A review on the calculation of non-point source pollution loads

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Abstract. The non-point source pollution account for a large amount of the total pollution into water after most of the point source pollution is controlled. Therefore, an accurate calculation of non-point source pollution is regarded as the first step for water ecological restoration. This paper reviews traditional and current trends in watershed modelling on the calculation of non-point source pollution loads, including export coefficient models, empirically based models and physically based models. The utilisation of artificial intelligence (AI) as part of a data-driven approach assists the empirically based models to yield better watershed modelling. The processes of modelling, required data and suited situation are introduced which may be helpful to policymakers in the business of pollution reduction and management.

1. Introduction

Water plays an essential role in the ecological balance of the Earth and water quality degradation threatens socioeconomic development and human health [1]. As the point source pollution has been monitored and treated, the current water pollution is mainly caused by non-point source (NPS) pollution [2]. In China, the quality of the water environment has declined sharply due to the increasing pollution loads like ammonia, total phosphorus (TP), total nitrogen (TN) and chemical oxygen demand (COD) from NPS pollution [3]. And agriculture is the biggest cause of NPS pollution due to the excessive use of chemical fertilizer [4]. In the coming decades, NPS pollution control will be one of the most important issues in water environmental protection [5].

The NPS pollution has become increasingly important for the study of water quality and pollutant transport processes in river catchments. The pollutants may be distributed into water through direct industrial discharge, domestic pollution, precipitation and the application of agrochemicals, and therefore may accumulate in the soil through the dry periods. As a result of snowmelt or rainfall, the pollutants (in dissolved or particulate phases) may migrate vertically into lower soil layers with vertical water movement and horizontal overland flows [6]. Moreover, spatial and temporal variations in the hydrologic behaviours of a watershed also impact the transport of pollutants from land to water. Dispersion, concealment, uncertainty and difficult-monitoring are the features of NPS pollution, which makes it difficult to measure and estimate the total load of the NPS.

There are many models to quantify effect of temporal–spatial changes on the NPS pollution. Model simulation is regarded as the most effective and direct method to estimate NPS pollutants [7]. These models may be served:

- to characterize runoff quantity and quality in spatial and temporal details;
- to provide inputs for a receiving water quality analysis;
to determine the pollution effects, magnitude, and optimum locations and combinations of control options;
• to perform frequency analysis on selected quality parameters;
• to provide inputs for cost-benefit analyses [8].

Matias et al applied the export coefficient model to study phosphorus loss in South Portugal and found that the control the sewage discharge was more efficient compared to the control of farming mode in semi-arid area [9]. Li et al established the empirically based model in the study pollution conditions of Poyang Lake watershed. It revealed that the ammonia nitrogen and total nitrogen from NPS account for 68.36% and 75.29% respectively, which are much higher than that of point source pollution [10]. Luo analyzed the pollution condition the Taizi River, Northeast China and evaluated the effect under best management practices like changes in fertilization mode, reduction of fertilization and increase of permeable area in SWAT model [11]. As these models are based on different theories, methods and data, performance varies greatly when they are put into practice. The application of these models to different projects would achieve different accuracies of the estimation of pollution load. In order to get an accurate pollution load for a specific region, a suitable model should be chosen from these models based on its characteristics.

This study is to summarize representative models for the calculation of NPS pollution load in watersheds, which include the export coefficient models, empirically based models and physically based models. In the era of artificial intelligence, innovative methods applied in water ecological restoration like artificial neural networks, fuzzy logic and support vector machine are reviewed. The process of modelling, required data and suited situation are reviewed and their advantages and disadvantages are highlighted, in order to provide insights for the selection of models to quantify temporal–spatial variations in NPS pollution for pollution reduction and management.

2. Calculation of non-point source pollution loads
The representative models for the calculation of NPS pollution load in watersheds may be grouped into three major categories: the export coefficient models, empirically based models and physically based models.

2.1. Export coefficient models
The export coefficient models (ECM) usually evaluate and forecast the effect of management policy in an annual period. It calculates the pollution load in the form of TN and TP while neglects pollutant transport and transformation in the water circle. However, this model is still regarded as an effective and efficient method to calculate NPS pollution.

Based on the theory of ECM, the early model has been improved and developed from different aspects to describe the heterogeneity within the study region. The early one of ECM was first established in North America in the 1970s to assess NPS agricultural pollution to lakes. It was based on the assumption that the pollution loads exported from a watershed are equal to the sum of the losses from individual sources. The model used an export coefficient approach to calculate the nitrogen (N) and phosphorus (P) loads delivered annually to a water body as the sum of the individual loads exported from each pollution source. The early ECM is written as follows:

$$L_{np} = \sum_{i=1}^{n} E_i A_i$$  \hspace{1cm} (1)

where, $L_{np}$ is the NPS pollution load; $E_i$ is the export coefficient for pollution source $i$; $A_i$ is the area of the catchment $i$; $n$ is the total number of pollution sources. There are deficiencies in the early model, for example, the classification of land uses was relatively simple, and various agricultural land uses were not accurately subdivided.

Based on the classification of land uses, Johnes modified the early version of the export coefficient model, adding the effects of livestock and population on the NPS pollution loads [12]. Different export
coefficients are adopted for cultivated land which are planted with different crops and for different kinds of livestock according to their quantity and distribution. Also, the export coefficient affected by the population is mainly determined by the discharge and treatment of domestic sewage. This modified model is written as follows:

\[ L_{np} = \sum_{i=1}^{n} E_i \left[ A_i \left( I_i \right) \right] + P \]  

(2)

where, \( A_i \) is the area of the catchment \( i \), or the number of livestock type \( i \); \( I_i \) is the input of the pollution to source \( i \); \( P \) is the input of the pollution from precipitation, which is given as:

\[ P = c \times a \times \alpha \]  

(3)

where, \( c \) is the concentration of the pollutant; \( a \) is the annual precipitation in the watershed; \( \alpha \) is the proportion of runoff formed by annual precipitation, namely runoff coefficient.

For the pollution caused by human waste, the coefficients reflect dietary, habit and society development, which is presented by the following equation:

\[ E_n = D_{wa} \times H \times 365 \times M \times B \times R_s \times C \]  

(4)

where, \( E_n \) is the annual export from population; \( D_{wa} \) is the daily output of pollutant per person; \( H \) is the number of population in the study area; \( M \) is the removal factor of pollutant after the mechanical treatment; \( B \) is the removal factor of pollutant after the biological treatment; \( R_s \) is the retention coefficient of the filter bed, and \( C \) is the coefficient for removal of \( P \) if phosphorus stripping takes place. It should be noted that the export coefficients would vary significantly in different regions. They may be obtained from literature reviews and results of in-situ measurement to determine the rate of the nutrient loss from every source to the water body.

Ding et al improved the export coefficient model by introducing a precipitation factor and a terrain impact factor which are based on the digital elevation model and land use map, since spatial and temporal variations in the hydrologic behaviors of a watershed directly impact pollution transport from land to water [13]. Their modified model is presented as follows:

\[ L_{np} = \sum_{i=1}^{n} \alpha \beta E_i \left[ A_i \left( I_i \right) \right] + P \]  

(5)

where, \( \alpha \) is the precipitation factor and \( \beta \) is the terrain factor. This model was applied to the calculation of NPS pollution load in the upper reach of the Yangtze River. It was shown that it can provide reliable results for large-scale of agricultural watershed. Yuan et al later validated Ding’s model for the calculation of NPS pollution load of Dongting Lake region [14]. The effects of rural livelihood transition on NPS pollution were considered. Wang et al and Wu et al adopted ECM which takes the factors of rainfall influence into consideration to estimate TN of Jinghe River and Yanhe River in Shaanxi Province [15,16]. The results indicated that the load intensity is closely related to rainfall intensity.

2.2. Empirically based models

The empirically based models (EBM) are statistical models, which are mainly based on a statistical analysis of a long series of rainfall, hydrological and water quality monitoring data. The process of pollutants transport and transformation is also neglected in these models. The empirical formulae were established through regression analysis for the data of NPS pollution load, rainfall and runoff to calculate NPS pollution load in different watersheds. Generally, the structure of the watershed should be relatively simple since the established relationship is usually linear or simply non-linearity. Representative EBMs include the base flow separation model based on flow separation method which contains base flow and direct flow, the model based on rainfall deduction method and the model based
on artificial intelligence method.

2.2.1. Base flow separation model. The base flow separation model (BFSM) separates the streamflow into a base flow that is a long-term steady flow and direct flow that is the response to a rainfall event [17]. How to separate the base flow may further be categorized into six methods: the linear segmentation method, slash segmentation method, hydrological modelling method, water balance method of Kalinin, environmental isotope method, and the digital filtering method [18]. It should be noted that these approaches do not have any physical or hydrological basis, but aims to generate an objective and repeatable index that can reflect the base flow response of a watershed to the NPS pollution.

The base flow separation model is assumed that direct flow caused by rainfall in flood season is the source of NPS pollution to stream. In the dry season, the pollution into the base flow is commonly caused by point source input. The flux of base flow is regarded to be steady throughout the year. The total pollution load transported into rivers can be written as:

$$L = L_p + L_{np} = \int_0^t \left[ C_p(t)Q_p(t) + C_{np}(t)Q_{np}(t) \right] dt$$  \hspace{1cm} (6)

where, $L$ is the total pollution load transported into rivers; $L_p$ is the point source pollution load; $C_p(t)$ is the point source pollution concentration; $Q_p(t)$ is the base flow; $C_{np}(t)$ is the NPS concentration; $Q_{np}(t)$ is the direct flow.

When lack of continuous monitoring data, equation (6) is written in the discrete form:

$$L = L_p + L_{np} = \sum_{i=1}^n C_{pi}Q_{pi}\Delta t + \sum_{i=1}^n C_{np}Q_{np}\Delta t$$  \hspace{1cm} (7)

Based on years of hydrological and water quality monitoring data, the total pollution load can be calculated by:

$$L = \sum_{i=1}^n C_iQ_i\Delta t$$  \hspace{1cm} (8)

Finally, the NPS pollution load is equal to the total pollution load minus the point source pollution load, which is written as:

$$L_{np} = L - L_p = \sum_{i=1}^n C_{pi}Q_{pi}\Delta t - \sum_{i=1}^n C_{np}Q_{np}\Delta t$$  \hspace{1cm} (9)

The model has been tested by Li et al in 2010 in the catchment of Dongjiang River, China and showed that 67% of the COD load come from NPS pollution in the period between 2000 and 2005 [19]. Moreover, Lu et al found that the TN loading from base flow was significantly higher than that from surface direct flow in the watershed of Changle River, China [20].

2.2.2. Rainfall deduction model. The rainfall deduction model directly establishes a relationship between the rainfall and the NPS pollution, ignoring the process of hydrological segmentation and the derivation of point source pollution [21], which can be written as:

$$L_n = f(R)$$  \hspace{1cm} (10)

$$L_p = C$$  \hspace{1cm} (11)

$$L = L_n + L_p = f(R) + C$$  \hspace{1cm} (12)
where, $L_n$ is the NPS pollution load; $f(R)$ is a function of precipitation $R$; $L_p$ is the point source pollution load, which is viewed as a constant $C$ during years.

Take consideration of the difference between any two years’ data of total pollution load and the precipitation:

$$\Delta L = L_i - L_j = f(R_i) + C - f(R_j) - C = f(R_i) - f(R_j) = f(R_i - R_j) = f(\Delta R)$$

(13)

where, $i$ and $j$ are denotations of different years.

With the constant $C$, $\Delta L$, the difference of the total pollution load, could be regarded as the difference of the NPS pollution resulted from the difference of precipitation. By the regression analysis, the direct relationship between the NPS pollution and precipitation was established. In terms of application and prediction, the accuracy is better in a normal year than in flood year and dry year.

2.2.3. Artificial intelligence models. Artificial intelligence (AI) is one of innovative methods for pollution calculation and prediction as part of a data-driven approach. The artificial intelligence models adopts AI techniques like the artificial neural networks (ANNs), fuzzy logic and support vector machine (SVM) [22,23].

![Figure 1. Illustration for artificial neural network [24.]](image)

ANNs are highly complex composite functions with the ability of computing non-linear problems [24]. ANNs have been widely applied to forecast water quality and pollution worldwide [25-27]. The model based on artificial neural networks has the ability of learning, processing, creativity and flexibility. An artificial neural network usually consists of three layers, including the input layer, the hidden layer and the output layer, shown in Figure 1. Data enter neural networks through the input layer and are extracted out through the output layer after the process of the hidden layer. Networks may be classified into 2-layer neural network (1 hidden layers), 3-layer neural network (2 hidden layers) and complex neural network due to the number of hidden layers. The number of neurons in the input layer depends on the specified problems and the number of independent variables. Whereas, the output layer is related to dependent variables. Every neuron has input connections and output connections. These connections have different weights, meaning that the value that is sent to every connection is multiplied by this weight factor. To select the best and most efficient model, the statistical correlation coefficient and mean square error are used to evaluate the quality of this model. Common input factors include non-agricultural population, GDP, water consumption, wastewater
discharge, sewage treatment rate etc. The output would be various like pollution index, pollutant concentration and so on. Relative modules are mature and provided in commercial softwares.

The fuzzy logic is an effective analytical method to deal with uncertain problems based on fuzzy sets, which express multiple level process among [0, 1] proposed by Zadeh in 1965. It has been used to evaluate water quality instead of discontinuous crisp set [28,29]. The structure of fuzzy logic includes fuzzifier, rule base and defuzzifier. The observed (real) data enter the logic through the fuzzifier and transform into a fuzzy form using a membership function, which is called the fuzzification. The rule base defines the relationship among the membership functions and the form of the result membership function. It has a set of antecedent’s propositions comprising of attributes for input variables. Finally, the real value can be output from the result membership function through defuzzifier. The fuzzy logic model converts the discrete evaluation criterion of water quality into the continuous form, which is promising for evaluating ecosystem sustainability [30].

The basic concept of SVM is based on the usage of the kernel functions to map original data into a high dimensional feature space and construct an optimal hyperplane to separate the two kinds of datasets [31]. Comparisons with other methods have proved that the prediction results of SVM performs better only in some cases [32,33].

2.3. Physically based models
A promising tool for the simulation of pollutant behaviour within watersheds may be provided by physically based models. These models together with detailed mathematical descriptions of soil erosion, rainfall runoff, pollutant transportation and transformation processes provide a spatial and temporal view on watershed contamination. These processes within the mass transfer, momentum and energy are simulated using partial differential equations which are solved by numerical methods such as the Saint Venant equations for surface flow, Richards equation for unsaturated zone flow, Penman-Monteith equation for evapotranspiration, Boussinesq equation for groundwater flow and Engelund-Hansen equation for sediment transport capacity. The hydrological process can be simulated not only to reveal the process of the transport and transformation, but also to evaluate the water environment too. Hence, these models have been widely applied in the world and achieved desirable results.

Popular models for NPS calculation includes ANSWERS, AnnAGNPS, HSPF, SWAT, and SWMM, etc. The application scale, input and output information, simulated pollutant types and required data accuracy of physically based models are different and applied in different problems. The related information are detailed in table 1.

Table 1. Comparison of five hydrological models.

| Model    | Module                                      | Time step                  | Enable application                                                                 |
|----------|---------------------------------------------|----------------------------|------------------------------------------------------------------------------------|
| ANSWERS  | Runoff/ infiltration, sediment, evaporation | One-minute /daily time step| Suitable for medium size agricultural watersheds; designed for ungauged watersheds; evaluate the effect of best management practices on reducing soil erosion and nutrient; capable of simulating pollutants transport and transformation. |
| AnnAGNPS | Hydrology, erosion, pollutant transportation, chemicals | Daily time step            | Suitable for agriculture watersheds; better result in annual and monthly simulation; better result in large scale simulation of runoff, soil erosion and nutrient runoff; evaluating the effect of conservation practices [34,35]. |
| HSPF     | Hydrology, erosion, pollutants              | One-minute /daily time step| Suitable for both agricultural and urban watersheds in long time series; access the effect of the point or non-point source pollution treatment and landuse change [36,37]. |
| SWAT     | Hydrology, meteorology, sediment, soil, crop growth, pollutants and agricultural chemicals [38] | Daily time step            | Very suitable for large agriculture watersheds; excellent for calculating total maximum daily loads; evaluate the effect of best management practices on reducing sediment and nutrient runoff. |
SWMM Runoff, extran, transport and storage/treatment [39] One-minute time step Suitable for an urban watershed in storm period; Emphasize the concept of simulation of detailed quality variation which is well applied to streams where the response time is short.

These models require enormous data, basically including meteorological data, soil data, land cover, digital elevation model (DEM) and historical hydrological data, water quality data. The regions, which are lack of complete monitoring networks, are not suited for these models. Researchers need to pay extra efforts to these regions. For example, with the help of “Burn in” function and ArcGIS, the models can delineate sub-basins and generate rivers lines accurately even in the flat plain area [40,41]. Many regional meteorological datasets (CMADS [42], CFSR [43]) perform better than weather generator in SWAT and well applied in places where meteorological stations are scarce.

3. Conclusion
The paper has reviewed the representative models for the calculation of NPS pollution loads, which can be grouped into three major categories: the export coefficient models, empirically based models and physically based models. The ECM models are adaptable for various regions, especially for those lack of adequate monitoring data. Empirically based models can forecast the pollution level by analyzing a long series of historical hydrological and water quality data. As computer develops, physically based models are the better one for watershed scale simulation and the simulation of the processes of pollution transport and transformation. It is noted that to achieve an accurate pollution load calculation, the model should be chosen case by case, and advancements in long series of datasets and wide area of monitoring would be helpful for enhancing the prediction quality of models.

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