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The precipitation driven correlation based mapping method (PCM) for identifying the critical source areas of non-point source pollution

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SUMMARY

Critical source areas (CSAs) are the areas that are relatively more erosion-prone and contribute significantly more pollutants per unit area. They have been widely recognized as optimal locations for the control of non-point source (NPS) pollution. Modeling approach has been frequently used to identify the CSAs of NPS pollution on a basin scale. In previous studies, CSAs were identified based on the simulated average annual nutrient yields for the simulation period at the levels of sub-basin or hydrologic response unit (HRU). However, this method did not consider the impact of uneven spatial distribution of precipitation, which is considered to be the driven force of NPS pollution. In many cases, due to limited length of qualified monitoring data collected, the simulation period may not cover a full spectrum of the precipitation characteristics so that some potential CSAs may be missed. In the present study, the precipitation driven correlation based mapping method (PCM) was proposed, which can reduce the impact of uncertain spatial–temporal distribution of precipitation and identify the CSAs of NPS pollution with a better coverage. This method was applied to the Zhang River Basin, a watershed in North China that occupies an area of 18,072 km^2. The SWAT (Soil and Water Assessment Tool) was used for simulation purposes. By using PCM, the maps of CSAs for controlling total nitrogen (TN) and total phosphorus (TP) were produced. This study has found that the monthly precipitation is highly correlated with the TN and TP yields. It was observed that TN yields have slightly higher correlation value with the precipitation than TP yields. Hence, the precipitation has more impacts on TN yields than TP yields. The impact is more substantial in urban areas than other areas.

1. Introduction

Water quality deterioration due to increasing amounts of nitrogen and phosphorus is a serious problem in China (Ma et al., 2008; Qiu et al., 2012). In 2010, 65% of lakes and 38% of reservoirs were listed as eutrophic water (Ministry of Water Resources of the People's Republic of China, 2011). Input of nitrogen and phosphorus to lakes and reservoirs are of major concern. With an effective control of point source (PS) pollutions, non-point source (NPS) pollutions, especially those from agricultural activities, have become a major cause of water quality degradation in China (State Environment Protection Administration of China, 2011; Hao et al., 2004) as well as in some developed countries (USEPA, 2003; Alexander et al., 2002; Braskerud, 2002; Bowes et al., 2005; Zhang et al., 2008; Darradi et al., 2012). As regular monitoring in the field on nutrient pollution is both expensive and time consuming, mathematical models have gained popularity in recent years in estimating NPS pollutions (Engel et al., 1993; Easton et al., 2008).

Mathematical models have been developed to assess the NPS pollution loads since 1960s, which can be divided into two categories, empirical or statistical models and physically based or process-based models (Shen et al., 2012). Empirical models rely on the typical monitoring data to build empirical relationship between hydrological parameters, such as the ECM (Export Coefficient Models) (Beaulac and Reckhow, 1982; Johnes, 1996) and ESTIMATOR (Cohn et al., 1992). However, due to the limitation of the monitoring data that may not cover the full spectrum of the population, the empirical model may not describe adequately the contaminant migration process and may not be able to apply the local knowledge to other places or to broader areas. A number of physically based models have been developed to predict runoff, erosion, sediment and nutrient transport from agricultural watersheds under different management regimes, including ANSWERS (Areal Non-point Source Watershed Environment Response

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Simulation) (Beasley et al., 1980), CREAMS (Chemicals, Runoff, and Erosion from Agricultural Management Systems) (Knisel, 1980), AGNPS (Agricultural Non-point Source Pollution) (Young, 1987), HSPF (Hydrological Simulation Program-FORTRAN) (Donigian et al., 1995), SWAT (Soil and Water Assessment Tool) (Arnold et al., 1998), LSPC (Loading Simulation Program in C++) (Shen et al., 2005), GWLF (Generalized Watershed Loading Function) (Lehning et al., 2002), etc. Among these models, SWAT has been used extensively and successfully for evaluating the impact of NPS pollution and for analyzing different management scenarios to minimize PS and NPS pollution. It also has many applications in hydrologic processes simulation and total maximum daily load (TMDL) studies (Liu et al., 2008; Lee et al., 2010; Ding and Pan, 2007; Jayakrishnan et al., 2005;Tripathi et al., 2003).

Conservation measures can significantly reduce NPS pollution, but effective control of soil and nutrient losses requires appropriate practices in vulnerable erosion-prone areas to minimize the mobilization of pollutants or intercept them en route to streams. Areas that contribute significantly more pollutants per unit area or show relatively more erosion-prone are often referred to as critical source areas (CSAs). These areas are often chosen as the optimal locations for conservation practices. Numerous studies have indicated that the placement of the conservation measures in CSAs has obviously influenced the overall effectiveness (Dickinson et al., 1990; Maas et al., 1985; Storm et al., 1986; Gitau et al., 2004; Heathwaite et al., 2005; Srinivasan and McDowell, 2007). With vulnerable erosion-prone characteristics, pollutant loads are generated and washed away from the CSAs during rainfall events. The concept of CSAs has been widely recognized as an important consideration in the placement of conservation practices for the effective and efficient implementation of watershed management program (Sivertun et al., 1988; Pionke et al., 2000; Gburek et al., 2002; Tripathi et al., 2003).

The SWAT model has been used to identify CSAs of NPS pollution for watersheds of different scales (Giri et al., 2014; Niraula et al., 2013; Busteed et al., 2009; Daggupati et al., 2011; Ghebremichael et al., 2010; Tripathi et al., 2003; White et al., 2009). Niraula et al. (2013) used SWAT and GWLF to identify CSAs of sediments and nutrients in the Saugahatchee Creek watershed, and it was observed that SWAT performed better than GWLF in predicting sediment, TN and TP loadings. Daggupati et al. (2011) used SWAT to demonstrate a field-scale targeting method and to assess the impact of topography, soil, land use, and land management source data on field-scale targeting results. Tripathi et al. (2003) verified a calibrated SWAT model for a small agricultural watershed and used it for identification and prioritization of CSAs to develop an effective management plan. It was confirmed that the SWAT model could accurately simulate runoff, sediment yield and nutrient losses from small agricultural watersheds. White et al. (2009) used SWAT coupled with satellite imagery to target CSAs and to quantify their relative pollution contributions within six separate watersheds (areas range from 230 km^2 to 1970 km^2).

The SWAT model has been widely used and recognized as an effective and practical tool to quantitatively identify and evaluate the CSAs at the watershed scale. In previous studies, CSAs were identified based on the simulated average annual nutrient yield for the total hydrological period at the levels of sub-basin or hydrologic response unit (HRU). Many factors may have impacts on the identification of CSAs including soil type, land use, management, precipitation, slope, the landscape, etc. Among these factors, precipitation has relatively greater spatial–temporal uncertainty than the others (Strauch et al., 2012; Zhang et al., 2014). Additionally, precipitation is one of the driven forces of NPS pollution; those relatively high nutrient loads from identified CSAs might just be the result of heavy rainfalls. However, previous study did not consider the impact of the uneven spatial–temporal distribution of precipitation. In many cases, due to the limitation of monitoring data for model validation, the modeling period may not cover a full spectrum of the precipitation characteristics. Therefore, there might be bias existing in the modeling results by using a limited period of records to evaluate the pollutant loads. To tackle this problem, a precipitation driven correlation based mapping method (PCM) was proposed in this study to identify the CSAs of NPS pollution within a watershed. The SWAT model was chosen to simulate the NPS pollution loadings, which provided a basis for the identification of critical source areas in order to develop an effective conservation management plan.

2. Materials and methods

2.1. Study area

The Zhang River Basin (ZRB) with an area of 18,072 km^2 is located on the south side of the Hai River Basin (HRB), North China as shown in Fig. 1. Two major tributaries to the Zhang River are Zhuozhang River and Qingzhang River. Zhuozhang River is in the south part and Qingzhang River is in the east part of the basin. The mean elevation of the basin is about 1089 m above the sea level and the mean slope is about 20.6%. The study area has a continental monsoon climate, which is characterized by a moderately dry winter season and a rainy summer season. The mean annual temperature ranges from 7.5 °C to 12 °C. The mean annual precipitation for the watershed is about 530 mm, most of which occurs during the summer months.

Agriculture (AGRR) was the dominant land use within the study area. Approximately 41.9% of the land within the basin was used for agricultural activities. Close to 32.5% of the total area was covered by pasture (PAST), about 22.8% under forests (FRST). The rest of the area was occupied by surface waters (WATR) and urban areas (URBN). The dominant soil of the catchment was Calcaric Cambisols (CMc). ZRB was selected for this study because it is a typical mountainous agricultural area with severe water scarcity and water quality deterioration in HRB.

2.2. The PCM

To study the effect of uneven spatial–temporally distributed precipitation, the areas which generate more nutrient loads during rainfall events are identified. The proposed PCM uses regression and correlation techniques, the popular tools widely used in hydrology (Seidou et al., 2007; Seidou and Ouarda, 2007; Daniels, 2007), to quantify the relationship between the nutrient generation and precipitation for each HRU based on the simulated nutrient yields at the HRU level. As the input of nitrogen and phosphorus to a water body is of major concern in water quality issues in most places in China, this study focused on the identification of CSAs for TN and TP pollution. The framework of the proposed identification CSAs method (PCM) is described in Fig. 2. The square of correlation coefficient was used to quantify the relationship between precipitation and nutrients. It was calculated in Eq. (1):

$$r_{xy}^2 = \frac{\left[\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})\right]^2}{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2} \quad (1)$$

where r_{xy}^2 is the square of correlation coefficient which quantifies the relationship between the x and y variables, and n is the number of sample data. The value of r_{xy}^2 varies between 0 and 1.

The larger the magnitude of r^2, the stronger the degree of the relationship (Moriasi et al., 2007; McBean and Rovers, 1998). In this study, the square of the correlation coefficient (r^2) is calculated