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A coupled model system to optimize the best management practices for nonpoint source pollution control

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ABSTRACT

Agricultural nonpoint source pollution (NPS) is the main water-use impairment in the upper watershed of the Miyun Reservoir in Beijing, China. Selection and placement of best management practices (BMPs) in heterogeneous watersheds, requires a multi-objective optimization framework to identify the most cost-effective conservation strategy to achieve desired water quality goals. In this paper, a novel optimization methodology was developed, utilizing a BMP database that includes BMP reduction efficiencies and costs, using a multi-objective sorting genetic algorithm (NSGA-II, nondominated sorting genetic algorithm-II) combined with the Soil Water and Assessment Tool (SWAT) served as the NPS watershed model. Cost-effectiveness curves (optimal fronts) between pollutant reduction and total net cost input were obtained for the upper watershed of Miyun Reservoir. The optimal combination of BMP, which include a combination of conservation tillage, careful timing of 30% less fertilizer application, contour planting, and use of a 10-m edge-of-field buffer strip, indicate that the least costly scenario reduced total nitrogen (TN) and total phosphorus (TP) loads by 33% at a cost of 1.02×10^6 China Yuan. The cost-effective scenario reduced TN and TP loads 44% and 68% at a cost of 2.52×10^7 and 5.64×10^7China Yuan. The greatest reduction scenario reduced TN and TP loads 55% and 76%, respectively, at a cost of 2.01×10^8 and 2.48×10^8 China Yuan. Watershed with poultry operations, required a 30% reduction in number of birds, along with a 30% reduction in the amount of manure applied was needed to achieve water quality goals. Use of the coupled BMP optimization model can assist the policy makers achieve a cost-effective implementation of best management practices to mitigate agricultural nonpoint sources at a watershed scale.

1. Introduction

The First General Survey and Evaluation of Pollution Sources (SGSEPS, MEP, China) show that over 50% of total nitrogen (TN) and total phosphorus (TP) to streams and lakes were from agricultural nonpoint sources in China (China, 2010). Agricultural nonpoint sources of N and P are now one of the major causes of eutrophication of streams and lakes in China (Ongley et al., 2010). Best management practices (BMPs) have been shown to be effective in controlling the movement of N, P, and sediment, into receiving waters (Giri et al., 2016; Udawatta et al., 2002; Zhuang et al., 2016). However, the effective mitigation of agricultural nonpoint TN and TP is difficult because of the spatial and temporal variability of sources and transport pathways (Ghebremichael et al., 2013; Jang et al., 2017; Shen et al., 2012). Some relevant studies indicate that the success of cost-effective nonpoint source mitigation strategies is greatly enhanced by use of a watershed-scale BMP selection and placement tool (Kurkalova, 2015; Noor et al., 2017).

In general, selection and placement of BMPs is constrained by several factors, which include different transport pathways of N than P, heterogeneous landscape features, and variable farm/field management (Cano et al., 2017; Maringanti et al., 2009; McDowell et al., 2014). In addition, BMPs often adopted at a farm scale, while desired water quality goals function at a watershed scale. The targets of BMPs implementation plans is to achieve the maximum pollutant loads reduction in a watershed and minimize the financial cost of the infrastructure and

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maintenance (Balana et al., 2011). The success of BMPs placement is often limited by financial support from farm, local government and so on (de Roo et al., 2012). Therefore, the placement and optimization of BMPs for control agricultural nonpoint source pollution at watershed can be transformed into a multi-objective optimization problem with spatial attributes (Bouraoui and Grizzetti, 2013).

For the multi-objective optimize process in any watershed scale, they are often including many farms that with non-uniform number and size of fields, as well as multiple BMPs alternatives. There could be numerous scenarios to achieve the cost-effective pollution reduction. This creates computational difficulties that increase with an increase in watershed area (Maringanti et al., 2011). For example, a watershed consisting of 1000 farms with six possible BMPs for each farm, would 6ˆ1000 forms of BMPs and its combinations can be served as a solution for control the agricultural nonpoint source pollution. This large number of options makes BMPs targeting and evaluation impractical based on the current computational technology (Volk et al., 2017).

An optimization technique that would prioritize selection and placement of BMPs for more efficient and effective mitigation planning is needed. Heuristic search algorithms, have been shown to perform well in solving global search problems, such as genetic algorithms (GA), tabu search, and simulated annealing (Gitau et al., 2005; Panagopoulos et al., 2011).

Studies show that successful NPS control efforts depending on a combination of watershed modeling technique, (e.g., SWAT, HSPF and AGNPS models), optimization algorithms (e.g., GA, NSGA-II and tabu search methods) and economic assessment functions (Chaubey et al., 2010; Gitau et al., 2004, 2006; Hsieh and Yang, 2007; Panagopoulos et al., 2013; Srivastava et al., 2003). The genetic algorithms and economic functions serve as the power engine for selection and targeted placement of BMPs in a watershed considering environmental and economic drivers.

Progress has been made using traditional genetic algorithms combined with a watershed model for the optimization of BMPs from field to small watershed scales (Gitau et al., 2005; Srivastava et al., 2003). However, there are remaining challenges include:

1. The objective function is an important part of genetic algorithm, it is composed by several objective functions that are estimated separately in the traditional optimization methods that through place a constraint on one objective function during optimization of the other. As there are no consensus weighting values for different objective functions. The potential solutions could be missed during optimization process in genetic algorithms, it will lead to the uncertainty and error of the optimization results (Yang and Best, 2015).
2. Lack of sensitivity analysis of GA parameters, influences solutions from the optimization process (Herman et al., 2015).
3. Computation times to run optimization models which coupled by GA or NSGA-II and SWAT model (Bekele and Nicklow, 2005; Maringanti et al., 2009) found computational costs associated with model runs, limited the size of watersheds that can be assessed to 3–133 km^2. These constraints will increase due to the need for mitigation strategies to lessen nonpoint-source water quality degradation in China.

In this paper, a novel multi-objective optimization framework was developed that incorporates the SWAT model, NSGA-II model and a BMP cost-effective tool. The overall goal of this study is to apply the new optimization framework to efficiently optimize selection and placement of BMPs in a watershed and provide alternative BMPs measures to achieve desired water quality targets under cost-effectiveness scenarios.

2. Materials and methodology

The multi-objective optimization technique framework is comprised of five components:

1. A series of BMPs were selected from the literature according to the agricultural NPS management needs in Chaohe River Watershed;
2. Set of empirical economic functions, describing the cost of BMP implementation and maintenance;
3. ArcSWAT (v2012) model were employed to estimated watershed and farm scale loads under baseline scenarios which is a physically based, spatially-distributed and continuous-time watershed model that operates on an ArcGIS 10× platform. It was developed by the United States Department of Agriculture (USDA) to predict the output of runoff, sediment and nutrients from watershed scale over long periods of time (Arnold et al., 1993, 1998). The long-time continued information such as climate, topography, soil properties, land use and management were required simulation (Arnold and Fohrer, 2005; Arnold et al., 2012). The study area will be delineating to two spatial scale which include the sub-watershed and Hydrological Response Units (HRUs) based on the Digital Elevation Model (DEM), land use and soil types. Each HRU is the combination of a unique land use and soil type which can be served as the smallest unit for placement the BMPs.
4. A dynamic BMPs database, of compiled nutrient losses and costs for all hydrologic response units (HRUs) and BMPs was established, it will save many times for optimization process because of the traditional combination of the GA and SWAT model will be replaced by a dynamic database in the form of a matrix, which don't need re-running the model every time when the model parameters are modified; and
5. An optimization engine of NSGA-II was created based on the MATLAB 2012a platform and was used to prioritize selection and placement of BMPs in the watershed, to achieve the maximize load reduction at the lowest cost.

2.1. Study area

The Chaohe River Watershed is located the upper watershed of Miyun reservoir, Beijing, China. The watershed area is 4888 km^2 and mean precipitation up to 600 mm (Fig. 1). The Miyun reservoir is Beijing's main drinking water source and crucial to the well-being of its residents. The Chaohe River is one of only two tributaries flowing into the Miyun reservoir which is an important supplemental water source for the Miyun reservoir that has become eutrophic in recent years (Jia and Cheng, 2002). About 77% of annual precipitation occurs between July to September, when high-intensity, short-duration storms can exacerbate nutrient and water loss. Elevations in the watershed range from 150 m to 1800 m above sea level. Soils are classified into four major categories: Cinnamon, Brown, Meadow and Chestnut soils, with Cinnamon the most dominant soil type in the watershed. Land use types are cropping, pasture, forest and water which accounting for 80% of the total area of this watershed.

2.2. Calibration and validation of the ArcSWAT model

ArcSWAT (v2012) was used to divide the Chaohe River Watershed into 39 sub-basins, which were further divided into 594 HRU. Each HRUs was defined as a sub-basin with similar land use and soil type. For the analysis, each HRU was approximated to be a farm and BMPs were selected for placement in each HRU.

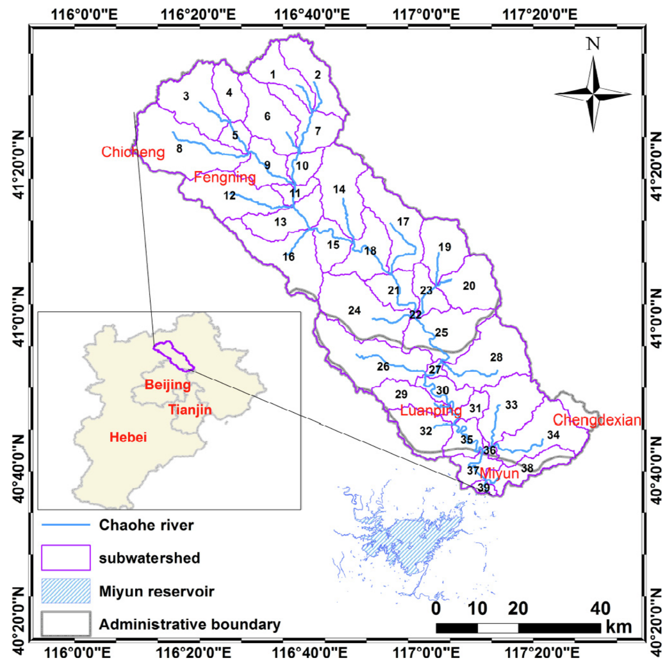

Fig. 1. Location of Chaohe River watershed in Beijing and Hebei province, location of China.

The SWAT-CUP model was used to process calibration and validation data (Arnold et al., 2012; Mehmood et al., 2017; Rusli et al., 2017; Singh et al., 2013). Runoff, TN, and TP concentrations and loads for the Chaohe River Watershed data were measured at the Xiahui hydrological gauging site at the of Chaohe River Watershed outlet (Fig. 1). The ArcSWAT model was calibrated and validated for flow, TN, TP and sediment at this gauging station, Coefficient of determination (R^2) and Nash-Sutcliffe efficiency coefficient (*NS*) were used to assess the accuracy of ArcSWAT model.

2.3. Prioritization and cost estimate of BMPs

In order to improve the precision of BMPs placement, a critical source areas (CSAs) analysis was conducted before prioritization of targeted-BMPs (Pongpetch et al., 2015; Sharpley et al., 2011). The detailed description of the CSA analysis in the Chaohe River Watershed is reported by (Geng et al., 2016). An empirical BMPs tool developed and used to assess the effectiveness of BMPs based on soil type and slope in CSAs (Geng et al., 2015a; Gitau et al., 2004; Mostaghimi et al., 1997; Pionke et al., 2000). A series of BMPs were selected for the optimization step, which include conservation tillage, timing of chemical fertilization, contour farming, 10-m filter strips, 30% reduction in fertilizer application, 30% reduction in poultry numbers and manure application, as well as poultry manure storage. Constant weather and land use conditions were used to estimate the effectiveness of each BMP (Cuttle et al., 2007) to develop the dynamic database (

BMP costs included construction and maintenance costs for a 15-year operation period, as well as loss of land-based income from implementation of BMPs based on equations proposed by (Arabi et al., 2006). The land-income loss represents reduced corn and wheat yields from each HRU, as well as revenue loss from a reduction in poultry numbers. Costs for conservation tillage in corn and wheat were obtained from a field questionnaire on the study farms conducted between April to September 2015. Other cost information for the various BMPs were based on published data and reports for this region (Geng et al., 2015b; Wang, 2011). All cost estimates were determined on a per unit area basis in China Yuan which marked by Yuan$\cdot$ha^{-1} (Table 1). Details of how costs were calculated is given in equation (1) (Geng, 2015).

$$C_{td}\left(\yen \bullet ha^{-1} \bullet a^{-1}\right) = C_0\left\{(1+s)^{td} + rm\left[\frac{(1+s)^{td}-1}{s}\right]\right\} \Big/ td \tag{1}$$

where $C_{td\ is}$ the total cost of each BMP (Yuan$\cdot$ha$^{-1}\cdot$a^{-1}), C_0 is the construction cost of each BMP (Yuan$\cdot$ha^{-1}), *rm* is the maintenance cost of each BMP, *s* is the fixed annual interest rates, here we use 6% as the fixed annual interest rates from the Bank of China, and *td* is the operation period of the BMP.

In this study, we assume that all BMPs can be placed singly or in combination for the same land use type. For example, six BMPs were selected to reduce runoff, which could be placed singly or in combination (A1, A1+A2, A1+A2+A3, A1+A2+A3+A4, A1+A2+A3+A4+A5, A1+A2+A3+A4+A5+A6). The total combinations of BMPs can be calculated, while the cost of each combinations could be estimated as the sum of the costs of single BMPs (Panagopoulos et al., 2012). Thus, the total number of the potential combinations of BMPs was 63 which for farm land management (Equation (2)):

$$\text{Farm land}_{\text{BMPs}} = \binom{6}{1} + \binom{6}{2} + \binom{6}{3} + \binom{6}{4} + \binom{6}{5} + \binom{6}{6} = 63 \tag{2}$$

Similarly, the total number of potential BMPs combinations to pasture land and orchard were 15 and 7, respectively. All the BMPs or BMPs combinations were selected as the original input data for the dynamic database and served as for inclusion to the optimization framework. There are 89 different BMPs combinations, which include the baseline scenario, were finally selected and numbered sequentially in Table 2.

2.4. Development of the dynamic BMP database

The BMP database, developed for use with the BMP optimal technique framework, stored losses of mean annual TN and TP, as well as the respective calculated costs arising from the implementation of each BMP to all HRUs. The database consisted of tables that contained information concerning the environmental or cost variables (in this case four tables for three variables (Panagopoulos et al., 2012): TN, TP and cost) for each HRU. The rows in these tables represented the HRUs of the catchment and columns represented the loads and costs that resulted after each BMP has been implemented in the specific HRU. In the case of the Chaohe river watershed each Table contained 594 × 89 cells, whereby 594 was the number of HRUs in the watershed and 89 was the number of BMPs totally tested (Table 2). The 89st was not actually a BMP but was incorporated to facilitate the expression of no interventions in non-agricultural areas.

The dynamic BMPs database were developed by the MATLAB and MS Excel platform in this paper, the detailed process was developed as follows.

1. MATLAB (v2012a, The MathWorks, Inc. U.S) was selected as an auto-simulated processor. Based on a set of scripts, MATLAB can active an auto-simulation of ArcSWAT (USDA-ARS) model to identify and re-writing BMPs representation parameters in each HRUs through found and opened the input file which with the name suffix of '*.mgt' in the output folder of ArcSWAT model. Auto-simulation then occurs to estimate TN and TP loads after BMPs

Table 1
Model parameters/management inputs used for representing BMPs implemented.

BMPs code	Scenario	Description	Representation in ArcSWAT	Cost ($Yuan \cdot ha^{-1} \cdot a^{-1}$)	Land use
No BMPs	Baseline	Current farming system, conditions before management changes			
A1	Conservation tillage	Reduce soil erosion, N mineralization and P mobilization	Tillage removal	−22.5	Farmland
A2 and O1	Timing change of chemical fertilization	Reducing the risk of nutrient transport	4/9 instead of 4/10	No cost	Farmland and orchard
A3	Contour farming	Reducing surface runoff and erosion	$P^{USLE} = 0.9$ $CN_{new} = CN$-3 (Arabi et al., 2006)	3577.9	Farmland
A4 and O2	Filter strips (10 m)	Delay runoff Trap sediments and nutrients	10 m strip width	40767.7	Farmland and orchard
A5	Fertilizers reduction 30%	Reducing N and P inputs to soil	−30% N and P	−691.5	Farmland
O3	Fertilizers reduction	Reducing N and P inputs to soil	−100% N and −50% P	−2617.5	Orchard
L1	Poultry numbers reduction 30%	Reducing N and P inputs to soil	−30% manure deposition	21 600	Pasture land
L2	Storage of poultry manure	Reducing manure N content	15% reduction in manure N content	7590	Pasture land
L3	Manure spread during the dry season	Reducing the risk of transport	Application from April to October	No cost	Pasture land
A6 and L4	Fence (10 m)	Reducing the risk of poultry manure directly into streams	Modeled as a 10 m Filter strips with amorphous fruticose	33442.7	Farmland and Pasture land

Table 2
BMPs combinations selected for AGRL, ORCD and PAST HRUs of the Chao River watershed.

BMPs number	BMPs	BMPs number	BMPs	Land use	BMPs number	BMPs	Land use
1	baseline	31	A1&A4&A6	AGRL	61	A1&A2&A4&A5&A6	AGRL
2	A1	32	A1&A5&A6	AGRL	62	A1&A3&A4&A5&A6	AGRL
3	A2	33	A2&A3&A4	AGRL	63	A2&A3&A4&A5&A6	AGRL
4	A3	34	A2&A3&A5	AGRL	64	A1&A2&A3&A4&A5&A6	AGRL
5	A4	35	A2&A3&A6	AGRL	65	baseline	ORCD
6	A5	36	A2&A4&A5	AGRL	66	O1	ORCD
7	A6	37	A2&A4&A6	AGRL	67	O2	ORCD
8	A1&A2	38	A2&A5&A6	AGRL	68	O3	ORCD
9	A1&A3	39	A3&A4&A5	AGRL	69	O1&O2	ORCD
10	A1&A4	40	A3&A4&A6	AGRL	70	O1&O3	ORCD
11	A1&A5	41	A3&A5&A6	AGRL	71	O2&O3	ORCD
12	A1&A6	42	A4&A5&A6	AGRL	72	O1&O2&O3	ORCD
13	A2&A3	43	A1&A2&A3&A4	AGRL	73	baseline	PAST
14	A2&A4	44	A1&A2&A3&A5	AGRL	74	L1	PAST
15	A2&A5	45	A1&A2&A3&A6	AGRL	75	L2	PAST
16	A2&A6	46	A1&A2&A4&A5	AGRL	76	L3	PAST
17	A3&A4	47	A1&A2&A4&A6	AGRL	77	L4	PAST
18	A3&A5	48	A1&A2&A5&A6	AGRL	78	L1&L2	PAST
19	A3&A6	49	A1&A3&A4&A5	AGRL	79	L1&L3	PAST
20	A4&A5	50	A1&A3&A4&A6	AGRL	80	L1&L4	PAST
21	A4&A6	51	A1&A3&A5&A6	AGRL	81	L2&L3	PAST
22	A5&A6	52	A1&A4&A5&A6	AGRL	82	L2&L4	PAST
23	A1&A2&A3	53	A2&A3&A4&A5	AGRL	83	L3&L4	PAST
24	A1&A2&A4	54	A2&A3&A4&A6	AGRL	84	L1&L2&L3	PAST
25	A1&A2&A5	55	A2&A3&A5&A6	AGRL	85	L1&L2&L4	PAST
26	A1&A2&A6	56	A2&A4&A5&A6	AGRL	86	L1&L3&L4	PAST
27	A1&A3&A4	57	A3&A4&A5&A6	AGRL	87	L2&L3&L4	PAST
28	A1&A3&A5	58	A1&A2&A3&A4&A5	AGRL	88	L1&L2&L3&L4	PAST
29	A1&A3&A6	59	A1&A2&A3&A4&A6	AGRL	89	NO BMP	OTHERS
30	A1&A4&A5	60	A1&A2&A3&A5&A6	AGRL			

Note: AGRL is means farm land, Orcd is means orchard and PAST is means pasture land. The representation of A1 to A6, O1 to O_3 and L1 to L4 can be find in Table 1.

implementation (Panagopoulos et al., 2012; Rodriguez et al., 2011). For example, corn with 10 m filter strips (#5 in Table 2) will placement in the HRUs which with farmland, the script will executed to identify and re-writing the representation parameters in '*.mgt' files with farmland as their land use type and re-set the filter strip value to 10 m instead of 0. Then, re-run the validated-ArcSWAT model to get the annual TN and TP load after implementing of NO. 5 BMPs from 2000 to 2011 years. After each run, the mean annual TN and TP loads from each HRU were obtained, as well as the respective cost estimates for each BMPs implemented, which were automatically stored in the BMPs database (Fig. 2).

2. The dynamic database includes mean annual TN and TP loss after implementation of various BMPs with their cost. For convenience of computing the difference before and after implement of BMPs, we transform loads to percentage changes of BMPs effectiveness (Panagopoulos et al., 2012). The database consisted of tables that contained 594 × 89 cells, where there were 594 HRUs in the watershed and 89 BMPs evaluated as the basic database to get the optimized BMPs plans for achieve the minimize of cost and nutrients loads by the process of NSGA-II (Table 2).

2.5. Multi-objective optimization

To obtain the most cost-effectiveness solutions of BMPs placement in Chaohe river watershed, there are 594 HRUs, for which the BMPs should to be searched and optimized to satisfy two objective

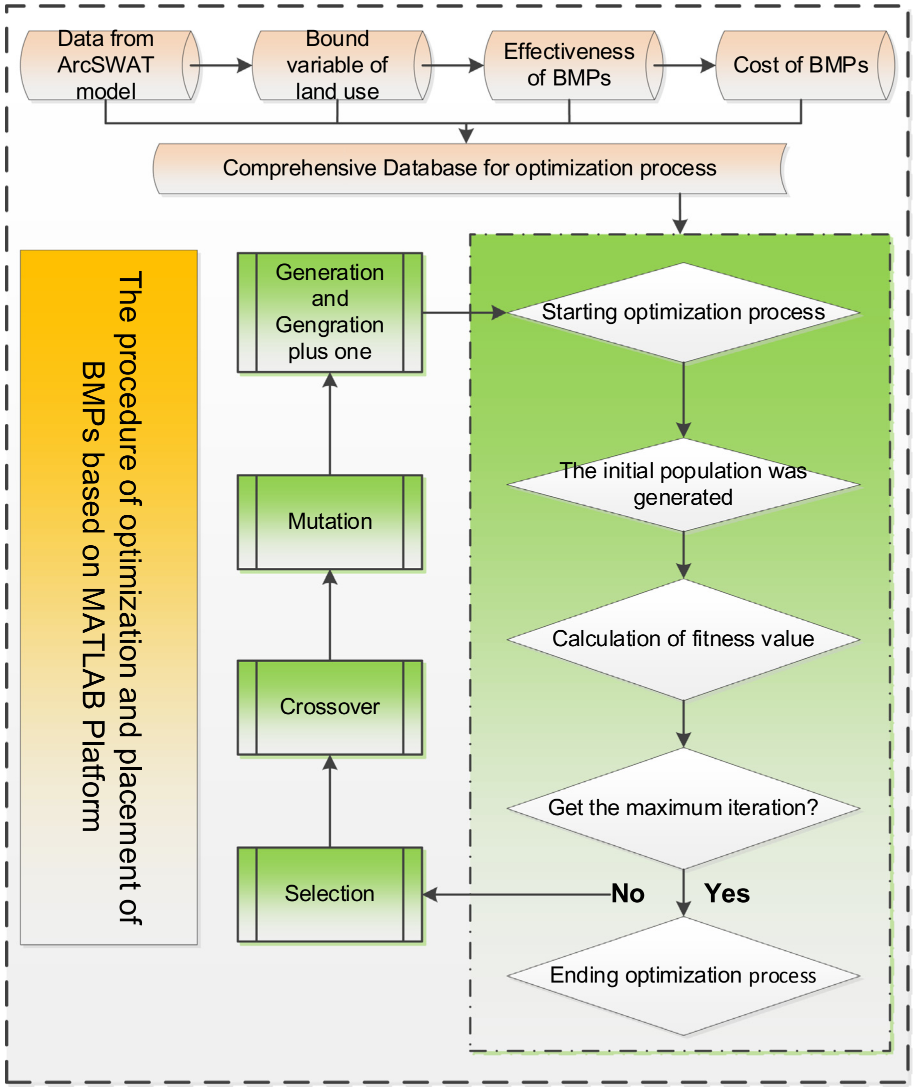

Fig. 2. Diagram of optimization process for BMPs in MATLAB platform.

functions: minimization of the net cost increase and TN and TP loads resulting from BMPs placement at the HRU level. Objective functions that need to be optimized in the MATLAB platform are mathematically expressed as (Equations (3)–(7):

$$\min\left[\sum_{i=1}^{564} TN(i,j) \wedge \sum_{i=1}^{564} TP(i,j) \wedge \sum_{i=1}^{564} Cost(i,j)\right] \tag{3}$$

$$\min = \sum_{i=1}^{564} TN(i,j), TN_{(HRUs,BMPs)} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,89} \\ \vdots & \ddots & \vdots \\ a_{564,1} & \cdots & a_{564,89} \end{pmatrix} \tag{4}$$

$$\min = \sum_{i=1}^{564} TP(i,j), TP_{(HRUs,BMPs)} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,89} \\ \vdots & \ddots & \vdots \\ a_{564,1} & \cdots & a_{564,89} \end{pmatrix} \tag{5}$$

$$\min = \sum_{i=1}^{564} Cost(i,j), Cost_{(HRUs,BMPs)} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,89} \\ \vdots & \ddots & \vdots \\ a_{564,1} & \cdots & a_{564,89} \end{pmatrix} \tag{6}$$

$$1 \le x_i^{AGRL} \le 64, 65 \le x_i^{ORCD} \le 72, 73 \le x_i^{PAST} \le 88, 89 \le x_i^{OTHER} \le 89 \tag{7}$$

where a_{ij}, is the element of the matrix, which corresponds to TN and TP loads and total cost from the i_{th} HRU after the j_{th} BMPs was implemented. x_i, is a set of lower and upper bounds values to ensure that the NSGA-II created only valid solutions (individuals) of the optimization process.

The optimization process includes three steps:

1. NSGA-II will randomly initialize the population,
2. HRUs (genes) in the Chaohe river watershed will be created (Maringanti et al., 2009; Muleta and Nicklow, 2005; Panagopoulos et al., 2012).

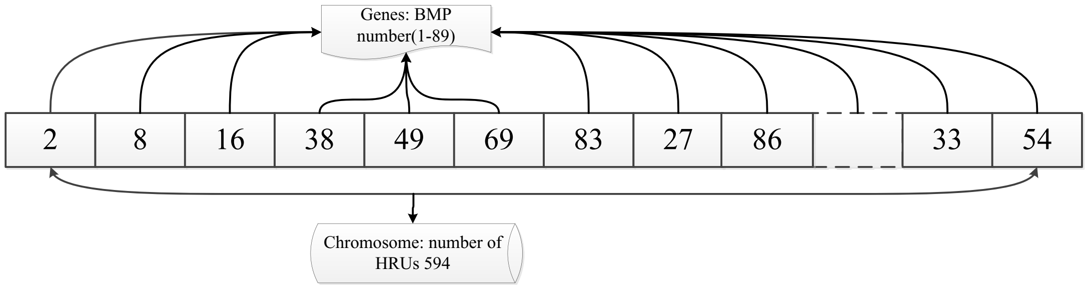

Fig. 3. A chromosomes representing a complete BMPs scheme in the Chao River watershed.

3. Genotype will be formed by each individual gene value. Thus, the combination of BMPs in the HRUs will be represented (phenotype) in Chaohe river watershed.

In this paper, we used a real integer coding to represent this process, representing the 89 alternative BMPs options will be placement in Chaohe river watershed (Table 2). Therefore, each complete, composite solutions for the whole watershed can be represented by one hypothetical individual (chromosome). The chromosome string (solutions) corresponding to the optimization problem consists of 594 HRUs by NSGA-II (Fig. 3).

For optimization of NSGA-II by MATLAB, each individual sample of the population was evaluated according to fitness functions under the range of lower and upper values, which includes a dynamic database TN and TP loss and implemented BMPs cost. To ensure that the algorithm created only valid solutions (individuals), a set of lower and upper bounds was also defined so that the NSGA-II was driven to select values from the first 64 columns of the BMP Database for HRUs with farmland, from the following 8 for HRUs with orchard and the next 16 for pastureland. For non-agricultural HRUs the NSGA-II was constrained to choose values only from the last (89th) column so that it would not delay by selecting between equal values stored in all the 89 columns. The NSGA-II will search for the best solutions to minimize all possible user defined criteria and an iterative selection and genetic operations (crossover, mutation) process of population evolution. After evaluation of the population, the algorithm compared generation number with a maximum generation counter, defined as the termination criterion. If the current generation number was equal to the maximum, the algorithm stopped, otherwise the population underwent the former process, to form a new population for the next generation until the best solutions produced.

2.6. Sensitivity analysis of NSGA-II parameters

Many studies show the precision of NSGA-II will be affect by such factors as population size, generations, mutation, and crossover probability (Ahmed and Deb, 2013; Mohapatra et al., 2014; Panagopoulos et al., 2012; Rodriguez et al., 2011; Shen et al., 2012). To ensure precision of NSGA-II, the sensitivity analysis was performed on NSGA-II parameters to determine the best-fit parameters to decrease the influence of these parameters on the Pareto-optimal front. Here, population size, generations, mutation and crossover probability were selected as key factors and changed one parameter at a time to evaluate the influence of each parameter on the Pareto-front (Rodriguez et al., 2011). The closer the Pareto-front curve was to the original value indicates the best solutions to minimize TN and TP loss and total cost simultaneously. Therefore, the parameter value with the Pareto-front was closest to the origin values in sensitivity analysis, it was chosen as the best fitted parameter for the optimization process (Maringanti et al., 2009). The default and pre-changed NSGA-II parameters are list in Table 3. The Pareto-optimal fronts were plotted after every run and the progress in the front was observed.

3. Results

3.1. Calibration and validation of ArcSWAT

The best-fitted parameters of different simulated values are list in Table 4. First, simulated runoff was compared with measured runoff for 1975 to 2011 at daily-time intervals, while the calibration and validation of TN, TP were conducted at monthly time intervals, based on monitoring data from 1989 to 2011. And for the calibration and validation of sediment were conducted from 1979 to 2011. In order to improve the effectiveness of the validation period and the comparability of the validation results. We set the period of validation for all variables which include runoff, sediment, TN and TP was from 1995 to 2011, however, due to the starting time is different for measured data, the period of calibration is different for these variables. The results indicated that the *NS* of flow, sediment, TN and TP were 0.95, 0.84, 0.82 and 0.85 in calibration period, respectively, and the R^2 of flow, sediment, TN and TP were 10.8%, 30.2%, 17.6% and 34.5% in calibration period, respectively, and while the *NS* of flow, sediment, TN and TP were 0.97, 0.71, 0.71and 0.84 in validation period, respectively, and the R^2 of flow, sediment, TN and TP were 7.5%, 26.4%, 20.1% and 24.5% in validation period, respectively, (Fig. 4). Therefore, the ArcSWAT model can reliably simulate

Table 3
Default and other parameters chosen for sensitivity analysis of NSGA-II.

Order of parameters change	Population size	Generations	Mutation probability	Crossover probability
1	20	100	0.1	0.0001
2	50	1000	0.3	0.0005
3	100	2000	0.5	0.001
4	200	5000	0.6	0.005
5	400	10000	0.7	0.01
6	800	20000	0.9	0.1
7	1000	40000	–	–
Default parameters	100	1000	0.9	0.0001

Table 4
The best fitted parameters of Chaohe River watershed.

Simulated value	Process parameters	Best value	Possible range of value	
			Minimum	Maximum
Flow	CN2	−0.0875	−0.1	0.9
	ALPHA_BF	0.655	0.5	0.9
	GW_DELAY	23.5	20	300
	ESCO	0.238	0	1
	CH_K2	303.125	150	400
	SOL_AWC	−0.0406	−0.8	0.01
	OV_N	0.0894	0.05	0.2
	SLSUBBSN	0.55	0	0.8
	SOL_K	−0.513	−0.6	0.8
	EPCO	0.769	0.5	1
	PRF	0.119	−0.5	1
	HRU_SLP	−0.511	−0.8	−0.1
Sediment	SPCON	0.00921	0.0001	0.05
	Ch_Cov	0.237	−0.001	1.0
	Usle_P	0.867	0	1.0
	Spexp	0.142	−0.46	1.0
	Ulse_C	−0.180	−0.80	0.80
Total nitrogen	Nperco	0.293	0	1.0
	Sol_No3	2.77	0	100
	SLSUBBSN	0.0587	0	0.5
	Sol_Orgn	71.5	0	1000
Total phosphorus	Pperco	1.569	1.0	7.5
	Phoskd	175	100	200
	Rchrg_DP	0.797	0	1.0
	Sol_Orgp	15.08	0	400

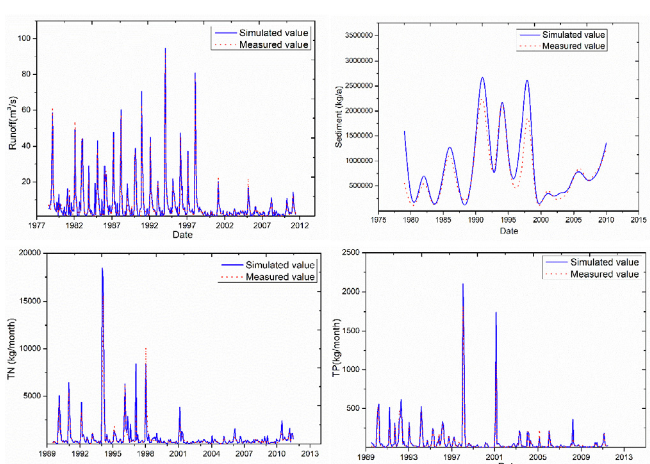

Fig. 4. Calibration and validation of ArcSWAT model.

flow sediment, TN and TP in Chaohe river watershed.

3.2. Sensitivity and estimation of NSGA-II operational parameters

Sensitivity analysis shows that the best-fit parameters of population size, generation, mutation and crossover probability are 800, 20 000, 0.6 and 0.01 respectively (Fig. 5). For the population size, the pareto-optimal front of the model are continues improved from range of the population size 20 to 800. However, the further improved were not observed with the increase of population size to 1000, therefore, we selected 800 as the best-fit parameter of population size.

A significant improvement of pareto-optimal front was observed when generations were increased from 100 to 20 000, and in this range of generations, the better spread of the solutions were observed. However, there was no further improvement when we increased generations to 40 000. Thus, 20 000 generations were

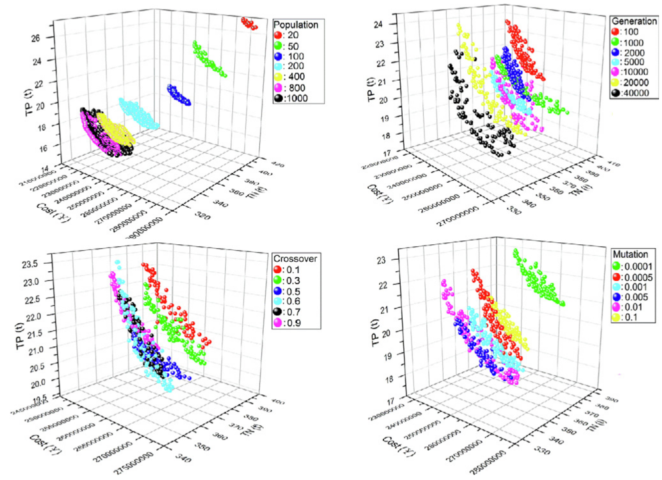

Fig. 5. Pareto-optimal fronts for the sensitivity analysis of NSGA-II.

selected as the best fit for NSGA-II in Chaohe river watershed.

For the crossover, the pareto front will constantly close to the original points with the increased of the crossover from 0.1 to 0.6. However, there was a reverse movement of pareto front when the crossover continuously increases to 0.9, indicating that the crossover 0.6 should serve as the best parameter selection for the optimization process.

Increasing mutation probability from 0.0001 to 0.005, significantly improved outcomes, although the improvement was not significant when mutation probability was increase to 0.01, even though the pareto-optimal were closer to the original point compared with other solutions. A value 0.01 was served as a mutation probability for further optimization process.

3.3. Cost-effectiveness analysis between total nitrogen and total cost

The optimization process of NSGA-II run with a set of best parameters such as population of 800 and generations of 20 000 were complete on a Inter Dual Core (TM) i5-4210 CPU @ 2.60 GHz computer. For the TN reduction effectiveness and total cost, the NSGA-II has generated a set of near optimal solutions through the selecting and placement BMPs combinations which the minimized total cost and TN loads were achieved at the whole watershed scale.

We selected three solutions (chromosomes) at different scenario from generation 20 000 (Fig. 6). In the first scenario, the TN load was reduced 33%, while the stakeholders get a return of 1.02×10^6 China Yuan. Here, cost is a main objective, where the decision-maker hopes to minimize total cost, while controlling NPSs to a certain extent.

In the second scenario, TN load was reduced 44%, while the total cost was 2.52×10^7 China Yuan. Here the marginal benefit

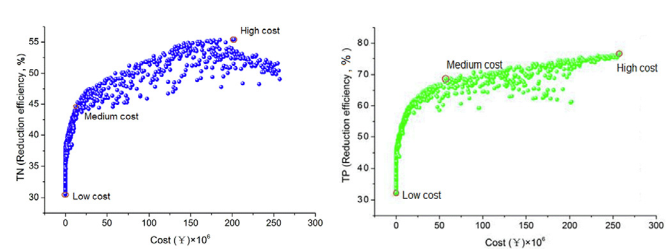

Fig. 6. Pareto-optimal front for total nitrogen, total phosphorus and total cost.

(reduction of TN) did not increase along with an increase in marginal total cost. Therefore, this scenario serves as the most cost-effectiveness for control of TN loss in the Chaohe River Watershed.

In the third scenario, the main object was to minimize TN load by BMPs implementation. Here, a 55% reduction of TN load was realized at a cost of 2.01×10^8 China Yuan.

3.4. Cost-effectiveness analysis between total phosphorus and total cost

As for TN, a significantly decrease of TP loads was observed after the optimization process. We also obtained a set of options to achieve TP control. Three scenarios were chosen from generations 20 000 after the termination of the NSGA-II optimization process, and are shown in Fig. 6. In the first scenario, TP was reduced 33%, while stakeholder income will be increased by 1.02×10^6 China Yuan.

In the second scenario, TP loads reduced 68%, while total was 5.64×10^7 China Yuan, which serves as the cost-effective scenario for NPS TP control. In the third scenario, the greatest reduction in TP of 76% was achieved, while total cost increased to 2.48×10^8 China Yuan.

3.5. The relationship of the effective between TN and TP

Many studies have shown that particulate phosphorus and nitrogen is the main form of TP and TN losses in Chaohe river watershed and accounts for more than 80% of the total losses (Wang, 2011; Yin et al., 2009). A general overview of particulate phosphorus loss mainly occur in surface runoff, as opposed to nitrogen loss are mainly groundwater driven and the leaching process (Sharpley et al., 2017). Nitrogen transport is dominated by subsurface flow of water and less in surface runoff, Best management practices that can decrease the import of TP on to farms, however, Sharpley founded that there may have some of the paradoxes or conflicts/tradeoffs of agricultural conservation management, such as conservation tillage or reduced tillage will encourage more hydraulic retention time and then decrease the particulate phosphorus losses, however, it willincrease leaching in soil where nitrogen might be lost (Sharpley, 2015). Therefore, the correlation analysis was conducted to test the relationship between TN and TP loads losses after BMPs implementation by the Spearman and Pearson model. The correlation coefficients were 0.901 and 0.790 for TN and TP, respectively (Fig. 7). The results show that the optimized BMPs plans can effectively avoid the mutual exclusion effect of the TN and TP co-control, and the selected BMPs can effectively achieve the surface and subsurface runoff control and then to decrease the losses of nutrients.

4. Discussion

4.1. Frequency analysis of TN control solutions

For all BMP cost implementation scenarios, TN loads were reduced by at least 30%. Fig. 8 shows implementation frequency of BMPs in the Chaohe River Watershed for the lowest-, the medium- and the highest-cost scenarios, respectively. BMPs scenarios 25 and 76 were low cost (Table 2), in which conservation tillage, timing of fertilizer application and a 30% reduction in fertilizer and manure spread during the dry season were major components. These four BMPs can be classified as source management practices for TN control. Constructed BMPs were not selected as low-cost options, due to higher investment and maintenance costs. However, there are may produce some uncertainties when the source management BMPs such as the conservation tillage, timing of fertilizer application was conducted, the major reasons can come down to human and social factors influencing the acceptance of BMPs adoption in many areas of the worldwide (Cherry et al., 2008; Meng et al., 2013; Merriman et al., 2009; Ongley et al., 2010; Sun et al., 2012). Therefore, the BMPs with the low-cost scenario would not be selected as the best recommended BMPs scenario for implementation in the Chaohe River Watershed.

For the medium cost scenario, the optimal BMPs combinations were 25 (composed by conservation tillage, timing change of chemical fertilization, fertilizers reduction 30%), 28 (composed by conservation tillage, contour farming, fertilizers reduction 30%), 76 (manure spread during the dry season) and 81 (composed by storage of poultry manure and manure spread during the dry season), in which contour farming and storage of poultry manure were used in the watershed TN control program, and which served as key components compared with the low cost scenario. In this scenario, TN loads were reduced 12.6% while total cost increase by 2.0×10^7 Yuan. The results revealed that conservation tillage combined with contour farming would lead a significant reduction of TN load. Similarly, when manure is only spread during the dry season combined with storage of poultry manure the effectiveness of TN loss reduction from pastureland will increase.

For the high cost solution, the highest implementation frequency of BMPs combinations were 28 (composed by conservation tillage, contour farming, fertilizers reduction 30%), 81 (composed by storage of poultry manure and manure spread during the dry season) and 87 (composed by storage of poultry manure, manure spread during the dry season and Fence with 10 m), these were account for 28%, 22% and 17%, respectively, for TN control.

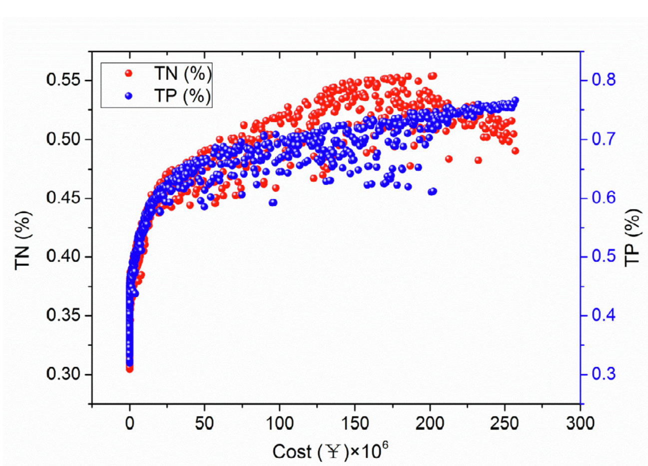

Fig. 7. Relationship between Total Cost, TN and TP on optimal trade-off frontiers.

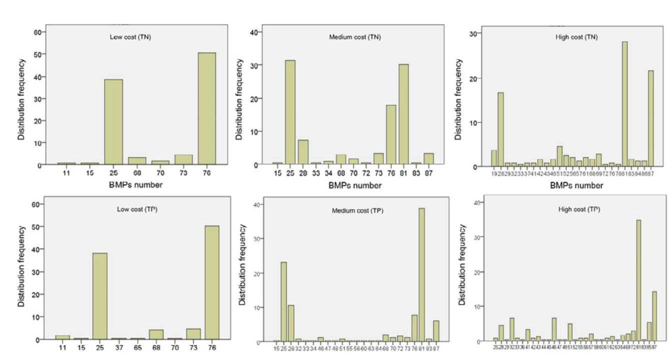

Fig. 8. Implementation frequency of BMPs under different scenario.

Conservation tillage, contour farming, fertilizer–use reduction of 30%, a 30% reduction in poultry numbers, storage of poultry manure, manure spread during the dry season, and stream fencing (10 m from the stream), were recommended as the starting practices for TN control from farm land and pasture land. In this scenario, constructed BMPs increased. The high TN reductions could be explained by the fact that the three major BMPs combinations mentioned above (28, 81 and 87), recommend implementing a fence (10 m from the stream). Several studies conducted in northwest Arkansas (Chaubey et al., 1995; Srivastava et al., 1996) have shown the effectiveness of fencing to reduce nutrient runoff from land areas treated with animal manure. In addition, BMPs combinations including a 30% reduction in poultry numbers were recommended for the pasture HRUs for the highest-cost solutions.

4.2. Frequency analysis of TP control solutions

Fig. 8 shows the percent frequency distributions of BMPs combinations selected for each of the cost solutions analyzed in Chaohe River Watershed. TP loads were reduced at least 30% under all cost implementation solutions. The NSGA-II assigned nine BMPs combinations that included conservation tillage, timing of chemical fertilization, 30% reduction in fertilizer use, and manure spread during the dry season for TP control under the low-cost program. Similar to TN, the non-constructed BMPs were the main alternatives. Manure spread during the dry season was placed on 50.2% of the HRUs for the lowest cost option, as livestock is the major source of TP loss. Conservation tillage offering permanent ground cover while reducing runoff, is preferred because producers need to maintain a maximum return during corn and wheat production.

The most common optimal BMPs combinations were 25 (composed by conservation tillage, timing change of chemical fertilization, fertilizers reduction 30%), 28 (composed by conservation tillage, contour farming, fertilizers reduction 30%), 76 (manure spread during the dry season) and 81 (composed by storage of poultry manure and manure spread during the dry season) (Fig. 8). These BMPs combinations were placed on 34 and 47% of the cropped and pasture HRUs, respectively, in the medium-cost scenario. Conservation tillage, timing of chemical fertilization, contour farming, 30% fertilizer reduction, 30% poultry number reduction, and storage of poultry manure, manure spread during the dry season were the preferred practices for cropped and pasture land and orchard. Constructed BMPs, such as the contour farming and storage of poultry manure resulted a significant reduction in TP loss up to 67.7% (Fig. 8), however, total costs were increased by 5.0×10^7 China Yuan.

Not surprisingly, high TP loading reductions were obtained when fence (10 m) and buffer strips (10 m) were used. Fences (10 m from the stream) were placed on at least 80% of the pastureland HRUs for highest levels of costs (Fig. 8). The highest-cost population placed a buffer zone in almost all of farmland HRUs. However, the total cost was four times greater than the medium cost scenario. Therefore, considering economic constraints but with a high TP reduction, the high cost solution would not be selected as a preferred program for TP control.

4.3. Spatial distribution of the BMPs plans

The spatial distribution of the most cost-effectiveness BMPs were depicted to demonstrate the spatial position of different BMPs included in the plans (Fig. 9 and Fig. 10). For farmland and orchard in Chaohe River Watershed, cost-effective solutions include the buffer strip with 10 m, fence within 10 m of a stream, and a set of alternative BMPs 32 (composed by conservation tillage, fertilizer reduction 30%, Fence with 10 m), 33 (composed by timing change of chemical fertilization, contour farming and filter strips with 10 m), 46 (composed by timing change of chemical fertilization, contour farming, filter strips with 10 m and fertilizer reduction 30%), 48 (composed by conservation tillage, timing change of chemical fertilization, filter strips with 10 m and fence with 10 m), 51 (composed by conservation tillage, contour farming, fertilizer reduction 30% and fence with 10 m), 55 (composed by timing change of chemical fertilization, contour farming, fertilizers reduction 30% and fence with 10 m), 56 (composed by timing change of chemical fertilization, filter strips with 10 m, fertilizers reduction 30% and fence with 10 m), 60 (composed by conservation tillage, timing change of chemical fertilization, contour farming, fertilizers reduction 30% and fence with 10 m), 63 (composed by timing change of chemical fertilization, contour farming, filter strips with 10 m, fertilizers reduction 30% and fence with 10 m) and 64 (composed by conservation tillage, timing change of chemical fertilization, contour farming, filter strips with 10 m, fertilizers reduction 30% and fence with 10 m).

Buffer strips and reduction in fertilizer application can effectively decrease TP runoff (Sharpley et al., 2009) and were included in most of the BMPs scenarios (Fig. 10), and were chosen in HRUs with larger area in crops on the northwestern regions of the Chaohe River Watershed. The results show that fertilizer consumption of 450–510 kg ha^{-1} was twice the standard fertilizer consumption according to the Food and Agriculture Organization. The brown soil with a low field water capacity (about 0.12 cm cm^{-1}) and permeability (the Hydrologic Soil Group is C), facilitates the nutrient runoff (Schoumans et al., 2013).

A wide range of possible BMPs (storage of poultry manure, manure spread during the dry season, Fence with 10 m) were applied on the HRUs with larger area pastures across the watershed and were mainly located on either side of the river. This is a flat area with large population density, with a relatively low permeability soil, where surface runoff frequently enters the Chaohe River. Reduction in livestock numbers and establishment of fencing 10 m from a stream or river will thus, decrease TN and TP runoff loss. It should be noted, however, that as these two BMPs for pastures are costly, there adoption will result in an increase in total remediation cost for the Chaohe River Watershed.

5. Conclusions and future research

In this study, a novel optimization framework was developed for selection and placement of BMPs at a watershed scale, which allowed TN, TP, and total cost to be minimized, producing and the most cost-effectiveness BMPs scenarios. There are three major conclusions as follows:

1. The dynamic linkage between the BMPs database, ArcSWAT, and NSGA-II significantly improves computation efficiency and has a robust ability to search and identify optimal BMPs scenarios that minimize nutrients loss and total cost, which can improve the precision and ease of development than previous methods.
2. The most cost-effectiveness of BMPs plans for the Chaohe River Watershed, which includes the conservation tillage, timing of fertilizer application, reduction in fertilizer application, contour farming, and buffer strip with 10 m, reduction in poultry numbers, and manure spread during the dry season combined with storage of poultry manure.
3. At the least cost scenario, TN and TP loads were reduced by 33%. At the cost-effectiveness scenario, TN and TP reductions of 44 and 68%, At the highest cost scenario, TN and TP reductions of 55 and 76%, respectively.
4. The methodology developed in this study can be extended to other watersheds to prioritize BMPs for NPS control. However,

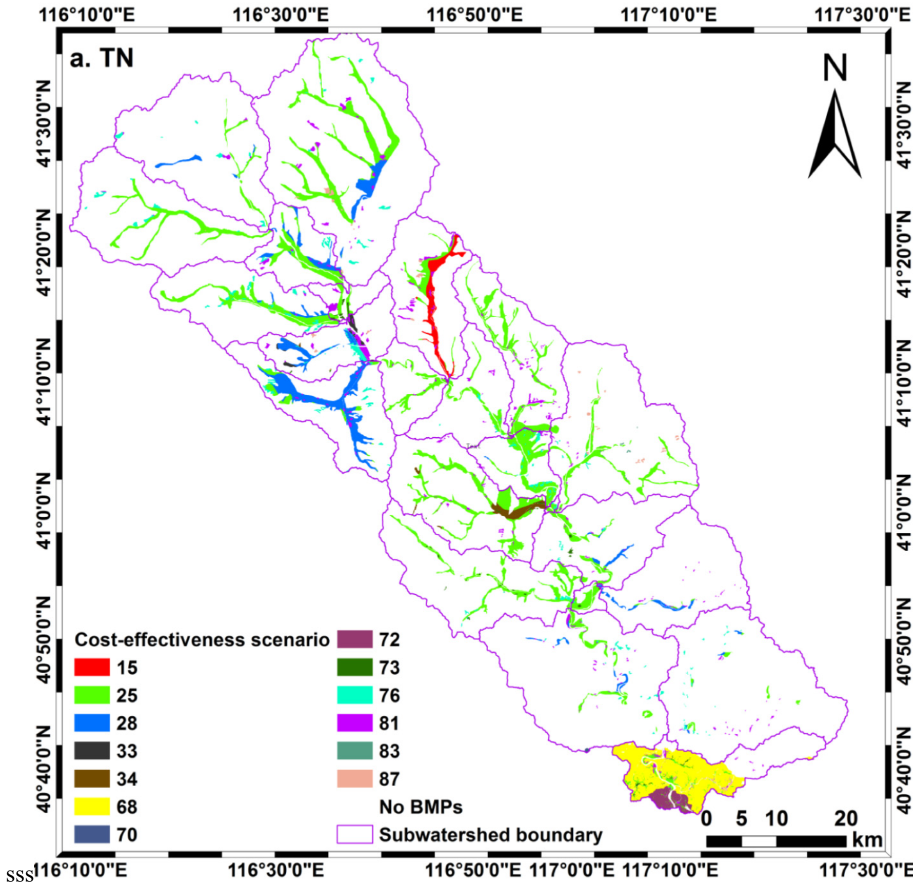

Fig. 9. Best BMPs allocation for TN control under cost-effectiveness scenario.
Note: The BMPs number can be find in Table 2.

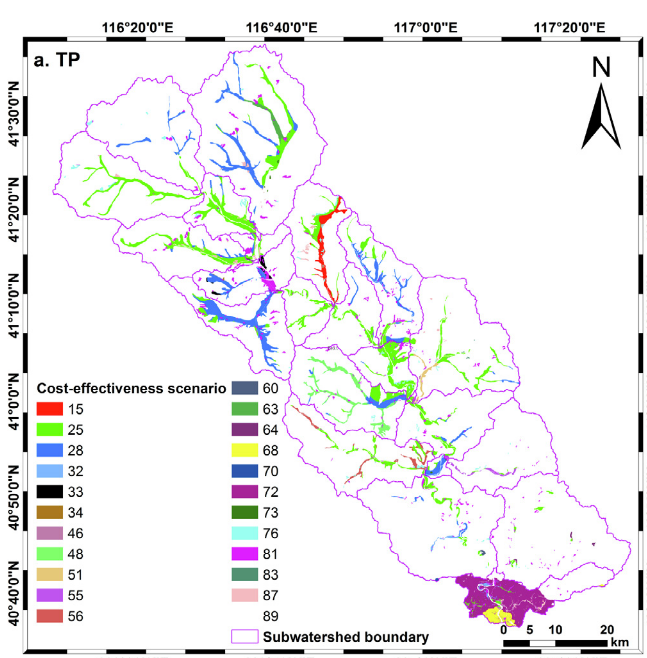

Fig. 10. Best BMPs allocation for TN control under cost-effectiveness scenario.
Note: The BMPs number can be find in Table 2.

future research also required, which incorporates new criteria and more efficient optimization techniques, as well as incorporate the stakeholder's interests index in the optimization process at the field scale.

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Abbreviations

AnnAGNPS: Annualized Agricultural Non-Point Source Pollution Model)
BMPs: best management practices
CSAs: critical source areas
GA: genetic algorithm
HRUs: hydrologic response units
HSPF: Hydrological Simulation Program-Fortran
N: nitrogen
P: phosphorus
NPS: nonpoint source pollution
NSGA-II: nondominated sorting genetic algorithm-II
SWAT: Soil Water and Assessment Tool
TN: total nitrogen
TP: total phosphorus