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Identifying non-point source critical source areas based on multi-factors at a basin scale with SWAT

Ruimin Liu *, Fei Xu, Peipei Zhang, Wenwen Yu, Cong Men

State Key Laboratory of Water Environment Simulation, School of Environment, Beijing Normal University, No. 19, Xinjiekouwai Street, Beijing 100875, China

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SUMMARY

The identification of critical source areas (CSAs) is a precondition for non-point source (NPS) pollution control at a basin scale, especially in areas with limited resources. Based on the Soil and Water Assessment Tool (SWAT), nutrient loads coupled with population density and water quality requirements are regarded as multi-factors for CSAs identification in Xiangxi river watershed, the first tributary of the Yangtze River. The results based on the calibrated model found that the subbasins heavily and seriously polluted by nutrient loads were different from the subbasins identified as CSAs, demonstrating integrating socio-economic factors like population density and water quality requirements to identify CSAs is of much necessity. The CSAs occupied 19.7% of the total subbasins, and accounted for 53% total nitrogen loads, 54% total phosphorus loads and 36% of the total population. Considering the model calibration and validation will take a long time as well as data deficiency in some subbasins, the influence of uncalibrated SWAT on CSAs identifications was discussed. The comparative results between CSAs identification with calibrated and uncalibrated SWAT model revealed that model calibration had little effect on nutrients distribution and CSAs locations in the study area. Uncalibrated SWAT model may be applied when the research objective is less related to model calibration. The results will be greatly effective for CSAs identification and NPS pollution control at a basin scale.

1. Introduction

Influenced by soil type, topography, land use, climate, hydrology, management and many other factors, non-point source (NPS) pollution typically presents a spatial and intermittent distribution (Arabi et al., 2006). Unlike point source (PS) pollution, NPS usually comes from diffuse sources, such as agricultural activities and animal breeding, which is difficult to be defined (Ongley et al., 2010). Nowadays, NPS pollution has aroused increasing attention around the world (Schaffner et al., 2009; Ongley et al., 2010; Duncan, 2014). In U.S., approximately 60% of water body impairments are due to NPS pollution (U.S. Environmental Protection Agency, 2013). The pollution situation of NPS in China also faces great challenges (Shen et al., 2012). The excessive inputs of chemical fertilizers and pesticides and other agriculture activities have been regarded as the most important sources for NPS pollution in China as well as other countries (Shen et al., 2012; Duncan, 2014; Huang et al., 2015).

Centralized processing is difficult to be applied for NPS pollution control since significant spatial difference among pollution loads of various landscape units (Behera and Panda, 2006; Ballantine et al., 2009). Some subbasins contribute more sediments and nutrients losses due to the different local weather, hydrological and topographical conditions, land management practices and agricultural activities (Ning et al., 2006; Ouyang et al., 2008). These areas are often referred to as critical source areas (CSAs) (Shore et al., 2014; Winchell et al., 2015). CSAs have been widely studied as the optimal locations for cost-effective management practices of subbasins (Keller and Cavallaro, 2008; Huang et al., 2015). Of all these studies, CSAs identification has played a significant role (Ouyang and Wang, 2008; Winchell et al., 2015). When resources are limited, CSAs identification toward NPS pollution control can be more instructive (Makarewicz, 2009).

CSAs identification is usually based on sediment and nutrient loads (Ouyang et al., 2008; Huang et al., 2015; Winchell et al., 2015). Total nitrogen (TN) and total phosphorus (TP) loads are two major water quality indexes in water environment assessment (Jeon et al., 2010). Eutrophication caused by excess nitrogen and phosphorus will aggravate algal bloom and result in other problems such as odor, low dissolved oxygen and the disorder of ecosystem functions (Gurung and Ankumah, 2013). Though nutrient loads as pollution source take a great effect on CSAs location, other factors such as population density and water quality require-

* Corresponding author. Tel./fax: +86 10 5880 0829.
E-mail address: liurm@bnu.edu.cn (R. Liu).

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ments are also highly associated (Tang et al., 2013; Pongpetch et al., 2015). Population is closely related to environment, and high population density could increase the pressure on aquatic environment (Ouyang and Wang, 2008; Chatterjee et al., 2015). Moreover, the subbasins with higher water quality requirements demand more rigid control standards than those with lower quality requirements, though all of the subbasins have been equally polluted (Maksimov et al., 2009; Rudolph, 2015). CSAs identification considering multi-factors which was defined as the combination of nutrient loads, population density and water quality requirements will be more accurate and accord with the demand of the social economic benefits.

Among all the factors for CSAs identification, nutrient loads are best estimated through regular monitoring in the field and source tracking techniques, which is usually labor-intensive and time-consuming (Thompson et al., 2013). As an alternative, distributed and process-based models have been widely introduced for nutrient loads estimation (Singh et al., 2012). In previous studies, models such as Soil and Water Assessment Tool (SWAT), agricultural non-point source pollution and AnnAGNPS (AGNPS), and areal non-point source watershed environment response simulation (ANSWER), have been commonly applied (Noll and Magee, 2009; Shen et al., 2012; Ramos and Martinez-Casasnovas, 2015). However, distributed and process-based models, such as SWAT, require a large number of good quality, spatially disaggregated data for model calibration and validation, and the process usually takes a long time (Panagopoulos et al., 2011; Huning and Margulis, 2015). Some subbasins restricted by geographical or economic conditions, especially in China, are lack of observed data (Chen et al., 2011; Prabhanjan et al., 2014). Data deficiency makes these models difficult to be implemented. Given the long time cost and data limits, uncalibrated SWAT model has been tried to identify CSAs of sediment, TN and TP (Niraula et al., 2012). In the following year, the identified CSAs have been modestly verified with observed data by comparing SWAT with Generalized Watershed Loading Function (GWLF) (Niraula et al., 2013). But the popularization of uncalibrated SWAT model on CSAs identification has yet to be further studied in other areas.

In this study, the Xiangxi River watershed (XXRW), a catchment in the Three Gorges Reservoir Area of China, is selected as the study region to identify CSAs using SWAT based on multi-factors. The objectives of this study are set to (1) estimate TN and TP nutrient loads; (2) identify CSAs with multi-factors using calibrated SWAT; (3) discuss the impact of parameter calibration on CSAs identification with multi-factors.

2. Materials and methods

2.1. Study area

The XXRW is located between 110.47° and 111.13° E, 30.96° and 31.67° N in the Hubei portion of the Three Gorges Reservoir. The drainage area controlled by the Xingshan hydrological gauge was selected as the study catchments, covering approximately 2995 km^2 (Fig. 1). Three important tributaries are included: Nanyang, Gufu and Gaolan. The river is 94 km long and the elevation ranges between 110 m and 3088 m. XXRW is located in humid subtropical monsoon climate zone, characterized by hot and humid summer, cold and dry winter. The annual average precipitation and temperature is 1015 mm and 16.6 °C. XXRW has typical mountainous landscapes and is comprised of approximately 70.9% forests, 6.5% farmland, 5.3% water, 4.4% wasteland. The study area, which is the first tributary affected by the impoundment of Three Gorges Reservoir, is only 38 km away from the Three Gorges Dam.

In recent years, affected by the relocation and metro construction, coupled with the influence of the special geographical environment and geological disasters caused by frequent flood, landslide, and debris flow, the ecological environment in the basin is faced with great challenges (Liu et al., 2013). Additionally, influenced by agricultural non-point source (ANPS) pollution, the agricultural source of TN and TP increased by 38.0% and 85.1% respectively from 2007 to 2013 (Liu et al., 2014). Livestock and poultry manure pollution is another main NPS pollution source in XXRW (Cui et al., 2015).

2.2. SWAT model and input data

SWAT is a typically semi-distributed, physically based NPS pollution model, which was originally developed by United States Department of Agriculture–Agriculture Research Service (USDA–ARS) (Arnold et al., 1998). It was primarily designed to predict the impact from different soils, land use and land management practices on water and sediment at watershed scale over long periods (Kiniry et al., 2005). In addition, SWAT has become an effective tool in the simulation of nutrients distribution and identification of CSAs for a few years (Kirsch et al., 2002; Srinivasan et al., 2005; Ouyang et al., 2008).

The major model inputs consist of topography, soil properties, land use/cover type, weather/climate data (precipitation, temperature, solar radiation, wind speed, and relative humidity), and land management practices (Kiniry et al., 2005). The basin is subdivided into subbasins and each subbasin is further divided into hydrological response units (HRU) based on homogeneous topography, land use and soil (Tian et al., 2012). The flow generation, sediment yield, and NPS pollution loads are computed separately at the HRU level and then summed together to determine the total loads from the subbasin (Ouyang et al., 2008). The data inputs in this study were listed in Table 1.

2.3. Model calibration and validation

Distributed hydrological models usually need to introduce large amounts of parameters to describe basin characteristics (Kang and Lee, 2014). Selecting rational parameters is critically important for SWAT application, and calibration and validation could improve SWAT performance (Pokhrel and Gupta, 2010; Malago et al., 2015). However, it is almost impractical to calibrate every parameter when SWAT is applied. Latin Hypercube Sampling (LHS) combining one-at-a-time (OAT) was carried out in this study to determine the most sensitive parameters for calibration (You et al., 2012).

SWAT model was parameterized at XXRW and run from 2006 to 2010. Monthly observed data of flow, TN and TP without separating the organic nutrients from mineral components in 2006–2008 and 2009–2010 were used for model calibration and validation, respectively. The method of the sequential uncertainty fitting algorithm (SUFI2) provided by SWAT-CUP was adopted for calibration and validation procedure. SUFI2 method takes the uncertainty of data into consideration, and selects a group of parameters systematically according to certain regulations automatically to make the objective function optimal (Abbaspour et al., 2001, 2004). Various hydrologic and water quality parameters changed to best fit the observed data within their ranges.

The performance of SWAT was evaluated by some indicators, including percent bias (*pb*), coefficient of determination (R^2) and Nash–Sutcliffle efficiency (*NSE*) (Moriasi et al., 2007; Niraula et al., 2012).

$$Pb = \frac{\sum_{i=1}^{n}(P_i - O_i) * 100}{\sum_{i=1}^{n} O_i} \quad (1)$$