

Developing and Applying a QGIS-Based Model That Accounts for Nonpoint Source Pollution Due to Domestic Animals

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Abstract: Watershed management must take into account both the quantity and quality of water. Therefore, many hydrological models have been developed for hydrological and water quality prediction for various purposes. The Spreadsheet Tool for Estimating Pollutant Loads (STEPL), which was developed in the United States for water quality regulation, can predict both the quantity and quality of water, and has the advantage of including information on livestock. However, complex characteristics of the watershed must be generated by users for use as input data, and simulations only yield annual average values. Therefore, in this study, we developed a model that overcomes these limitations using geographic information data and enabling monthly predictions. The model developed in the study estimates monthly direct runoff and baseflow using daily rainfall data, while the STEPL model employs average annual approaches that are limited to consider seasonal variances of hydrological behaviors. It was developed for use within the QGIS software, and was applied to a watershed covering an area of 128.71 km², considering information on livestock, soil, and land use. The model exhibited good predictive accuracy for four nonpoint source (NPS) pollutant loads and river flow, displaying acceptable criteria greater than 0.83 for river flow rates and 0.71 for all NPS pollutant load rates during calibration and validation.

Keywords: nonpoint source pollution; QGIS; STEPL; watershed management



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1. Introduction

Urbanization and industrialization increase the impervious area, and thus limit water flow into groundwater and increase direct runoff. Because these changes can increase the loads of nonpoint source (NPS) pollutants, watershed management is necessary to secure water resources and manage pollutants. Various watershed-scale hydrological models have been developed for watershed management [1–5].

The Hydrological Simulation Program—FORTRAN (HSPF) is a watershed model for modeling the hydraulics and water quality of stormwater runoff; it was developed in the early 1960s as the Stanford Watershed Model. It has been continuously improved and supported by the US Environmental Protection Agency and United States Geological Survey, and thus has attracted many users [6–8]. The HSPF model is a physics-based semi-distributed model that consists of multiple modules for modeling hydraulics, hydrology, and water quality. In addition, it can apply various watershed spatial characteristics and meteorological data to subwatersheds and rivers constructed within the model [9]. The Soil Water Assessment Tool (SWAT) model [10] is a semi-distributed stormwater runoff model that can predict the long-term runoff of complex watersheds with multiple land use types. Hydrological response units (HRUs), which reflect land use type and hydrological soil group (HSG), are the fundamental unit of hydrological modeling using the SWAT model; they are used to simulate the initial abstraction, evapotranspiration, surface flow, baseflow, and soil moisture using the water balance equation [11]. The Long-Term Hydrologic Impact

Assessment (L-THIA) model [12] was developed to assess the long-term effect of changes in land use. It was initially developed in a spreadsheet format and was later improved to predict river water and NPS pollutant loads using geographical information [13]. The Spreadsheet Tool for Estimating Pollutant Loads (STEPL) [14] is a spreadsheet-based model developed to model the annual average NPS pollutant loads. It can predict NPS pollutant loads for various land use types. Furthermore, it can estimate the NPS pollutant load reduction resulting from low impact development and best management practices. The STEPL calculates annual direct runoff using the annual average precipitation and National Resource Conservation Service curve number (NRCS-CN) method.

Hydrological models are used for hydrological behavior analyses; For example, Bieger et al. [15] analyzed the land use change impacts using the SWAT model for three land use scenarios. In their study, they reported that cropland, forest, and orchard area changes of +265.32%, −34.48%, and 204.51% led to 46.1% increases in surface flow. Guse et al. [16] estimated the impacts of five crop rotations, and reported that nitrate loads could be reduced by dynamic changes using the crop rotations. Martin et al. [17] employed the regional hydro-ecological simulation system model [18], and discovered that land use changes led to 37–88% increases in high flows and 23–37% increases in low flows. Kibii et al. [19] used the SWAT model and reported that terrace implementations on steep agricultural areas decreased direct runoff and increased groundwater recharges significantly. Hou et al. [20] used the HSPF model, revealing that controlling via a rural domestic lifestyle can reduce total nitrogen (T-N) by 37.86% and total phosphorus (T-P) by 66.95%, while fertilizer control can reduce T-N and T-P by only 5.07% and 2.01%, respectively.

Although these hydrological models differ in methods and complexity, they can all be used to analyze watershed flow rates and NPS pollutant loads. However, because a watershed consists of multiple types of land cover with various soil properties, the spatial properties based on geographical information must be considered [13]. In addition to these watershed properties, NPS pollutants discharged by livestock have a non-negligible impact on watershed quality [20,21]. In addition, to increase the probability that a hydrological model is used by practitioners (for example, construction companies) or policymakers, it is necessary to simplify the models used to construct the input data and simulations [13,22].

A comprehensive review of the above models suggests that it is nontrivial to apply livestock conditions in the SWAT and HSPF, which are less simple than the STEPL model. Although livestock-based conditions can be applied in the STEPL, it is based on Microsoft Excel, which does not use geographical information and is capable of predicting only annual average values. The L-THIA model uses geographic information, and is similar in simplicity to the STEPL, but livestock conditions cannot be implemented. Consequently, removing the limitations of the STEPL (that users manually generate input data, and that it models only annual average values, which makes it impossible to include the seasonal characteristics of watersheds) will enable better prediction of watershed conditions compared to other models.

Therefore, this study applies the STEPL and aims to improve it to automatically extract spatial information on watersheds using geographical information, and to facilitate monthly prediction in order to better reflect the seasonal characteristics of watersheds.

2. Materials and Methods

2.1. Addressing the Limitations of the STEPL

The STEPL was developed to determine the total maximum daily load (TMDL), which is the standard used in US water quality regulation. It can be used to predict flows such as annual average direct runoff and baseflow, as well as the annual average loads of nitrogen, phosphorus, suspended solids (SS), biochemical oxygen demand (BOD), and *Escherichia coli* [14]. This study focuses on this model because it facilitates the inclusion of livestock conditions, which is not commonly supported in other models.

However, this model has two main limitations. First, spatial information on the watershed must be input by users. Second, it supports only the prediction of annual averages.

To address the first limitation, the spatial characteristics of a watershed, namely, the land use and soil types, can be reclassified into a few to tens of subcategories. However, to predict the quantity and quality of water, both types of information must be used [23–25]. HRUs in which two conditions are combined may exhibit significant variation, which may be further complicated if spatial information is also considered. Thus, it is very difficult to manually generate information for each HRU. Therefore, the land use types and HSG map must be used to automatically generate HRUs that are spatially distributed across watersheds to facilitate the prediction of water quantity and quality for each HRU.

Regarding the second limitation, this model was developed to determine the TMDL, and can only predict the annual average load. Predictions of the annual average water quantity and quality cannot reflect seasonal changes in precipitation, which are a significant factor in predicting NPS pollutants [26,27]. The advantage of this model, in which the regional annual average precipitation database is stored for immediate access during simulation, is, simultaneously, a limitation, as daily precipitation data cannot be used [5].

Therefore, this study seeks to exploit the advantage of this model, which allows livestock information to be considered when calculating NPS pollutant loads, while further reducing the limitations of this model using the geographical information system and facilitating monthly predictions.

2.2. Predicting Direct Runoff and Baseflow

Direct runoff can be computed using the NRCS-CN method (formerly the Soil Conservation Service curve number method) [28]. The STEPL model applies this method to predict annual direct runoff on the basis of annual precipitation. However, the results obtained by this method show a non-negligible discrepancy from those of calculations based on the NRCS-CN method [5]. Therefore, this study follows the computational method of the STEPL, but takes the approach of the NRCS-CN method.

The NRCS-CN method uses the CN defined by HSG and land use type to determine the potential maximum retention after runoff begins (S , mm) and the initial abstraction (I_a , mm). In addition, the direct runoff depth (Q , mm) only occurs when the precipitation (P , mm) is greater than I_a (Equations (1)–(4)).

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S} \text{ for } I_a < P \quad (1)$$

$$Q = 0 \text{ for } I_a \geq P \quad (2)$$

$$I_a = 0.2S \quad (3)$$

$$S = \frac{25,400}{CN} - 254 \quad (4)$$

The direct runoff depth Q is calculated for each HRU defined by a combination of land use types and HSG. The area of each HRU is multiplied by the direct runoff depth to obtain the runoff volume (m^3).

Because river flow consists of direct runoff and baseflow, these parameters must be estimated to predict the flow rate. The baseflow consists of stormwater that moves toward rivers after penetrating the ground surface; therefore, it may not be as simple to predict direct runoff. To address this difficulty, Lee et al. [29] classified 20 watersheds, ranging in area from 5695 to 155,806 ha, into seven categories based on land use: urban (URBN), agriculture (AGRL), forest (FRST), pasture (PAST), wetland (WTLD), bare (BARE), and water (WATR). The baseflow (m^3) for month i is predicted from the land use area (ha), coefficient for each land use type, and monthly precipitation (Equation (5)).

$$Baseflow_i = P_i \times (C_{URBN} \times A_{URBN} + C_{AGRL} \times A_{AGRL} + C_{FRST} \times A_{FRST} + C_{PAST} \times A_{PAST} + C_{WTLD} \times A_{WTLD} + C_{BARE} \times A_{BARE} + C_{WATR} \times A_{WATR}) \times 10.0 \quad (5)$$

In this equation, C is the coefficient for each land use type, which can vary between watersheds, and A is the land use area (ha).

In Equation (5), the land use coefficient C is a model parameter that can be calibrated for each land use type in the model area. Lee et al. [23] proposed default values of $C_{URBN} = 0.04$, $C_{AGRL} = 0.40$, $C_{FRST} = 0.20$, $C_{PAST} = 0.18$, $C_{WTLT} = 0.48$, $C_{BARE} = 0.15$, and $C_{WATR} = 0.22$. In an extension of this study, Lee et al. [13] predicted the direct runoff using the NRCS-CN method and the baseflow using Equation (5). They compared the predicted values to the measured flow rate in 15 watersheds with areas between 5841 and 81,107 ha. The Nash–Sutcliffe efficiency (NSE) and coefficient of determination (R^2) during model calibration were 0.601–0.868 and 0.743–0.917, respectively. In addition, for model validation, the NSE and R^2 were 0.611–0.917 and 0.676–0.946, respectively, which suggests that the NRCS-CN method and Equation (5) can be used to predict the flow rate.

Therefore, the hydrological model developed in this study calculates the direct runoff and baseflow using the NRCS-CN method and Equation (5), respectively.

2.3. NPS Pollutant Prediction

The goal of this study is to develop a model that can take into account various nutrients produced by livestock and predict the quantity of NPS pollutants according to the land use and soil types in the watershed. The method used in the STEPL model was applied.

The STEPL model can simulate the average annual nitrogen (N), phosphorus (P), BOD, and SS. In this model, the SS load is predicted using the universal soil loss equation (USLE) [30,31]. In addition, for the N, P, BOD, and *E. coli* loads, the direct runoff (m^3) and pollutant coefficients (mg/L) are used to determine the nutrient loads from land. These loads are determined by multiplying the sediment values and amount of lost soil that reaches a river by the corresponding coefficients for nutrients. Then, the nutrient loads from livestock are determined using the type of livestock, nutrient emission for each type, and number of livestock [14].

The nutrient loads from land, sediment, and livestock are summed to determine the NPS pollutant loads. Here, the nutrient loads from land can be calculated as monthly loads based on monthly direct runoff, and the nutrient loads from sediment can be calculated on a monthly basis if the monthly soil loss is provided. Additionally, because the number of livestock has low monthly variability, the monthly nutrient loads from livestock were calculated by assuming the same type of livestock, nutrient emissions by livestock, and number of livestock. That is, the nutrient loads from land and sediment, which change by month, and nutrient loads from livestock, which have the same value for each month, are summed to yield the monthly NPS pollutant loads.

2.4. Developing Software to Predict Flow Rate and NPS Pollutant Load

Direct runoff is predicted using the NRCS-CN method, which is based on a combination of land use type and HSG and yields the direct runoff (m^3) according to precipitation and area. In addition, the baseflow can be calculated using Equation (5), which requires knowledge of the land use type and area. Therefore, it is prohibitive to manually provide the information for a large number of HRUs based on the land use type and HSG of watersheds. To address this problem, this study uses geographical information to perform this procedure in the QGIS software Version 3.10 [32].

HSG and land use maps, which contain spatial information on soil and land use, respectively, are needed to compute the direct runoff. A CN table that lists the CN values according to the HSG and land use maps is also needed. The CN table is a CSV file that contains CN values specified by users. It superposes the HSG and land use maps spatially and generates a CN map by retrieving the appropriate value from the CN table (Figure 1).

After the CNs for HRUs distributed across watersheds are obtained, precipitation data can be used to calculate the direct runoff. The precipitation data may include measurement data for multiple sites within or near the watershed. If precipitation was measured at a single site, the precipitation must be uniform across the watershed. However, if the

precipitation was measured at multiple sites, all the data must be used. To this end, a rain gauge station map and subwatershed map are used, and the precipitation data from the closest measuring site within or near the subwatershed are used (Figure 1). This process generates the HRU information file, which contains information on HSG, land use, CN, rain gauge station number, and subwatershed number for all the HRUs (Figure 2). This information helps predict not only the direct runoff, but also the baseflow, because it contains information about the area occupied by each land use type. This operation requires the land use map, soil map, CN table, subwatershed map, and rain gauge station map, which can be submitted as input in the interface (Figure 3).

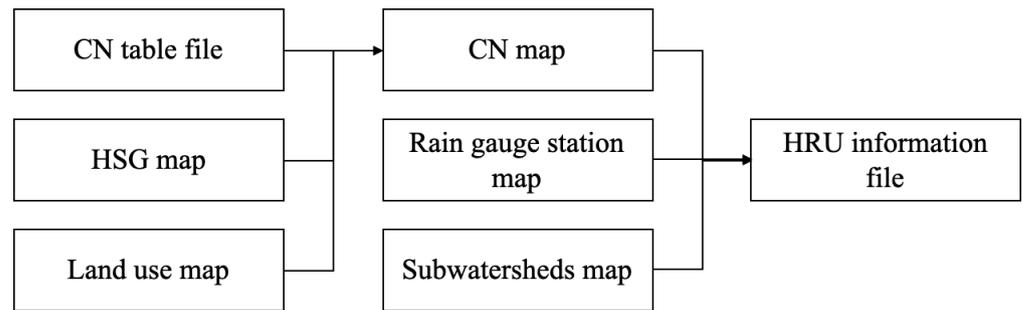


Figure 1. Schematic illustration of HRU information file.

	A	B	C	D	E	F	G
1	HRUnum	Rainstation	CAT_ID	CN	GRIDCODE	SOILCODE	area
2	1	131	30110707	0	500	3	7786
3	2	131	30110707	0	500	2	61418
4	3	131	30110707	0	500	1	10439
5	4	131	30110707	0	500	4	112478
6	5	131	30110707	86	100	3	557610
7	6	131	30110707	78	100	2	1271626
8	7	131	30110707	66	100	1	38192
9	8	131	30110707	89	100	4	98840
10	9	131	30110707	75	300	3	223589
11	10	131	30110707	66	300	2	4947020
12	11	131	30110707	83	300	4	1683
13	12	131	30110707	0	700	3	6756
14	13	131	30110707	0	700	2	15267
15	14	131	30110707	0	700	1	1558
16	15	131	30110707	0	700	4	121137
17	16	131	30110707	86	400	3	350298
18	17	131	30110707	79	400	2	1570725
19	18	131	30110707	68	400	1	65534
20	19	131	30110707	89	400	4	161072
21	20	131	30110707	91	600	3	28531

Figure 2. Example of HRU information file.

After the HRU information file is obtained, the direct runoff, baseflow, and NPS pollutant loads can be computed. Using the HRU information file and precipitation data from one or more sites, the direct runoff and baseflow are first calculated. Then, using the nutrient loads from livestock and pollutant coefficients, the nutrient loads from land for direct runoff and baseflow are calculated. In addition, the nutrient loads from sediment are calculated using the monthly soil loss data. Next, these three nutrient loads are summed to define the monthly NPS pollutant loads (Figure 4).

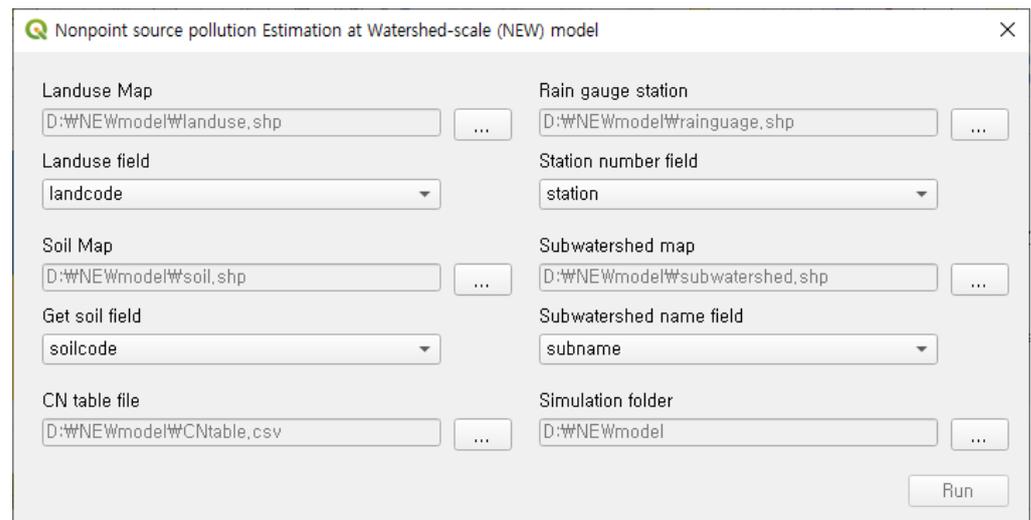


Figure 3. Interface for generating HRU information file.

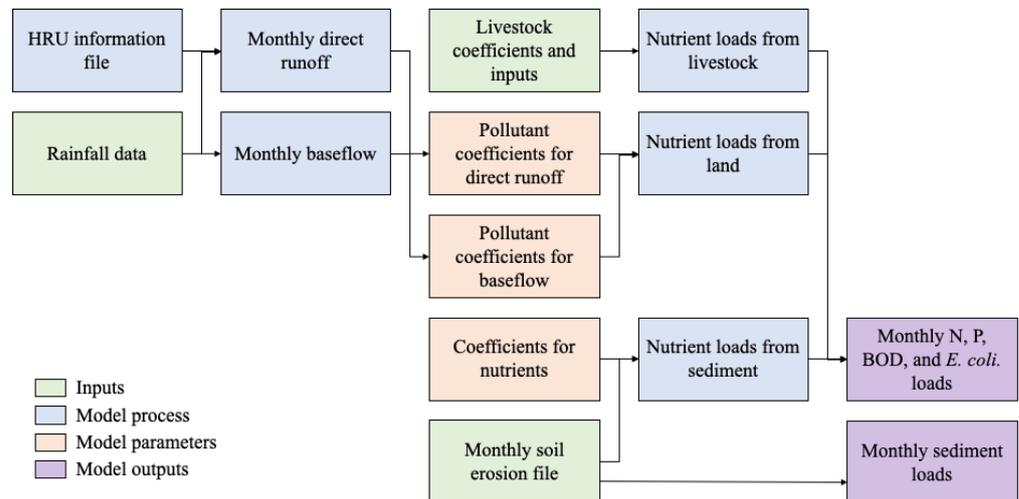


Figure 4. Schematic illustration of streamflow and NPS pollutant load estimation.

A graphical user interface (GUI) was developed for the computation of the direct runoff, baseflow, and NPS pollutant loads using the HRU information file (Figure 5). This GUI displays information regarding the HRU information file, and requires precipitation data and monthly soil loss data as input from users. The CN and baseflow coefficients in Equation (5) for each land use type can be modified in this GUI.

The STEPL model first calculates the direct runoff and baseflow, and then uses the pollutant coefficients to compute the NPS pollutant loads. The pollutant coefficients can vary between watersheds. In addition, the type, number, and unit loads for each livestock animal (kg) must be defined for each watershed. Inputting this information into a single interface can be extremely complicated. Thus, supplementary GUIs are accessible from the main GUI in Figure 5, so that this information can be entered or modified (Figure 6). These supplementary GUIs can be used to modify the model parameters of the STEPL: the nutrient concentration of direct runoff from agriculture and pastureland (Figure 6a), nutrient concentration of direct runoff from other land use types (Figure 6b), nutrient concentration of baseflow (Figure 6c), nutrient concentration of sediment (Figure 6d), and number of animals and daily BOD per animal (Figure 6e). Additionally, the number of livestock can be entered (Figure 6f).

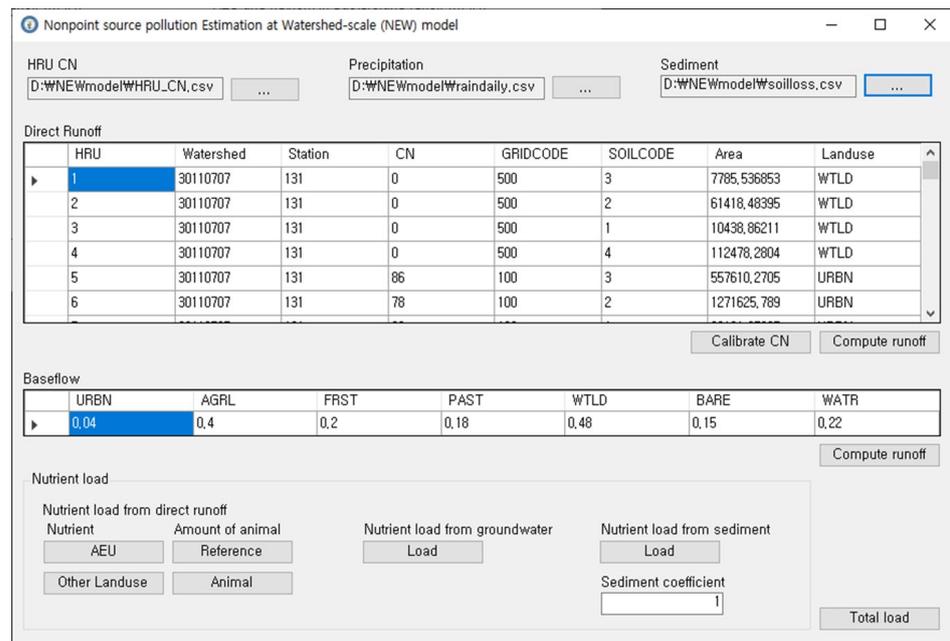


Figure 5. Graphical user interface (GUI) for estimating monthly streamflow and NPS pollutant loads.

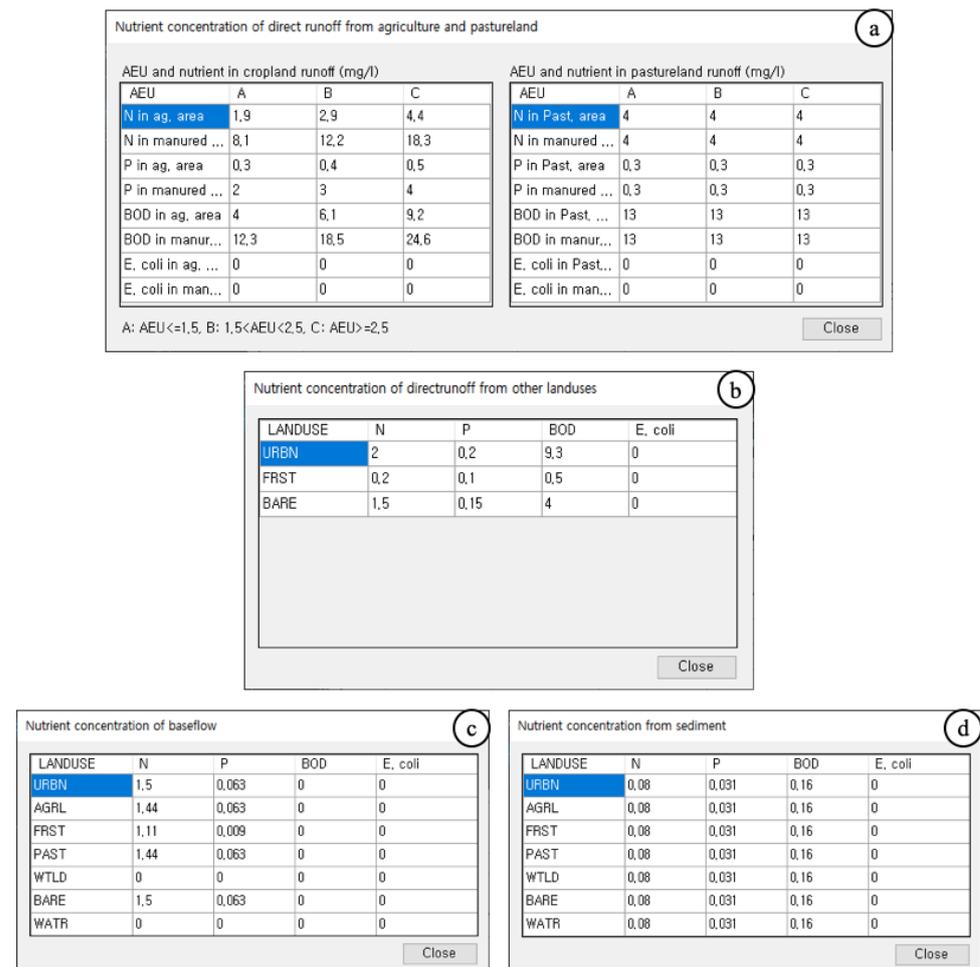


Figure 6. Cont.

(c) Amount of animals and daily BOD from animal

	Livestock	Typical Animal Mass(lb)	BOD,lb/day/1000lb animal	BOD per Animal, lb/day	BOD per Animal lb/yr
▶	Beef Cattle	1000	1.6	1.28	467.1
	Dairy Cattle	1400	1.6	2.24	818
	Swine(Hog)	200	3.1	0.42	153
	Sheep	100	1.2	0.07	26
	Horse	1000	1.7	1.7	621
	Chicken	4	3.3	0.01	5
	Turkey	10	2.1	0.03	11
	Duck	4	0	0	0

(f) Agricultural animals

	HRUs	# of months manure applied	Beef Cattle	Dairy Cattle	Swine(Hog)	Sheep	Horse	Chicken	Turkey	Duck	Goose
▶	16	8	30	0	238	30	0	1369	0	0	0
	17	8	138	1	1088	139	0	6463	0	0	0
	18	8	5	0	44	5	0	256	0	0	0
	19	8	13	0	109	14	0	629	0	0	0
	24	8	42	0	333	43	0	1915	0	0	0
	25	8	226	2	1779	231	0	10220	0	0	0
	26	8	0	0	2	0	0	21	0	0	0

Figure 6. Supplementary GUIs for nutrient and livestock inputs for editing (a) nutrient concentration of direct runoff from agriculture and pastureland, (b) nutrient concentration of direct runoff from other land use types, (c) nutrient concentration of baseflow, (d) nutrient concentration of sediment, and (e) number of animals and daily BOD per animal, and (f) for entering number of months during which manure is applied and number of animals for each HRU.

2.5. Applying the Developed Model

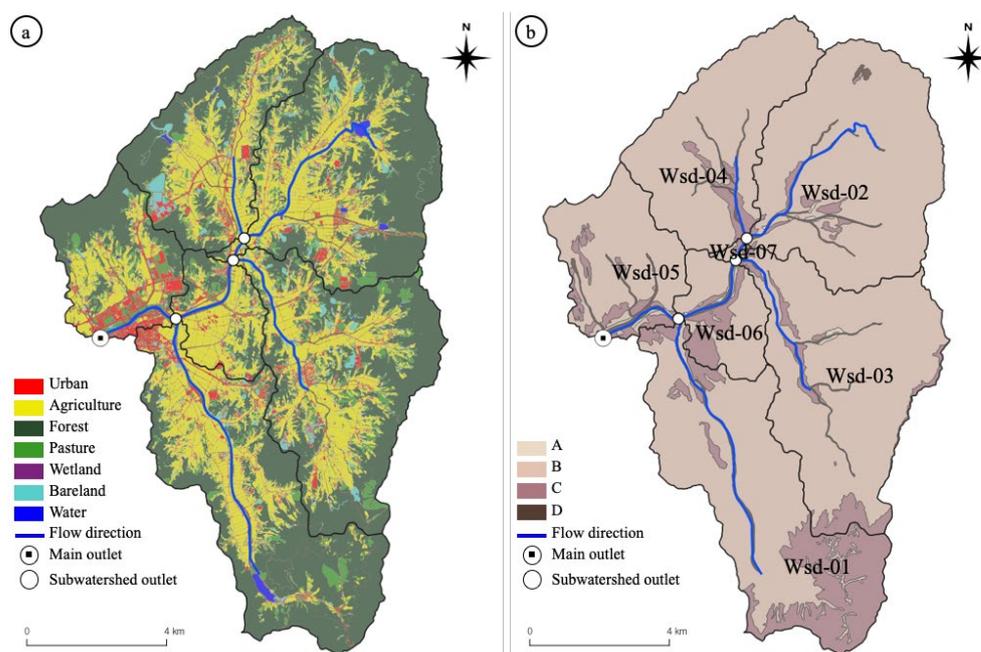
To assess the applicability of the Nonpoint source pollution Estimation at Watershed-scale (NEW) model developed in this study, the model was applied in designated areas. The input data consisted of land use data from the Environmental Geographic Information Service (1:5000 scale) [33], daily precipitation data from the Korea Meteorological Administration [34], daily flow data, and water quality data measured every 8 days by the Water Resources Management Information System (WAMIS) [35]. In addition, monthly soil loss data from the USLE-based monthly soil loss map data provided by the Nonpoint Source Pollution Modeling Research Group [36] were used. Regional agricultural animal data provided by the National Pollutant Survey System [37] of the National Institute of Environmental Research were collected to calculate the pollution from direct runoff, specifically, nutrients produced by agricultural animals. The model was applied to watersheds in which the outlets coincide with WAMIS measuring sites for flow and water quality. The watershed consists of seven subwatersheds with areas ranging from 39 to 2995 ha (Figure 7 and Table 1). The number and types of agricultural animals were also used for modeling. The number was largest for chicken (598,133) and smallest for dairy cattle (172) (Table 2).

Table 1. Land use area of subwatersheds where model was applied.

Subwatershed	Area (ha)							Total
	Urban	Agriculture	Forest	Pasture	Wetland	Bare Land	Water	
Wsd-01	213	774	1534	329	53	64	28	2995
Wsd-02	170	761	1494	381	33	95	31	2964
Wsd-03	167	817	1368	398	32	108	11	2901
Wsd-04	147	562	849	259	19	99	6	1942
Wsd-05	197	318	517	215	19	27	14	1307
Wsd-06	69	346	161	112	17	14	6	723
Wsd-07	5	12	10	6	3	3	1	39

Table 2. Number of agricultural animals in subwatersheds where model was applied.

Subwatershed	Agricultural Animals				
	Beef Cattle	Dairy Cattle	Swine (Hogs)	Sheep	Chickens
Wsd-01	951	9	7521	971	43,031
Wsd-02	2124	58	23,792	1131	318,575
Wsd-03	1920	15	19,907	2086	30,929
Wsd-04	1824	81	12,054	1185	155,363
Wsd-05	460	3	3641	468	21,146
Wsd-06	475	5	3779	453	24,533
Wsd-07	50	1	350	31	4556

**Figure 7.** Watersheds where model was applied: (a) land use map; (b) HSG map.

The model was applied from January 2016 to December 2020; the monthly flows in the watersheds ranged from $0.08 \times 10^6 \text{ m}^3$ to $49.71 \times 10^6 \text{ m}^3$. Because the proposed model produces monthly predictions of the NPS pollutant loads, water quality data measured by the Load Estimator [38] every 8 days were converted to monthly loads for comparison with the model prediction.

3. Results

3.1. Model Calibration

Various values have been suggested for comparing measured river flow to the values estimated by hydrological models. The credibility criteria proposed by Duda et al. [39] are $R^2 > 0.65$ and a difference of $<45\%$, whereas Skaggs et al. [40] suggested an NSE value of >0.50 . The criteria of Wang et al. [41] are $NSE > 0.50$, $R^2 > 0.60$, and a percent bias (PBIAS) of $\pm 15\%$, whereas Engel et al. [42] and Moriasi et al. [43] proposed criteria of $R^2 > 0.60$, $NSE > 0.50$, and $PBIAS < 15\%$. That is, although metrics such as NSE and R^2 are often used, various standards are used to evaluate the credibility of a model. This study assessed the model credibility using scatter plots along with the NSE and R^2 .

The NEW model was calibrated using data from January 2016 to December 2017 for the monthly flow rate and NPS pollutant loads. The NSE and R^2 values for river flow were 0.8903 and 0.9327, respectively; the NSE for the NPS pollutant loads was 0.7376–0.9527, whereas R^2 was 0.9187–0.9906 (Table 3 and Figure 8).

Table 3. NSE and R^2 for measured and estimated monthly streamflow and NPS pollutant loads in model calibration.

	NSE	R^2
Streamflow	0.8903	0.9327
T-N	0.9851	0.9906
T-P	0.8238	0.9793
BOD	0.7376	0.9187
SS	0.9527	0.9805

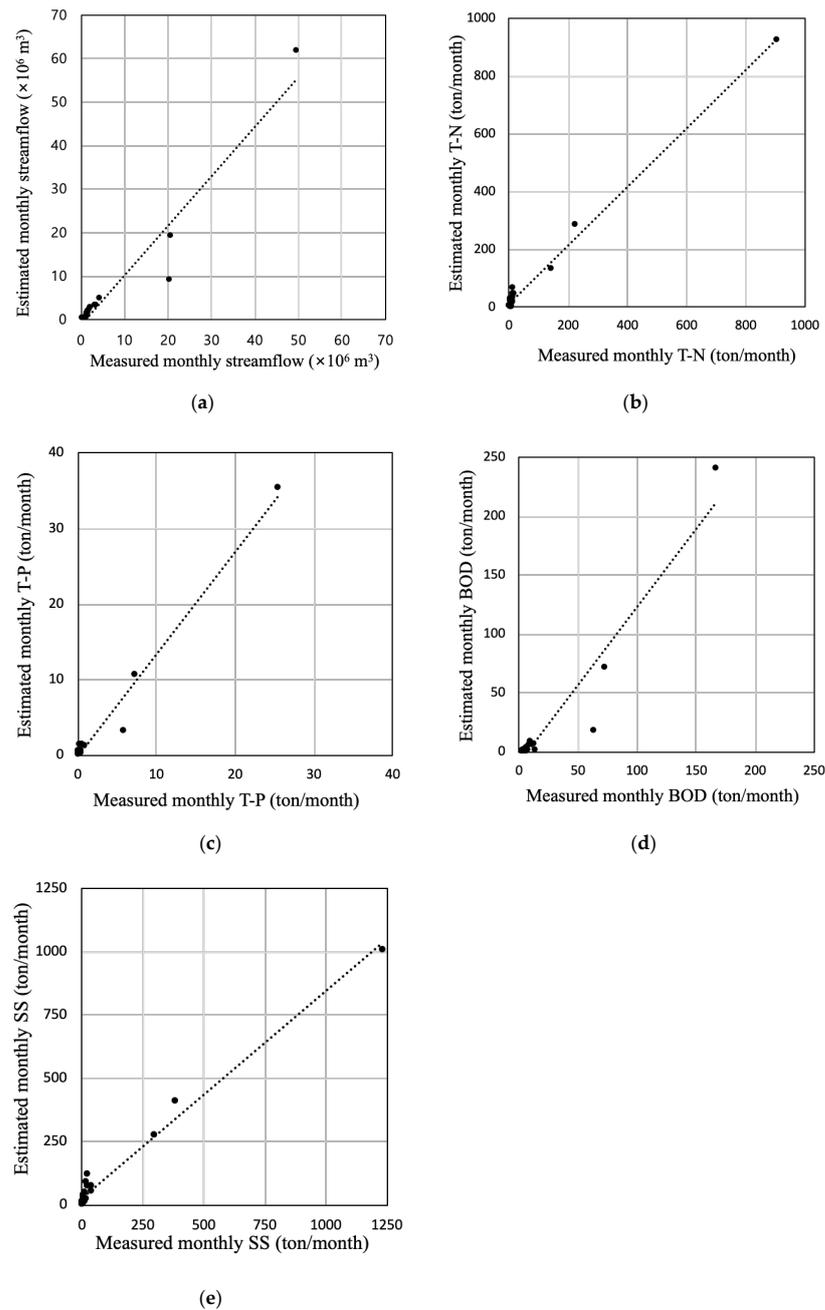


Figure 8. Scatter plots of measured and estimated monthly streamflow and nutrients in model calibration: (a) streamflow; (b) T-N; (c) T-P; (d) BOD; (e) SS.

Therefore, model calibration was successful for the designated areas, and the predicted streamflow can be considered to be credible.

3.2. Model Validation

The model was validated for the period of January 2018 to December 2020. The NSE and R^2 values for river flow were 0.8329 and 0.8633, respectively. The NSE for the NPS pollutant loads was 0.7111–0.7981, and R^2 was 0.7546–0.9032 (Table 4). In the scatter plots for both calibration and validation, the estimated and measured values showed a close linear relationship for all values (Table 3 and Figure 9). Thus, as in the calibration step, the model showed credible performance in the validation procedure.

Table 4. NSE and R^2 for measured and estimated monthly streamflow in model validation.

	NSE	R^2
Streamflow	0.8329	0.8633
T-N	0.7111	0.7546
T-P	0.7356	0.7869
BOD	0.7236	0.7596
SS	0.7981	0.9032

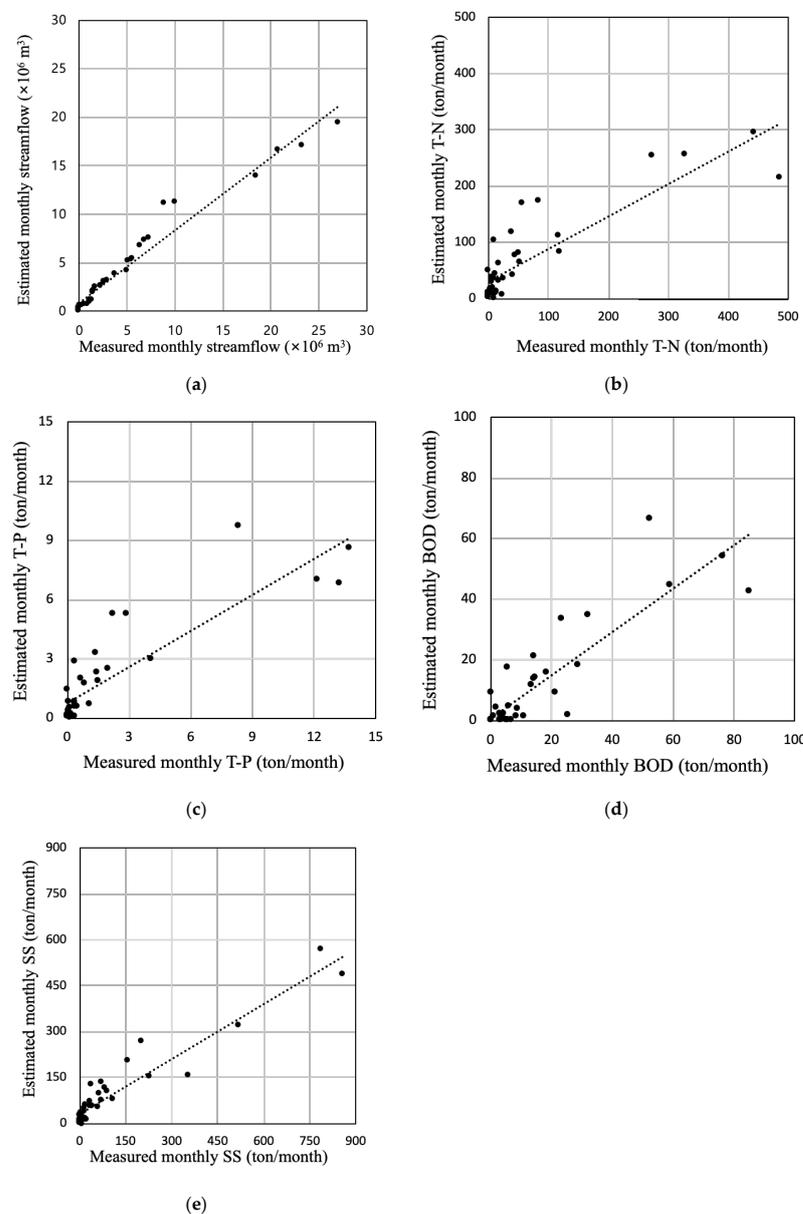


Figure 9. Scatter plots of measured and estimated monthly streamflow and nutrients in model validation: (a) streamflow; (b) T-N; (c) T-P; (d) BOD; (e) SS.

4. Discussion

Various hydrological models have been developed and used for watershed management. Analyses or simulations for watershed management must include land use and rainfall pattern changes such as urbanization, industrialization, and climate changes. This indicates that it is required for the models to consider the watershed properties of land use and rainfall variances. The watershed management scenarios by watershed-scale hydrological models displayed that direct runoff, baseflow, groundwater, and NPS loads varied by land use [1–5]. Additionally, predictions of the annual average water quantity and quality cannot reflect seasonal changes in precipitation, which are a significant factor in predicting NPS pollutants [26,27]. In addition to land use and rainfall in the watershed, rural domestic animals, including livestock, are also influential components in NPS estimations [20,21]. Therefore, there is a need to consider land use and domestic animals in NPS load estimations in watershed-scale analyses. In addition, to increase the probability that a hydrological model is used by practitioners or policymakers, it is necessary to simplify the models used to construct the input data and simulations [13,22].

Thus, a GIS-based model was developed in the present study, improving the STEPL model. The STEPL model can be used to estimate direct runoff, baseflow, nitrogen, phosphorus, suspended solids, and biochemical oxygen demand, and it facilitates the inclusion of livestock. However, the model has two main limitations; one is that spatial information on the watershed must be input by the users, and the other is that it only enables the prediction of annual averages. To address these two limitations, this study developed a model that can extract spatial information on watersheds from geographical information and use daily rainfall data. This model was applied to a watershed with an area of 128.71 km² for the period between January 2016 and December 2020. The land use types, HSG maps, and types and numbers of livestock were used. The NSE and R² were used to assess the prediction accuracy of the model. For river flow, both criteria were greater than 0.8 in model validation and calibration. In addition, for the four NPS pollutant loads, both criteria were calculated to be greater than 0.7. Thus, the model showed credible performance in analyzing the hydrological and water quality characteristics of the watershed.

Therefore, it was concluded that the NEW model can be used to estimate monthly streamflow and NPS loads at watershed, facilitating the inclusion of livestock.

5. Conclusions

Watershed management must take into account both the water quantity and quality of watersheds. Additionally, it is important to consider various watershed conditions to understand how they affect water quantity and quality. Thus, multiple hydrological models have been developed using various software packages (e.g., ArcGIS, QGIS, and Microsoft Excel) to use different methods of hydrological and hydraulic prediction for various purposes.

The STEPL model was developed as a tool for evaluating the TMDL, a standard used in US water quality regulation, and is based on Microsoft Excel. Although it has the advantage of including livestock information when NPS pollutant loads are computed, it has two limitations: geographical information cannot be used, and thus, users must manually specify the spatial characteristics of watersheds, and the seasonal characteristics of precipitation cannot be considered because its approach is based on annual averages. This study developed a model to resolve these limitations; the proposed NEW model has the following advantages.

- It provides user convenience by applying a graphical user interface.
- HRUs are determined by land use and HSG maps in the QGIS software.
- It facilitates the inclusion of livestock.
- Seasonal variances are provided in direct runoff, baseflow, and NPS load estimations.

One of reasons for using the STEPL model is that the model provides the opportunity to estimate the effects of best management practices and low impact developments by applying NPS reduction coefficients for various practices. The NPS loads reduction

estimations can be implemented by the users, manually selecting the practices for HRUs in the STEPL model. Thus, it is challenging to develop the optimum practice scenario to meet target loads. Thus, there is a need to improve the NEW model to provide optimized practice scenarios so that the model can be used as decision support model for watershed management policy.

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