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A novel spatial optimization model for achieve the trad-offs placement of best management practices for agricultural non-point source pollution control at multi-spatial scales

Runzhe Geng [a, *], Andrew N. Sharpley [b]

[a] Policy Research Center for Environment and Economy, Ministry of Ecology and Environment of the People's Republic of China, PO Box, 100029, Beijing, China

[b] University of Arkansas, Department of Crop, Soil and Environmental Sciences, 115 Plant Sciences Building, Fayetteville, 72701, USA

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ABSTRACT

The efforts to management agricultural non-point source pollution from the field to watershed scale is an ongoing challenge that needs to take into account trade-offs between environmental and economic objectives. Best management measures (BMPs) are considered as an effective means to achieve this balance in the management of agricultural non-point source pollution. Many studies have focused on a single spatial scale for placement of the BMPs, however, the effectiveness in improving water quality at different scale will affect by many factors such as the land use, soil type and the river network and so on. In order to demonstrating the relationship or impact of spatial scale changes on the allocation and effectiveness of BMPs. The present study attempts to development a novel multi-scale model framework and indices as a decision support platform for solve the impact of spatial scale change on the optimization of best management measures in the Chaohe River Watershed in Beijing and Hebei province. And used it in a drinking water source area which was affected by the agricultural nonpoint source pollution in recent decades in Beijing, China. A series of the utility functional between the utility of the water quality improvement and the number of watersheds, watershed size, the unit cost of BMPs and integrated these three functional relations by Generalized Reduced Gradient Algorithm. We found that the nonlinear threshold response function can play a key role in the configuration of BMPs from field to watershed scale. The results show that 1) the utility functions for pollution load reduction and the number of watersheds can be described by the log-sigmoid curve, and the optimal number of watershed for total nitrogen (TN) and total phosphorus (TP) control are 25 and 23 respectively, 2) the most utility function for the pollution load reduction and the mean sub-watershed area is exponential function curves, and the optimal mean sub-watershed areas are168 km^2 and 214 km^2 for TN and TP, respectively, 3) the relationship between pollution load reduction and cost of per unit after BMPs implemented can be drawing by the logistic curves, and the optimal average unit cost are 4622 and 7692 $CNY \cdot ha^{-1}$ for TN and TP, respectively, 4) the comprehensive optimal of these above functions shown that the total cost of BMP plans is 2.01×10^7 and 4.7×10^7 CNY for TN and TP, respectively at the trad-offs scenario. This study will provide a systematic approach to determine more reasonable and feasible management practices system on more reasonable spatial scale for the protection of water quality and safety in watershed.

1. Introduction

In recent years, agricultural nonpoint source (ANPS) pollution has become the main source of eutrophication in most lakes and rivers. The wicked nature of this problem poses substantial challenges to the design and implementation of effective and efficient management policies in the worldwide(Shortle and Horan, 2017). Agricultural activities, such as livestock and poultry breeding and rural activities, were found to be the major sources of ANPS, with more than 50% of N and P loadings in many watersheds in China (Qu and Fan, 2010). Increased nutrients loading accelerates eutrophication of surface waters (Conley et al., 2009).

* Corresponding author.
E-mail address: geng.runzhe@prcee.org (R. Geng).

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Total nitrogen and total phosphorus from agricultural nonpoint source pollution can be successfully controlled by implementing the structural or non-structural BMPs of the right type, in the right place, in the right combinations, and right level of adoption within different spatial scale watershed (Cherry et al., 2008; McDowell et al., 2014; Xu et al., 2017). However, hydrologic, meteorological, and geomorphologic factors at field, farm, sub-watershed and watershed scales, are important factors that confound response to ANPS pollution (Dai et al., 2016; Panagopoulos et al., 2011; Petit-Boix et al., 2017). Their effectiveness for water quality improvement through pollution load reduction must be quantified before BMPs are adopted at various spatial and temporal scales. Although the effectiveness of individual BMPs has been usually assessed by field plots (generally less than 1.0 ha), it is necessary to find out the trade-offs of BMPs from the field to watershed scale to ensure that practices taken will be adequate to achieve the water quality goals (Smets et al., 2008; Wu et al., 2018; Yang and Best, 2015).

For the sake of resolving the increasingly complicated problems, research has invented many spatially optimized models based on the evolutionary algorithms to support better placement the BMPs at field, small watershed, sub-watershed and large watershed scales to achieve the most cost-effectiveness scenario. For example, the combined optimization engines which include of Soil and Water Assessment Tool (SWAT) and Genetic Algorithm (GA) or Non-dominated Sorting Genetic Algorithm (NSGA-II) (Chen et al., 2016; Gitau et al., 2004; Panagopoulos et al., 2011; Panagopoulos et al., 2011; Panagopoulos et al., 2012; Rodriguez et al., 2011; Veith et al., 2003; Zhang and Chui, 2018), Annualized Agricultural Non-Point Source (AnnAGNPS) and linear programming model and other combinations of hydrological models and Heuristic search algorithms (Barton et al., 2008; Doody et al., 2012). Although these techniques need further refinement, they illustrate the types of optimization models proposed. These models provided a potential foundation for developing the multi-scale, hierarchical framework for optimization and placement of BMPs.

However, there are limitations, which include;

1. Previous research has focused on single spatial scale, where the influence of regional and spatial scale was ignored. This has led to inappropriate BMP configurations (Gurnell et al., 2016).
2. Time scales and temporal changes are not considered in all frameworks, where the basic spatial data for simulation of ANPS were applied to one year, land use, and soil type. However the effectiveness of many BMPs were conducted over several years is not represented by one year of spatial data (González del Tánago et al., 2015).
3. BMPs have been shown to be effective at reducing edge-of-field TN, TP, and sediment losses from farmland to surface waters. However, these benefits have rarely been shown to act at a broad spatial scale that can be linked to water quality improvements. Moreover, the effect of agricultural BMP implementation on stream water quality is rarely measured or accounted for.
4. Indicators used in the optimize process represent spatial hydrological pathway of N and P transport, although the spatial differences in BMPs efficiencies were not included (McCluney et al., 2014; Rinaldi et al., 2013, 2015).
5. BMPs often adopted by farmers are based on pollution reduction at an edge-of-field scale; however, watershed management decision to meet water quality targets are made at a watershed scale.

Previous research shows that the number of sub-watersheds in the BMPs mitigation plans, total sub-watershed area used to implement BMPs, and marginal cost benefit of BMPs plans within watersheds (Moss, 2008), were the three major factors to be considered to achieve multi-scale prioritization of BMPs within watersheds.

How many sub-watersheds are needed to implement a BMPs plan at a watershed scale? How many fields are needed to implement an optimal BMP in a sub-watershed was used? What is the marginal cost and benefit of BMPs to achieve the most cost-effective BMP plans from field to watershed scale? In order to answer with these complex questions, an integrated approach will more effective for planning BMP implementation at various scales (Arheimer et al., 2005; Barton et al., 2008; Heathwaite et al., 2005; Kalaugher et al., 2013; Naramngam and Tong, 2013; Shen et al., 2011; Volk et al., 2008).

This is the third in a series of three papers derived from our research in the CRW (Chaohe River Watershed, CRW). In the first paper, we are used a statistical model to test the alternative scenarios of BMPs combination at field, sub-watershed and watershed scales (Geng et al., 2015). A relationship between ANPS pollution reduction after BMP implementation and a statistical improvement in water quality was reported. In the second article, an integrated framework based on the ArcSWAT model and NSGA-II (Non-dominated Sorting Genetic Algorithm II) was applied at a field scale to optimize and place BMPs and obtain ANPS load reductions based on ArcSWAT for each HRU from 2000 to 2011(Geng et al., 2019).

Here, we use results from the above model framework as an intermediary, to develop a nonlinear relationship between the number of sub-watersheds for BMPs implementation to achieve the desired pollution reduction. In view of the uncertainty and complexity associated with water-quality of watershed scale responses to BMPs reduction in field or sub-watershed scale, design of a set of adaptive BMPs approaches at different spatial scales are critical to achieving an improvement in water quality at the outlet of the CRW.

This study proposes an integrated model approach for ANPS pollution control, based on a theory of “Up-Bottom and Bottom-Up.” Up-bottom is mean that the optimization of BMPs at the watershed through the combination of ArcSWAT and NSGA-II, the optimized placement of BMPs at each fields will achieve in this step(Geng et al., 2019), Bottom-up is mean that transfer the utility of BMPs from field scale to watershed scale through select the key indicators and this is the main target in this study. This approach includes optimal location for placing multiple BMPs at different spatial scales, trade-off curves of optimal plans for BMP placement, and a series of prioritized plans for BMPs execution in watershed. Optimal combinations consider three key indices, which include the number of sub-watersheds for BMPs placement, the average sub-watershed size for BMPs placement, and the average cost for each BMPs and their combinations as a set of explanatory variables for development of a total program budget. The expected results will provide a set of useful suggestions to policy makers for achieve the water quality targets through management the agricultural nonpoint source pollution by BMPs implemented.

2. Materials and methods

2.1. Study area

For a long time in the past, both Miyun reservoir and Guanting reservoir were important drinking water sources of the China's capital, Beijing. However, with the repaid development of industrial in the recent two decades, the water quality of Guanting reservoir is deteriorating rapidly and can no longer serve as a drinking water source, therefore, the Miyun reservoir becomes the only drinking water source of Beijing, which is of great strategic significance to the sustainable development of Beijing. The total area of the Miyun reservoir basin is 15788 km^2, There are include two main rivers at the upstream area which are the Bai river and Chao rive, The Chao River Watershed (CRW) is lies to the east of the upper watershed of Miyun reservoir which is a part of the upper watershed of Miyun reservoir (Fig. 1). The total area of CRW is 4888 km^2 and total length of the Chao river is 459 km. More than 90% of the farmland were cultivate corn and wheat and with corn and wheat rotation in CRW, while the over 50% of the land are the forest in CRW. Due to the increase of pesticide and fertilizer application intensity in CRW in recent years, the risk of deterioration of river water quality is increasing, and there are some hidden dangers to the water quality of Miyun reservoir, it is urgent to adopt BMPs to control the agricultural non-point pollution sources while achieve the economic goals (Jia and Cheng, 2002).

2.2. Methodology

Based on the literature review, we are establishing the water quality significantly improvement as the kernel theory. A new coupled-model framework was development based on a set of multivariate statistical analysis models, and a novel methodology for solution techniques involving cost-effectiveness assessment of BMPs. From this, we obtain the optimal number of sub-watersheds, average area of sub-watershed, and cost of BMP designs at different spatial scales are proposed:

1. Develop an integrated simulation modeling system to assist BMPs planning in from field to watershed scale;
2. Develop a logistic function to conduct various nonlinear fitting regression analysis to get the relationship between the number of sub-watershed and water quality improvement in the outlets of watershed;
3. Develop an exponential function to conduct various nonlinear fitting regression analysis to get the relationship between the area of sub-watershed and the population size of benthic macro-invertebrates within sub-watershed;
4. Develop a logarithm function to conduct various nonlinear fitting regression analysis to get the relationship between the average unit cost and marginal benefit expand of the BMPs plans and the probability of water quality in the outlets of each sub-watershed within whole watershed;
5. Develop a synthesis cost function to conduct an integration optimized procedure based on above three curves to get the optimal combination between the number of sub-watersheds, the area of sub-watershed and the average unit cost and benefit expand of the BMPs plans, therefore, to achieve the most cost-efficient BMPs plans from field to watershed scale.

2.3. Data sources

Data that used in this research were collected by field monitoring, questionnaire surveys, and simulation methods detailed in Table 1. The digital elevation model, stream delineation, soil type, land use, and meteorological data were obtained from the Institute of Geographic Sciences and Natural Resources Research, Chinese

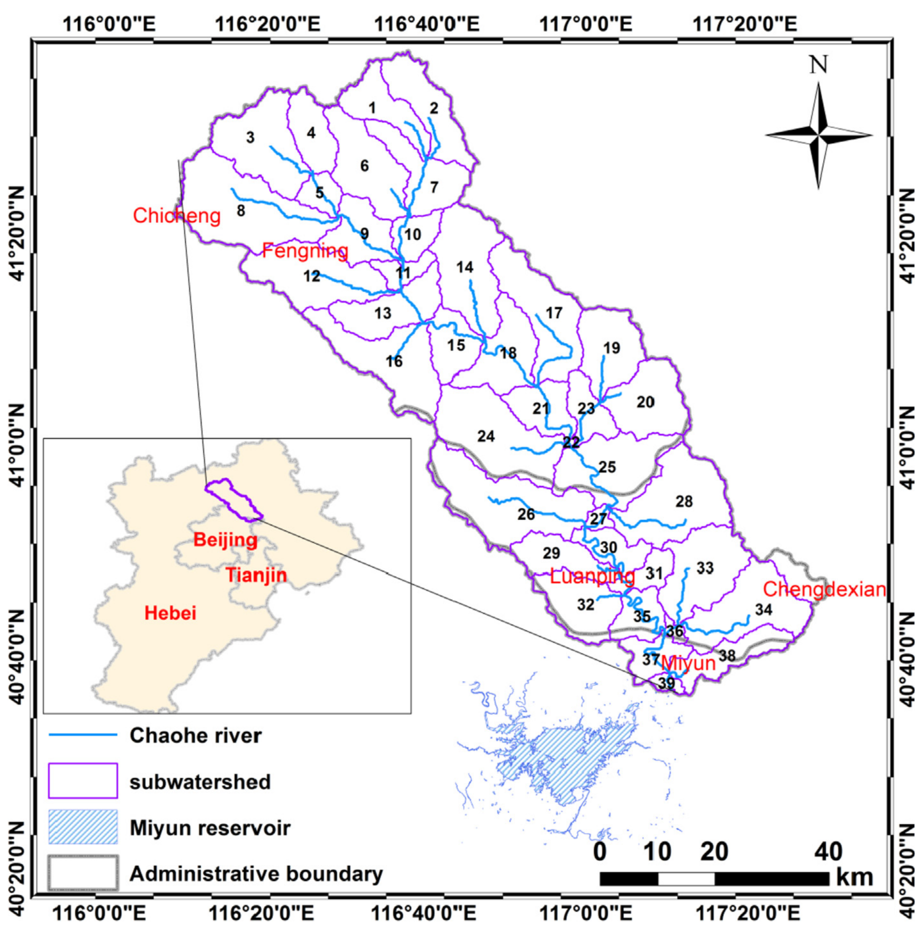

Fig. 1. Location of Chaohe River Watershed in Beijing and Hebei province, location of China.

Table 1
The data used in current research.

Types	Contents	Data precision	Period	Storage
Digital Elevation Model	Elevation, slope, aspect	30 × 30 m	2014	Grid
Stream	Chao River and tributary	1:100, 000	2014	vector
Soil type	Physical and chemical soil properties	1000 × 1000 m	2010	Grid
Land use	Distribution of the land use within CRW	30 × 30 m	2014	Grid
Meteorological data	Precipitation, wind speed, temperature, relative humidity, and solar radiation	Daily	2010–2014	*.txt and *.xls
Hydrology and water quality data	Runoff, sediments, TN and TP concentration	Daily	1991–2014	*.txt and *.xls
***Benthic macroinvertebrates* monitoring data**	total taxa, taxa, intolerant taxa	Years	2011–2014	*.xls
Socioeconomic data	Miyun, Fengning, Luanping and Chengde county	Years	2000–2014	*.txt and *.xls
Best management practices	Buffer strips, conservation tillage, and nutrient management	Years	2000–2014	*.txt and *.xls

Academy of Sciences. Hydrology and water quality data (1991–2009) were collected by China Institute of Water Resources and Hydropower Research, and the water quality data collected by the field monitoring from 2010 to 2014. Socioeconomic data were obtained from the 2014 China Statistical Yearbook. The type and economic availability of different BMPs implemented in CRW were obtained from a 2014 survey.

3. Results

We have designed a novel model system to assess how trade-offs among the number of sub-watersheds, average area of sub-watershed, and marginal cost-benefit of BMPs plans within watersheds, can improve water quality. We used this approach to identify optimal designs of BMP plans to achieve TN and TP reduction across a range of budgetary costs. Based on this we delineated a series of 39 sub-watersheds, which include 564 fields (hydrological response units; HRUs) to be used to implement BMP plans in CRW.

3.1. Relationship between the number of sub-watershed and water quality improvement

Considering the difference between the population mean value, sample variance, and significance level, the statistical utility of any different test scenarios is related to the number of observed samples. Based on 39 sub-watershed in CRW, we set sub-watershed sample size at the 10, 20, and 40, and then developed the *log-sigmoid* functions to test fitting curves based on the midpoint 5, 10, and 20 sub-watersheds, respectively. Results indicate that when the N is 40, the *log-sigmoid* model will produce the best performance for fitted of TN and TP reduction and the number of sub-watersheds. In order to test the difference of fitted effect of N from 10 to 40, we conduct an ANOVA (Analysis of variance) test in SPSS v18.0. The results shown that there are no significant differences between N of 20 or 40, with a correlation coefficient of over 0.9 (Table 2,Fig. 2). The equations are:

$$U_{N-TN} = \frac{0.983}{1 + 0.962e^{\frac{\ln(M)-\ln(N)}{0.5}}} \tag{1}$$

$$U_{N-TP} = \frac{0.982}{1 + e^{\frac{\ln(M)-\ln(N)}{0.5}}} \tag{2}$$

Table 2
The results of ANOVA for utility Curve of TN.

Size	Index	TN	TP
N=40	sum-of-squares	19.11	20.04
	df	3	3
	mean square error	6.37	6.68
	R^2	0.94	0.94
N=20	sum-of-squares	7.42	10.27
	df	3	3
	mean square error	2.47	3.42
	R^2	0.93	0.94
N=10	sum-of-squares	4.14	5.34
	df	3	3
	mean square error	1.38	1.78
	R^2	0.72	0.78

3.2. Relationship between the area of sub-watershed and the population size of benthic macro-invertebrates

In order to develop the relationships between the area of sub-watershed and the aquatic species, we used benthic macro-invertebrates as an aquatic species index from field monitoring in 2011–2014. A scenario in which the BMPs are placement from the upper to down along the main river networks within CRW was established as a baseline scenario. Because stream grade will increase with increase of the watershed area, watershed area can be regarded as the most important factor to determine the grade of rivers (Leopold and Maddock, 1953). Stream grade has a significant impact on the number of biological populations in rivers. With the improvement of river grade, the richness and number of aquatic biological populations in rivers will continue to increase (Lyons, 1996; Maxted et al., 2009), such that the population size of benthic macro-invertebrates will increase downstream. In addition, better water quality will increase benthic macro-invertebrate's population size. Because the relationship of benthic macro-invertebrates, average area of sub-watershed, and water quality can be drawing as the nonlinear curves, we can identify an optimal mean area of sub-watershed that will maximizes the benthic macro-invertebrates-to-area ratio, and then achieve a significant water quality improvement at the outlet of CRW.

Based on the above methods, a macro-invertebrate population size accumulation curve was created by cumulatively plotting macro-invertebrates' preferred stream grade versus the mean area of each sub-watershed. The mean area of each sub-watershed utility function was generated by expressing these values as a percentage of the total number of benthic macro-invertebrates species in the CRW (Fig. 3) and then selecting and fitting a modified exponential function to express the relationship between

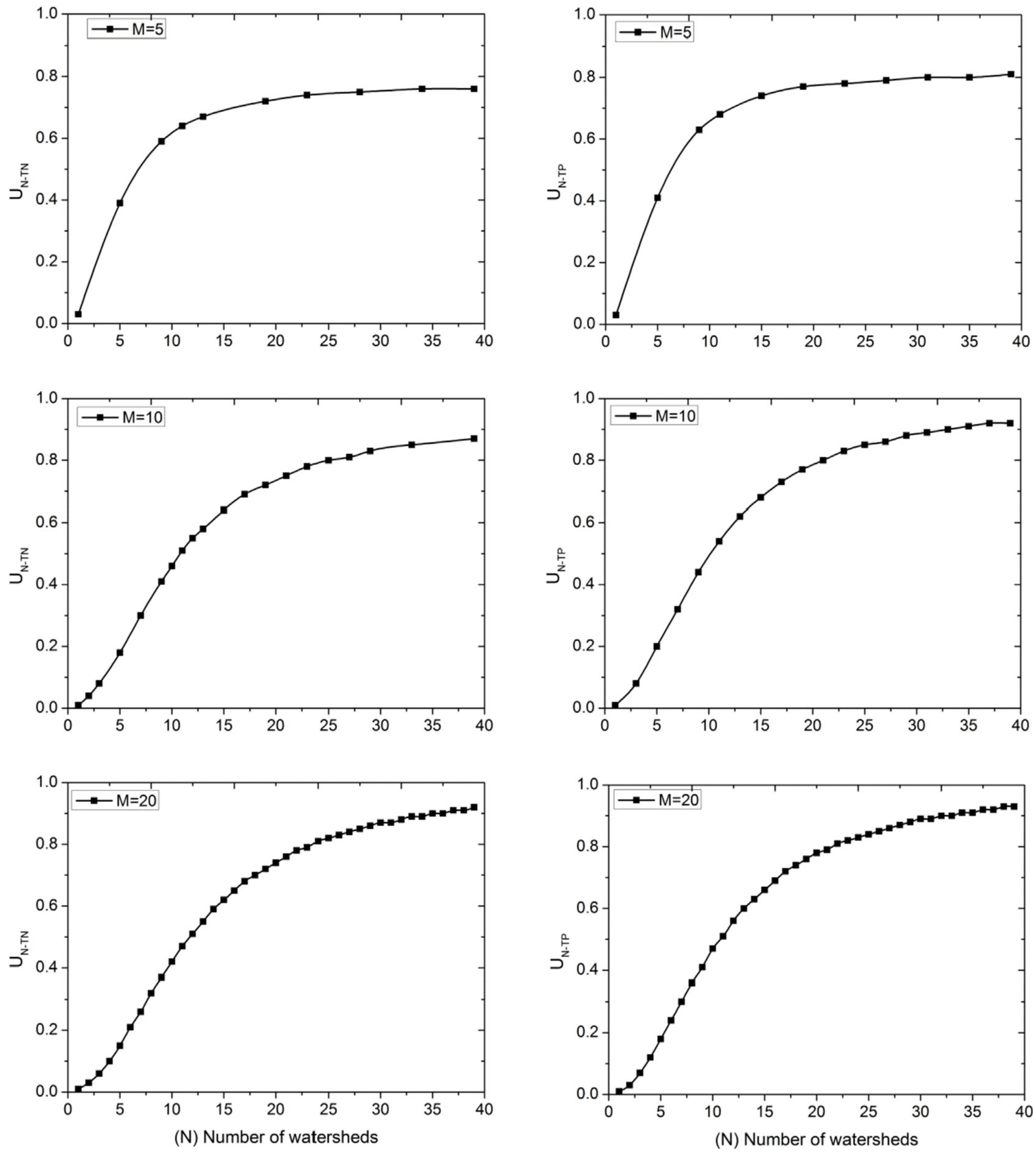

Fig. 2. Utility functions for TN, TP and the number of watersheds.

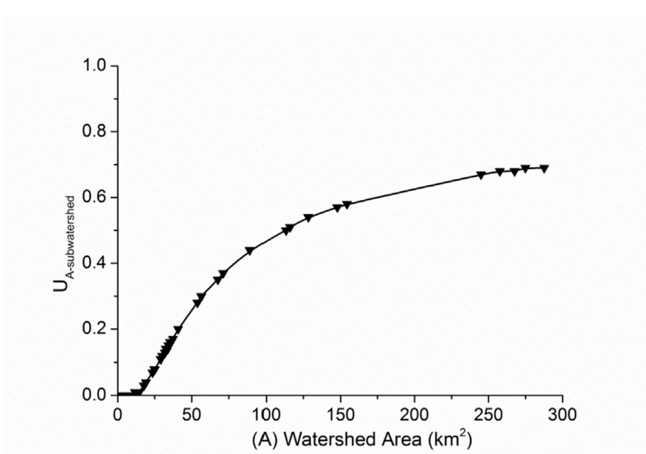

Fig. 3. Utility gained from watersheds with the given mean watershed area.

species and the mean area of sub-watershed. The equation described as:

$$U_{A-subwatershed} = 0.856\left(e^{-60/A}\right) \tag{3}$$

3.3. Relationship between the area of sub-watershed and average unit cost for BMPs implement

To estimate the utility as a nonlinear function of the marginal cost of BMPs, we are development two functions, 1) marginal cost of BMPs and the pollution load reduction and 2) the probability of a statistically significant water quality improvement developed by Geng and Wang (Geng et al., 2015). The BMPs implemented included conservation tillage, timing of chemical fertilization, contour farming, filter strips, reduce fertilizer application by 30%, reduce poultry numbers by 30%, poultry manure storage, manure spread during the dry season, and fencing to restrict animal access to streams.

We coupled Integrated Farm System Model (IFSM) which is a comprehensive farm-scale model used to simulates long-term environmental and economic benefits of the nutrients from typical farms, farm-level economic and farm-gate environmental impacts of management strategies (Ghebremichael et al., 2007; Rotz et al., 2002). The result from IFSM model was used to estimate nutrient reduction at a field scale and ArcSWAT at a watershed scale with BMPs adoption. The estimated TN and TP load reductions were based on marginal cost of BMPs in each sub-watershed. The resulting equation are:

$$R_W = 0.00025E + 0.298 \tag{4}$$

$$R_W = 0.00011E + 0.117 \tag{5}$$

As TN and TP concentrations in rivers vary temporally and spatially as a result of natural factors such as the difference of land use, soil type, slope, and slope length, small amounts of TN and TP load reductions are difficult to statistically identify. A set of statistical models were used to describe how the probability of detecting a statistically significant TN and TP load reduction at the outlet of CRW. This follows a sigmoid function (Geng et al., 2015):

$$P_{W_{TN}} = \frac{1.041}{1 + 60\left(e^{-10.092R_{W_{TN}}}\right)} - 0.041 \tag{6}$$

$$P_{W_{TP}} = \frac{1.103}{1 + 60\left(e^{-7.684R_{W_{TP}}}\right)} - 0.103 \tag{7}$$

Substituting Equations (4) and (5) into (6) and (7), and setting $P_{W_{TN}}$ and $P_{W_{TP}}$ as the utility, and then gives the utility function for marginal cost of per unit BMPs as:

$$U_{E_{TN}} = \frac{1.041}{1 + 60\left(e^{-0.00025E-3.007}\right)} - 0.041 \tag{8}$$

$$U_{E_{TP}} = \frac{1.103}{1 + 60\left(e^{-0.000845E-0.896}\right)} - 0.103 \tag{9}$$

Thus, the relationship between the marginal cost of additional per unit of BMPs plans and the probability of water quality improvements are described in (Figs. 6 and 7).

4. Discussion

4.1. Relationship between the water quality improvement and the number of sub-watersheds, average area of sub-watershed and the average unit cost of BMPs

In general, ANPS pollution reduction will increase with the number of sub-watersheds that implement BMPs. However, the marginal pollution reduction obtained by adding additional ssub-watersheds where BMPs plans were implemented, will decreases as the total number of sub-watersheds increase. Therefore, there is an assumption that the relationship between pollution reduction and number of sub-watersheds will be nonlinear. Similar results were found by (Chen et al., 2016; Hsieh and Yang, 2007; Liu et al., 2014). The regression (curve fitting) function shows that there is a non-liner relationship between the number of sub-watershed and water quality improvement probability. The concentration of TN will decline as the number of the sub-watersheds in which BMPs are used increased; however, the slope of the curve decreases when the number of sub-watersheds over 25 (Fig. 2). For TP, concentrations will not decrease when the number of sub-watersheds is over 23 (Fig. 2). These results show that the water quality improvement probability will achieve the highest point when the BMPs on 23 to 25 sub-watersheds for TN and TP control, adding one additional sub-watershed to an already optimized plan provides little additional improvement in water quality. Although adding more sub-watersheds and placement more BMPs would clearly improvement the water quality and yield greater total benefits, the marginal benefits obtained from adding an additional sub-watershed in an adaptive management– based program decreases as the total number of sub-watersheds increases.

In general, water quality will continue improvement as the area of each sub-watershed that used BMPs increases. In addition, population size of aquatic species also expansion constantly with the river water quality improvement, because some of the aquatic species will not occurred in the relatively smaller streams (Lyons, 1996; Lyons et al., 1996). Although the relationship between

Table 3
Dataset of Wilcoxon signed-rank test method for TN and TP.

TN		TP	
pollution laod reduction	probability of water quality improvement	pollution laod reduction	probability of water quality improvement
0.05	0	0.05	0
0.1	0	0.1	0
0.15	0	0.15	0
0.2	0.002	0.2	0
0.25	0.006	0.25	0
0.3	0.018	0.3	0.001
0.35	0.107	0.35	0.01
0.4	0.43	0.4	0.055
0.45	**0.854**	0.45	0.218
0.5	0.920	0.5	0.420
0.55	0.946	0.55	0.585
0.6	0.97	**0.6**	**0.870**
0.65	0.99	0.65	0.99
0.7	0.99	0.7	0.99
0.75	1	0.75	1
0.8	1	0.8	1
0.85	1	0.85	1
0.9	1	0.9	1
0.95	1	0.95	1
1	1	1	1

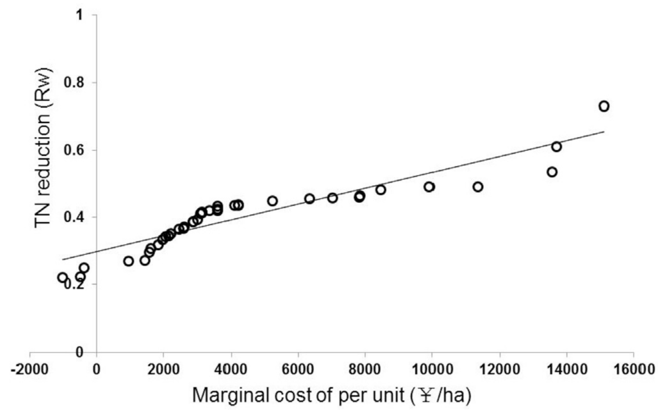

Fig. 4. Relationship between TN reduction (%) and marginal cost of per unit (¥/ha) after BMPs implemented.

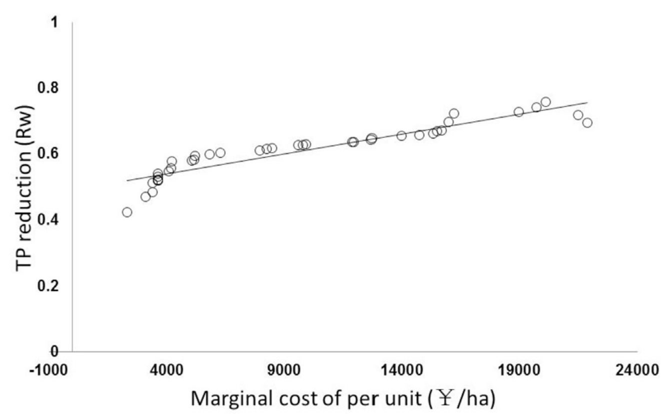

Fig. 5. Relationship between TP reduction (%) and marginal cost of per unit (¥/ha) after BMPs implemented.

population size of aquatic species and pollution reduction are complex and uncertain, research has shown that the relationships can represent nonlinear exponential, logistic, and binomial functions (Maxted et al., 2009). With an increase in average area of sub-watersheds, the population density of benthic macroinvertebrates increases as an exponential function curve. The utility of water quality improvement can be up to 0.6 when the average area of sub-watershed is 170 km^2, while the slope of the curve was decreased significantly. Although, the utility of water quality improvement just increases 0.12 and can be up to 0.72, the average area of sub-watersheds with BMPs will increase two times and up to 284 km^2 (Fig. 3). This suggests that when the average area of sub-watersheds is up to 170 km^2, adding additional BMPs will increase the marginal cost and utility ratios and will not be economically viable. Therefore, optimal BMPs placement occurs on 170 km^2 of the target 25 and 23 sub-watersheds.

Improving the acceptability of BMPs is a primary step in water quality improvement, and BMP adoption rates are typically closely related to the ratios of cost-effectiveness of BMPs and its combinations (Prokopy et al., 2008). In general, the ANPS pollution reduction will increase as the number of BMPs implemented increases. This suggests that with a greater investment in BMP adoptions, the more pollution load will be reduced. However, the benefit derived from each additional unit of marginal cost of BMPs may not be expressed as a linear relationship. For the relationship between the probability of achieve a statistically significant improvement of water quality and the average unit cost. It also can be representing by the sigmoid (threshold) function curve (Table 3). For TN control, when the pollution load reduction up to 45%, while the probability of water quality improvement was 0.854. For TP control, when the pollution load reduction up to 60%, the probability of water quality improvement was 0.87. This suggests that above these two threshold points, adding more BMPs to the targeted sub-watershed will not produce a significantly water quality improvement.

The relationship between TN and TP load reduction and marginal BMP cost was linear relationship, with correlation coefficients of 0.847 and 0.771 for TN and TP, respectively (Fig. 4 and Fig. 5).

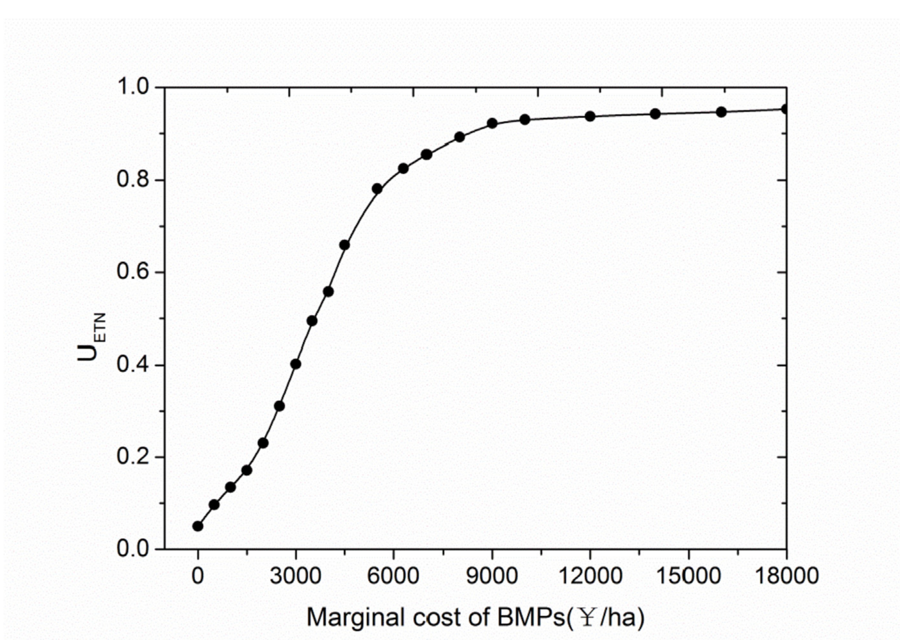

Fig. 6. Relationship between the marginal cost of per unit of BMPs and the probability of statistical improved for TN.

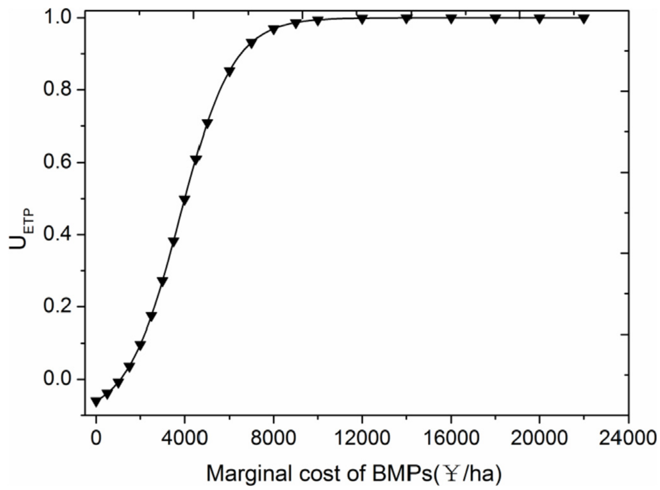

Fig. 7. Relationship between the marginal cost of per unit of BMPs and the probability of statistical improved for TP.

Integrating these two curves, water quality will significantly improve when average unit cost were 7000 yuan/ha and 9000 yuan/ha for TN and TP control, respectively. Thus, 7000 yuan/ha and 9000 yuan/ha are optimal costs for the BMP placement and adding more cost will not get a significantly improvement of water quality (Figs. 6 and 7).

4.2. Optimal combination between the number of sub-watersheds, the area of sub-watershed and the average unit cost

The optimal combination of number of sub-watersheds, average area of sub-watershed, and average unit cost, varied strongly as a non-linear function of total program budget. For TN concentration decrease, the BMPs plans for a lowest cost project with a 6400 CNY budget was 2 sub-watersheds of 15 km^2 each, with an average unit cost of 218 CNY/ha. The optimal design for a highest cost program with a 2.0×10^8 Yuan budget was 39 sub-watersheds of 288 km^2 each, with an average unit cost of 18000 CNY/ha (Fig. 8).

For TP control, BMPs plans for a lowest cost project with a 6367 CNY was 1 sub-watershed of 23 km^2, with an average unit cost of 283 CNY/ha. Optimal BMPs plans for a highest cost program with a 2.4×10^8 CNY was 39 sub-watersheds of 288 km^2, with an average unit cost of 22391 CNY/ha (Fig. 9).

Across the range of budgets considered here, the average unit cost was high and varied over than 80 times. In contrast, the optimal combination of the number of watersheds, average area of sub-watershed and average unit cost with a strongly positive correlation as a function of the total cost of BMPs plans. The calculation of optimal BMPs plans was conducted across a range of total cost, ranging from 6400 to 2.4×10^8 CNY.

4.3. Cost-effectiveness plans for BMPs placement in different spatial scale

We estimate the BMPs plans efficiency as total utility divided by total cost. The BMPs plans efficiency was estimated across the range of the total cost and used to identify the most cost-effectiveness BMPs plans. For TN control, the number of sub-watersheds increased faster than the average area of sub-watershed until a total cost of 2.01×10^7 CNY, after which sub-watershed area increased more rapidly. Our estimate of program cost-effectiveness was greatest with a program budget of 2.01×10^7 CNY. This budget can serve as the threshold point for BMP placement with 27 sub-watersheds, the average area of sub-watershed is 168 km^2, and the average unit cost is 4622 CNY/ha. Meanwhile in this point with a highest total utility are 0.89 (Fig. 10).

For TP control, average sub-watershed area will increase with the number of sub-watersheds up to a total cost of 4.7×10^7 Yuan, after which the number of sub-watersheds will increase more rapidly. The cost-effectiveness of BMPs plans was highest at a program cost of 4.7×10^7 CNY. This program can serve as the threshold point to placement the BMPs plans for TP control, in

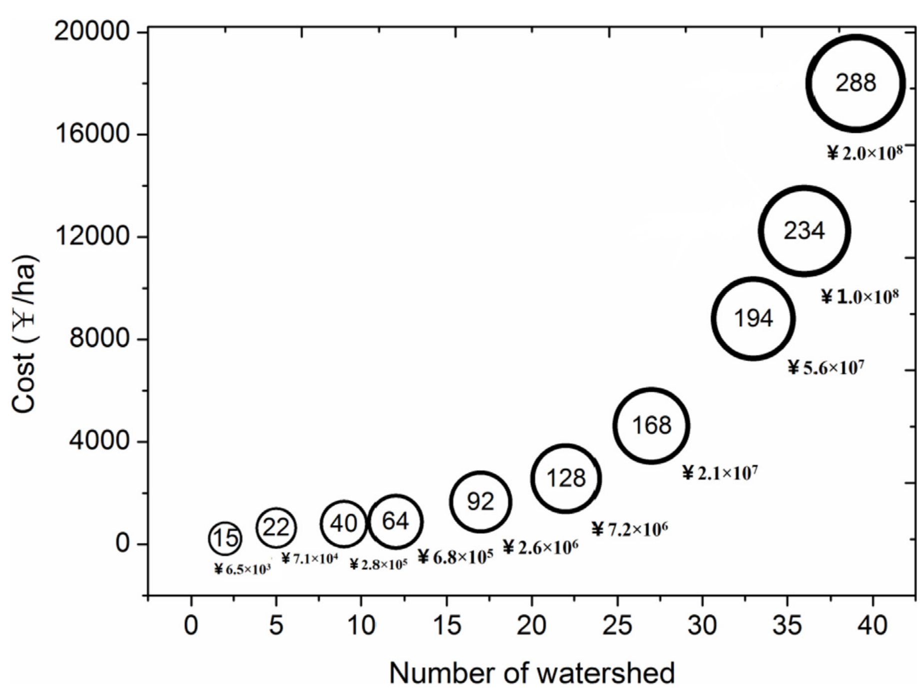

Fig. 8. Optimal program characteristics across a range of program budgets for TN.

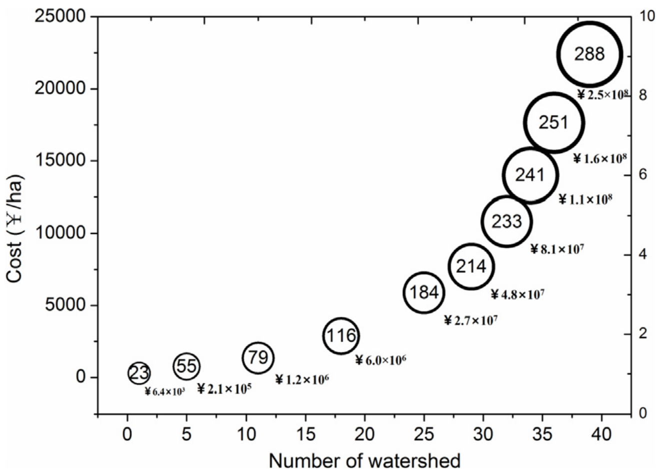

Fig. 9. Optimal program characteristics across a range of program budgets for TP.

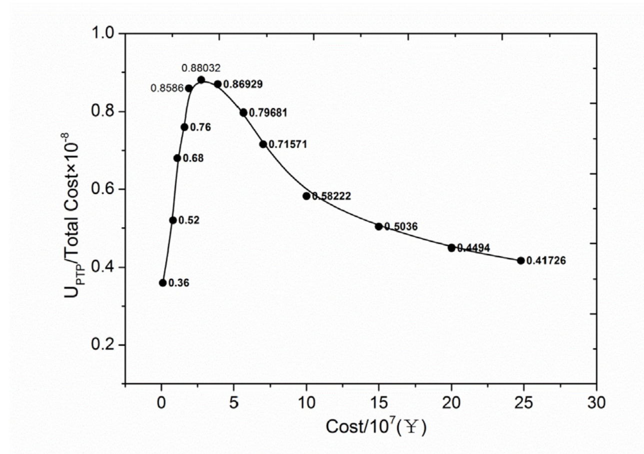

Fig. 11. Total program utility (U_P) per unit cost across a range of program budgets for TP.

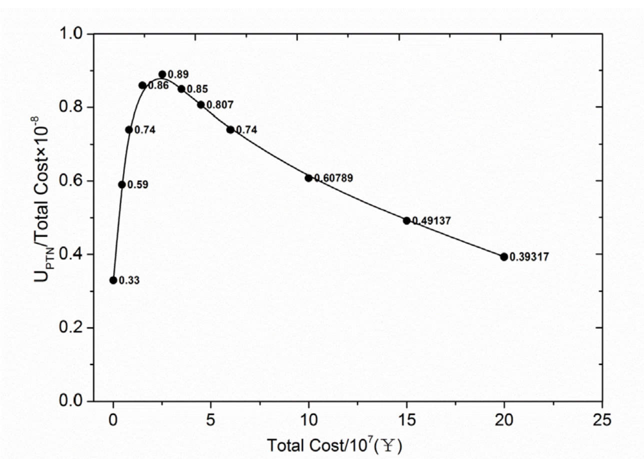

Fig. 10. Total program utility (U_P) per unit cost across a range of program budgets for TN.

which the number of sub-watersheds is 29, average area of sub-watershed is 214 km^2, and average unit cost is 7692 Yuan/ha. Meanwhile in this point with a highest total utility are 0.89 (Fig. 11).

In this paper, we are attempt integrate the number of sub-watershed, the area of the BMPs implemented and costs of BMPs, to build the nonlinear response function model respectively, through the multi-objective model for achieve the optimal BMPs plans in different spatial scales, This model is simpler and easier to operate than other models and to maximize the cost and benefit of BMPs scheme and solve the problem of spatial scale conversion in the process of BMPs configuration.

5. Conclusion

In this study, we are attempts to construct a simple and feasible BMPs optimal configuration scheme at different spatial scales through integrate the nonlinear functions about the number of sub-watershed, the area of the BMPs implemented and costs of BMPs to achieve the maximize of the water quality improvement probability and the cost from field to watershed scale in Chaohe River watershed which located in the upper watershed of Miyun Reservoir of Beijing, China.

1. The optimal BMPs plans for TN control includes the number of sub-watersheds is 27, the mean area of sub-watershed is 168 km^2, and the average unit cost is 4622 CNY/ha under the total cost of 2.01×10^7 CNY. The optimal BMPs plans for TP control includes the number of sub-watersheds is 29, the average area of sub-watershed is 214 km^2, and the average unit cost is 7692 CNY/ha under the total cost of 4.7×10^7 CNY. In these scenarios, the TN and TP concentration will be significantly decrease and achieve a statistical powered improvement.
2. The relationship between three indexes (i.e., number of sub-watersheds, average area of sub-watershed, and average unit cost) and the water quality significantly improvement are depicted by non-liner relationships, but with different functions types, the number of sub-watershed and the water quality improvement utility is the log-sigmoid curves, the average area of sub-watershed and the water quality improvement utility is the modified exponential function curve, while the average unit cost and the water quality improvement utility also is the logistic (threshold) function. Although the utility function for these three indexes may also vary depending on the number of BMPs, the types of BMPs and the expected effect size of those BMPs plans. However, these findings can be served as an important reference for selected a set of preferred sub-watershed features to placement the BMPs.
3. The framework presented here provides practical guidance for development of BMPs plans to improve water quality in an agricultural nonpoint source-controlled watershed. This approach is designed to achieve significant improvements in water quality at targeted locations and to maximize benefits about water quality response to conservation practices strategies from field to watershed scales. The results of this research will provide a systematic approach to determine reliable and viable conservation management scenarios on multi-spatial scales. It will provides scientific technical and theoretical support for promoting agricultural clean production level in drinking water source areas

Author contributions

Runzhe Geng conceived and designed the methodology, figures, conducted the data collection, data analysis and wrote the wrote the main manuscript text; Andrew Sharpley designed the methodology with Runzhe Geng, and review the main paper and give revised suggestions.

Conflicts of interest

The authors declare no conflict of interest.

Additional information

The authors declare no competing interests.

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