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Research article

Performance of AnnAGNPS model in predicting runoff and sediment yields in Nan Province, Thailand

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ABSTRACT

Land use changes such as deforestation and urban development influences the river discharge, soil erosion and sediment yield. It is important to evaluate tools which can be used to assess such impacts on water and sediment yield. Therefore, this study evaluated the Annualized Agricultural Non-Point Source Pollutant (AnnAGNPS) model's performance in simulating runoff and sediment loads in Nan Province, Thailand using seven years of continuous monitoring data. The river discharge and sediment yield data from 2011–2013 were used for calibration, and data from 2014–2017 were used for validation. Several input parameters were computed using methods suggested by other researchers and previous studies. In this study, the runoff curve number, soil erodibility factor (K), and RUSLE-C value were used to accurately simulate runoff and sediment loads. The results indicate that the model satisfactorily simulated runoff and sediment loads (R^2 = 0.65 and NSE = 0.53 for runoff volume, and R^2 = 0.62 and NSE = 0.60 for sediment yields). Moreover, the model estimated the total sediment yield, which contributed 12,932 hundred tons of material to the Nan River in 2017. The maximum sediment yield was obtained below the catchment (Na Noi sub-district, Na Noi district), which corresponds to areas with high crop densities. Cropland generated the highest soil erosion of all investigated land use (87.52% of total soil erosion). Thus, the AnnAGNPS model has the potential to use for investigating management practices to reduce soil erosion and controlling floods and droughts in Nan Province of Thailand.

1. Introduction

Nan Province is located in the northern Thailand. Approximately 85% of the province's total land area is mountainous, while lowland areas located in the central part of the province account for only 2.51% (Kitchaicharoen et al., 2015). A slope map generated from elevation maps shows that Nan Province has slope gradients ranging from 0 to >35% and is composed of lowlands, uplands, and highlands. The Nan River, whose watershed originates in this province and which flows southward to the Sirikit dam, joins with other rivers to form the Chao Phraya River. The Chao Phraya River is the main river in Thailand, contributing 45% of the total river volume (Kajitvichyanukul et al., 2012), and is used for agriculture and daily life. Agriculture, particularly maize cultivation, is the major source of income for the local people in Nan Province; however, areas suitable for agriculture are limited in this region.

Maize is a commercial crop grown by local farmers in Nan Province. Maize cultivation has expanded rapidly, more than doubling from 576.26 km^2 (with a production of 230,000 tons) in 2007 to 1,366 km^2 (with a production of 451,802 tons) in 2016 (Office of Agricultural Economics, 2017). Presently, Nan Province has the second largest maize crop area in Thailand (Office of Agricultural Economics, 2017). However, agricultural areas represent only 12% of the province's total land area (Nan Provincial Labour Office, 2017). Therefore, maize crop areas have extended onto steep slopes in the uplands and are a primary reason for recent decreases in natural forest areas. Maize cultivation in the uplands of Nan Province has a variety of potential impacts, including soil erosion on slopes and high areas (if watershed forests are damaged, soil erosion can increase by as much as tenfold), sedimentation of water courses, nutrient loss from soil, landslides, and flash floods (Achavanuntakul et al., 2013). Moreover, other land use changes, such as deforestation and urban development, are also responsible for highland erosion.

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Highland erosion and sediment production can be simulated using numerical models. Hydrological models are a suitable tool and are increasingly used to support environmental exposure and risk assessments, water and environmental resource management, and decision-making (Abbaspour et al., 2015; Devia et al., 2015; Bouslihim et al., 2016). Several hydrological models have been developed to assist in understanding hydrological systems, sediment transport, and pollutant loading. These range from simple planning models, such as the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), to complex hydrological processing models, such as Chemical, Runoff, and Erosion from Agricultural Management Systems (CREAMS) (Knisel, 1980), Area Nonpoint Source Watershed Environment Response Simulation (ANSWERS) (Beasley et al., 1980), Erosion Productivity Impact Calculator (EPIC) (Williams et al., 1884), Groundwater Loading of Agricultural Management Systems (GLEAMS) (Leonard et al., 1987), Agricultural Non-Point Source Pollution Model (AGNPS) (Young et al., 1989), Pesticide Fate and Dynamics in the Environment (PESTFADE) (Clemente et al., 1993), Dynamic Watershed Simulation Model (DWSM) (Borah et al., 2002), Soil and Water Assessment Tool (SWAT) (Arnold et al., 2012), and many others. Detailed reviews of many hydrological models at the watershed-level have summarized model strengths and limitations in terms of erosion and sediment transport modeling (Borah and Bera, 2003; Merritt et al., 2003). The differences between these models depend on their complexities, the processes considered, and the data required for model calibration and validation. Because there is no single best model for all applications, the most suitable model will depend on its intended use and the characteristics of the watershed being studied.

The Annualized Agricultural Non-point Source Pollutant (AnnAGNPS) model is a simulation tool that can be used to evaluate the effects of land use and management activities on watershed hydrology and sediment transport (Bingner et al., 2015). The model was built as a series of interconnected modules by integrating different models (USDA, 2019). The model operates on a daily time step and enables analyses at any location in the watershed. The AnnAGNPS model has been successfully applied to simulate hydrology and sediment, nutrient, and pesticide transport in watersheds of various sizes (Shrestha et al., 2006; Licciardello et al., 2007; Shamshad et al., 2008; Chahor et al., 2014; Luo et al., 2015; Karki et al., 2017), while other models can only address a few of these components. While AnnAGNPS can be applied on a long-term continuous basis to watersheds with areas up to 3,000 km^2 (Young et al., 1989), most of its previous applications have involved relatively small watersheds (0.3–125 km^2). Further, studies that have applied the AnnAGNPS model in Thailand are scarce. One such study was conducted on the Songkhla Lake basin, which covers an area of 1,042 km^2 (Kitbamroong et al., 2010); however, only the curve number value was calibrated. Another study analyzed the Ping watershed, which has an area of 722 km^2 (Punbune, 2007) and included short-term calibration and validation phases (2002–2003 for calibration and 2004 for validation). Thus, the present study aimed to evaluate the performance of the AnnAGNPS model for conditions in Thailand at larger scales (i.e., 11,000 km^2, scale of Nan Province).

This study aimed at preparing a database to simulate runoff and suspended sediment transport using the AnnAGNPS model and to calibrate and validate the model for the Nan watershed in Thailand. This study addressed the following research questions: (a) How accurately does the AnnAGNPS model simulate runoff and sediment loads in a mountainous region of a tropical country? Testing this question is of crucial interest to water management, in that a large region comprised of various mixed land use types was investigated. (b) How much of the sediment load is contributed to the tributaries of the Nan River? (c) Where is most of the sediment produced? The results of this study support water quality management for sustainability and the assessment of watershed areas in Thailand and in other Southeast Asian countries with similar environmental conditions.

2. Materials and methods

2.1. Study area

The upper Nan watershed is located in Thailand's Nan Province (Figure 1a) between 17°89′ N–19°37′ N and between 100°24′ E–101°06′ E. The watershed covers an area of approximately 11,000 km^2, with elevations ranging from 124 to 2,057 m above mean sea level. Nan Province has slope gradients ranging from 0 to 300% (Figure 1b) and consists of lowlands (slope <2%), uplands (slopes between 2 and 25%), and highlands (slope >25%) (Kitchaicharoen et al., 2015). Most of the province is comprised of upland and highland areas.

The upper part of the Nan watershed has a tropical savanna climate (Kitchaicharoen et al., 2015). Winters are dry and very warm, lasting from November to February, with an average temperature range of 15–31 °C. Summers are very hot, lasting from late February to the middle of May, with an average temperature range of 21–35 °C. The monsoon season extends from late May to the end of October, with heavy rain and somewhat cooler temperatures during the day, although nights remain warm, with an average temperature range of 23–32 °C. The annual rainfall is approximately 1,243.1 mm (Kitchaicharoen et al., 2015).

Given the prevalence of highland and mountainous areas in this region, the regional watershed includes several rivers and branches. The longest river in the watershed is the Nan River, which flows through Nan Province and joins other rivers to form the Chao Phraya River. The soil depth in the watershed ranges from shallow to deep, with a low to very-low pH, moderate to good drainage, low soil, and a high potential for soil erosion on sloping land (Kitchaicharoen et al., 2015). Based on the 2012 land use map (Figure 2a) generated by the Land Development Department of the Ministry of Agriculture and Cooperatives, forests covered the largest area (62.20%), followed by maize fields (23.64%), other agricultural land (11.4%), and pastures (0.34%). Agriculture has long been the basin's main economic activity, accounting for 35.1% of the overall land use.

2.2. AnnAGNPS input preparation

2.2.1. Hydrological and sediment-load data

The measured daily runoff data along the Nan River at stations N.1 and N.13a (Figure 1a) were provided by the Upper Northern Region Irrigation Hydrology Center of Thailand's Bureau of Water Management and Hydrology Royal Irrigation Department. Daily sediment load data from station N.1 were obtained from the same source.

2.2.2. Digital elevation model

A digital elevation model (DEM) with a 30-m resolution was obtained from the United States Geological Survey for the upper Nan watershed (USGS, 2017). The DEM was run in the TOPAGNPS program of the AnnAGNPS model to calculate the stream network or reach, to delineate the basin or cell, and to generate data for the AnnAGNPS input file, including cell area and cell slope. The values of the critical source area (CSA) and minimum source channel length (MSCL) were set to 6000 ha and 7000 m, respectively, which divided the flow network into 68 reaches and the basin into 168 cells (Figure 2b).

2.2.3. Climate data

The AnnAGNPS model requires a climate file that describes daily climate data. Specific required inputs included maximum and minimum daily temperatures, daily precipitation, the average daily dew point, sky cover, and wind speed. Climate data for 2011–2017 from four meteorological stations within the study area, including Thung Chang, Tha Wangpha, Nan Agrometeorological, and Nan stations, were provided by the Thai Meteorological Department. Thiessen polygons were used to

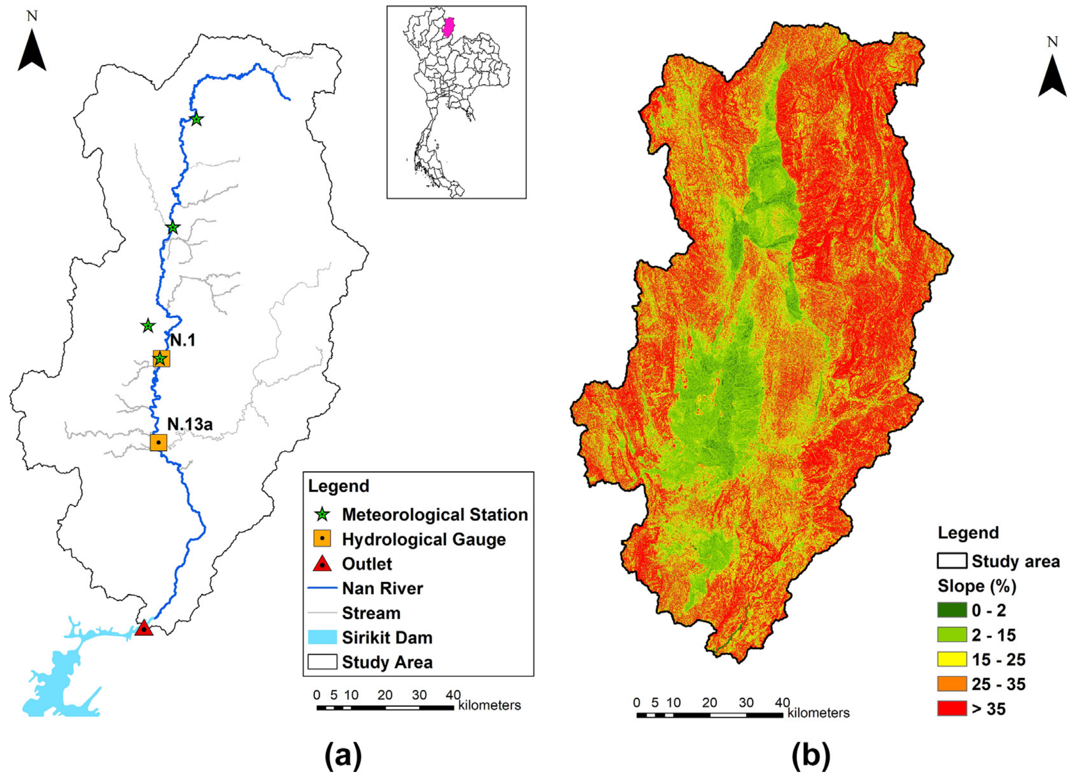

Figure 1. (a) Upper Nan watershed, including the locations of meteorological stations, hydrological gauges, and the outlet; (b) slope map of the study area.

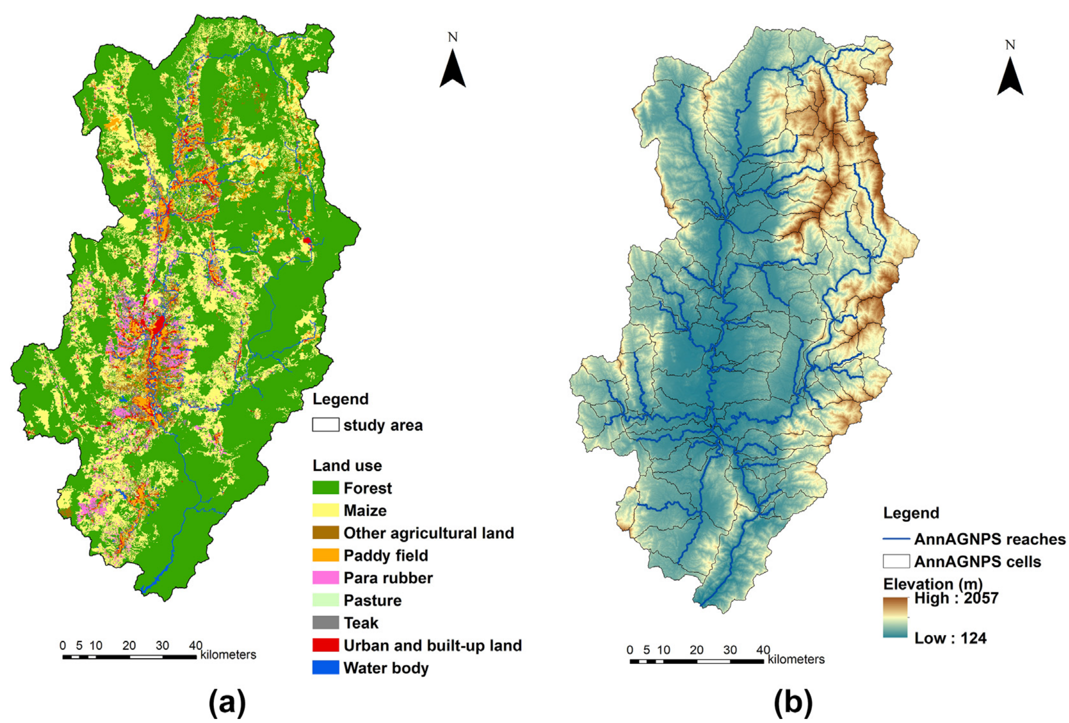

Figure 2. (a) Land use map of the upper Nan watershed; (b) AnnAGNPS cells and reaches of the upper Nan River watershed.

calculate the spatial distributions of the climate data from the gauge stations in the watershed.

2.2.4. Soil data

Soil files, which consisted of descriptions of soil texture, depth, particle size fraction, bulk density, pH, organic matter content, saturated conductivity, field capacity, wilting point, and soil structure, were used in the AnnAGNPS model. The soil data were provided by the Land Development Department (LDD), Thailand. The soil in the study area consisted of 46 major soil types that varied from sandy loams to clays (Figure 3a). Moreover, a hydrologic soil group map is shown in Figure 3b.

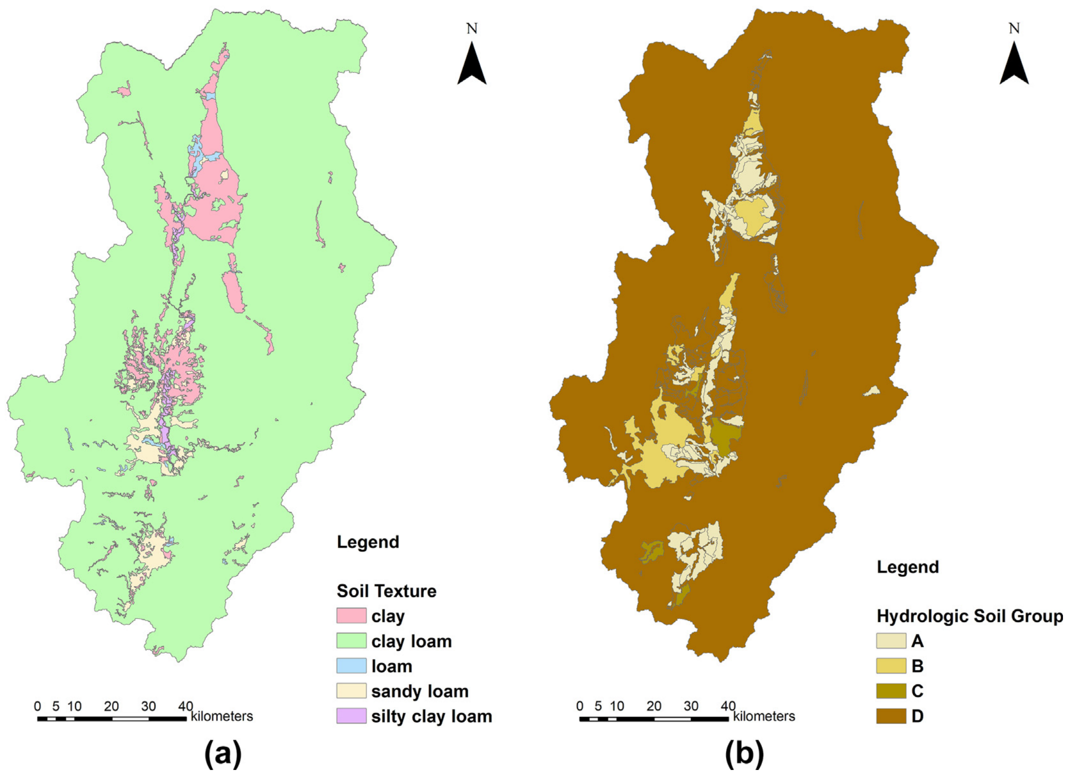

Figure 3. (a) Soil texture map of the study area; (b) Hydrologic soil group of the upper Nan watershed.

2.2.5. Land use data

The 2012 land use map (Figure 2a) obtained from the Land Development Department of Thailand's Ministry of Agriculture and Co-operatives, while data of field operation, field management, crop, and non-crop obtained from field observations by the technical staff of the Nan Land Development Station, Nan Agricultural Research and Development Centre, the Nan Provincial Agricultural Extension Office, and by interviewing local farmers (Table 1).

2.3. AnnAGNPS model

The AnnAGNPS is a distributed parameter, physically based, continuous-simulation watershed-scale model based on the single event model (Bingner et al., 2015). The USDA Agricultural Research Service (ARS) and the Natural Resources Conservation Service (NRCS) developed the model to evaluate the impacts of agricultural non-point source pollution on watershed hydrology and sediment transport (Bingner et al., 2015). The AnnAGNPS model simulates surface water and sediment export through the channel network of a watershed, the reaches of the model, at a daily time step (Bingner et al., 2015). The model operates using a cellular approach, in which the watershed is divided into grid cells that are homogeneous in terms of their soil type, land use, and land management (Bingner et al., 2015). These interconnected cells define a network of channels and reaches in which water and sediment are transported. Cells and reaches are generated from a digital elevation model of the catchment using TOPAGNPS, which provides all of the required topographic information (Bingner et al., 2015).

Surface runoff was simulated using the Soil Conservation Service curve number (CN) method (USDA, 1986). A reference CN was assigned for each type of field operation, and the CN was then modified by the model based on the soil moisture condition. After that, the modified curve number was used to calculate the retention time (Eq. (1)), and the runoff was calculated using Eq. (2).

$$S = 254\left(\frac{100}{CN} - 1\right) \tag{1}$$

$$Q = \frac{(WI - 0.2S)^2}{WI + 0.8S} \tag{2}$$

where S is the retention parameter (mm), CN is the curve number, Q is the runoff (mm), and WI is the water input to the soil (mm).

The revised universal soil loss equation (RUSLE) was used to estimate the sheet and rill sediment of each cell (Renard et al., 1997). The RUSLE is given in Eq. (3) as:

$$A = R \times K \times LS \times C \times P \tag{3}$$

where A is the rate of soil loss in tons/ha/y, R is the rain fall runoff erosivity factor, K is the soil erodibility factor, L is the slope length factor, S is the slope steepness factor, C is the cover management factor, and P is the support practice factor.

Because RUSLE estimates the amount of erosion but does not consider the transport of eroded particles, the hydro-geomorphic universal soil loss equation (HUSLE) was used (Bingner and Theurer, 2016). The HUSLE considers the particle size and fall velocity of five classes of eroded particles (clay, silt, sand, small aggregates, and large aggregates) to predict the transport of particles from one point to another. The amount of sediment loading can be determined by considering stream reach, sediment transport capacity, and sediment deposition. The HUSLE is given in Eq. (4) (Theurer and Clarke, 1991) as:

$$S_y = 0.22 \times Q^{0.68} \times q_p^{0.95} KLSCP \tag{4}$$

where S_y is the sediment yield (Mg/ha), Q is the surface runoff volume (mm), q_p is the peak surface runoff rate in mm/s, and K, L, S, C, and P are the RUSLE factors defined above.

Table 1. Management schedules and operations identified in the upper Nan watershed.

Management Schedule	Event Date (Day/Month)	Management Operation	Non-Crop/Crops
Maize fields	4/30	Burn stubble	Maize
	6/1	Planting	
	6/2	Spray glyphosate	
	6/8	Spray atrazine	
	7/1	Fertilize	
	10/1	Harvest	
Paddy fields	4/1	Tillage	Rice
	6/1	Planting	
	7/1	Fertilize	
	10/1	Harvest	
Orchards	9/1	Tillage/Planting	Fruit
	1/1	Harvest	
	4/1	Fertilize	
	6/1	Fertilize	
	1/1	Fertilize	
	4/1	Fertilize	
	6/1	Fertilize	
	7/1	Harvest	
Forest			Forest
Urban			Residential

In this study, runoff and suspended sediment were simulated using the AnnAGNPS model version 5.45 (Figure 4).

2.4. RUSLE factors

The simulation-period data file requires the use of the rainfall runoff erosivity factor (R) (Figure 5a). R can be calculated from the average annual precipitation and can be used to assess the relative erosion rates for different water management, crop, and soil conditions (Renard and Freimund, 1994). The mathematical expression of R (Srikhajon et al., 1994) is given in Eq. (5) as:

$$R-factor = 0.4669P - 12.1415 \tag{5}$$

where R is the rainfall runoff erosivity factor (MJ mm ha^{-1} h^{-1} year^{-1}) and P is the mean annual precipitation (mm).

The AnnAGNPS model requires the use of the 10-year frequency storm erosion index (EI_{10}). This value was calculated using Eq. (6) (Renard and Freimund, 1994):

$$EI_{10} = 5.954(R-factor)^{0.6987} \tag{6}$$

Further, the soil erodibility factor or K-factor must be included in the data file (Figure 5b). Soil series in the study area were obtained from the Land Development Department, and the erodibility index was calculated for each soil series using Eq. (7) (Lal, 1994):

$$K = 2.8\left(10^{-7}\right)\left(M^{1.14}\right)(12-a) + 4.3\left(10^{-3}\right)(b-2) + 3.3\left(10^{-3}\right)(c-3) \tag{7}$$

where K is the soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1}), M is the particle size parameter [(%silt + %VSF)*(100 – %clay)], a is organic matter (%), b is the soil structure code (very fine granular = 1; fine granular = 2; medium or coarse granular = 3; blocky, platy or massive = 4), and c is the profile permeability class (rapid = 1; moderate to rapid = 2; moderate = 3; slow to moderate = 4; slow = 5 and very slow = 6).

In the upper Nan watershed, soil erodibility factors were identified for 46 major soil series. The Chiang Rai series had the highest soil erodibility factor ($K = 0.0622$), while the Pak Chong-dark brown variant series had the lowest value ($K = 0.0172$).

The slope length and steepness (LS) factor of each AnnAGNPS cell was derived from the DEM via the TOPAGNPS module (Figure 5c). The cover management factor (C) and practice support factor (P) were determined within AnnAGNPS using the provided field management, field operation, and crop and non-crop data. The C values ranged from 0.24–0.7 for cropland and from 0.001–0.01 for non-cropland (Figure 5d). The P-factor values ranged from 0.7–1.0 (Figure 5e).

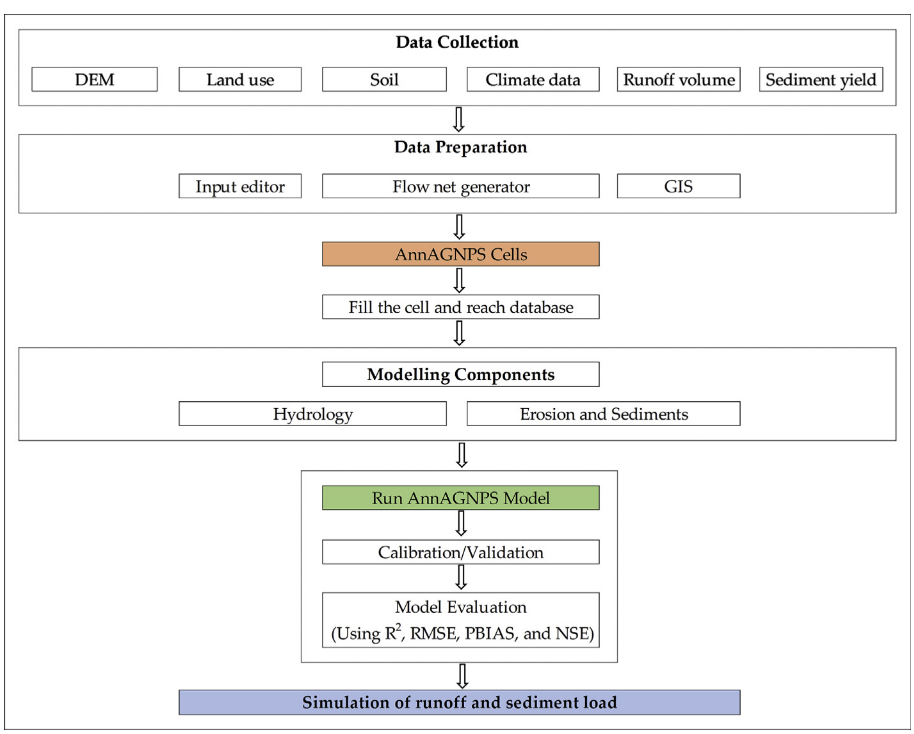

Figure 4. Framework for the application and evaluation of the performance of AnnAGNPS in simulating runoff and sediment loads in Nan Province.

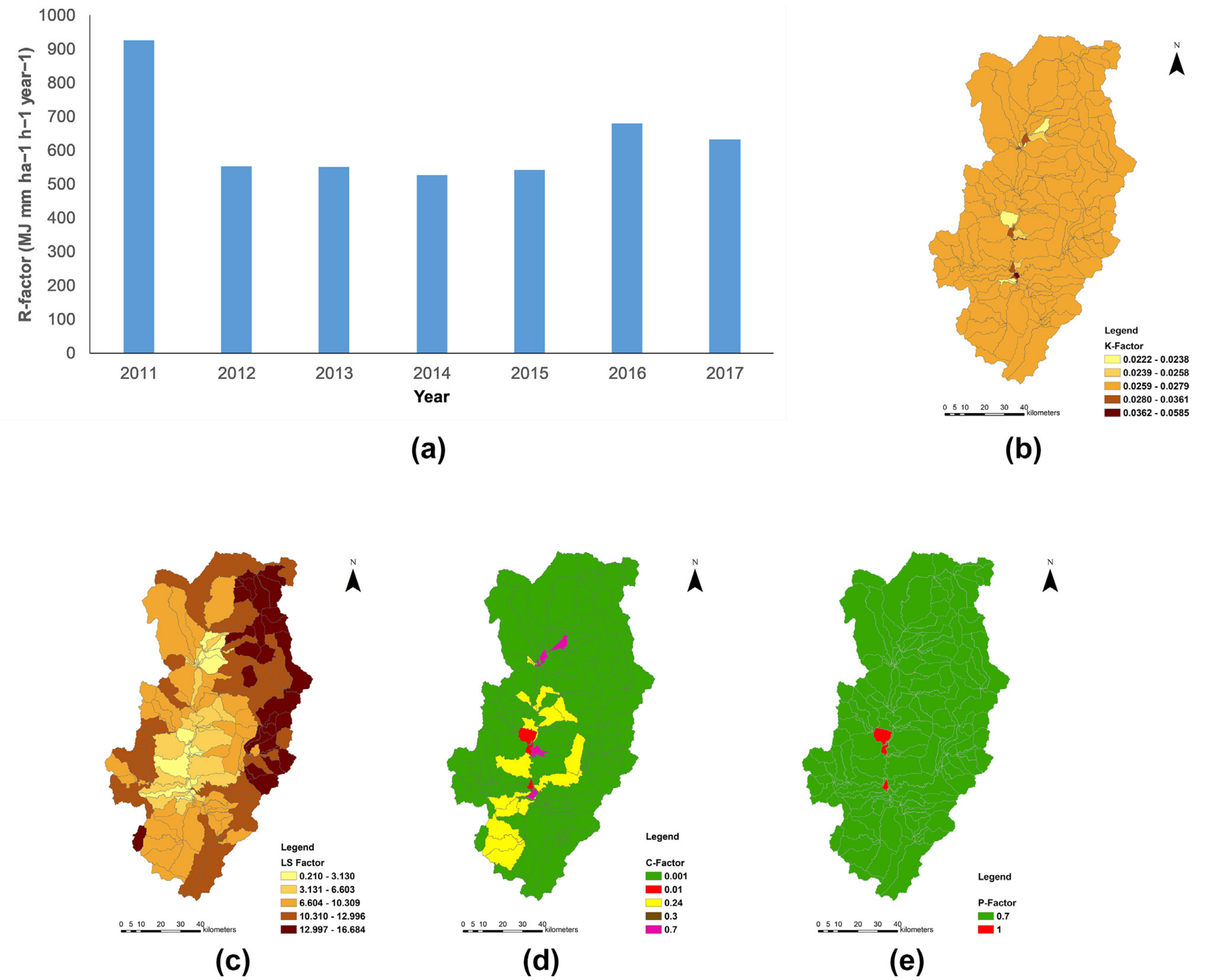

Figure 5. Datasets for factors (a) R; (b) K; (c) LS; (d) C; and (e) P after filling the cell and reach database.

2.5. Model calibration and validation

In this study, the model was calibrated using runoff volume and suspended sediment export data acquired from 2011 to 2013, whereas data from 2014 to 2017 were used for model validation. Hydrological model calibration is a hierarchical process, which begins at runoff calibration, followed by the calibration of the sediment load. This order was also followed in this study. Calibration was performed on a daily scale.

Most of the previous studies that have evaluated the AnnAGNPS model (Shrestha et al., 2006; Licciardello et al., 2007; Shamshad et al., 2008; Chahor et al., 2014; Luo et al., 2015; Karki et al., 2017) found that CN was the most sensitive input parameter for surface runoff prediction. In this study, we successfully calibrated the AnnAGNPS model for runoff simulation by adjusting the CN values (Table 2). The initial CN was adopted from TR-55 (USDA, 1986), based on land use and soil hydrological group.

Most studies of sediment simulation using AnnAGNPS have performed model calibration by adjusting different AnnAGNPS input parameters without a sensitivity analysis, either by modifying the surface roughness (Shrestha et al., 2006), Manning's roughness coefficients (Shrestha et al., 2006), Manning's sheet and reach coefficients and the support practice factor (RUSLE-P) (Luo et al., 2015), or root mass, crop residue, and canopy cover (Licciardello et al., 2007; Luo et al., 2015; Sarangi et al., 2007). However, some studies have performed sensitivity analyses that involved various input parameters, such as soil erodibility factor (*K*) and RUSLE-C or RUSLE-P (Das et al., 2008). These parameters represent both susceptibility of soil to erosion and the rate runoff rate, reflect the effect of cropping and management practices on erosion rates,

Table 2. Uncalibrated and calibrated runoff curve numbers (CNs).

Hydrological soil group	Uncalibrated CN				Calibrated CN			
	Forest	Pasture	Urban	Cropland	Forest	Pasture	Urban	Cropland
A	30	39	77	67	38	49	96	84
B	55	61	85	78	69	76	100	98
C	70	74	90	85	88	93	100	100
D	77	80	92	89	96	100	100	100

Table 3. Model parameters used for suspended sediment calibration.

Model Parameters	Values before calibration	Values after calibration
Soil-erodibility factor (K)	0.0222–0.0585	0.0177–0.0468 (20% decrease)
RUSLE-C of maize	0.24	0.06

and reflect the impact of support practices and the average annual erosion rate, respectively.

In this study, the soil-erodibility factor (*K*) and RUSLE-C input parameters were adjusted to predict the sediment loads (Table 3) without a sensitivity analysis.

2.6. Model evaluation

Modeling results for runoff and suspended sediment loads during the calibration and validation phases were compared with measured values. The results of the predicted runoff volumes were evaluated at stations N.1 and N.13A, and those for suspended sediment exports were assessed at station N.1. This evaluation was performed at a daily time scale using both qualitative and quantitative assessments. The qualitative evaluation consisted of a graphical comparison of the observed and simulated values, while statistical criteria were used for the quantitative assessment: coefficient of determination (R^2), root mean square error (RMSE), percent bias (PBIAS), and Nash-Sutcliffe coefficient of efficiency (NSE).

Percent bias (PBIAS) measures the average tendency of the predicted data to be under- or overestimated compared to the observed data (Gupta et al., 1999). The optimal value of PBIAS is 0, with a negative value indicating a model bias towards overestimation, and a positive value indicating a bias towards underestimation (Gupta et al., 1999). Very good, good, satisfactory, and unsatisfactory results for runoff prediction are considered to be PBIAS $<\pm10$, $\pm10 \leq$PBIAS $<\pm15$, $\pm15 \leq$ PBIAS $<\pm25$, and PBIAS $\geq\pm25$, respectively, and PBIAS $<\pm15$, $\pm15 \leq$ PBIAS $<\pm30$, $\pm30 \leq$ PBIAS $<\pm55$, and PBIAS $\geq\pm55$, respectively, for the equivalent sediment load predictions (Moriasi et al., 2007).

The Nash–Sutcliffe coefficient of efficiency (NSE) estimates the level of agreement between the simulated and observed values and how well the plot of the observed versus predicted values fits the 1:1 line (Nash and Sutcliffe, 1970). The range of NSE lies between 1.0 (perfect fit) and $-\infty$; an efficiency of less than 0 indicates that the mean value of the observed time series is a better predictor than the model output (Van et al., 2003). Unsatisfactory, satisfactory, and good results are considered to be NSE <0.36, 0.36–0.75, and >0.75, respectively (Van et al., 2003).

3. Results and discussion

3.1. Runoff calibration and validation

The CN value is the most important factor for accurate predictions of runoff and sediment yields. The uncalibrated simulation runoff statistics for station N13a exhibited a satisfactory NSE (0.36) and a good linear relationship between the observed and simulated runoff volumes ($R^2 = 0.61$) but had an unsatisfactory PBIAS value (72%). The simulated runoff for station N.1 had unsatisfactory NSE and PBIAS values (Table 4).

Runoff CNs were calibrated to increase the runoff volumes and to better match the observed values. Based on the statistical analysis, the best calibration was achieved when the CN was increased by 25%. The calibrated runoff was underestimated at station N.13a downstream of the catchment (Figure 6). Figure 7 shows the evaluation results of the predicted runoff at station N.13a. The NSE (0.63) and R^2 (0.73) values were satisfactory, but the PBIAS was unsatisfactory (49%). The PBIAS was only satisfactory (20%) at station N.1, as shown in Table 4.

The daily time scale validation results that could be considered satisfactory (Table 4) were the PBIAS at station N.1 (16%) and the NSE at station N.13a (0.53). According to Moriasi et al. (2007), runoff estimates can be judged as satisfactory if they have an NSE greater than 0.50. The PBIAS values were positive, which indicates a model underestimation bias. These results confirm the ability of the model to predict surface runoff after calibration. Moreover, the runoff validation also showed underestimation at station N.13a (Figure 8). Similar to the calibration

Table 4. Evaluation of uncalibrated, calibrated, and validated runoff predictions.

Evaluation method	Uncalibrated CN		Calibrated CN		Validated runoff	
	Station N.1	Station N.13a	Station N.1	Station N.13a	Station N.1	Station N.13a
Coefficient of determination, R^2	0.49	0.61	0.61	0.73	0.59	0.65
Root mean square error, RMSE (MCM/s)	13	12	15	15	11	12
Percentage bias, PBIAS	55	72	20	49	16	47
Nash-Sutcliffe model efficiency coefficient, NSE	0.25	0.36	0.17	0.63	−0.13	0.53

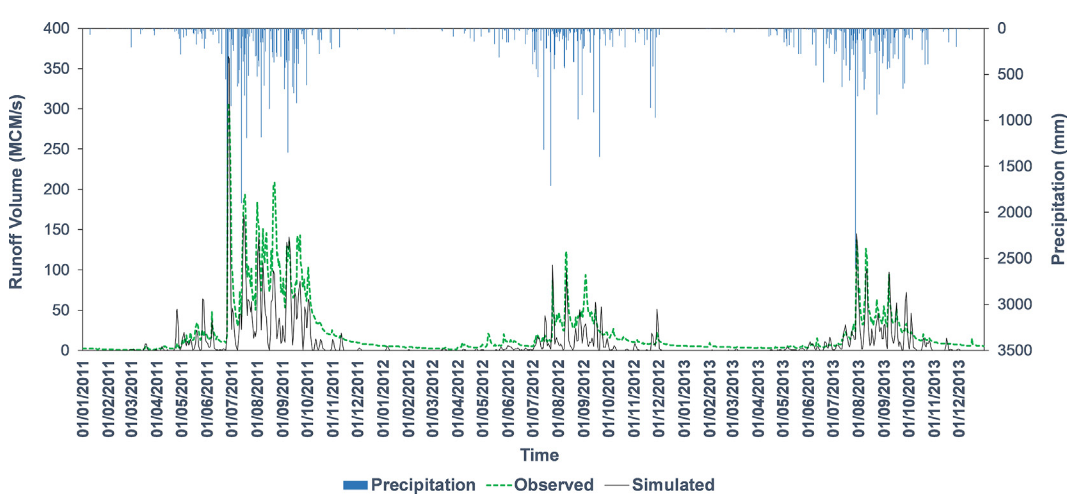

Figure 6. Effect of model calibration on estimated runoff volumes (observed vs. simulated) at station N.13a during 2011–2013.

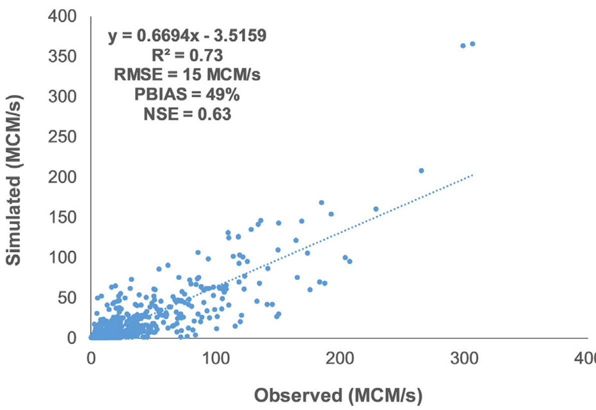

Figure 7. Plot of the observed vs. predicted runoff at station N.13a (line indicates calibrated simulation results) (2011–2013).

results, the runoff data time series indicates overestimations and underestimations during the monsoon season between July and September. The simulated values were generally below the observed values during the pre- and post-monsoon seasons from October to June.

The AnnAGNPS model underestimated runoff generation at low rainfall volumes, while the model overestimated the runoff generated at higher rainfall volumes. Similar results were obtained by Shrestha et al. (2006), Chahor et al. (2014), and Das et al. (2008), who reported that the model underestimated surface runoff during dry periods.

The CN is the most important factor for the accurate prediction of runoff (Grunwald and Norton, 2000), and it depends on land use, soil type, and hydrologic condition. A combination of a hydrologic soil group (soil) and land use and treatment class (cover) is a hydrologic soil-cover complex. Curve numbers are assigned to such complexes to indicate their specific runoff potential. The greater the CN, the greater the surface runoff volume. Therefore, the selection of an accurate CN is essential for the better performance of the model. Other studies on AnnAGNPS that adopted the CN methods also experienced the underestimation of runoff generation at low rainfall volume (Shrestha et al., 2006; Chahor et al., 2014; Das et al., 2008). Grunwald and Norton (2000) mentioned that the deviation in runoff estimation was primarily due to the inappropriate assignment of curve numbers. The accuracy could be significantly improved if CN was properly calibrated.

Furthermore, Das et al. (2008) found that, in some cases, the daily simulated surface runoff failed to match the observed records, with the simulated peak occurring one or two days earlier than the observed peak. In addition, the model did not predict any surface runoff when the observed data indicated a runoff event in some cases. Das et al. (2008) explained that these discrepancies could be due to many factors. For example, the AnnAGNPS model considers that all generated surface runoff is delivered at the outlet on the same day, which may not reflect actual conditions in the study area. Errors could also stem from a lack of rainfall event and peak flow data at the outlet and the spatial distribution of rainfall throughout the watershed.

3.2. Sediment yield

After the model had been calibrated by adjusting the CN values, the observed and predicted surface runoff values were similar. However, the model was further refined to produce better sediment yield predictions.

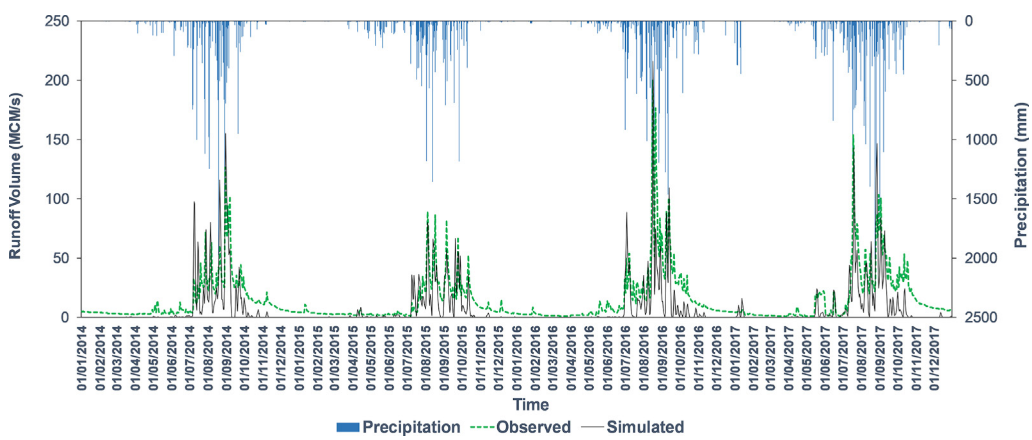

Figure 8. Comparison of observed and simulated runoff values at station N.13a during the validation period (2014–2017).

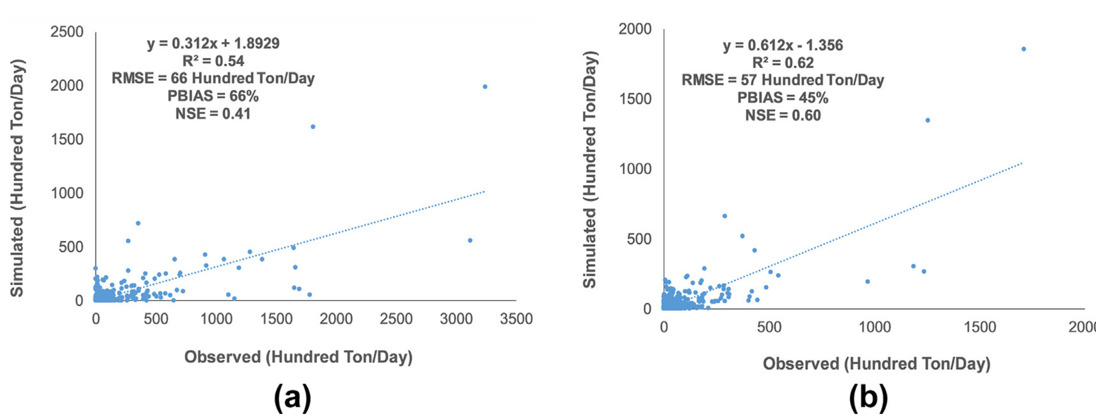

Figure 9. (a) Observed vs. predicted sediment loads at station N.1 during the calibration phase (2011–2013); (b) and the validation phase (2014–2017).

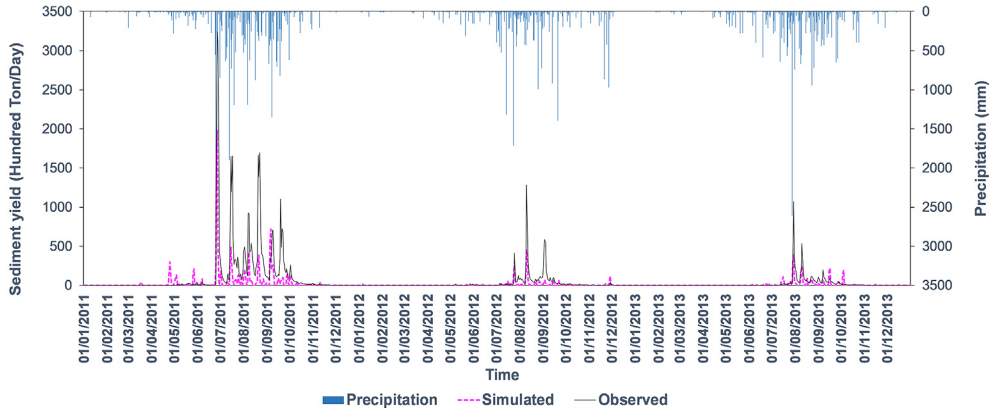

Figure 10. Observed and simulated sediment yields at station N.1 during the calibration phase (2011–2013).

Table 5. Estimated statistical parameters for sediment yield simulations at station N.1 for uncalibrated, calibrated (2011–2013), and validated (2014–2017) predictions.

Evaluation method	Uncalibrated	Calibrated	Validation
Coefficient of determination, R^2	0.50	0.54	0.62
Root mean square error, RMSE (Hundred ton/day)	195.26	66	57
Percentage bias, PBIAS	-3.63	66	45
Nash-Sutcliffe model efficiency coefficient, NSE	0.24	0.41	0.60

Among the adjusted parameters were the soil erodibility factor (*K*) and RUSLE-C. The linear relationship between the observed and simulated sediment yields at station N.1 exhibited satisfactory results, with $R^2 = 0.54$ and NSE = 0.41, but had an unsatisfactory PBIAS value (66%) (Figure 9a). The calibrated sediment yield simulations exhibited an underestimation (Figure 10).

A summary of the sediment yield and the corresponding evaluation results is presented in Table 5. The linear relationship between the observed and simulated sediment yields at station N.1 was satisfactory during the validation phase (Figure 9b), with $R^2 = 0.62$, NSE = 0.60, and PBIAS = 45%. Errors were found between the observed and predicted sediment yields at station N.1 during the validation stage on some days and exhibited an overestimation during the rainy period from July to September (Figure 11).

The AnnAGNPS model can estimate total sediment yields at the sub-watershed scale (AnnAGNPS cells). A map of total annual sediment yields per sub-basin area for 2017 is shown in Figure 12a. The amount of sediment supplied to the Nan River in 2017 was 12,932 hundred tons/y. The maximum sediment yield was 1,488 hundred tons/y in the southern part of the catchment (Na Noi sub-district, Na Noi district), which corresponds to areas with a medium soil-erodibility factor value (Figure 12b) and high crop densities (RUSLE-C of maize; Figure 12c), including areas with medium LS-factor values (Figure 5c) and an agricultural RUSLE-P (Figure 5e). Sediment yields of more than 120 hundred tons/y accounted for approximately 20% of the total catchment area. Regarding land use type and sediment yield, it was found that areas planted with maize generated the highest sediment yield (73.66% of total sediment yield) (Table 6). Furthermore, comparisons of observed and simulated sediment yields for this period indicated an overestimation during the monsoon season (Figure 13).

Sediment yields also varied throughout the year based on land use and management practices (Das et al., 2008). The results from both the calibration and validation periods exhibited lower sediment yields from October to June and high yields during the monsoon season (July to September). Rainfall events, agricultural land use, and steeper slopes could explain the higher sediment yields (Das et al., 2008; Karki et al., 2017). Moreover, the locations of the meteorological stations can result in orographic effects being covered in Nan Province during the monsoon season, which is the cause of increasing sediment yields.

Sediment yields had a trend similar to that of runoff generation, whereby the model seemed to underestimate sediment yields at low rainfall volumes and overestimate values at higher rainfall volumes. Similar results were obtained by Shrestha et al. (2006), Shamshad et al. (2008), and Karki et al. (2017). Suttles et al. (2002) suggested that runoff and sediment load plots exhibited the same trends due to the sediment transport capacity. Sediment and runoff loading were proportional to the sediment transport capacity of the relevant reach and stream. A larger

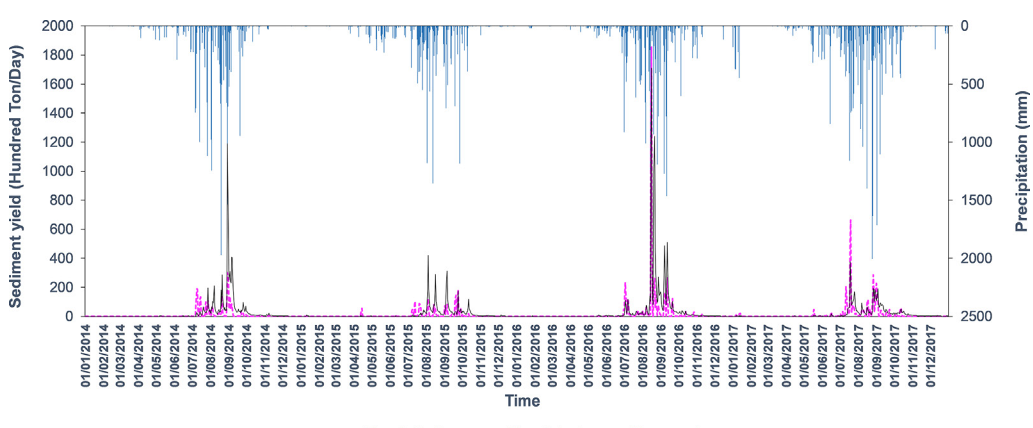

Figure 11. Observed and simulated sediment yields at station N.1 during the validation phase (2014–2017).

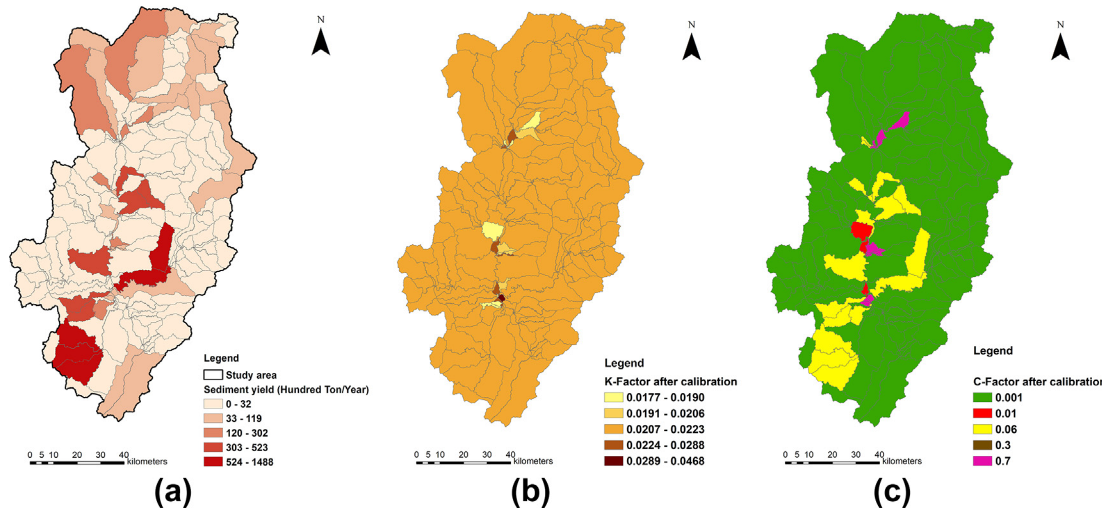

Figure 12. (a) Total sediment yields by sub-watershed in 2017; (b) dataset for the K-factor after calibration; (c) dataset for the C-factor after calibration.

runoff volume corresponds to a larger sediment yield capacity, thus delivering more sediment to the outlet. In addition, the role of antecedent soil conditions and the relationship between rainfall intensity and duration on soil erodibility is related to sediment yield predictions. The soil texture in Nan Province consists of sandy, silty, and clayey loams with moderate to good drainage and a high potential sediment yield. Kain et al. (2018) noted that high-intensity rainfall effects on soil saturation generate flooding. After the summer, high-intensity rainfall occurred on dry ground for an extended period, such that high velocity flow was maintained, which was related to larger sediment yields.

Table 6. Land use type, sediment yield, and soil erosion for 2017.

Land use type	Sediment yield (Hundred Tons/ Year)	Percent (%)	Soil erosion rate (Tons/Hectare/ Year)	Percent (%)
Forest	2,513.04	19.43	2,269	8.18
Urban and built-up land	1.88	0.01	1,193	4.30
Maize	9,526.22	73.66	12,921	46.60
Paddy field	890.7	6.89	11,232	40.50
Other agricultural land	0.45	0.00	116	0.42
Total	12,932.29	100.00	27,731	100.00

3.3. Erosion rate

The AnnAGNPS predicted soil erosion of the watershed as 27,731 tons/ha/year for 2017, with an annual rainfall of 1,382 mm. High erosion rates in the study area were observed in the central and southern parts of the watershed (Figure 14). The erosion rate was related to the LS-factor, soil properties, and land use, where the highest erosion rate was observed for maize (46.60% of the total soil erosion) followed by paddy fields (40.50% of the total soil erosion) (Table 6). These land use types also had high LS factors (10.11 and 13.28, respectively), and the soil texture class was clay and silty. Contrastingly, a low rate of soil erosion was observed in the lowland, forest, urban areas, and locations with sandy loam and loam soil textures.

In Thailand, the erosion rate severity level has been defined in the Land Development of Thailand (2000) report, which defined five classes as very slight (<6.25 t/ha/yr), slight (6.25–31.25 t/ha/yr), moderate (31.25–125 t/ha/yr), severe (125–625 t/ha/yr), and very severe (>625 t/ha/yr). In this study, the area with very slight erosion was 6%, slight was 51%, moderate was 30%, severe was 4%, and very severe was 9%.

The GIS-supported USLE and the RUSLE module of the IDRISI are capable of assessing the erosion risk area, Bahadur (2009) and Plangoen et al. (2013) studied the Upper Nan Wa watershed and the Mae Nam Nan catchment (both in Nan Province of Thailand), respectively. Both studies found soil erosion rates ranging from <2 t/ha/yr to over 400 t/ha/yr. The erosion rates were similar to this study, which indicated that erosion can be severe in several areas of Nan Province. Tingting et al. (2008)

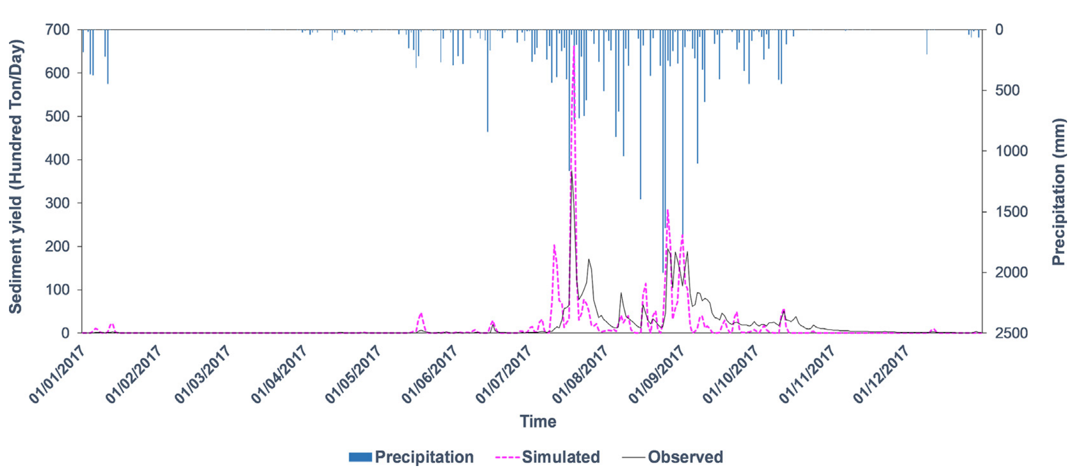

Figure 13. Observed and simulated sediment yields in 2017.

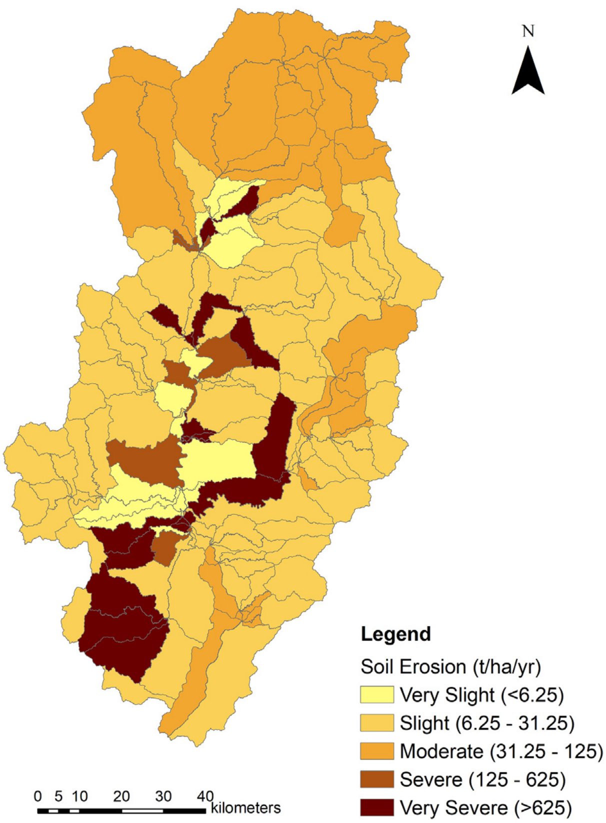

Figure 14. Soil erosion map of the watershed in 2017.

studied soil erosion risk in northern Thailand using the Integrated Model to Assess the Global Environment (IMAGE)-land degrade model (LDM). They found that the soil erosion risk in the high-altitude areas was lower than in the lower altitude areas, and the soil erosion grade was the highest in the transitional zone between forest and agriculture, where the altitude was from 100 m to 400 m. One important causative factor is the encroachment of agricultural activities on forest areas.

In the study area, maize generated the highest sediment yield and soil erosion rate because areas cropped with maize extend onto steep slopes in the uplands, which increases the risk of erosion. The cultivation of maize in the highlands is considered an unsustainable crop practice and an effect of extremely poor ecological and social conditions. Thus, the government and agricultural sector should manage and control land use. This can be achieved by creating data-based land use management, which distinctly divides the land use area, setting up committees and funds to support the restoration of upstream ecosystems, supporting farmers to maintain ecosystems in watershed areas, identifying local products and increasing their product value, creating a learning society, transferring and applying indigenous knowledge to increase agricultural productivity, helping farmers to increase soil fertility by examining their soil, and providing suggestions, methods, and tools to increase soil fertility.

4. Conclusions

The suitability of the AnnAGNPS model was tested for use under the regional conditions and climate at the scale of Nan Province (11,000 km^2) in Thailand. The model's performance in predicting surface runoff and sediment yields was evaluated using observational data from January 2011 to December 2017. The AnnAGNPS model exhibited a satisfactory performance in simulating surface runoff after calibration, which consisted of adjusting the initial CN values, and during validation, yielding statistics such as NSE = 0.63 during calibration and NSE = 0.53 during validation. Sediment yields were simulated by adjusting the soil erodibility (*K*) and RUSLE-C factor values. The model performed satisfactorily in simulating sediment yields, with NSE = 0.41 during calibration and NSE = 0.60 during validation. The total sediment supplied to the Nan River in 2017 was 12,932 hundred tons/y. The maximum sediment yield was 1,488 hundred tons/y, in the Na Noi sub-district, Na Noi district, and corresponded to areas with high crop densities. Cropland generated the highest soil erosion of all investigated land use types (87.52% of total soil erosion). The calibration procedures of the runoff CN, soil erodibility (*K*), and RUSLE-C factor values were adjusted to accurately predict runoff and sediment yields. Therefore, this study determined that the AnnAGNPS model can be used to simulate surface runoff and sediment yields in the Nan River watershed in Thailand with mixed land use types. However, the performance of the model in predicting sediment yields could be increased by improving the input parameters for both the RUSLE and HUSLE, which should be undertaken by future studies. Moreover, future studies should also evaluate the implications of scenario analyses, which are critical for sediment management in Nan Province and potentially in other watersheds, particularly in developing countries.

Declarations

Author contribution statement

Arisa Jirasirichote, S. Ninsawat, S., Shrestha, and N.K. Tripathi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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