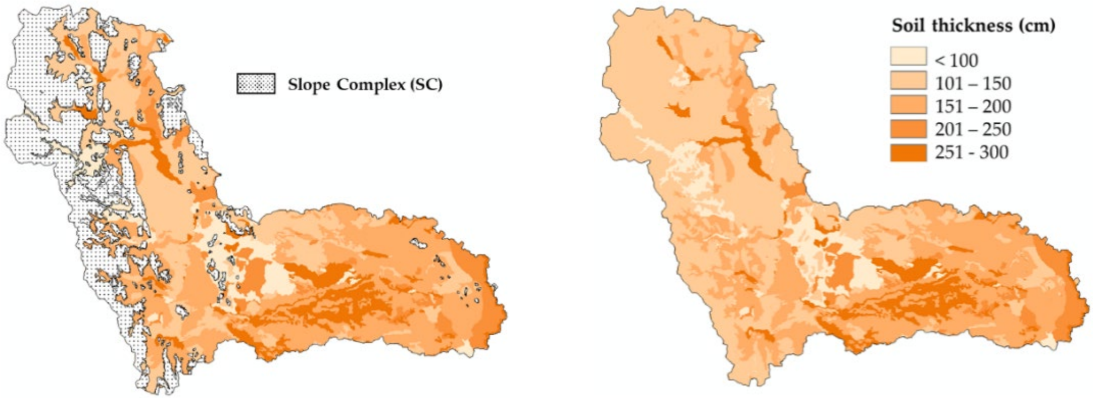
1) Estimation of missing soil properties

The physical properties of soil, predicted by SLEEP tool, included the thickness of soil layer (Figure 3), the percentage of organic matter

(Figure 4), the fraction of clay particle (Figure 5), and the fraction of sand particle (Figure 6). The maps on the left side of Figure 3(a) to Figure 6(a) showed the coverage of the SC where data were not available. The predicted data by SLEEP were shown on the right hand side of map in Figure 3(b) to Figure 6(b).

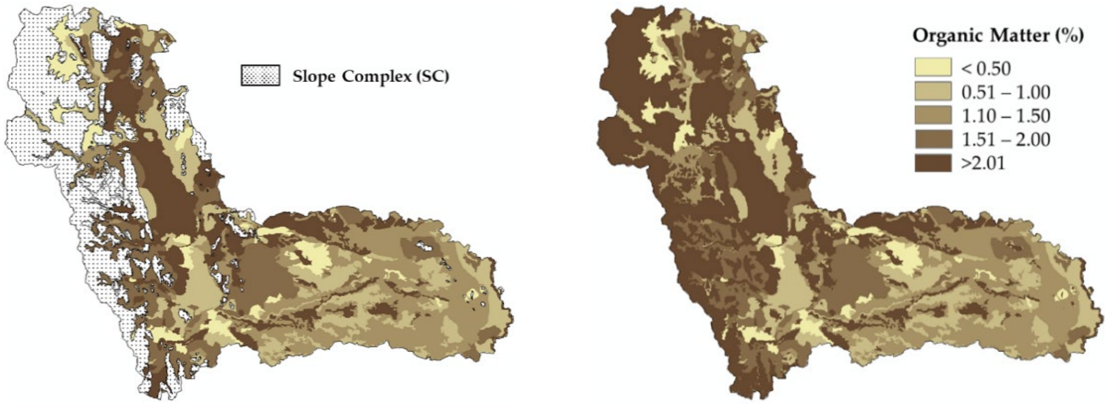
The physical properties of soil predicted using the SLEEP included the soil thickness in cm, percent of organic matter (OM), fraction of clay particle (CLAY), and fraction of sand particle (SAND) (SM 2). The soil thickness varied between 88 cm and 233 cm, OM between 0.27% and 4.80%, CLAY between 1.18% and 84.27%, and SAND between 0.67% and 89.50%.

The prediction properties of soil (Soil-SLE) were compared with the pre-selected observation points from LDD soil map (Figure 7). The scatter plots of the properties of Soil-LDD data and those of Soil-SLE prediction were considered to be a validation of the regression equations of soil properties. The soil properties included: soil thickness (Figure 7(a)), OM (Figure 7(b)), CLAY (Figure 7(c)), and SAND (Figure 7(d)). Soil thickness showed a good correlation with R^2 of 0.88. Percentage of OM was somewhat good correlation (R^2=0.77). CLAY and SAND presented relatively poor correlation with the R^2 of 0.34 and 0.44, respectively. From the scatter plot (Figure 7(c) and (d)), more deviation from the predicted lines can be observed when the fractions are high. The percentage of silt fraction can be calculated from the residual of CLAY, SAND and OM fraction.



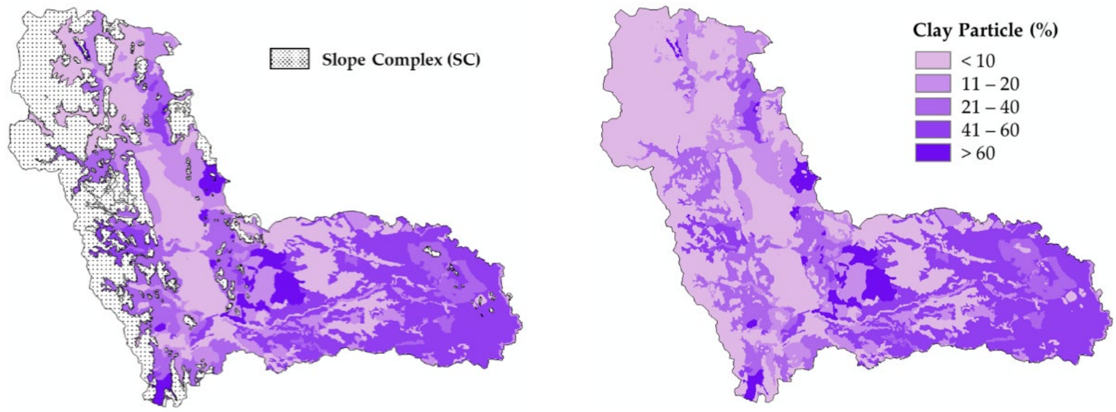
(a) LDD data (b) SLEEP prediction

Figure 3 Pictures showing soil thickness (cm) from the (a) LDD data and (b) SLEEP prediction.



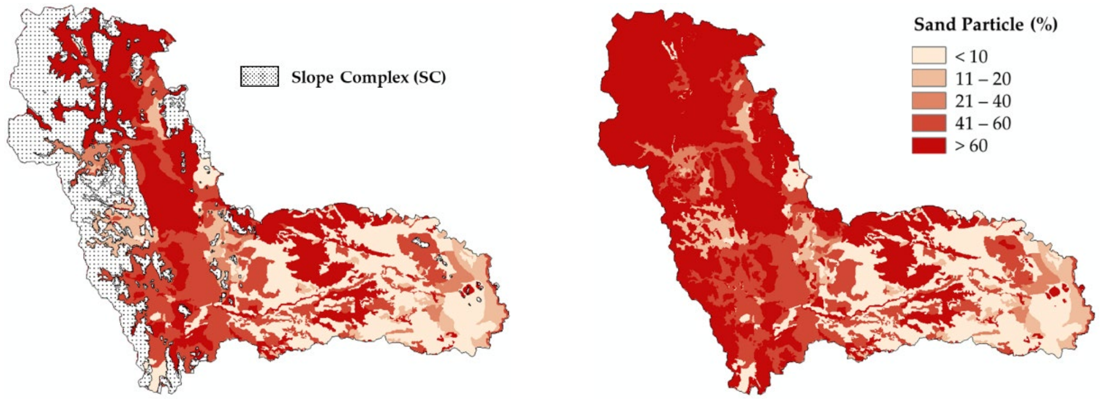
(a) LDD data (b) SLEEP prediction

Figure 4 Pictures showing organic matter (%) from the (a) LDD data and (b) SLEEP prediction.



(a) LDD data (b) SLEEP prediction

Figure 5 Pictures showing fraction of clay particle (%) from the (a) LDD data and (b) SLEEP prediction.



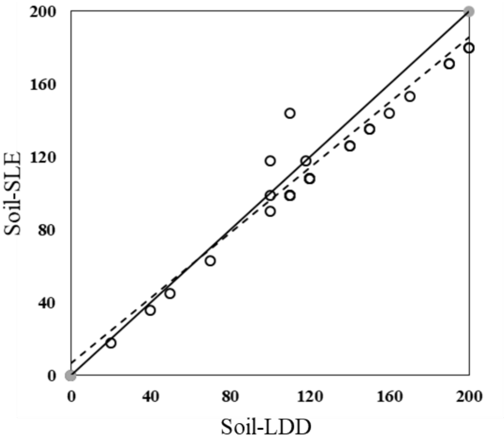
(a) LDD data (b) SLEEP prediction

Figure 6 Pictures showing sand particle (%) from the (a) LDD data and (b) SLEEP prediction.

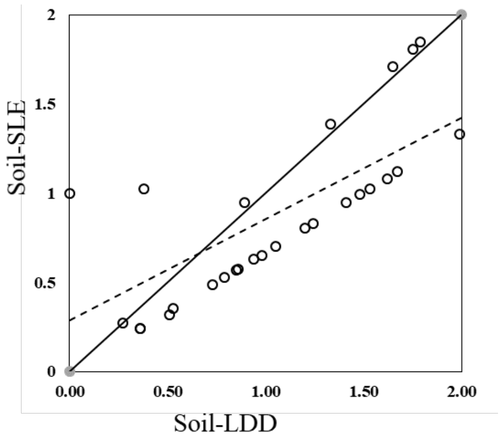
The fractions of soil particle are the key information in the prediction of soil-water properties by the PTFs (SM 3). The predicted soil-water properties included the bulk density in g cm^{-3} (BD), the available water content (AWC) in mm mm^{-1}, and the saturated hydraulic conductivity in mm h^{-1} (SOL_K). The BD varied between 1.35 g cm^{-3} and 1.65 g cm^{-3}, the AWC between 0.13 mm mm^{-1} and 0.19 mm mm^{-1}, and the SOL_K between 2 mm h^{-1} and 420 mm h^{-1}. The hydraulic properties of soil-AWC, or SOL_K depend highly on the heterogeneity of soil properties and management conditions. The spatial linear regression used by SLEEP was unsuccessful to consistently predict highly non-linear hydraulic properties of soil. The well-grounded method, PTFs [21-22] is a better alternative.

The properties of soil in the SC were predicted (SM 4). These data were defined as the input options in SWAT model: (a) constant properties assumed as medium texture in LDD dataset (Soil-LDD), and (b) spatial properties predicted by the soil-landscape evaluation approach (Soil-SLE).

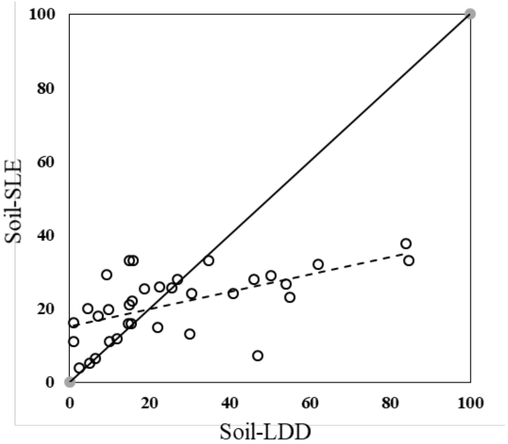
The complete mapping of soil properties can be achieved by the SLEEP coupling with the ROSETTA. However, not all types of soil property can be accurately predicted by the soil-landscape approach. The soil thickness and the percentage of organic matter provided satisfactory results with R^2 about 0.8, while fractions of clay and sand remained mediocre. Spatial linear regression model was unsuccessful to consistently predict the hydraulic properties of soil. The PTFs method using soil particle fraction is recommended.



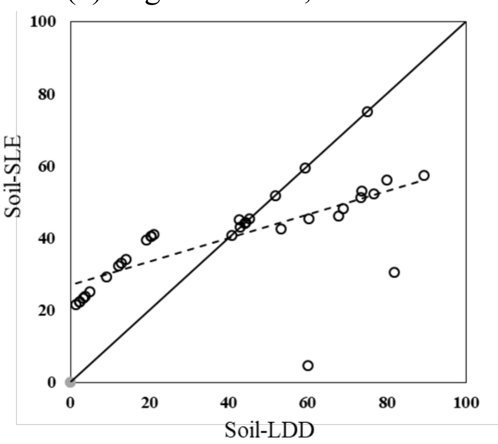
(a) Soil thickness, R^2=0.88



(b) Organic matter, R^2=0.77



(c) Clay fraction, R^2=0.34



(d) Sand fraction, R^2=0.44

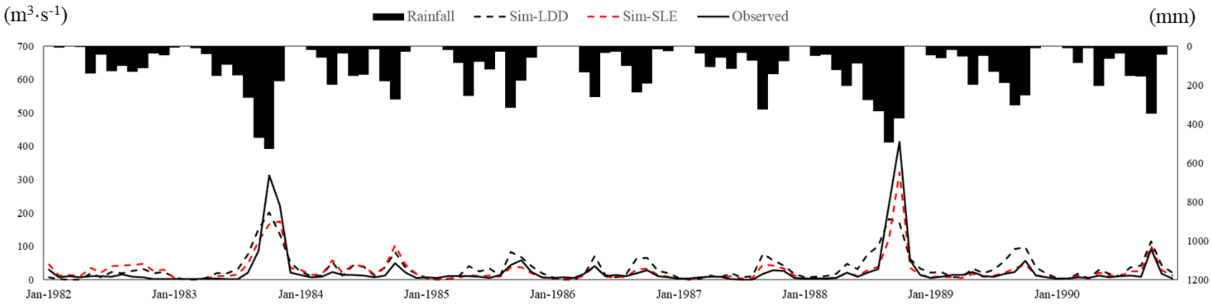
Figure 7 Scatter plots between the properties of Soil-LDD data and those of Soil-SLE prediction: (a) soil thickness (cm), (b) organic matter (%), (c) fraction of clay particle (%), and (d) fraction of sand particle (%).

2) Evaluation of SWAT model performance

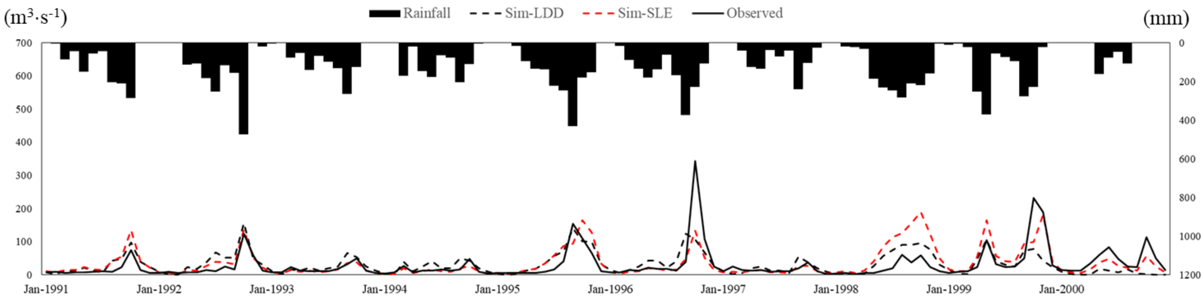
SWAT model was executed using different soil inputs: Soil-LDD and Soil-SLE. Figure 8 showed the streamflow hydrographs at the Krasioa Reservoir from 1982 to 1990 (Figure 8(a)) and from 1991 to 2000 (Figure 8(b)). The observed data estimated from water balance analysis at the the Krasioa Reservoir (black solid line). The simulated hydrographs were calculated by SWAT model using the Soil-LDD input (black dashed line) and the Soil-SLE input (red dashed line). Figure 9 showed the scatter plot between the observation and the simulations (Soil-LDD input in circle and the Soil-SLE input in triangle). Trend line of the Soil-LDD input showed in black dashed line and that of the Soil-SLE input in red dashed line. The model performance was summarized in Table 1. The indicators included R^2 and NSE, and PBIAS.

Table 1 Performance of SWAT model in simulation of streamflow at Krasioa Reservoir using different soil inputs (Soil-LDD and Soil-SLE)

Performance indicator	Soil-LDD	Soil-SLE
R^2	0.51	0.62
NSE	0.50	0.60
PBIAS (%)	+16.85	+17.27



(a) 1982 to 1990



(b) 1991 to 2000

Figure 8 Comparisons of streamflow at Krasioa Reservoir between the observation and the simulation by SWAT using different inputs (Soil-LDD and Soil-SLE).

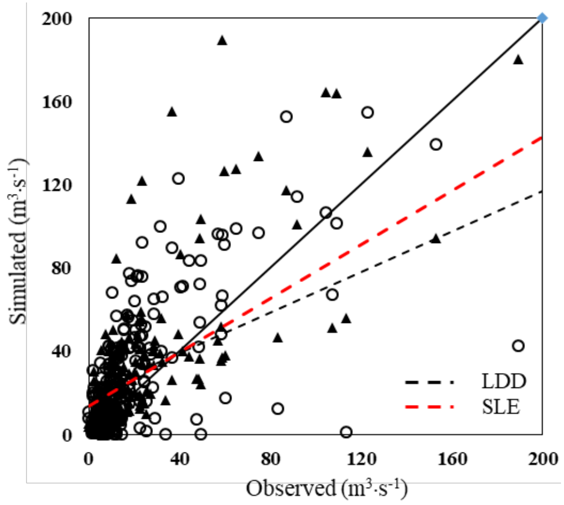


Figure 9 Scatter plots between the observed streamflow at Krasioa Reservoir and the simulated streamflow by SWAT using different inputs (Soil-LDD and Soil-SLE).

Streamflow simulation using properties of medium soil texture (Soil-LDD) presented somewhat acceptable without model calibration (R^2 and NSE>0.5, PBIAS<25) [28]. Positive values of PBIAS indicated model underestimation bias [33]. The systematic prediction of soil properties (Soil-SLE) showed an improvement on model performance ($R^2$and NSE>0.6); all indicators of model performance were increased. The model would attain the optimal performance when the R^2 and NSE are close to 1 [32], while the PBIAS is close to 0.

The preparation of input data in SWAT modeling is tremendous task. The physical and hydraulic properties of soil are indispensable for process-based hydrological model. The SLEEP coupling with the pedo-transfer functions (ROSETTA) can fulfill the requirements. The appropriate data for model inputs generate reasonable output. Model performance can further be improved by calibration [34].

Conclusions

This paper demonstrated the application of soil-landscape evaluation approach for predicting the missing physical properties of soil which resulted on enhancement of model performance in streamflow estimation by process-based hydrological model. The physical properties of soil, predicted by SLEEP, included soil thickness, fraction of soil particles (clay, sand, organic matter). The additional properties of soil (bulk density, hydraulic conductivity, available water content) were estimated using pedo-transfer function (PTF) by ROSETTA. The SLEEP models showed satisfactory performance in predicting soil thickness and the percentage of organic matter, but relatively poor in predicting the fractions of clay and sand. The spatially predicted soil properties improved the performance of SWAT model for streamflow estimation at the Krasioa Reservoir. Streamflow simulation using assumed medium texture (Soil-LDD) presented somewhat acceptable without model calibration (R^2 and NSE>0.5). A systematic prediction of soil properties showed an improvement on model performance (R^2 and NSE>0.6). The soil-landscape approach coupling with the pedo-transfer functions can fulfil the required data for hydrological simulation by SWAT model.

Acknowledgements

This research was supported by grants from the Faculty of Engineering at Kamphaeng Saen and the Graduate School, Kasetsart University, Thailand. The authors would also like to express their gratitude to developers of the SLEEP, ROSETTA and SWAT models for granting the licenses for this research.

References

[1] Manus, C., Anquetin, S., Braud, I., Vandervaere, J.P., Creutin, J.D., Viallet, P., Gaume, E. A modeling approach to assess the hydrological response of small mediterranean catchments to the variability of soil characteristics in a context of extreme events. Hydrology and Earth System Sciences Discussions, 2009, 13, 79-97.

[2] Moore, I.D., Gessler, P., Nielsen, G., Peterson, G. Soil attribute prediction using terrain analysis. Soil Science Society of America Journal, 1993, 57, 443-452.

[3] Merz, J., Mosley, M.P. Hydrological behaviour of pastoral hill country modified by extensive landsliding, northern Hawke's Bay, New Zealand. Journal of Hydrology New Zealand, 1998, 37, 113-139.

[4] Bouma, J. The role of soil science in the land use negotiation process. Soil use and management, 2001, 17, 1-6.

[5] Gassman, P.W., Sadeghi, A.M., Srinivasan, R. Applications of the SWAT model special section: Overview and insights. Journal of Environmental Quality, 2014, 43, 1-8.

[6] Li, X., Zhang, Q., Ye, X. Effects of spatial information of soil physical properties on hydrological modeling based on a distributed hydrological model. Chinese Geographical Science, 2013, 23, 182-193.

[7] McBratney, A.B., Mendonça Santos, M.L., Minasny, B. On digital soil mapping. Geoderma, 2003, 117, 3-52.

[8] Lamsal, S., Grunwald, S., Bruland, G.L., Bliss, C.M., Comerford, N.B. Regional hybrid geospatial modeling of soil nitrate-nitrogen in the Santa Fe River Watershed. Geoderma, 2006, 135, 233-247.

[9] Tavares, W.F., Julich, S., Nunes, J.P., Gonzalez-Pelayo, O., Hawtree, D., Feger, K.H., Keizer, J.J. Combining digital soil mapping and hydrological modeling in a data scarce watershed in north-central Portugal. Geoderma, 2016, 264, 350-362.

[10] Gessler, P.E., Moore, I.D., McKenzie, N.J., Ryan, P.J. Soil-landscape modelling and spatial prediction of soil attributes. International Journal of Geographical Information Systems, 1995, 9, 421-432.

[11] Mehammednur, S.N., Yitaferu, B., Kibret, K., Ziadat, F. Soil-landscape modeling and remote sensing to provide spatial representation of soil attributes for an Ethiopian Watershed. Applied and Environmental Soil Science, 2013, 2013, 1-11.

[12] Ziadat, F.M. Analyzing digital terrain attributes to predict soil attributes for a relatively large area. Soil Science Society of America Journal, 2005, 69.

[13] Ziadat, F.M. Land suitability classification using different sources of information: Soil maps and predicted soil attributes in Jordan. Geoderma, 2007, 140, 73-80.

[14] Ziadat, F.M., Yeganantham, D., Shoemate, D., Srinivasan, R., Narasimhan, B., Tech, J. Soil-landscape estimation and evaluation program (SLEEP) to predict spatial distribution of soil attributes for environmental modeling. International Journal of Agricultural and Biological Engineering, 2015, 8, 158-172.

[15] Boluwade, A., Madramootoo, C. Modeling the impacts of spatial heterogeneity in the castor watershed on runoff, sediment, and phosphorus loss using SWAT: I. Impacts of spatial variability of soil properties. Water, Air, & Soil Pollution, 2013, 224, p1692.

[16] Bossa, A., Diekkrüger, B., Igué, A., Gaiser, T. Analyzing the effects of different soil databases on modeling of hydrological processes and sediment yield in Benin (West Africa). Geoderma, 2012, 173, 61-74.

[17] Moriasi, D., Starks, P. Effects of the resolution of soil dataset and precipitation dataset on SWAT2005 streamflow calibration parameters and simulation accuracy. Journal of Soil and Water Conservation, 2010, 65, 63-78.

[18] Li, R., Zhu, A.X., Song, X., Li, B., Pei, T., Qin, C. Effects of spatial aggregation of soil spatial information on watershed hydrological modelling. Hydrological Processes, 2012, 26, 1390-1404.

[19] Kimala, V., Kositsakulchai, E. Estimation of streamflow by SWAT model in Sedon River Basin, Lao PDR. In Proceedings of PAWEES 2012 International Conference Thailand, 2012, 38-49.

[20] Ding, W., XiangYang, L. Application of ArcGIS in the calculation of basins rainfall-runoff. Procedia Environmental Sciences, 2011, 10, 1980-1984.

[21] Schaap, M.G., Leij, F.J., Van Genuchten, M.T. Rosetta: A computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. Journal of hydrology, 2001, 251, 163-176.

[22] Pachepsky, Y., Rawls, W.J. Development of pedotransfer functions in soil hydrology, 1st ed.; Elsevier: Amsterdam; Boston, 2004, pp. 512.

[23] Saxton, K.E., Rawls, W.J. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. Soil Science Society of America Journal, 2006, 70, 1569-1569.

[24] van Genuchten, M.T. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils 1. Soil Science Society of America Journal, 1980, 44, 892-898.

[25] Neitsch, S., Arnold, J., Kiniry, J., Williams, J. Soil and water assessment tool theoretical documentation version 2009, Texas Water Resources Institute Technical Report No. 406. System, College Station, 2011.

[26] Neitsch, S., Arnold, J., Kiniry, J., Srinivasan, R., Williams, J. Soil and Water Assessment Tool Input/Output File Documentation Version 2005, Grassland. Soil and Water Research Laboratory Angriculture Research Services & Black Land Research Center Texas Agricultural Experiment station, 2004.

[27] El-Nasr, A.A., Arnold, J.G., Feyen, J., Berlamont, J. Modelling the hydrology of a catchment using a distributed and a semi-distributed model. Hydrological Processes, 2005, 19, 573-587.

[28] Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L. Model evaluation guidelines for systematic quantification of accuracy in watershed

simulations. Transactions of the ASABE, 2007, 50, 885-900.

[29] Soulis, K.X., Valiantzas, J.D. SCS-CN parameter determination using rainfall-runoff data in heterogeneous watersheds - the two-CN system approach. Hydrology and Earth System Sciences, 2012, 16, 1001-1015.

[30] Harmel, R.D., Smith, P.K., Migliaccio, K.W. Modifying goodness-of-fit indicators to incorporate both measurement and model uncertainty in model calibration and validation. Transactions of the ASABE, 2010, 53, 55-63.

[31] Krause-Buchholz, U., Schobel, K., Lauffer, S., Rodel, G. Saccharomyces cerevisiae translational activator Cbs1p is associated with translationally active mitochondrial ribosomes. Biological Chemistry, 2005, 386, 407-415.

[32] Nash, J.E., Sutcliffe, J.V. River flow forecasting through conceptual models part I-A discussion of principles. Journal of Hydrology, 1970, 10, 282-290.

[33] Gupta, H.V., Sorooshian, S., Yapo, P.O. Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. Journal of Hydrologic Engineering, 1999, 4, 135-143.

[34] Abbaspour, K.C. SWAT-CUP: SWAT calibration and uncertainty programs - A user manual; Swiss Federal Institute of Aquatic Science and Technology (Eawag), 2015.