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Development of EMC-based empirical model for estimating spatial distribution of pollutant loads

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ABSTRACT

In this paper, a new and integrated approach to easily calculate pollutant loads from agricultural watersheds was suggested and verified. The basic concepts of this empirical tool were based on an assumption that variations in event mean concentrations (EMCs) of pollutants from a given agricultural watershed during rainstorms were only attribuTable to the rainfall pattern. Fifty one sets of EMC values were obtained from nine different watersheds, and these data were used to develop prediction tools for the EMCs in rainfall runoff. The results of statistical tests of these formulas showed that they were fairly good in predicting actual EMC values of some parameters, and useful in terms of calculating pollutant loads for any rainfall event time span such as daily, weekly, monthly, and yearly. As part of this study, we were able to examine the field applicability of the empirical model. In an effort to improve the water quality of a reservoir, all water were drained and followed by a cleanup of the sediments. Later, the rainfall water storage and the change in water level began. The predicted values of the chemical oxygen demand (COD) corresponded well with observed values. The predicted total nitrogen (TN) moderately matched the observed values. However, there was a great difference in suspended solid (SS) and total phosphorus (TP) between the two parts. Finally, we concluded that the EMC-based empirical model could be considered as a simpler, more feasible, and useful solution in evaluating timely distribution of nonpoint pollution loads in agricultural and forested watersheds in constructed and other complicated watershed models.

Keywords: EMC; Empirical model; Non-point source pollution; Spatial distribution

1. Introduction

For many years, nonpoint pollution in rural areas has been identified as a significant cause of surface water quality degradation and has been studied widely in the world. For instance, agricultural sources are responsible for impairment of more than one-half of the rivers and lakes in the United States [1]. However, the causes and processes involved in the problems of nonpoint pollution are complicated and locally vary because of a variety of precipitation, soil erosion, agricultural drainage, the influence of topography, and types of land use [2].

To estimate nonpoint pollution loads in rural areas, many efforts have been conducted to develop prediction models and to produce some detailed models which have been successfully applied to specific sites. Regarding complexity, the estimating methods can be categorized as:

1. simple methods;
2. mid-range models; and
3. detailed models.

Simple methods are widely used in the United States for nonpoint management in small rural watersheds

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due to their simplicity, practicality and easy identification [1]. Nevertheless, they are typically derived from empirical relationships between physiographic characteristics of watershed and pollutant export, and focus on continuing monitoring efforts. Accordingly, the output is in mean annual values or storm loads, and the predictive results are rough and have low transferability to other regions due to empirical details. In addition, simple methods consider few detailed representations of pollutant transport within and from the watershed.

Mid-range watershed models are generally midway between the cost, complexity, and accuracy of simple methods. The Agricultural Nonpoint Source (AGNPS) model is widely used as a kind of mid-range model and is validated for different conditions ranging from agricultural to forest areas, and can be used to simulate runoff, sediments, and chemical transport from a single storm event. Although AGNPS is a distributed model in the sense that watershed geometry is represented by uniformly distributed cells, its components are primarily empirical and lumped. For example, the AGNPS model uses the curve number (CN) and universal soil loss equation (ULSE) in estimating runoff and erosion from agriculture land [3]. The Annualized Agricultural Nonpoint Source (AnnAGNPS) is further improved and upgraded as a distributed parameter model for watershed scale and continuous simulation [4].

For a more accurate estimation of the load of nonpoint source pollutants, comprehensive models have been developed. The Hydrological Simulation Program–Fortran (HSPF), Soil and Water Analysis Tools (SWAT), and Better Assessment Science Integrating Point and Nonpoint Sources (BASIN) are used in watershed management to simulate nonpoint pollutant transportation under various hydrological conditions [5]. Incorporated with the `(GIS), these models cover a range of variations in complex physical, chemical, and biochemical processes, and help estimate the effects of agricultural management measures and practices [1]. Conversely, these models are complicated and require considerable time and expenditure for data collection and model application. They involve many parameters such as velocity, settling, decay, and other processes. Hence, the calibration and application of this model requires professional training.

As mentioned previously, the simple methods lack detail and application to different regions, while detailed models are complex and difficult to apply. In this paper, we develop general and useful empirical tools with a simple and reasonable approach.

Basic concepts of this empirical tool were based on the assumption that variations in event mean concentrations (EMCs) of pollutants from a given agricultural watershed during rainstorms were only attribuTable to the rainfall pattern; this pattern includes rainfall intensity, rainfall duration, antecedent dry days and rainfall [6]. EMCs represent the concentration of a specific pollutant contained in stormwater runoff coming from a particular land-use within a watershed, which are generally calculated from local stormwater monitoring data.

Obtaining the necessary data for calculating site-specific EMCs can be cost-ineffective, and researchers often use the values which can be available in the literature. If site-specific figures are unavailable, regional or national averages can be used, although the accuracy of these data is not reasonable to apply the model. Due to the specific meteorological and topographical characteristics of individual watersheds, agricultural and urban land uses can be shown in wide range of variability in nutrient export.

Developing a simple prediction model for general application in a small rural area would make the management of nonpoint pollution *become* convenient and efficient [7,8]. We seek to establish a useful empirical model through the compilation and analysis of EMC data sets obtained from different watersheds. *The prediction model developed in this study is a new and integrated approach to easily calculate pollutants loads from agricultural watershed. It can be applied with some simple and general parameters such as watershed and rainfall characteristics. Also it can be effectively applied to other watersheds.*

Based on these backgrounds, this study has three objectives: 1) to statistically characterize EMCs and loads in nine different rural watersheds; 2) to develop an equation to predict the runoff volume, loads, and EMCs using easily-measurable physical parameters such as watershed information and rainfall; and 3) to examine the application of the proposed model based on a comparison between the predicted and observed values in a reservoir.

2. Model development

The most important variable for a prediction model is event mean concentration (EMC) which can be defined as [9]:

$$EMC = \frac{Load_{total}}{Volume_{total}} = \frac{\sum (Q_i \times C_i \times \Delta t)}{\sum (Q_i \times \Delta t)} \tag{1}$$

where EMC = event mean concentration of a particular event (mg/l); Q_i = discharge during time interval Δt (m^3/h); C_i = concentration of pollutant during time interval Δt (mg/l).

If the EMCs from the rainfall events are available, the pollutant load can be estimated based on the simple method, described as

$$L = EMC \times C \times \mathrm{Re} \times A \times f \qquad (2)$$

where L = nonpoint source load of pollutant in the nth rain event (kg); EMC = event mean concentration of pollutant (mg/l); Re = rainfall depth (mm); C = runoff coefficient (dimensionless); A = area of the watershed (ha); f = conversion constant (0.01).

Even though there are same watersheds, the EMC range changes significantly with diverse rainfall patterns. For that reason, we focused on finding a relationship among the main influence factors including the characteristics of watershed, rainfall information, and flow parameters. The general description can be expressed as:

$$\mathrm{EMC} \propto f(LANDUSE, SLOPE, RAINFALL, ADD) \qquad (3)$$

where EMC is a function of *LANDUSE, SLOPE, RAINFALL, Antecedent Dry Days (ADD)* and other factors.

If reasonable results from a prediction EMC model were acquired, it can estimate the cumulative pollution load based on rainfall events for any time scale, as described in Eqs. (4)–(7) [10]:

$$SS_{Load} = \sum_{i=1}^{n} \left(EMC_{SSi} \bullet \mathrm{Re}_i \cdot C \bullet A \bullet f \right) \qquad (4)$$

$$COD_{Load} = \sum_{i=1}^{n} \left(EMC_{CODi} \bullet \mathrm{Re}_i \cdot C \bullet A \bullet f \right) \qquad (5)$$

$$TN_{Load} = \sum_{i=1}^{n} \left(EMC_{TNi} \bullet \mathrm{Re}_i \bullet C \bullet A \bullet f \right. \qquad (6)$$

$$TP_{Load} = \sum_{i=1}^{n} \left(EMC_{TPi} \bullet \mathrm{Re}_i \bullet C \bullet A \bullet f \right. \qquad (7)$$

Fig. 1 describes procedures to estimate the load of nonpoint source pollutants in a rural area. Starting with the rainfall depth and pollutant concentration, hydrograph, pollutograph, and loadograph data were produced. If an EMC value is obtained from Eq. (3) for the rainfall event, the pollution load can be easily computed using Eq. (2), and the cumulative load for the specific time span can be calculated using Eqs. (4)–(7).

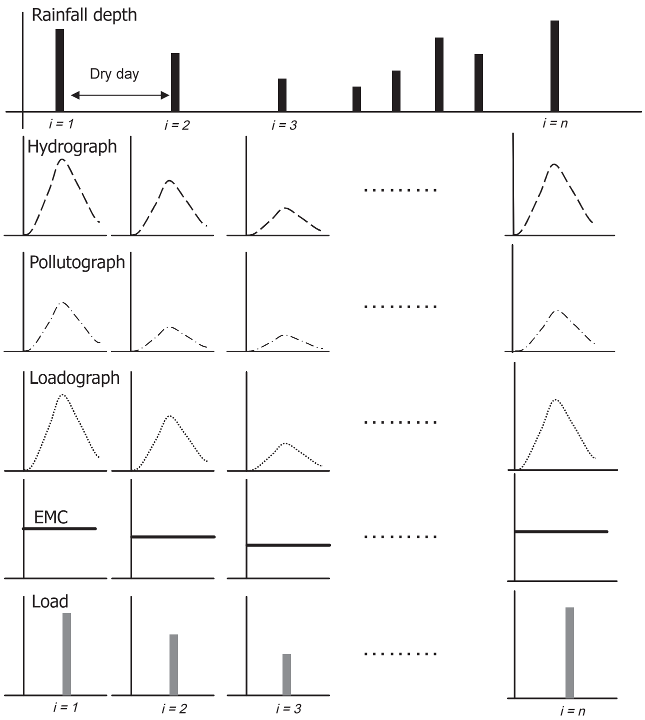

Fig. 1. Procedure for calculating nonpoint pollution load.

3. Material and methods

3.1. EMC data collection

To ensure the diversity of rural watersheds based on different land uses and regional specifications, nine watersheds in Korea were selected to analyze the characteristics of EMC and pollution load. Each watershed is comprised of agricultural areas, forest, agricultural-forest, and hybrid areas as shown in Fig. 2 (A–D).

The watershed of Rural 1 and Rural 2 is located in Seosan City. They drain out to the agricultural reservoir, and then flow into a regional class II River (status of the stream defined by Korean Government) located downstream. Rural 3 is mainly composed of unpolluted forest, and Rural 4 consists of a hybrid area of rice paddy and forest.

The data for the other five watersheds (Rural 5 to Rural 9) are collected from the agricultural NPS pollutant investigation programs granted by the Korea Rural Community Corporation. The specific site information is summarized in Table 1. NPS monitoring was conducted from March to September, 2002. The specific information regarding sampling is presented in Table 2. The measurement of all water quality parameters was performed in accordance with standard methods [11]. A total of 51 data sets (the number of the

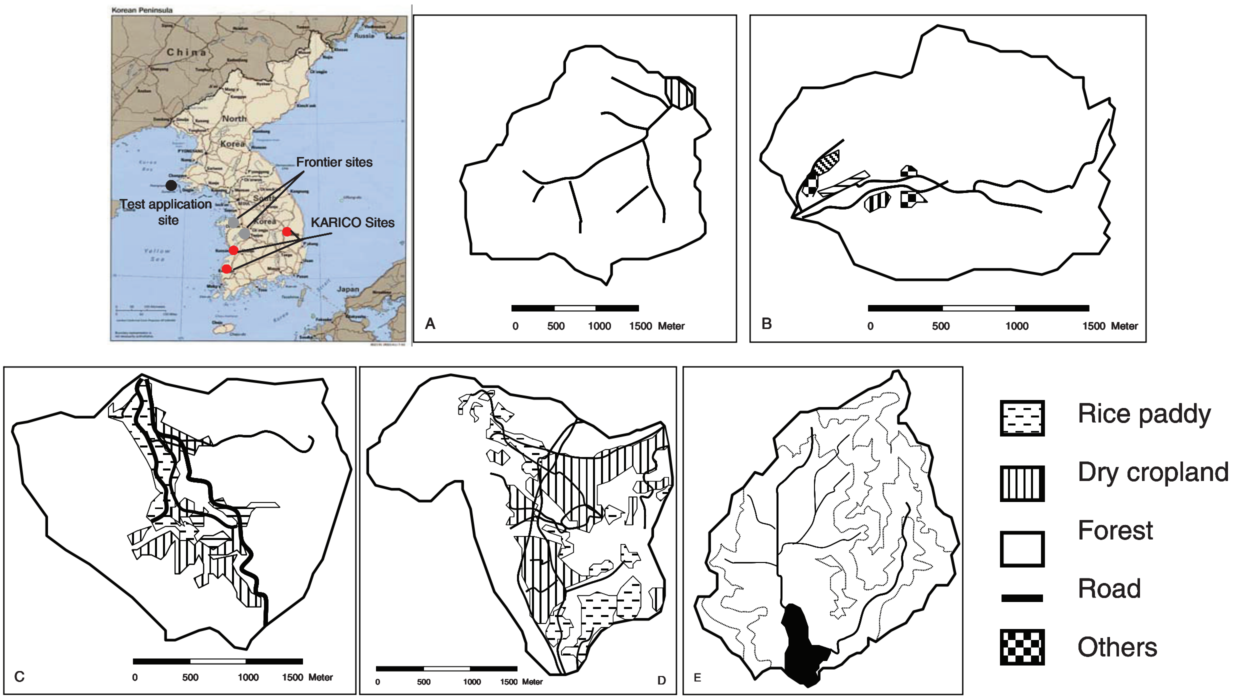

Fig. 2. Location of water quality monitoring points: (A) Study watershed 1—the Kyeryong Mountain; (B) Study watershed 2—Seosan city; (C) Study watershed 3—Haemi, Seosan City; (D) Study watershed 4—Shinheung, Daejon city; (E) The watershed and reservoir for model verification in Backryeong Island.

rainfall events) from nine watersheds were collected and analyzed.

3.2. Model establishment

Statistical software SPSS 10.0 was employed to analyze the 51 sets of EMC data. The specific procedure was performed as follows:

1. Descriptive statistical analysis;
2. Analysis of influence factors on the EMC values based on correlation matrices. The factors selected include the characteristics of watershed (area, land use, slopes, etc.); rainfall information (rainfall depth, rainfall intensity, duration, dry days, etc.); and hydrologic parameters (average flow rate, maximum flow rate, dry flow rate, etc.);
3. Forward-stepwise multiple regressions to relate EMC to the ratio of agricultural land use (AGRO), watershed slope (SLOPE), the depth of rainfall (Re), and advanced dry days since the last rainfall event (ADD), which are generally thought to be the most crucial factors [8,10].

Since the EMCs reflect the contributions of many factors, a multiplicative equation was used to fit the nonlinear model. Microsoft Excel® spreadsheet software was used to solve for the adjusTable parameters of the four factors previously mentioned, and the optimized solution was acquired.

3.3. Site used for examining model application

An opportunity to examine the field applicability of the empirical model came while a water quality problem in a reservoir on Backryeong Island in Korea was being studied. The reservoir was constructed by the local government and designated exclusively for head water. During the operation of this reservoir, it was determined that the water quality of the reservoir did not meet the water quality standards guaranteed by the consulting company. In an effort to improve the water quality of reservoir, all the water was drained out and followed by a clean-up of the sediments. Afterward, the reservoir started to store rainfall runoff. The changes of the water level and water quality parameters were monitored at various locations in the lake.

The watershed is covered with forest and agricultural area (*See* Fig. 2 (E)). This island is a military protection zone, so no further information can be provided. A scene showing the dredging of sediments can be seen

Table 1
Hydrological and land use descriptions of the study watersheds

Site	Location	Area[a] (km^2)	Length[b] (km)	Mean width[b] A/l (km)	Shape factor[c] A/l^2	Density[d] l/A	Mean slope[e] (%)	Land use (%)
Rural 1[a]	Seosan city Chungnam province	2.85	1.575	1.575	2.003	0.317	22.641	Rice paddy 1.8, cropland 0.7, forest 94.2, road 0.7, others 2.6
Rural 2[a]	Seosan city Chungnam province	4.97	1.649	2.652	1.827	0.487	41.17	Rice paddy 8.4, cropland 6.4, forest 82.3, road 1.4
Rural 3[a]	Daejon city Chungnam province	3.38	2.875	0.991	0.345	1.009	62.614	Forest 99.5, road 0.1, others 0.4
Rural 4[a]	Daejon city Chungnam province	27.37	6.173	4.434	0.718	0.226	5.97	Rice paddy 35.9, forest 44.8, road 4.7, residential 13.3, others 1.3,
Rural 5[b]	Iksan city Jeonbuk Province	2.28	1.560	1.67	1.07	0.60	26.0	Rice paddy 12.3, cropland 8.2, road 1.2% Forest 78.3
Rural 6[b]	Iksan city Jeonbuk Province	1.19	2.39	0.94	0.39	1.07	15.3	Rice paddy 27.5, cropland 9.2, forest 63.3
Rural 7[b]	Muhan city eonnam Province	5.87	2.95	2.15	0.73	0.47	7.2	Rice paddy 3.7, cropland 7, forest 89.3
Rural 8[b]	Muhan city Jeonnam Province	5.05	3.78	1.34	0.35	0.75	19.0	Rice paddy + cropland 38.2, forest 61.8
Rural 9[b]	Andong City Kyungbuk Province	8.33	3.32	2.51	0.76	0.40	3.32	Rice paddy + cropland 20.9, forest 79.1

[a]Frontier Research Program; [b]KARICO BMP Design Project.

Table 2
Hydrological and land use description of the study watersheds

Event number	Rural 1			Rural 2			Rural 3			Rural 4			Rural 5		
	RAIN[a]	T[b]	ADD[c]	RAIN	T	ADD	RAIN	T	ADD	RAIN	T	ADD	RAIN	T	ADD
1	1.0	3	3	1.0	2	3	18.5	7	7	18.5	7	7	3.0	1	9
2	16.5	5	6	16.5	5	6	67.0	12	13	66.5	12	13	15.7	6	1
3	44.2	15	9	22.0	13	14	14.4	5	3	14.4	5	3	33.8	3	2
4	129.5	13	2	129.0	13	2	43.5	6	2	43.5	6	2			
5	24.0	12	7	24.0	12	7	44.5	12	1	44.5	12	1			
6	0.1	1	1	0.1	1	1	259.8	6	2	259.8	6	2			
7	19.5	20	7	19.5	20	7	35.0	9	2	35.0	9	2			
8	89.5	34	2	89.5	34	2	4.5	6	5	4.5	6	5			
9	12.0	8	7	12.0	8	7	37.0	5	5	135.0	10	1			
10	118.0	12	2				135.0	10	1						

Event number	Rural 6			Rural 7			Rural 8			Rural 9		
	RAIN	T	ADD	RAIN	T	ADD	RAIN	T	ADD	RAIN	T	ADD
1	15.7	4	2	49.0	6	1	28.0	7	1	28.0	7	1
2	33.8	3	2	32.5	5	7	36.0	12	5	80.0	13	1
3	38.5	2	1	47.7	6	18				36.0	12	5

[a]Rainfall depth (mm); [b]Duration (h); [c]Advanced dry days.

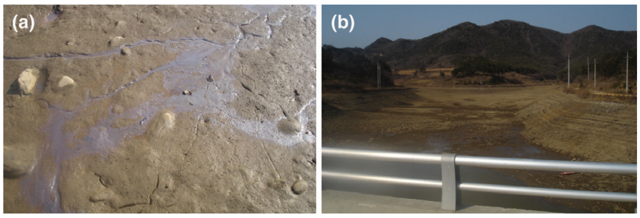

Fig. 3. Reservoir on Backryeong Island: (a) Sediments before clean-up; (b) The reservoir after clean-up.

in Fig. 3. Specific information about the reservoir and its watershed is summarized in Table 3.

The reservoir or lake is normally assumed to be a continuously stirred tank (CSTR). Consequently, the pollutant concentration in the reservoir water (initially there was no water) can substitute for the EMC value within a short period of time after a rainstorm has passed.

For this purpose, a sampling program was established and the instantaneous pollutant concentrations at the various upper and lower layers of the reservoir during 17 consecutive rainfall events from 1 July to 15 August in 2007 were monitored. In order to validate the model, EMC values calculated from the EMC-based model we developed was compared to the values measured in the reservoir.

4. Result and discussion

4.1. Characterization of storm water runoff

Table 4 summarizes the EMC values from nine individual watersheds during different rainfall events. Apparently, it was observed that the SS shows great variability across two or more magnitude in most watersheds, which indicates that the SS transport is associated with rainfall patterns and also with characteristics of individual watersheds.

The EMC values for COD, TN, and TP have less variability compared to SS. It implies that these types of pollutants have relatively sTable establishing mechanisms. As an overall analysis for the EMC data, Fig. 4 gives the statistical distribution of different pollutants, and clearly shows that the EMC of SS lies in wide range comparable to other parameters such as COD, TN, and TP.

Correlation coefficients were calculated between EMC of pollutants and influence factors (*See* Table 5). Generally, SS, COD, and TP has a correlation with rainfall depth, rainfall intensity, and runoff volume. In particular, all the parameters were associated with *rainfall intensity*, and it is natural that heavy intensity can carry more pollutants during the surface runoff process. As a practical application of model development, only event rainfall depth was selected as an explanatory variable.

The agricultural activity in the watershed was identified as the most important factor influencing the discharge of pollutants. As shown in Table 1, Rural 1 and Rural 3 are dominated by forested area with proportions of 94.2% and 99.5%, respectively. Other watershed areas are undergoing agricultural activity (rice paddy and cropland) with a range of 10.7% (Rural 7) to 38.2% (Rural 8) of agricultural area. Based on this fact, watershed was classified into two groups: forest area and hybrid area. In order to determine the difference between these two groups, the distribution of the pollutant is provided in Fig. 5. It is observed that in the hybrid area, the EMC values of TSS, COD, TN, and TP are much higher than that in the forest area, which indicates that agricultural activity probably has a predominant influence over other factors.

ADD seems to have a weak relationship with EMC in this rural watershed, unlike many observations in impervious area. In paved area, as ADD becomes longer, a higher EMC value can be attained [7] because of the longer accumulation time for pollutants.

A weak relationship between EMC and ADD may be due to several reasons. In an agricultural area, a longer ADD does not mean a higher accumulation of pollutants because pollution is mainly related to farming activity and changes with seasonality. Even though there is no such evidence, a longer ADD would probably provide more time for plant uptake and microbial activity, thereby decreasing the amount of pollutants during storm water discharges. *And the EMC can also be affected by the rainfall intensity, runoff volume and land use et al., in most runoff studies, EMCs vary from event to event [6], this declines the relationship between EMC and ADD to a certain extent.*

The transport of pollutants during a rainfall event is determined by ADD and other factors such as rainfall pattern, watershed characteristics, and pollutant types.

Table 3
Reservoir and watershed examined for applicability of the EMC-based equations

Watershed			Reservoir		
Area	Land use	Slope	Area	Storage capacity	Mean depth
71 ha	Cropland 21.9% Forest 69.2 % Reservoir 8.9%	0.15~0.45	6.3 ha	200,000 m^3	9.6 m

Table 4
Descriptive statistics of runoff EMCs by the site

Parameters	Watershed	*n*	Mean	SD	Minimum	Maximum
SS	Rural 1	10	62.2	67.4	3.1	195.4
	Rural 2	9	122.5	174.8	5.6	523.5
	Rural 3	10	5.1	11.3	0.5	37.0
	Rural 4	9	110.0	208.8	8.4	662.0
	Rural 5	3	35.7	26.9	5.0	55.0
	Rural 6	3	177.3	131.1	30	281.0
	Rural 7	3	78.0	68.2	25	155.0
	Rural 8	2	52.0	32.5	29	75.0
	Rural 9	3	98.0	135.5	10.0	254.0
COD	Rural 1	10	7.2	2.8	3.2	10.9
	Rural 2	9	16.6	14.4	2.8	49.8
	Rural 3	10	6.9	4.7	2.8	16.6
	Rural 4	9	20.7	11.0	6.0	37.5
	Rural 5	3	16.0	6.1	9.0	20.0
	Rural 6	3	17.3	5.5	11.0	21.0
	Rural 7	3	15.0	11.5	6.0	28.0
	Rural 8	2	6.5	0.7	6.0	7.0
	Rural 9	3	8.7	2.9	7.0	12.0
TN	Rural 1	10	0.9	0.2	0.7	2.3
	Rural 2	9	2.1	0.5	1.3	2.6
	Rural 3	10	0.9	0.7	0.1	2.2
	Rural 4	9	4.8	2.4	1.9	10.6
	Rural 5	3	6.0	2.6	4.0	9.0
	Rural 6	3	4.7	2.1	3.0	7.0
	Rural 7	3	6.7	2.1	5.0	9.0
	Rural 8	2	–	–	–	–
	Rural 9	3	–	–	–	–
TP	Rural 1	10	0.16	0.07	0.03	0.28
	Rural 2	9	0.62	0.52	0.09	1.77
	Rural 3	10	0.29	0.13	0.10	0.52
	Rural 4	9	1.34	0.53	0.88	2.29
	Rural 5	3	0.67	0.46	0.40	1.20
	Rural 6	3	0.70	0.26	0.40	0.90
	Rural 7	3	0.67	0.29	0.50	1.00
	Rural 8	2	1.15	0.07	1.10	1.20
	Rural 9	3	1.20	0.26	1.10	1.50

n = number of data, SD = standard deviation.

In other words, it can be caused by comprehensive influencing mechanisms. Even on shorter dry days, the heavy rainfall can discharge more pollutants, while on longer dry days the small amount of rainfall can cause less transport of pollutants. This can be observed from the collected EMC data with a wide range of rainfall events (data not shown).

4.2. Empirical EMC-based model

As noted previously, linear correlations between EMC values and explanatory variables are not strong, and this reflects the combined effect of many factors on EMC in rural areas. However, including more variables in the model may decrease model efficiency and lead to the difficulty of applicability in different regions.

In an effort to make prediction equations, the four main factors—agricultural land ratio (AGRO), watershed slope (SLOPE), rainfall depth (Re), and advanced dry day (ADD)—were taken into account in establishing multiplicative nonlinear regression models for estimating the EMC induced by rainfall events. These four factors were chosen based on two considerations: first, as described previously, agricultural activity was iden-

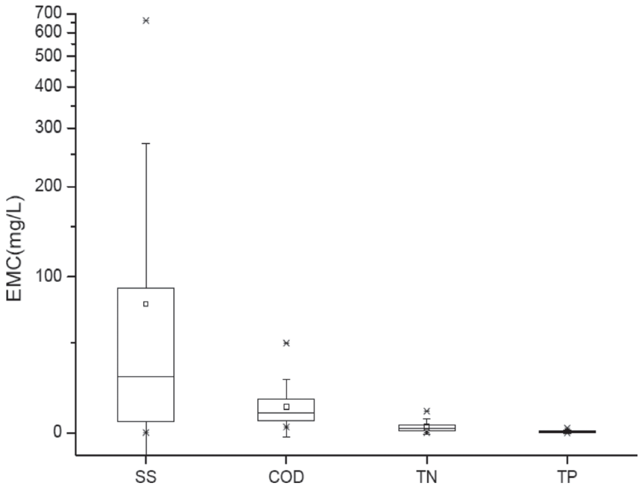

Fig. 4. Box plots of different pollutants.

Table 5
Correlation coefficient between EMC and rain and watershed variables

	Storm variables				
	Depth	Duration	Intensity	Runoff	ADD
TSS	0.217	0.244	0.100	0.185	0.041
COD	0.195	–0.007	0.175	0.251	–0.026
TN	–0.047	–0.290	0.131	–0.013	–0.047
TP	0.142	–0.027	0.157	0.168	–0.129

tified as the most important influence factor. Second, slope in the watershed reflects the easiness or difficulty concerning with pollutant transport for particles contained in the storm water runoff especially.

As a result of the analysis and solution for the 51 data sets, the following equations were obtained:

$$EMC_{SS} = 1.3 \bullet AGRO^{1.3} \bullet ADD^{0.5} \bullet SLOPE \bullet \mathrm{Re}^{0.7} \quad (8)$$

$$EMC_{TCOD} = 1.5 \bullet ADD^{0.17} \bullet AGRO^{0.34} \bullet \mathrm{Re}^{0.32} \quad (9)$$

$$EMC_{TN} = 1.5 \bullet AGRO^{0.37} \bullet \mathrm{Re}^{0.19} \quad (10)$$

$$EMC_{TP} = 1.1 \bullet AGRO^{0.64} \bullet \mathrm{Re}^{0.1} \quad (11)$$

As mentioned earlier, land use is generally regarded as the most important index in estimating nonpoint source pollutant. In agricultural areas, the higher AGRO values reflect, the more heavy pollutant load due to farming activity. Thus, it is natural to find the occurrence of AGRO in the four equations.

For the other parameters, the ADD and Re values indicate a buildup/wash-out mechanism of the pollutants. As previously mentioned, the basic assumption underlying the development of the model is that the change of EMC is only a function of the rainfall pattern as long as land use has not changed. As such, longer dry days until the next rainfall event would accumulate more pollutants in the watershed, and the rainfall runoff will carry out pollutants established during the ADD period, which is clearly reflected in Eqs. (8) and (9).

From Eq. (8) to Eq. (11), the index of *Re* decreased gradually, which indicates the different weighing factors on different pollutants. SS has the largest index value of 0.7, while TP shows the smallest index of 0.1. This was unexpected—it was thought that phosphorus and ammonium are easily combined or adsorbed well with fine particles such as clay soil, whose transportation from cultivated farms does not require heavy rain.

It is noteworthy that SLOPE was included only in the SS equation, suggesting that particle transportation is strongly associated with topography factors. In fact, in USLE, the slope factor of the drainage area is one of the main parameters in estimating erosion and soil loss.

On the contrary, the ADD is not included in the TN and TP in Eqs. (10) and (11), which means that shorter or longer ADD does not significantly affect nutrient level in stormwater from agricultural areas; e.g., the accumulation effect is not significant, which was discussed in the previous section.

EMC values in the nine watersheds were calculated and compared with the measured values to evaluate the prediction accuracy of the empirical model (Fig. 6). The Figure shows that the increases and decreases in predicted and observed EMC values are well simulated. TSS and TP give fine regressions ($R^2 = 0.64, 0.60$), while the prediction of COD and TN is relatively weak ($R^2 = 0.28, 0.32$). As previously discussed, TSS and COD are associated with soil particles and they are convenient to be estimated, while the other two parameters have more complicated components and transposition mechanisms. It must be noted that above proposed equations presents a useful approach in estimating general nonpoint source pollutant for an individual area.

Maniquiz et al. developed some modes using rainfall variables (antecedent dry days, rainfall, rainfall duration and rainfall intensity) to predict the EMCs of urban runoff, it was found out that most important rainfall variables to estimate loads and EMCs were total rainfall, rainfall duration and average rainfall intensity, and all were associated with runoff volume [6]. Some EMCs predictive models of stormwater runoff in urban area were established using rainfall variables (precipitation, rainfall duration, rainfall intensity and antecedent dry days) and watershed variables (watershed area,

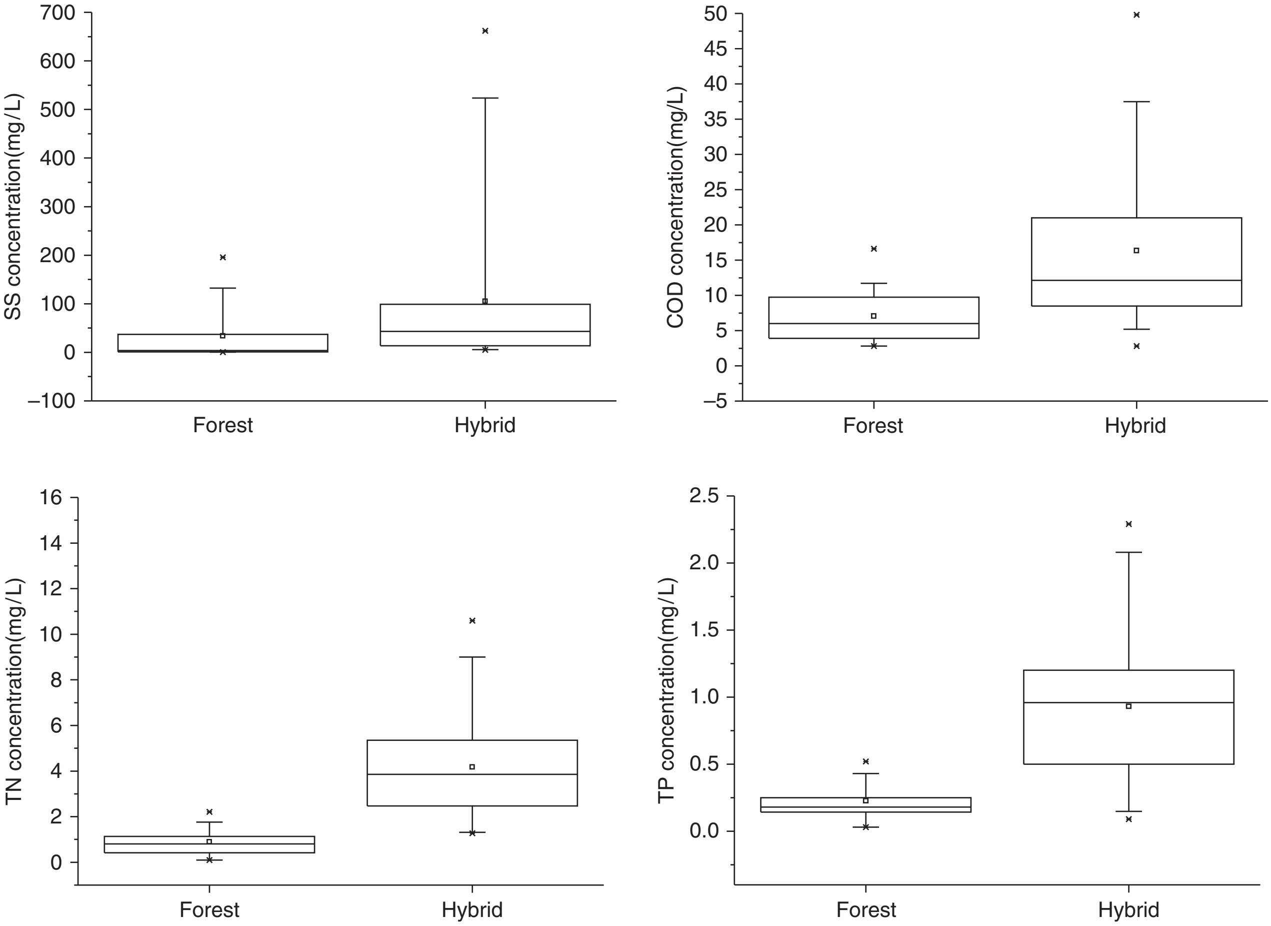

Fig. 5. Comparison between forest area and hybrid area.

residential area, and land-use fraction) [12], the results indicated that the most useful variables to predict runoff EMCs were rainfall duration and antecedent dry days.

4.3. Application of the prediction model

The developed model has several advantages over similar models. A distribution of EMC values can be easily acquired with limited information (watershed and rainfall factors) for a given rural watershed. Furthermore, calculation of the temporal pollution load distribution also can be pursued. In order to provide an example for the application of the model, the monthly calculated EMC distribution and total load in watershed Rural 5 during three years (2000 to 2002) was computed and the results were shown in Fig. 7. Rural 5 is a watershed for a small agricultural reservoir. The probability distribution of EMCs is shown in Fig. 8, and some random dry sampling data collected during a similar period were added to the graph so that the comparison between two different data sets can be made.

Fig. 8 shows that both the EMC and dry day concentration of nitrogen does not show a significant difference. The load distribution graph indicates that heavy rainfall causes the major pollution, while light rainfall could be neglected (*see* Fig. 7). It is reasonable that heavy rain highly affects pollution due to high flow.

4.4. Examination of model application

Although the prediction model is certain to be effective in this study, it should be applied to other watersheds to determine its application. We tried to examine the empirical model in a reservoir as discussed in Section 3.

Fig. 9 shows the rainfall information and sampling trips. The rainfall events were very concentrated in July

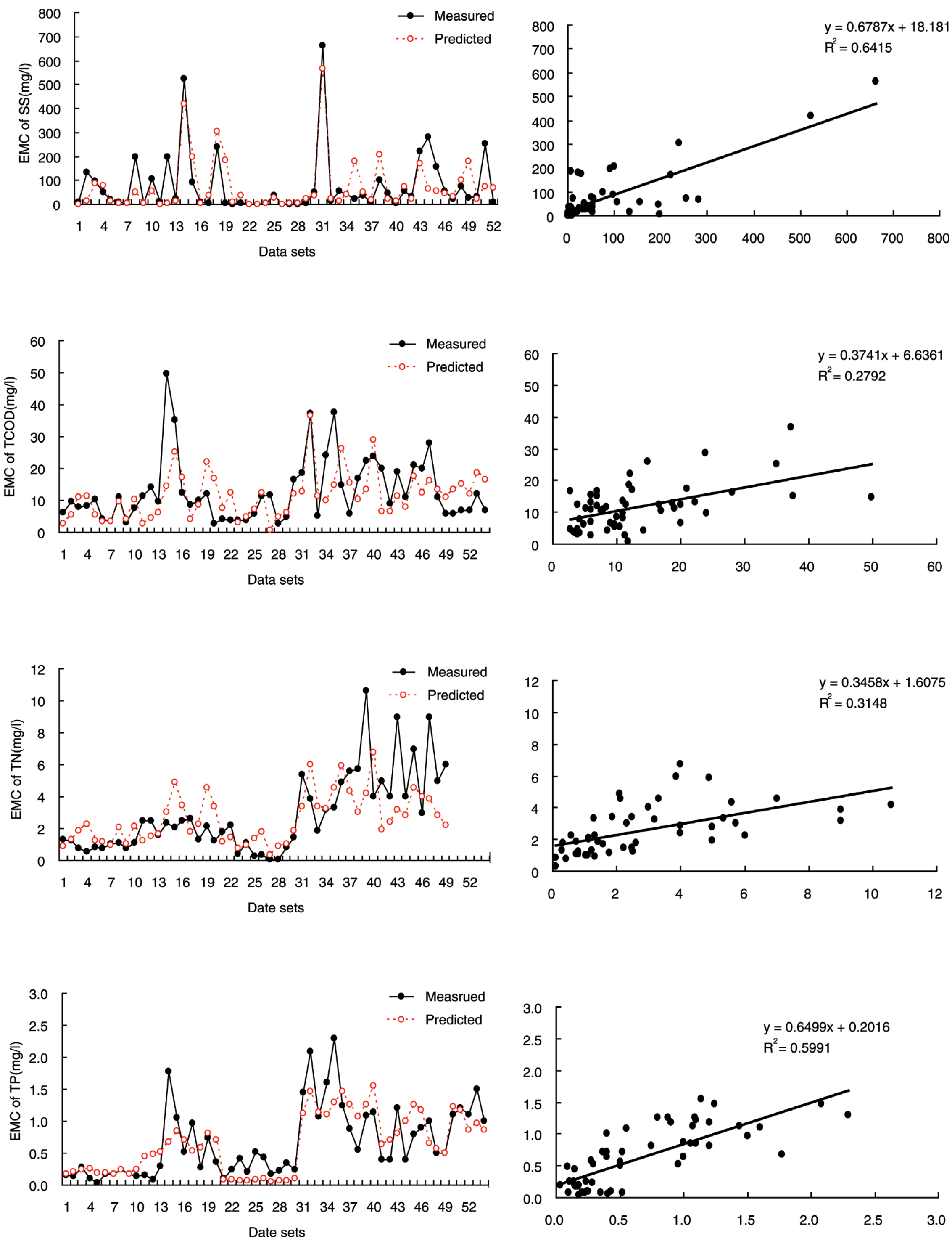

Fig. 6. Comparison between observed and predicted EMCs.

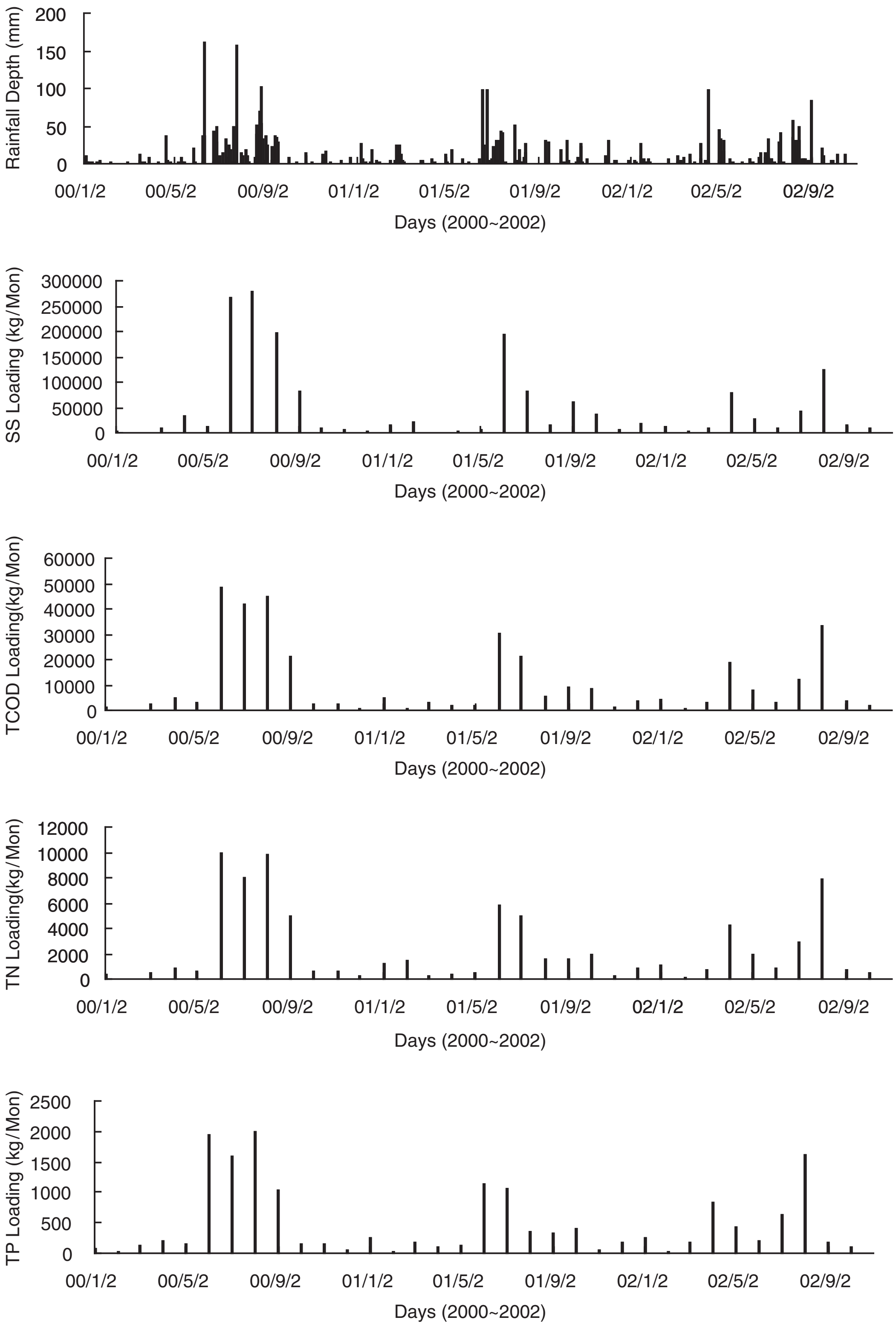

Fig. 7. Monthly distributions of predicted pollutant loads in Rural 5.

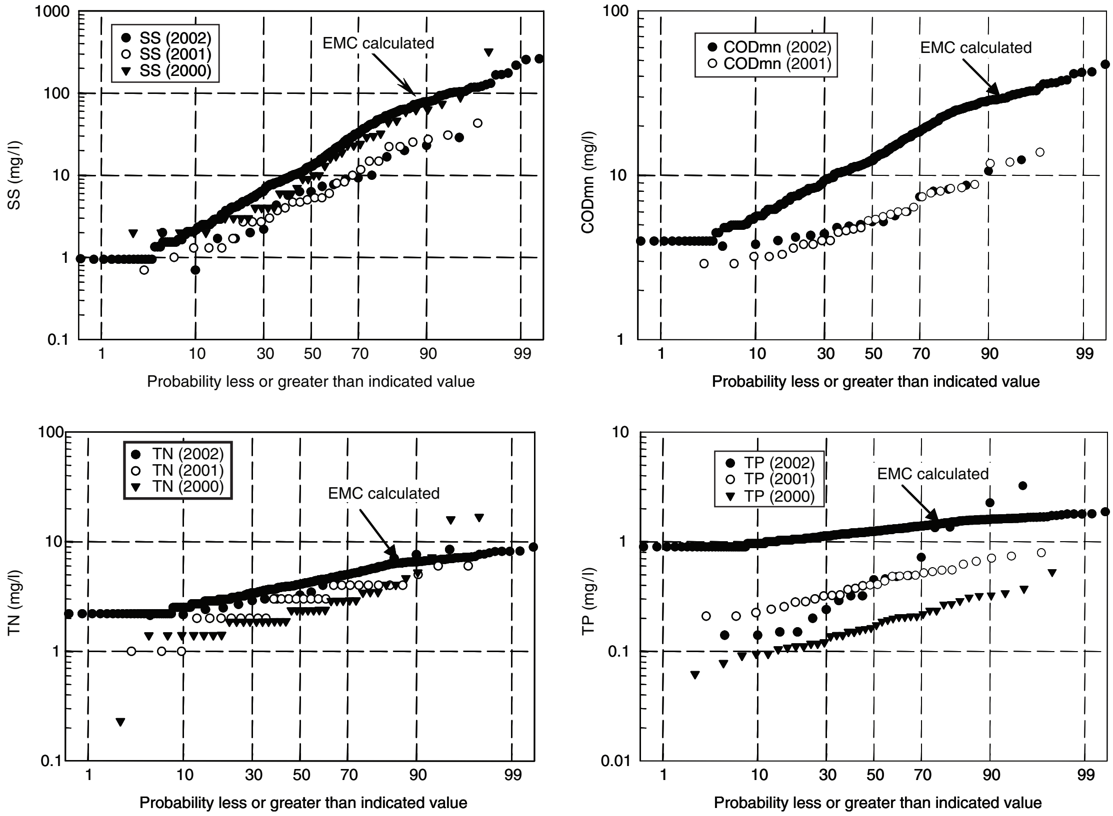

Fig. 8. The probability distribution of EMC values.

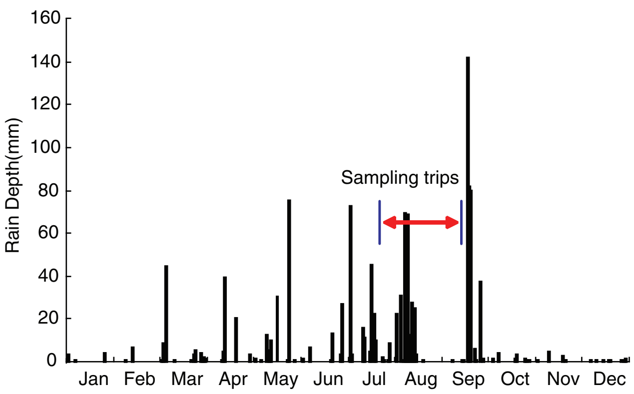

Fig. 9. Rain event distribution and sampling trip period.

and the first two weeks of August, and consecutively 17 events occurred in this period. Nine field experiments were conducted, and water was collected from the upper and lower layers at three points in the reservoir.

Fig. 10 shows comparative result between the predicted EMC values and measured concentrations for TSS, COD, TN, and TP. The predicted values of COD correspond well with observed values. Similarly, we calculated concentrations of TN and TP and also compared them with measured concentrations, which shows that predicted total nitrogen moderately matched the observed values. However, there was a large difference in SS and TP between the two parts. This was thought to be due to the fact that these components were largely associated with particles; i.e., some portion of particle-nitrogen and phosphorus was deposited at the bottom of reservoir between periods of ADD.

Based on the examination of models developed in this study using other watershed measured values, we can conclude that the prediction models can be applied to other cases effectively.

The matching of COD values between the predicted and the measured values further validates the utility of the estimation method. For TN and TP, it also preserves stability in the reservoir. On a long term scale, the nutrients in the reservoir will approach balance and stability. It is noteworthy that the pollutants in the reservoir are unsTable after the dredging.

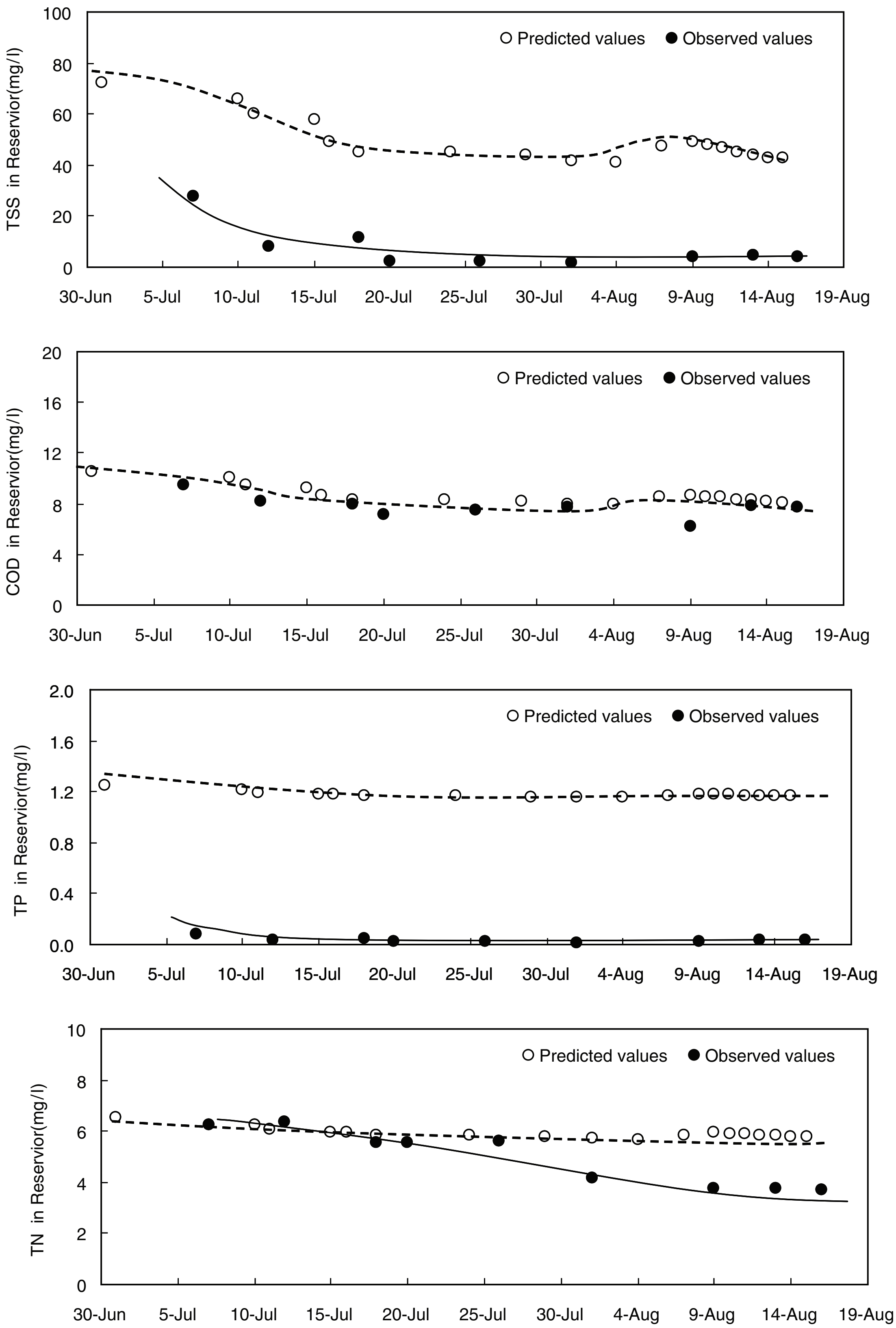

Fig. 10. Comparison between predicted and observed pollutant concentrations in the reservoir.

5. Conclusions

The EMC values for nine small rural watersheds in Korea were collected and statistical analysis was employed to determine the most important influence factors affecting the nonpoint source pollution load. AGRO, SLOPE, ADD, and Re were identified as the main influence variables.

Based on these variables, we developed an empirical prediction model with the objective of evaluating pollutant loads. Four equations involving TSS, TCOD, TN, and TP were developed. As an application of this model, the EMCs and loads in Rural 5 were calculated and compared with the monitoring data.

The prediction model was applied to solve the problem of water quality in a reservoir. The EMC of TSS, TCOD, TN and TP can be determined just using the four variables: AGRO, SLOPE, ADD, and Re, which can be easily collected. It indicated that the proposed equations can be successfully applied in other unmonitored areas, especially when most of the information is not easily available.

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