Applied Geography 90 (2018) 200–213

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Effects of best management practices on nitrogen load reduction in tea fields with different slope gradients using the SWAT model

Wei Wang [a], Yujing Xie [a, *], Mengfei Bi [b], Xiangrong Wang [a, **], Yi Lu [a], Zhengqiu Fan [a]

[a] Department of Environmental Sciences and Engineering, Fudan University, 220 Handan Road, Shanghai 200433, PR China
[b] The Environmental Monitoring Station of Huangshan City, 35 Hongxing Road, Tunxi District, Huangshan City, Anhui Province, PR China

ARTICLE INFO

Article history:
Received 14 March 2017
Received in revised form
25 August 2017
Accepted 29 August 2017
Available online 22 December 2017

ABSTRACT

Increasing fertilizer inputs in tea (*Camellia sinensis* L.) fields, especially in hilly areas, poses serious potential risks of surface water contamination. Best management practices (BMPs) have been extensively implemented to control nutrient loads from non-point sources. However, little research has been conducted to evaluate the effects of dynamic BMPs on nitrogen (N) load reductions in tea fields with different slope gradients. This study is conducted in subtropical tea fields in the Machuan River watershed, which adjoins Huangshan Mountain of Anhui Province in China. Three BMP scenarios, viz., avoiding fertilizing before rain, contour planting and applying slow-release fertilizers, are simulated to model the N load reduction using the Soil and Water Assessment Tool (SWAT). The objectives of this study are as follows: (1) to build a calibrated SWAT model for the Machuan River watershed, (2) to evaluate and compare the effects of three BMPs on N load reduction in tea fields with different slope gradients, and (3) to identify critical slope gradients and BMPs for effective N load control. The results indicate that three BMP scenarios significantly impact N losses reduction in tea fields and that their effects vary among different slopes and months. Compared with the baseline condition, the N losses rate could be reduced by approximately 24%, 28%, and 66% for three scenarios, respectively. Generally, tea planted on steep-sloping land leads to great losses of N, and tea fields on slopes exceeding 15° should be prioritized for BMP implementation as tea fields planted here tend to have the highest N losses. This will offer sound information for the development of better pollution-control strategies for tea fields in the Machuan River watershed.

1. Introduction

Non-point source (NPS) pollution is one of the most uncontrollable issues in water quality management (Zhai, Zhang, Wang, Xia, & Liang, 2014). Agriculture-related activities are considered the largest threat for the contamination of surface water and ground water resources (Duchemin & Hogue, 2009; Ongley, Zhang, & Tao, 2010; Yang & Best, 2015; Yang, Jiang, Luo, & Zheng, 2012). Considerable nitrogen (N) and phosphorus (P) fertilizers, pesticides and other nutrients leak into surface runoff and enter aquatic ecosystems (Guo, Fu, Ruan, Ge, & Zhao, 2014). In China, agricultural NPS pollution has become a particularly serious problem since the 1990s (Ongley et al., 2010), and by 2008, the annual application of synthetic nitrogen fertilizers had increased by 50.7% (Sun et al., 2012). China has become the largest user of synthetic nitrogen fertilizers in the word, which has contributed substantially to the emission of pollutants into water bodies and soils (Sun et al., 2012). Accordingly, the number of eutrophic lakes, which are associated with increased toxic algal concentrations and oxygen depletion, has dramatically increased during the past decades (Gao & Zhang, 2010; Shen, Qiu, Hong, & Chen, 2014). Indeed, five of the six largest freshwater lakes in China are in a eutrophic state (Gao & Zhang, 2010).

Losses of N and P are considered to be major sources of NPS pollution (Carpenter et al., 1998), and heavy N fertilizer is generally applied to tea fields to achieve the necessary yield increase (Ruan, Wu, Shi, & Ma, 2001; Tokuda & Hayatsu, 2001). Tea is a major cash crop in the tropical and subtropical areas of China (Ruan, Ma, & Shi, 2013), and the total tea plantation area is approximately 2.74 million ha (NBSC, 2014). The average N fertilizer application rate is

* Corresponding author.
** Corresponding author.
E-mail addresses: xieyj@fudan.edu.cn (Y. Xie), xrxrwang@fudan.edu.cn (X. Wang).

https://doi.org/10.1016/j.apgeog.2017.08.020
0143-6228/

approximately 533 kg ha^{-1} yr^{-1} in tea fields, and the highest value can reach 1200 kg ha^{-1} yr^{-1} (Wu et al., 2016). The input of N fertilizer to tea fields was approximately 573 kg ha^{-1} yr^{-1} in Xinchang (green tea) in Zhejiang Province and 439 kg ha^{-1} yr^{-1} in Anxi (oolong tea) in Fujian Province (Ruan et al., 2001). Similarly, in Japan, heavy application of N fertilizer—often exceeding 1000 kg ha^{-1} yr^{-1}—has been used to increase the yield and quality of Japanese green tea (Tokuda & Hayatsu, 2001). A study performed in forest-dominated tea-cultivating areas in Shizuoka, central Japan, revealed that the expansion of tea fields within this basin has significantly increased the total N (TN) concentration and that the excess N load might accelerate the P shortage in aquatic ecosystems (Nagumo, Yosoi, & Aridomi, 2012). Many tea plantations, which are mainly located in hilly areas, have the potential to contaminate surface water (Liu, Yang, Yang, & Zou, 2012). Therefore, research regarding the control and management of N pollution in tea fields is crucial for water quality protection.

Best management practices (BMPs) have been widely implemented to eliminate or reduce the losses of nutrients or pollutants from NPSs to receiving water (Chaubey, Chiang, Gitau, & Mohamed, 2010; Lee et al., 2010; Logan, 1993). BMPs are designed to reduce the adverse effects of water quantity and quality problems (Chaubey et al., 2010; Liu, Zhang, Wang, Chen, & Shen, 2013; Sun, Tong, & Yang, 2016). The significant factors that influence the losses of nutrients must be identified before BMPs can be applied. Previous studies indicated that the loss of N in runoff is mainly determined by climatic conditions, geomorphology, geohydrology, and farmers' practices (Liu et al., 2012; Zvomuya, Rosen, Russelle, & Gupta, 2003). To reduce the TN concentration, the fertilizer N rate should be reduced and the fertilizer efficiency enhanced by, for example, combining slow-release coated urea with cultivar selection (Nagumo et al., 2012). The replacement of conventional chemical fertilizers with organic or slow-release fertilizers would not significantly affect tea yields while reducing N losses (Liu et al., 2012; Noellsch, Motavalli, Nelson, & Kitchen, 2009). Farming on steep-sloping land generally causes great losses of plant nutrients (Meng, Fu, Tang, & Ren, 2008). Indeed, previous research has suggested that farmland on slopes over 15° should be abandoned (Fu et al., 2004) or that an improved cultivation method should be adopted to efficiently control NPS pollution (Choi, 2008). The effect of rainfall frequency on the N concentration is a function of the rainfall amount and timing of poultry litter application. As the time between litter application and rainfall-runoff increases, the concentration of N in the runoff decreased (Sharpley, 1997). Contour farming/planting consists of performing field operations along the contour, and has been proposed and proven to be effective at reducing N losses (Guto, Pypers, Vanlauwe, de Ridder, & Giller, 2011) because it can prevent sheet and gully erosion, especially under low and moderate intensive storm erosion conditions (Liu et al., 2013). In this study, both structural (*e.g.,* contour farming/planting) and non-structural (*e.g.,* fertilizer management) BMPs were simulated to determine their effects on reducing N loads.

Water quality models are increasingly used to evaluate the effectiveness of BPMs for reducing pollutant loads or sediment losses from a watershed (Kirsch, Kirsch, & Arnold, 2002; Lamba, Thompson, Karthikeyan, Panuska, & Good, 2016; Schilling & Wolter, 2009). Models can simulate the effects of BMP implementation on a watershed scale and allow for comparisons among different load reduction strategies (Schilling & Wolter, 2009). A number of models have been applied to address BMP optimization, such as the Soil Water and Assessment Tool (SWAT) (Ghebremichael, Veith, & Hamlett, 2013), the Annualized Agricultural Nonpoint Source model (AGNPS) (Bhuyan, Marzen, Koelliker, Harrington, & Barnes, 2002; Mostaghimi, Park, Cooke, & Wang, 1997), the Hydrological Simulation Program-FORTRAN (HSPF) (Chichakly, Bowden, & Eppstein, 2013; Shenk, Wu, & Linker, 2012) and the Storm Water Management Model (SWMM) (Lee et al., 2012). The SWAT model has emerged as one of the best available water quality models on the watershed and river basin scale for simulating the effectiveness of BMPs (Liu et al., 2013) and has been extensively used for a broad range of hydrological and environmental problems (Arabi, Frankenberger, Engel, & Arnold, 2008; Dixon & Earls, 2012; Gassman, Sadeghi, & Srinivasan, 2014; Schilling & Wolter, 2009; Ullrich & Volk, 2009). Especially in agricultural fields, numerous SWAT studies on agricultural BMPs (such as filter strips, contour farming, parallel terraces, grassed waterways and nutrient management plans) have been proposed to reduce the losses of sediment and nutrient loads at different spatial levels and temporal scales (Behera & Panda, 2006; Bracmort, Arabi, Frankenberger, Engel, & Arnold, 2006; Kaini, Artita, & Nicklow, 2012; Lam, Schmalz, & Fohrer, 2011; Tuppad, Kannan, Srinivasan, Rossi, & Arnold, 2010; Vaché, Eilers, & Santelmann, 2002). It is reported that implementing individual BMPs could reduce the average annual load for TN from 1% to 24% at the watershed outlet (Tuppad et al., 2010).

The Machuan River watershed is a major tea plantation area in Huangshan City, China. The Machuan River gathers water from Huangshan Mountain that is a World Heritage Site. Improved understanding of the effects of BMPs on reducing N loads in the Machuan River watershed is crucial for developing strategies to control the N concentration in downstream receiving water and mitigate the damage to the drinking water sources used by downstream cities. Three BMP scenarios, viz., avoiding fertilizing before raining, contour planting and applying slow-release fertilizers, were applied to model the N load reduction using SWAT 2012. This study differs from previous work using SWAT to simulate N loads in the following ways: 1) Different BMPs for the reduction of N loads in tea fields, which has scarcely been discussed, were simulated. 2) Because tea fields are mostly located in hilly areas, the effects of BMPs on N losses reduction at different slope gradients were evaluated and compared, which could contribute to identifying critical areas for the effective implementation of BMPs. 3) The fertilizer data were surveyed by investigating every town in the watershed, which is more reliable than statistical data.

2. Materials and methods

2.1. Study area

The Machuan River is one of the longest tributaries of TaiPing Lake, which is the largest artificial lake in Anhui Province in China and plays a significant role in the municipal water supply. The river originates from Lotus Peak and Heavenly Capital Peak of Huanshan Mountain. Its watershed covers a drainage area of approximately 662.09 km^2, as shown in Fig. 1. The Machuan River watershed has a typical temperate humid monsoon climate with an annual average temperature of approximately 15.5 °C and precipitation of approximately 1600 mm with considerable spatial and temporal variability observed from 1978 to 2011. Precipitation in the watershed mostly occurs from May to July and is heavily influenced by monsoons. The watershed is typical of a northern subtropical mountainous landscape. Approximately 85.1% of the area is covered by forests. Urban area, paddy fields, tea fields, water bodies and wetlands account for 2.2%, 6.0%, 4.7%, 1.6% and 0.4% of the land coverage, respectively. The total population is approximately 38,400. The region is mostly hilly with flat areas in the middle, and its surface elevation ranges from approximately 120 m to nearly 1900 m. No industrial point source pollution was located in the watershed during our study period. The major NPSs of N in the watershed are soil mineralization and nitrogen fertilizer

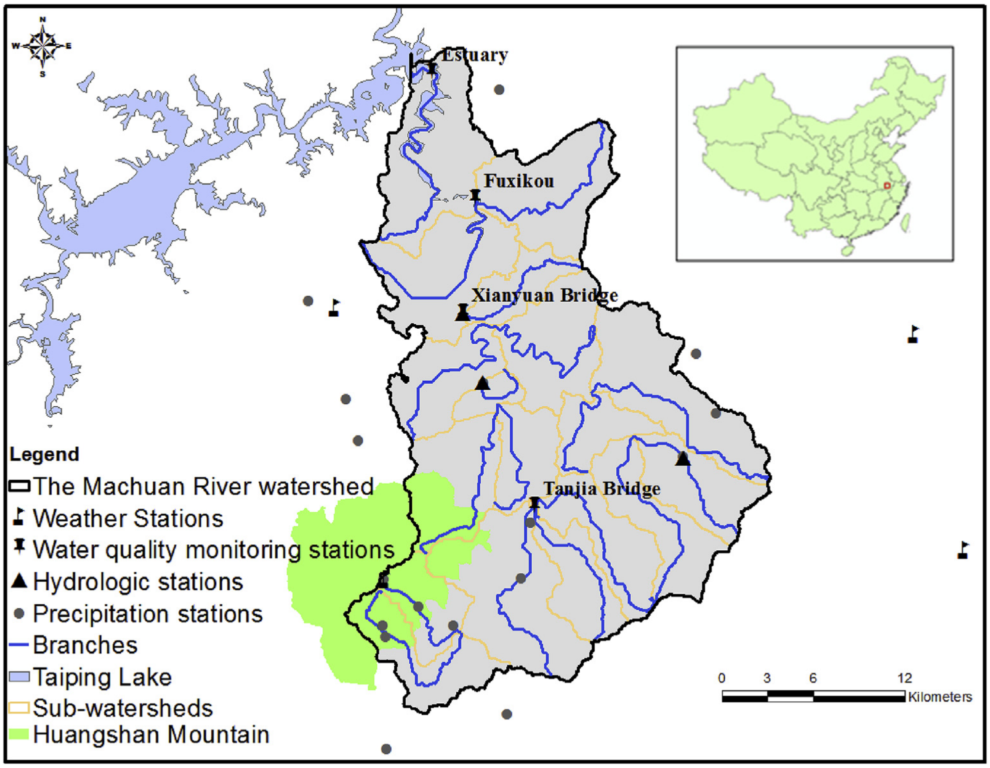

Fig. 1. The location of the Machuan River watershed.

Table 1
Summary of basic SWAT inputs for the calibrated Machuan River watershed model.

Input description	Scale	Data
DEM	10 m	Elevation, slopes and lengths
Land use map	30 m	HJ-1A/B, LANDSAT 5&7, and land survey data from the Huangshan Municipal Bureau of Land and Resource
Soil map	1:1000 000	Soil classification, soil physical and chemical properties
Precipitation	19 stations (2010–2013)	Daily and hourly precipitation
Weather	4 stations (2010–2013)	Daily maximum/minimum temperature, relative humidity and sunshine hours
Hydrology	3 stations (1978–2011)	Monthly runoff (1978–2011) Daily runoff (2010–2011)
Water quality	4 stations (2010–2013)	Monthly N
Application of fertilizers and pesticides		Face-to-face interviews with selected farmers

application to cropped fields, which primarily consist of rice and tea fields.

2.2. Data collection and processing

2.2.1. Data collection

The necessary data sets included topography, land use, soil, hydrology, climate, water quality and fertilizing data. All of the data used in our model are shown in Table 1. The 2010 land use and land cover (LULC) data, obtained from HJ-1B (with a resolution of 30 m) and LANDSAT 5&7, were rectified by the land survey data from the Huangshan Municipal Bureau of Land and Resource. The soil types and properties were estimated using the Soil-Plant-Air-Water (SPAW) model and Harmonized World Soil Database (HWSD). The 10-m digital elevation model (DEM) was used to delineate the sub-basins, which were further divided into hydrological response units (HRUs). Each HRU represents homogeneous LULC, soil and slope characteristics (Fig. 2). Daily records of maximum and minimum temperature, relative humidity, sunshine hours, wind direction and speed at four weather stations from 2010 to 2013 were acquired from the Meteorological Administration of Anhui Province. Daily solar radiation was estimated using the Angstrom-Prescott equation (Prescott, 1940) from daily sunshine hours. Daily and hourly rainfall data collected by 19 rainfall stations from 2010 to 2013 were obtained from the Hydrological Bureau of Anhui Province. Monthly runoff data from 1978 to 2011 and daily runoff data from 2010 to 2011 at 3 hydrological stations were provided by the Hydrological Bureau of Anhui Province. Monthly observations of the TN concentration at four stations from 2010 to 2013 were obtained from the Environmental Protection Bureau of Huangshan City. Face-to-face interviews with 817 randomly selected farmers representing every town were conducted to collect information on current tea and rice management practices in the watershed.

2.2.2. The distribution and slope classification of tea fields

In the Machuan River watershed, the area of the tea fields was approximately 31.06 km^2 in 2010 and occupied 4.7% of the total study area. Tea fields were scattered across the entire study area, and their elevations mainly ranged from 120 m to 940 m. Approximately 83.4% of the tea fields were concentrated at

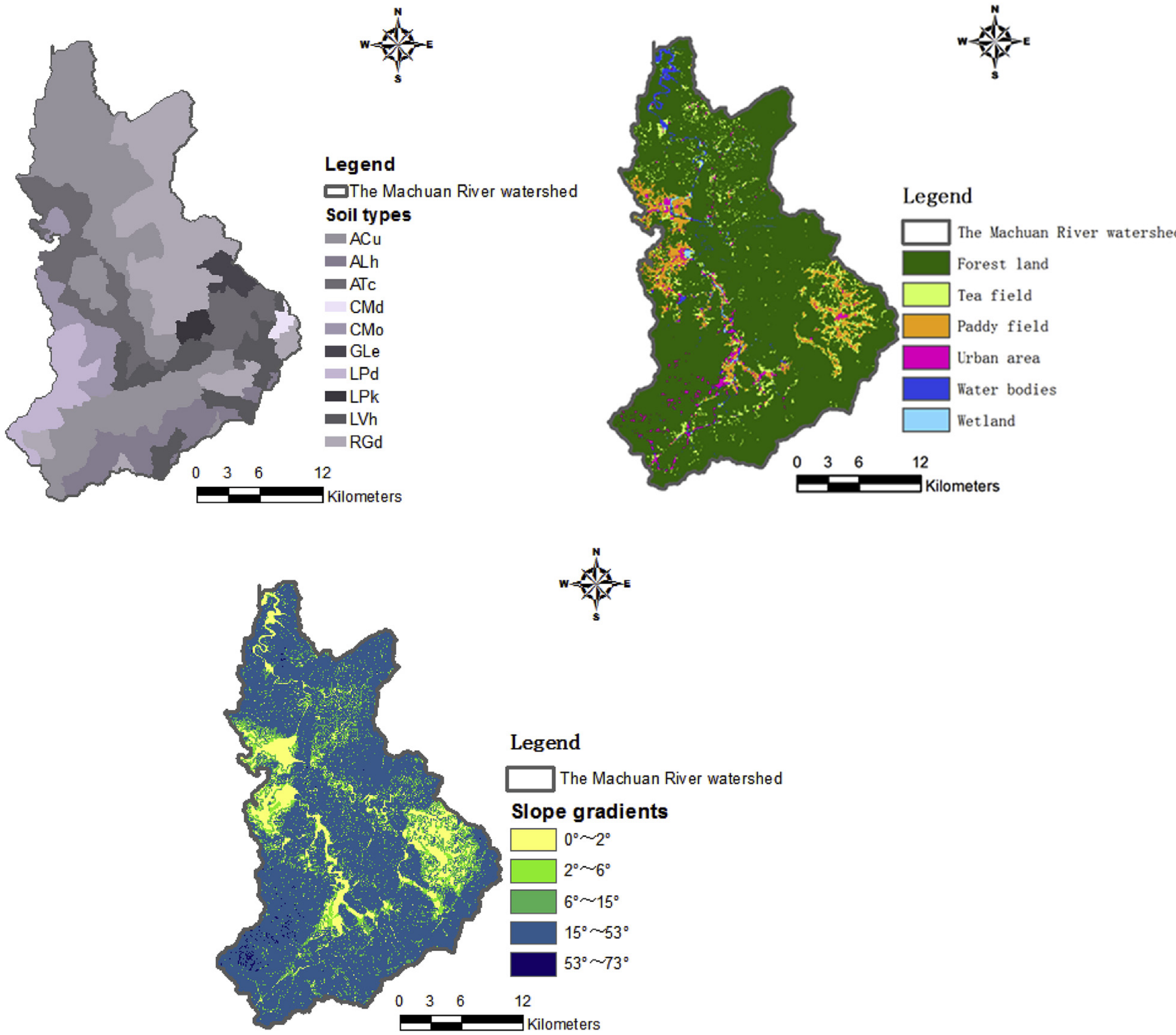

Fig. 2. Data used for building HRUs: a) soil types, b) land use types, and c) slopes.

elevations between 175 m and 600 m because of both the characteristics of tea growth and the climate in the watershed. The highest tea field slope in the watershed was 53°. According to “The Second National Land Survey” in China, the slope of tea fields in our study area was classified into four grades: 0°~2°, 2°~6°, 6°~15° and 15°~53°. As shown in Fig. 3, approximately 73% of the tea fields were planted at slopes exceeding 6°, and 58% were planted at slopes over 15°. The effectiveness of BMPs for N losses reduction were estimated and compared for different slope grades.

2.2.3. *The survey of tea plantation and fertilization*

The tea field distribution and timing of fertilizing are closely related to the N concentration. In our SWAT model, the fertilization data were collected by administering questionnaires in every village in the Machuan River watershed in 2012. Combined with the related studies of the Tea Research Institution of the Chinese Academy of Agricultural Sciences, this work revealed that the application of fertilizers for tea mainly occurred between March and November. According to a typical tea growth cycle in our study area, there were 5 applications of fertilizer within a year total, as shown in Fig. 4. Base fertilizer was applied around October before planting tea in next year. For paddy field, 3 applications of fertilizer mainly occurred between May to September.

The applications of compound fertilizer, urea and N element in tea fields in different towns of the watershed are shown in Fig. 5. The highest applications of compound fertilizer and urea exceeded 1000 kg ha^{-1} yr^{-1} and 500 kg ha^{-1} yr^{-1}, with average values of approximately 633 kg ha^{-1} yr^{-1} and 255 kg ha^{-1} yr^{-1}, respectively. Indeed, the average application of compound fertilizer and urea was also very high in tea fields in nearby She Town in Huangshan City, China (Ma et al., 2012), with 1023 kg ha^{-1} yr^{-1} and 322 kg ha^{-1} yr^{-1} in 2009 and 2010. According to our field investigation, the application of N element was averagely 316 kg ha^{-1} yr^{-1} in the entire watershed (Fig. 5). Obvious spatial discrepancies existed in the applications of fertilizers and N element. Towns with heavy fertilizer application mainly included Xinming Town, Xianyuan Town and Sankou Town, where tea plantations were concentrated.

2.3. *SWAT model calibration and validation*

The Machuan River watershed was divided into 19 sub-watersheds and 852 HRUs by the Arc SWAT 2012 interface. The areas of these sub-watersheds and HRUs ranged from 8.37 km^2 to 66.10 km^2 and from 0.8 km^2 to 13.7 km^2, respectively. Model

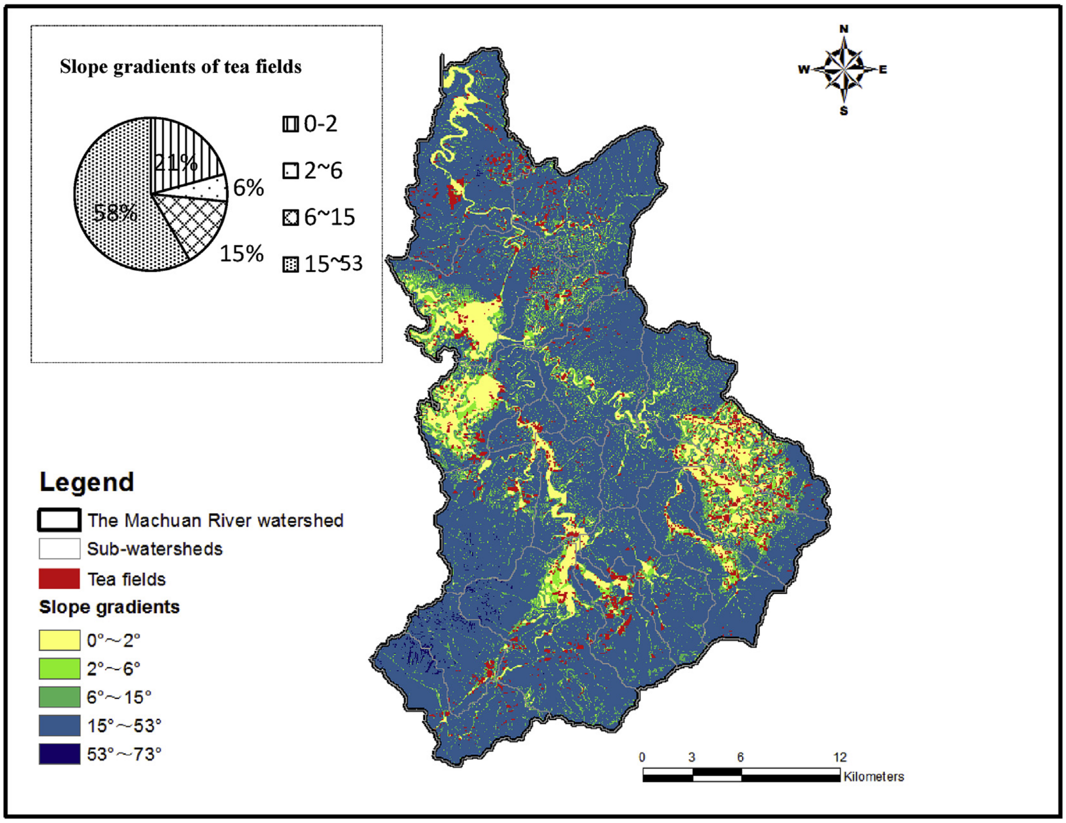

Fig. 3. Spatial distribution of tea fields in the Machuan River watershed.

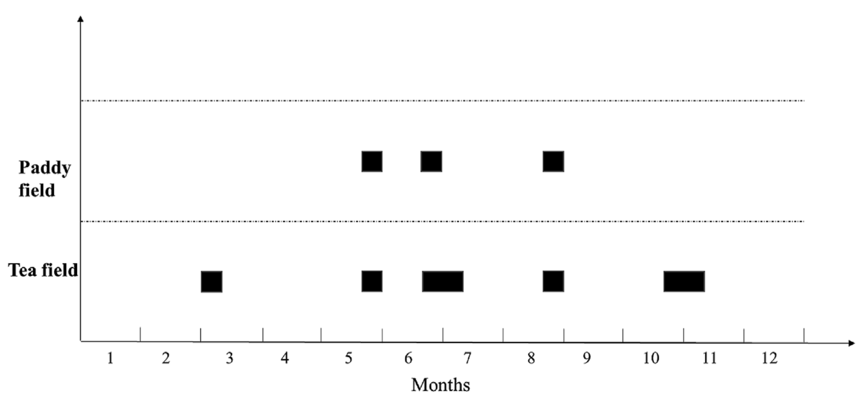

Fig. 4. The timing of fertilizer application for tea and paddy fields in the watershed.

calibration is the process of adjusting model parameters within recommend ranges to optimize the agreement between the model output and the measured stream flow and calculated N loads (Tolson & Shoemaker, 2007). A pre-selection and aggregation step was adopted to select the parameters that were important in the calibration. 14 parameters were chosen for calibration in the Machuan River watershed. The type, brief description, initial range and final range of the parameters are listed in Table 2.

The calibration and validation of the SWAT model were conducted using the SWAT Calibration and Uncertainty Programs (SWAT-CUP) package. The Sequential Uncertainty Fitting ver. 2 (SUFI2) algorithm in the SWAT-CUP software package (Abbaspour, Johnson, & Van Genuchten, 2004, 2007), was used for model calibration, validation and uncertainty analysis. The calibration process was initiated by first calibrating the stream hydrology and then calibrating the N concentration. The degree to which all uncertainties are recognized is measured by an index referred to as the *P-factor*, which is the fraction of measured data bracketed by the 95% prediction uncertainty (95PPU). The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable. *P-factor* varies from 0 to 1, where 1 indicates 100% bracketing of the measured data within model prediction uncertainty (Abbaspour et al., 2015). Another measure to quantify the strength of a calibration/uncertainty analysis is *R-factor* which is the ratio of the average width of the 95PPU brand and the standard. SUFI-2 seeks to bracket most of the measured data (large P-factor, maximum 1 (*i.e.*,100%)) with the smallest possible value of *R-factor* (minimum 0) (Akhavan et al., 2010; Schuol, Abbaspour, Srinivasan,

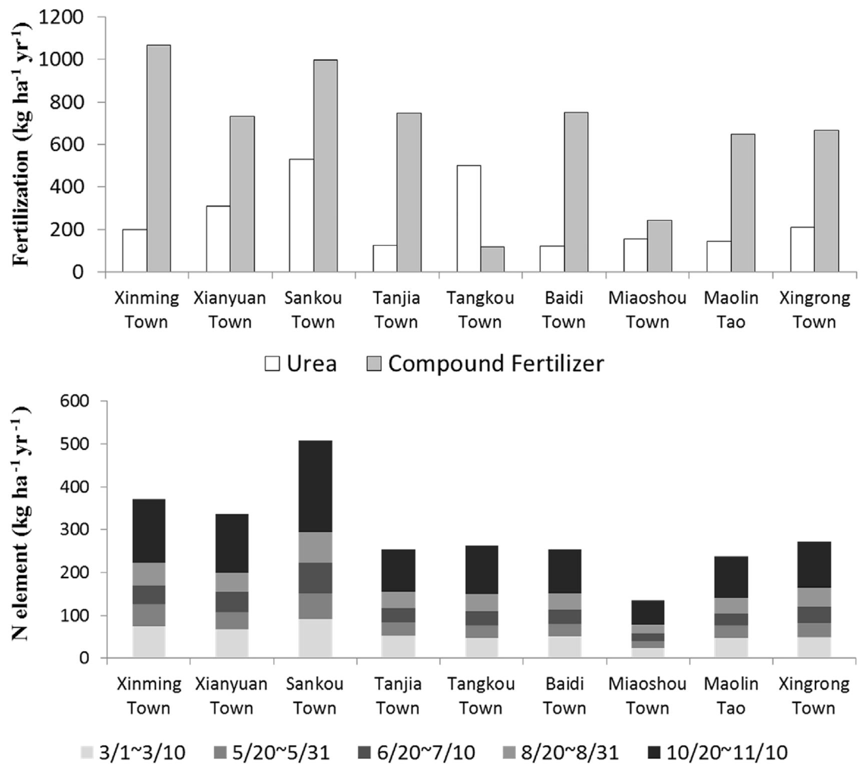

Fig. 5. Applications of fertilizers and N element in different towns in the watershed.

Table 2
Parameters used for calibration in SWAT.

Parameters	Description	Initial range	Final range
CN2	Initial SCS runoff curve number for moisture condition II	35–98	35–76
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	0–5000	2327–3900
RCHRG_DP	Deep aquifer percolation fraction	0–1	0.29–0.86
ESCO	Soil evaporation compensation factor	0–1	0.44–0.85
SOL_AWC	Available water capacity of the soil layer	−0.3–0.3	−0.1–0.3
SOL_K	Saturated hydraulic conductivity	−0.3–0.3	−0.06–0.10
GW_REVAP	Groundwater revap coefficient	0.02–0.2	0.02–0.14
CANMX	Maximum canopy storage	0–100	15.67–53.16
ALPHA_BF	Base flow recession factor	0–0.3	0.13–0.30
GW_DELAY	Groundwater delay time	0–100	31–90
CH_K2	Effective hydraulic conductivity in main channel alluvium	−0.01–500	17.0–172.3
REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur	0–500	96.2–270.9
SURLAG	Surface runoff lag coefficient	1–10	2.31–5.53
EPCO	Plant uptake compensation factor	0–1	0.44–0.87

& Yang, 2008). The goodness-of-fit measures were the coefficient of determination (R^2) and the Nash-Sutcliffe efficiency (E_{NS}) developed by Nash and Sutcliffe (Nash & Sutcliffe, 1970).

2.4. Detailed information of different BMPs in the Machuan River watershed

BMPs have proven to be effective for controlling NPS pollution in agricultural areas. The watershed BMPs considered in this study were grouped into two categories: nutrient management (amount and timing of fertilizer application) and till management (contour planting). These scenarios were selected according to the detailed interactions with stakeholders and the past implementation of BMPs in the watershed. Three BMP scenarios, viz., avoiding fertilizing before raining, contour planting and applying slow-release fertilizers, were applied to model the N load reduction using SWAT 2012; the other land cover types and management practices were assumed to remain constant. The detailed information of each scenario was provided as follows.

2.4.1. Scenario 1: avoiding fertilization before raining

Rainfall amounts, rainfall intensity and their seasonal variations are statistically significantly correlated with losses of nutrients (Ramos & Martınez-Casasnovas, 2004). To illustrate the influences of avoiding fertilizing before raining on decreasing N load losses in tea fields, the time of fertilizer application was chosen to be three days after a moderate rain (10 mm in 24 h) and five to ten days before the next moderate rain in our SWAT model. The frequency and time periods of fertilization were not varied, mainly occurring between March and November, as shown in Fig. 4.

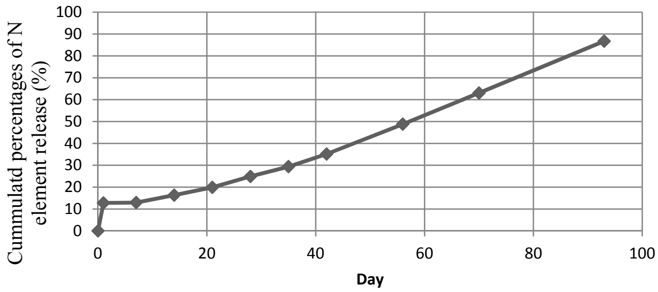

Fig. 6. Cumulated percentages of N element release for "HF-2" sulphur coated urea.

2.4.2. Scenario 2: contour planting

Contour planting tea involves performing field operations along the contour. Contour planting is believed to be capable of preventing sheet and gully erosion and protecting gentle high-slope fields against storm erosion (Guto et al., 2011; Liu et al., 2013; Ng, Cai, Ding, Chau, & Qin, 2008). To examine the impact of contour planting on reducing the N losses from tea fields, all the tea fields were simulated as being terraced with an interval of 1 m by changing the HUR, including the parameters of CN2, SLSUBBSN and USLE_P. The value of CN2 was changed to −25% of the original setting value. The values of SLSUBBSN and USLE_P were adjusted depending on the slope of the HRU according to other studies (Liu et al., 2013; Wang, He, & Zhang, 2013).

2.4.3. Scenario 3: applying slow-release fertilizers

Slow-release fertilizers exhibit have a lag in release and could meet the nutrient demands for crops for the entire season (Shaviv & Mikkelsen, 1993), which could increase the effectiveness of the fertilizer and reduce the impact of nutrient losses caused by rainfall. In current SWAT models, simulating slow-release fertilizers is difficult. The timed and quantitative fertilizer in scenario 3 was considered to simulate the slow-release fertilizers in our model. "HF-2" sulphur coated urea, instead of compound fertilizer and traditional urea, was used to simulate the reduction effects on N losses. "HF-2" sulphur coated urea was produced by Hanfeng slow-release fertilizer company in China, containing 37.6% elemental N. According to the cumulated percentages of N element release of "HF-2" sulphur coated urea, shown in Fig. 6, the time and amount of fertilization were varied at 4 times of top dressing between March and August (see Fig. 5).

3. Results

3.1. Model calibration and validation

3.1.1. Flow calibration and validation

The annual runoff data from 1978 to 2011 obtained from stations in the Machuan River watershed were selected as the warm-up period to minimize uncertainties, such as soil moisture and ground water, in the SWAT model. The data from January 2010 to April 2011 were used in the calibration phase, and the data from May to December 2011 were employed for model validation. The relationship between the observed runoff and simulated runoff is presented in Fig. 7. The calibration results indicate that our SWAT model accurately tracked the annual and monthly stream flow trends between 2010 and 2011. During the simulation period in 2010, the modeled average annual runoff was 11.01 $m^3\ s^{-1}$, which was very close to the measured value (12.65 $m^3\ s^{-1}$) over the 12-month simulation period. The statistical values of R^2 and E_{NS} for monthly comparisons were 0.95 and 0.92 in the calibration period and 0.98 and 0.95 in the validation period, which exceed 0.75 and indicate quiet satisfactory results (Van Liew, Arnold, & Bosch, 2005). The model performance, as represented by the *P-factor* and *R-factor*, was quite reasonable. Small uncertainty was seen, as shown in Fig. 6.

3.1.2. Water quality calibration and validation

The observed monthly N loads from 2010 to 2011 at Xianyuan Bridge station were used for the calibration, and the data from 2012 to 2013 collected at Tanjia Bridge station, Fuxikou station and the Machuan River estuary were used for the validation process. As shown in Fig. 8, the simulation and measured monthly nitrogen loads were consistent in both the calibration and validation periods. The R^2 values for the Xianyuan Bridge station, Tanjia Bridge station and Fuxikou station exceeded 0.8. The values of E_{NS} were 0.76, 0.84 and 0.76, respectively. Both R^2 and E_{NS} can be considered satisfactory during both the calibration and validation periods. Small uncertainties, as represented by *P-factor* and *R-factor*, were seen in these three stations, as shown in Fig. 8. However, the simulation results at the Machuan River estuary were not

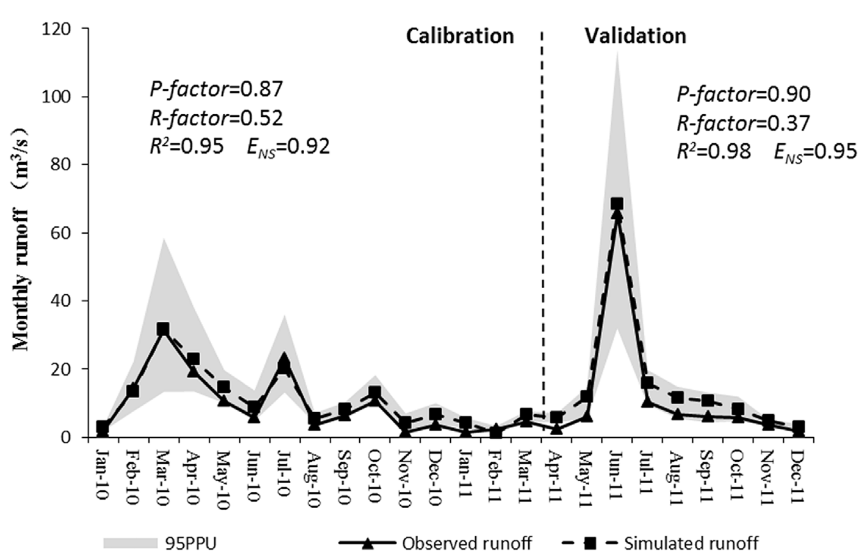

Fig. 7. Extracts of monthly calibration and validation results showing the 95% prediction uncertainty intervals (95PPU).

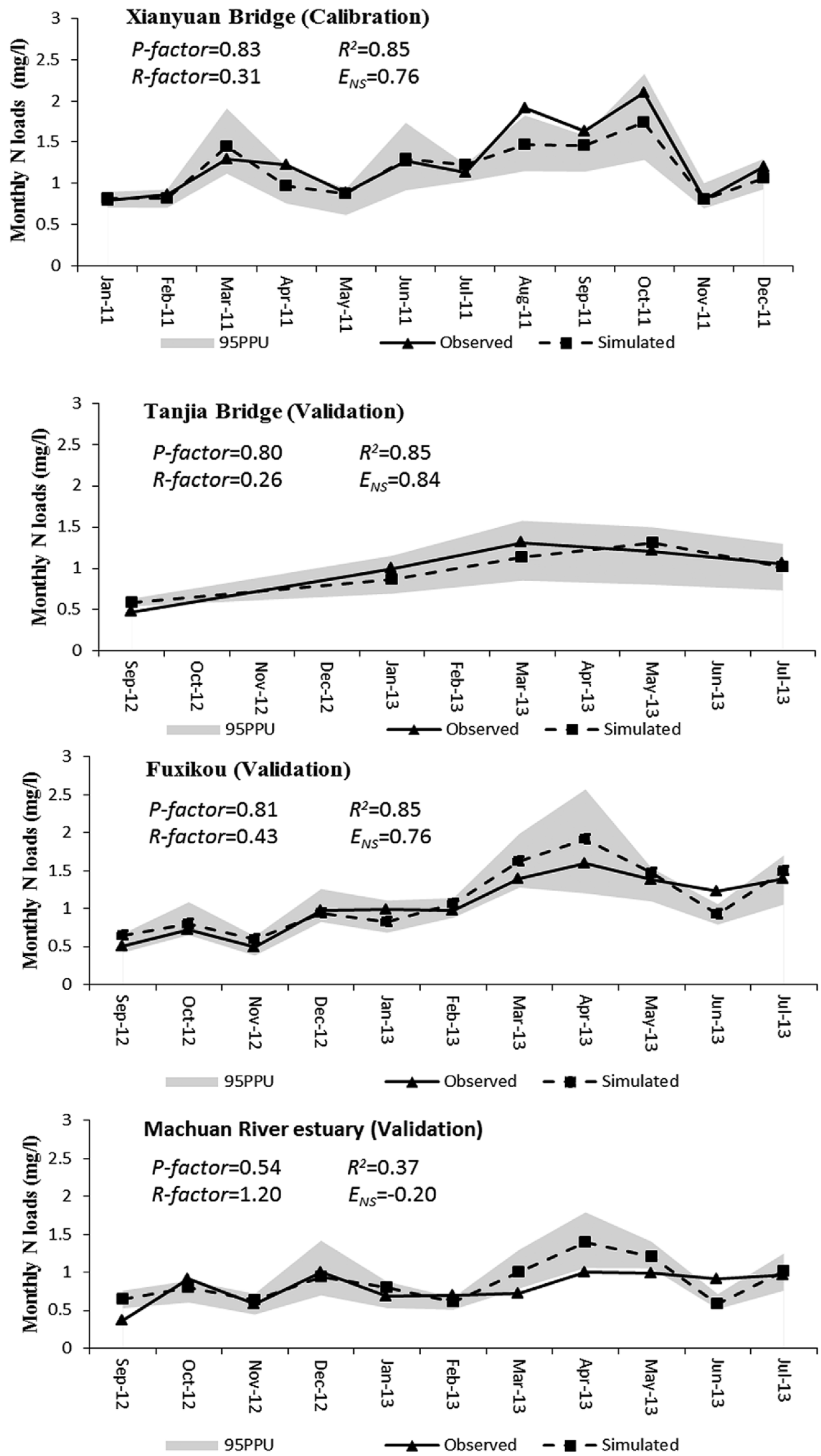

Fig. 8. Illustration of observed and simulated monthly N loads (mg/l) for different water quality monitoring stations, including statistics R^2, E_{NS}, *P-factor* and *R-factor*.

satisfactory because of the increase of the river width. The values of R^2, E_{NS} and *P-factor* were 0.37, −0.20 and 0.54, respectively. Thus, the SWAT model, which was built for river watersheds, might not be applicable for an estuary. Overall, although the simulated and observed values showed some errors, they met the simulation requirements for the SWAT model. The SWAT model can be successfully applied to simulate the N loads in our study area. In addition, the N concentration was highest in the summer at the Tanjia Bridge and Fuxikou stations and highest in the fall at the Xianyuan Bridge station. This phenomenon might be mainly attributable to the seasonal changes in the load from tea and rice plantation.

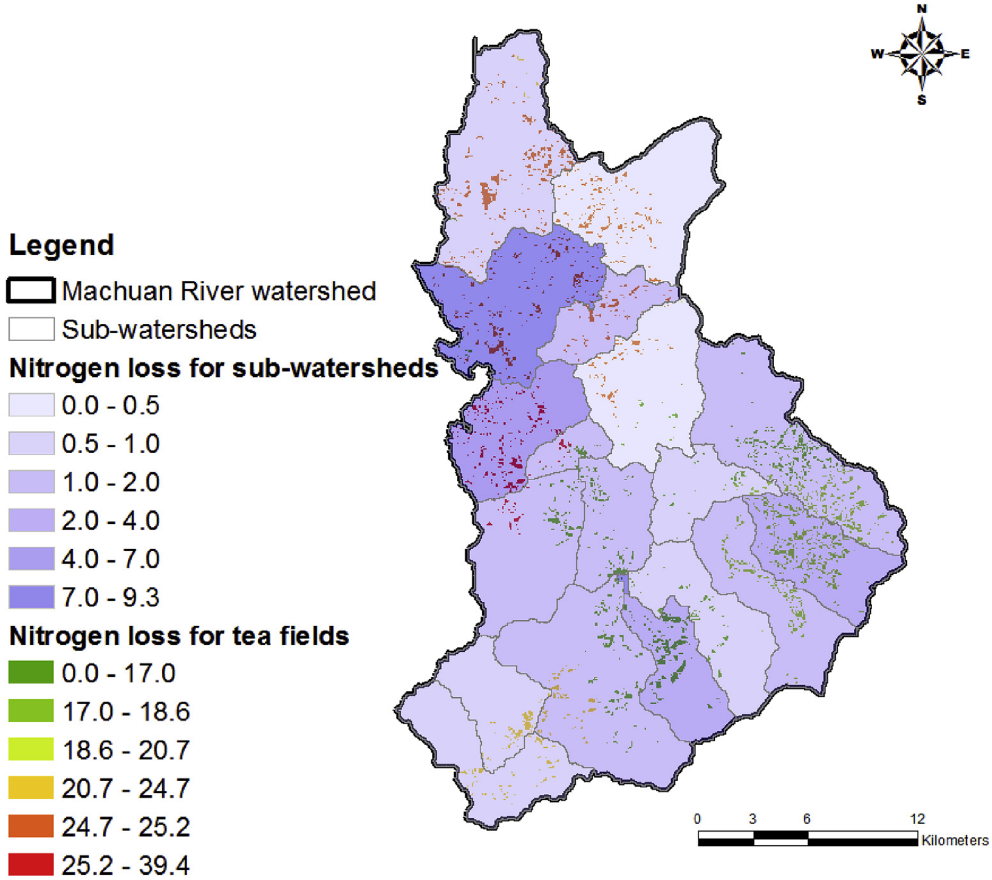

Fig. 9. Spatial distributions of annual N losses (kg ha^{-1}) for sub-watersheds and tea fields (baseline condition).

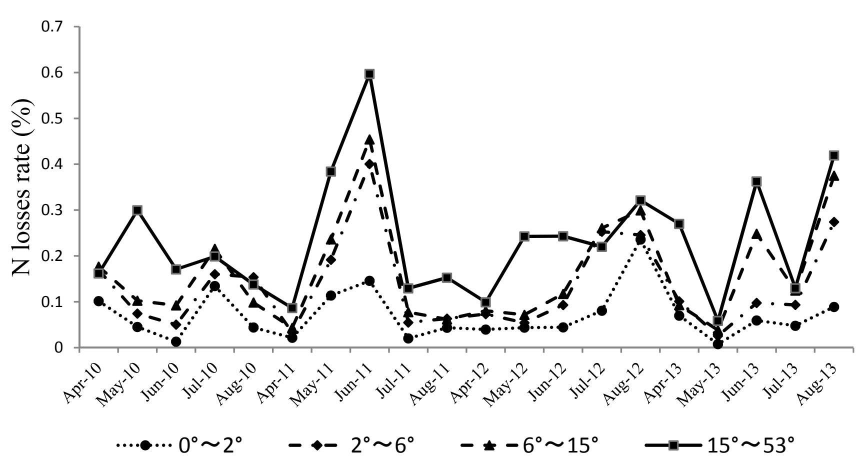

Fig. 10. Monthly N losses rates for different slopes (baseline condition).

3.2. The spatial distribution of N losses

3.2.1. The spatial distribution of N losses for sub-watersheds and tea fields

The spatial distribution of NPS pollutants can be used to identify the critical land use types and areas associated with nutrient losses. The simulation of the spatial distribution of N losses (baseline condition) in the sub-watersheds is shown in Fig. 9. The average annual N losses exported from the 19 sub-watersheds ranged from 0.4 kg ha^{-1} y^{-1} to 9.3 kg ha^{-1} y^{-1}, and the average value was approximately 2.3 kg ha^{-1} y^{-1}. Three of the 19 sub-watersheds had N losses greater than 4.0 kg ha^{-1} y^{-1}. The highest N losses were mainly concentrated in sub-watersheds in the middle-northern watershed area, followed by some parts of the southeastern watershed that contained tea-planted areas. As shown in Fig. 9, the average annual N losses for tea fields were much higher than that for sub-watersheds. The highest annual N losses for tea fields were 39.4 kg ha^{-1} y^{-1}, with an average value of 22.6 kg ha^{-1} y^{-1}.

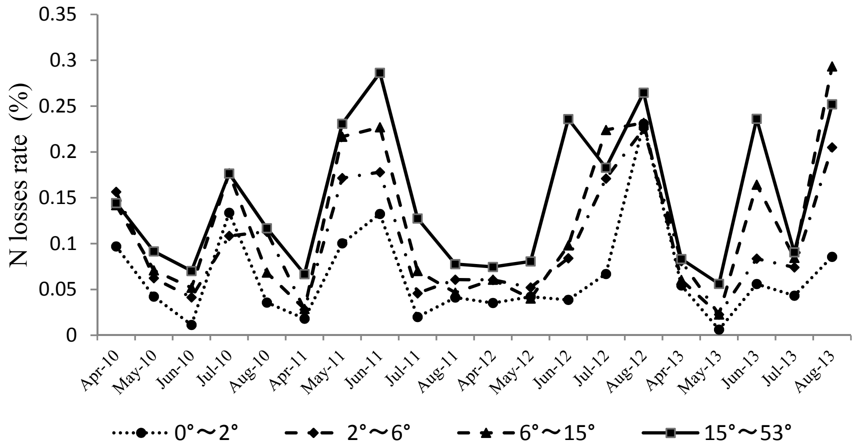

Fig. 11. Monthly N losses rates for different slopes under scenario 1: Avoiding fertilizing before raining.

3.2.2. *The N losses of tea fields on different slopes on baseline condition*

To study the influences of elevation on the N loads, the monthly N losses of tea fields at four slops grades—0°~2°, 2°~6°, 6°~15° and 15°~53°—were analyzed. The analysis spanned five months from April to August during the period from 2010 to 2013, including almost all of the 4 times of top dressing. This period was also selected to show the impacts of BMPs on N losses in different months. Under the baseline conditions, as shown in Fig. 10, the average N losses rates (as NPS pollution) for the four slope grades were 0.07%, 0.13%, 0.16% and 0.23%, respectively. The N losses were positively related to the slope when the rainfall and farming conditions were constant. The N losses rate for slopes exceeding 15° was roughly three times higher than that for slopes between 0° and 2°. The N losses for slopes between 2° and 6° and between 6° and 15° were similar. In addition, the N losses for all slope grades varied with time. The highest average value of N losses was observed in June, followed by August, July, May and April.

3.3. *Effects evaluation of BMP scenarios*

3.3.1. *Scenario 1: avoiding fertilization before raining*

The N losses rates of different slopes under the scenario of avoiding fertilizing before raining are shown in Fig. 11. The average N losses rates for the four slope grades were 0.06%, 0.10%, 0.12% and 0.15%. Planting tea on steep-sloping land was associated with a great loss of N. Indeed, the N losses rate for slopes exceeding 15° was approximately four times than that of slopes between 2° and 6°. The largest N losses reduction occurred in June (37.5%), followed by May (34.3%), April (26.5%), August (22.1%) and July (18.4%). Compared with the baseline condition, as shown in Fig. 10, the N losses rates under this scenario would be reduced by approximately 8%, 24%, 27% and 37% for different slopes, respectively.

3.3.2. *Scenario 2: contour planting*

The N losses rates for different slopes under the scenario of contour planting tea are shown in Fig. 12. The average N losses for the four slope grades are 0.07%, 0.07%, 0.12% and 0.16%. The rate of N losses for slopes exceeding 15° was approximately two times that of slopes between 0° and 2°. In contrast, the N losses for the different slope grades dropped by 5%, 48%, 25% and 34% of the losses under the baseline conditions, as shown in Fig. 10. The greatest drop was observed for slopes between 2° and 6°. This result is generally consistent with those of other studies (Guto et al., 2011; Ng et al., 2008), which suggests that when the slope ranges from 3% to 8%, contour planting has the greatest influence on preventing soil erosion. Similarly, the N losses also varied with the simulated months, and the largest N losses reduction occurred in August (13.9%), followed by June (13.7%), July (9.2%), May (8.6%), and April (6.4%).

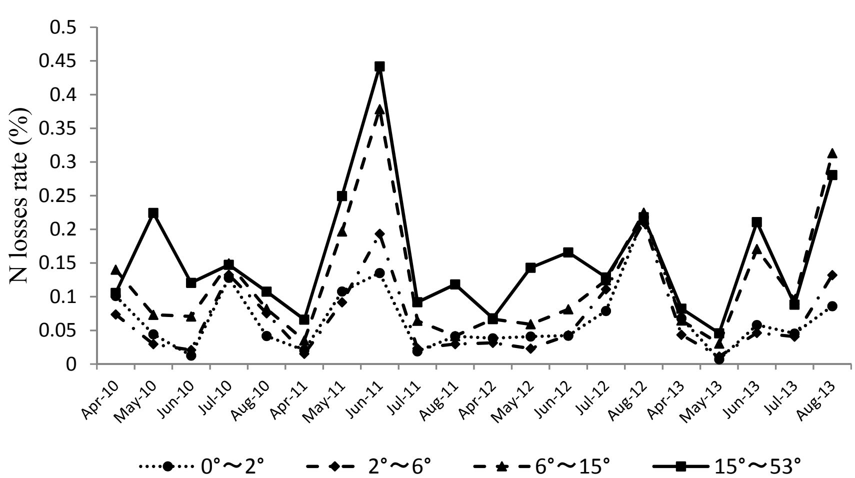

Fig. 12. Monthly N losses rates for different slopes under scenario 2: Contour planting.

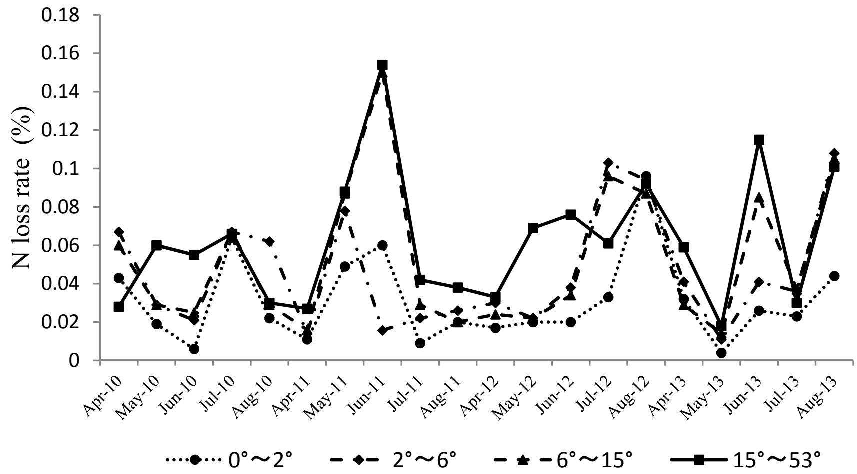

Fig. 13. Monthly N losses rates for different slopes under scenario 3: Applying slow-release fertilizers.

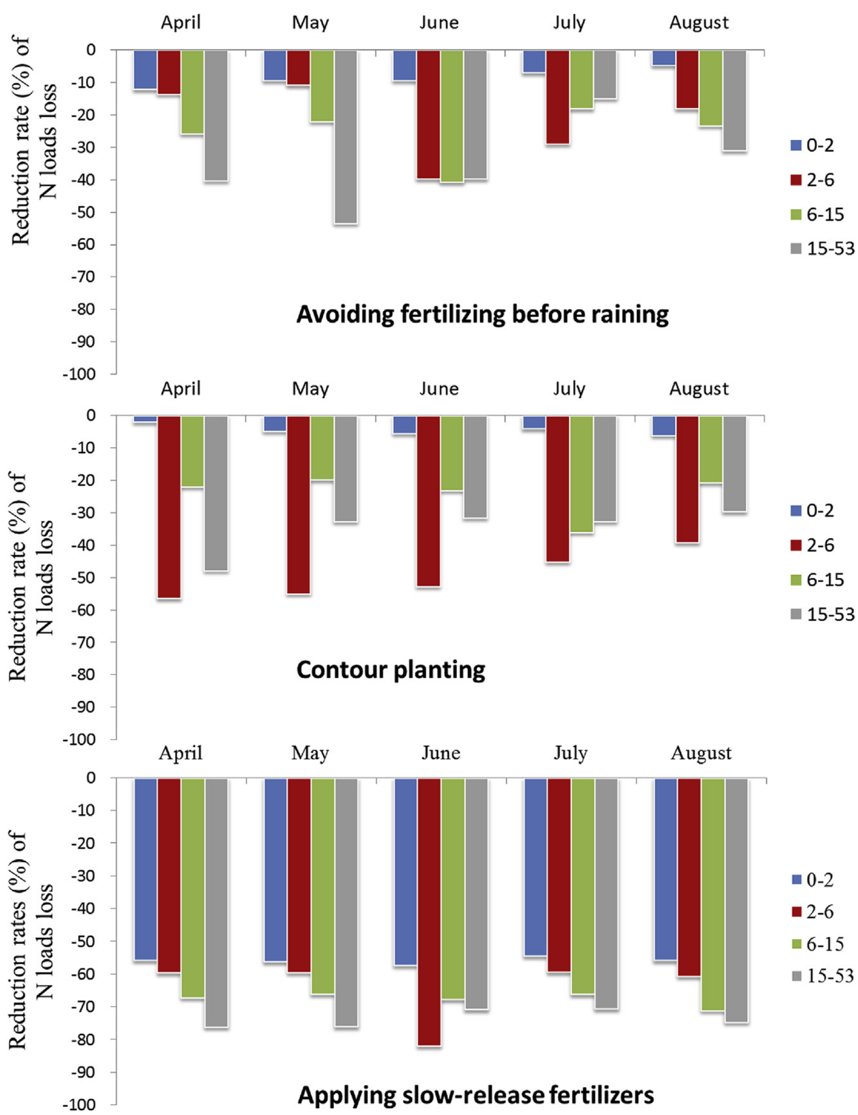

Fig. 14. The reduction rates (%) of N loads losses under three BMPs scenarios by compared with baseline condition.

3.3.3. Scenario 3: applying slow-release fertilizers

The N losses for different slopes under the scenario of slow-release fertilizers are shown in Fig. 13. The inclusion of scenario 1 (avoiding fertilization before raining) in scenario 3 substantially reduced the N losses. The average N losses rates for the four slope grades were 0.03%, 0.05%, 0.05% and 0.06%, respectively. In contrast, the slope had little influence on the N losses in this scenario. Indeed, compared with the baseline condition, as shown in Fig. 10, the N losses rates for the different slopes were reduced by approximately 56%, 65%, 68% and 74%. Moreover, the largest N losses reduction occurred in June (71.1%), followed by May (68.9%), August (67.7%), April (67.2%) and July (64.3%).

4. Discussion

4.1. Effects of BMPs on N load reduction and its implications

Numerous field studies have illustrated the positive effects of BMPs on water and nutrient fluxes (Kaplowitz & Lupi, 2012; Liu et al., 2013; Strauch, Lima, Volk, Lorz, & Makeschin, 2013). Three BMP scenarios (viz., avoiding fertilizing before raining, contour planting and applying slow-release fertilizers) were simulated by a SWAT model, and their effectiveness was evaluated by comparison with the baseline condition. Indeed, the monthly loss rates of N in our study were not high. Also, in She Town in Anhui Province, China, the yearly loss rate of N in tea fields was very small ranging from 0.049% to 0.453% (Ma et al., 2012). Similarly, the loss rate of N in Taihu Lake Region was approximately 1.008% (Xi et al., 2010). However, due to the high amount of fertilization in our study area, the N losses in tea field ranged from 1.4 kg ha^{-1} yr^{-1} to 39.4 kg ha^{-1} yr^{-1}, which was much higher than the average N losses in sub-watersheds. As a result, although tea field covers only 4.7% of the total area, the N losses in tea fields accounted for 30.4% of the total N losses in the entire watershed. By applying three BMPs simulated by SWAT model, the N losses rates in tea fields can be reduced by 24%, 28% and 66%, respectively. Consequently, the total effects of N losses reduction in the watershed could reach 7%, 9% and 20% for three BMPs, respectively. Similar results were obtained by other studies, which suggested that implementing individual BMPs could reduce the average annual load for TN loads from 8.6% to 20.5% (Lam et al., 2011) and from 1% to 24% at the watershed outlet (Tuppad et al., 2010).

As shown in Fig. 14, scenario 1 (avoiding fertilizing before rain) and scenario 2 (contour planting) had similar effects on N losses reduction. The N losses rates could be reduced by approximately 24% and 28%, respectively, compared with the baseline condition. Generally, as the slope increases, the nitrogen losses become more substantial, and tea fields planted on slopes exceeding 15° have the highest N losses in most observed months, except in scenario 2 for slope grades between 2° and 6°. Considering the variations from April to August, the highest N losses in runoff water were generally observed in June in scenario 1. This finding is reasonable because during the rainy season, heavy rainfall events that occurred shortly after fertilizer application activities caused significant nutrient losses (Karlen et al., 2005; Udawatta, Motavalli, Garrett, & Krstansky, 2006). The application of slow-release fertilizers (scenario 3) also included avoiding fertilizing before rain and had the largest impact on N load reduction. Compared with the baseline condition, the N losses rate could be reduced by approximately 56%, 65%, 68% and 74% at four slops grades 0°~2°, 2°~6°, 6°~15° and 15°~53°, respectively. Slow-release fertilizer is believed to facilitate reducing the N concentration (Guertal, 2009), and many studies observed no yield differences between crops grown with compost and chemical fertilizer (Eghball & Power, 1999). In our study, if conventional chemical fertilizers could be replaced with slow-release fertilizer in tea fields, and if fertilizer application could be performed before rain events or even avoid rain events for several days, the N losses in the runoff would be critically reduced. Overall, the impacts of BMPs on N losses reduction in tea fields are significant.

4.2. Uncertainty in the effects of BMPs at different slope grades

Substantial uncertainties exist in the SWAT model for N loading simulations because large amounts of data are incorporated (Xu et al., 2016; Yen, Jeong, Feng, & Deb, 2015). Uncertainty also stems from the model structure, parameters and output processes (Wechsler, 2007). Although this study was simulated the effects of BMPs on various slope gradients, the observed differences might also be influenced to a certain degree by the accuracy of the input DEM (Ruiz, Diaz-Mas, Perez, & Viguria, 2013; Tan, Ficklin, Dixon, Yusop, & Chaplot, 2015; Zhang et al., 2014). Specifically, slope gradients are closely associated with the resolutions, sources and resampling techniques of DEM. Indeed, the accuracy of the input DEM has been proven to determine the reliability of the extracted topographical and hydrological features (Charrier & Li, 2012; Chen, Li, Cao, & Dai, 2014; Murphy, Ogilvie, Meng, & Arp, 2008). In addition, the resolution of the DEM can also influence the river network extraction, flow direction and accumulation in the stream flow simulation process of the SWAT model (Duchemin & Hogue, 2009; Tan et al., 2015; Wu, Li, & Huang, 2008; Xu et al., 2016). Further work would be conducted to evaluate the effects of different DEM resolutions and sources on the impacts of slope gradients on N loads, which would improve our understanding of the exact linkage between the effectiveness of BMPs and slope gradients. Additionally, identifying which DEM resolution and source are appropriate for the SWAT model in the studied watershed would be useful.

5. Conclusions

In this study, a SWAT model was developed and calibrated for the Machuan River watershed. Both the calibration and validation results of the stream flow and N concentrations suggested good agreement between the observed and simulated data, as confirmed by the values of R^2 and E_{NS}. Small uncertainty, presented by *P-factor* and *R-facto*r, were seen. Three BMP scenarios were simulated to evaluate their effects on N loss reduction in tea fields. Different slope gradients were chosen to determine the influence of topography on the effectiveness of BMPs. The results suggest that the rainfall, fertilizer timing and type, and tillage management measures are important factors that influence the N concentrations in runoff from tea fields. Compared with the baseline condition, the N losses rate could be reduced by approximately 24%, 28%, and 66% for three scenarios, respectively. Among the three BMP scenarios, the application of slow-release fertilizer, which includes avoiding fertilizing before rain, shows the greatest effect on the nitrogen load reduction. Compared with the baseline condition, the N losses rate could be reduced by approximately 56%, 65%, 68% and 74% at four slops grades 0°~2°, 2°~6°, 6°~15° and 15°~53°, respectively. Generally, tea planted on steep-sloping land leads to great losses of N. Based on this information, the tea fields on slopes exceeding 15° should be prioritized for the effective implementation of BMPs. Future studies should be conducted to evaluate the effects of DEM resolutions and sources on the influence of the slope gradient on the effectiveness of BMPs. These results should provide useful information for the nutrient control and management of tea fields in other watersheds or river basins.

Acknowledgments:

This work was financially supported by the National Key Research and Development Program of China (No.2016YFC0502705) and the National Natural Science

Foundation of China (No.41501194). We acknowledge the Huangshan Municipal Bureau of Land and Resource for providing the land survey data, the Meteorological Administration of Anhui Province for providing the weather data, the Hydrological Bureau of Anhui Province for providing the precipitation and stream flow data, the Environmental Protection Bureau of Huangshan City for providing the nitrogen concentration data, and the Cold and Arid Regions Science Data Center in China for providing the HSWD data.

References

Abbaspour, K. C., Johnson, C. A., & Van Genuchten, M. T. (2004). Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone Journal, 3*(4), 1340–1352.

Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology, 524*, 733–752.

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., et al. (2007). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology, 333*(2), 413–430.

Akhavan, S., Abedi-Koupai, J., Mousavi, S. F., Afyuni, M., Eslamian, S. S., & Abbaspour, K. C. (2010). Application of SWAT model to investigate nitrate leaching in Hamadan–Bahar Watershed, Iran. *Agriculture, Ecosystems & Environment, 139*(4), 675–688.

Arabi, M., Frankenberger, J. R., Engel, B. A., & Arnold, J. G. (2008). Representation of agricultural conservation practices with SWAT. *Hydrological Processes, 22*(16), 3042–3055.

Behera, S., & Panda, R. K. (2006). Evaluation of management alternatives for an agricultural watershed in a sub-humid subtropical region using a physical process based model. *Agriculture, Ecosystems & Environment, 113*(1), 62–72.

Bhuyan, S. J., Marzen, L. J., Koelliker, J. K., Harrington, J. A., & Barnes, P. L. (2002). Assessment of runoff and sediment yield using remote sensing, GIS, and AGNPS. *Journal of Soil and Water Conservation, 57*(6), 351–363.

Bracmort, K. S., Arabi, M., Frankenberger, J. R., Engel, B. A., & Arnold, J. G. (2006). Modeling long-term water quality impact of structural BMPs. *Transactions of the ASABE, 49*(2), 367–374.

Carpenter, S. R., Caraco, N. F., Correll, D. L., Howarth, R. W., Sharpley, A. N., & Smith, V. H. (1998). Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological Applications, 8*(3), 559–568.

Charrier, R., & Li, Y. K. (2012). Assessing resolution and source effects of digital elevation models on automated floodplain delineation: A case study from the camp creek watershed, Missouri. *Applied Geography, 34*, 38–46.

Chaubey, I., Chiang, L., Gitau, M. W., & Mohamed, S. (2010). Effectiveness of best management practices in improving water quality in a pasture-dominated watershed. *Journal of Soil and Water Conservation, 65*(6), 424–437.

Chen, C. F., Li, Y. Y., Cao, X. W., & Dai, H. L. (2014). Smooth surface modeling of DEMs based on a regularized least squares method of thin plate spline. *Mathematical Geosciences, 46*(8), 909–929.

Chichakly, K. J., Bowden, W. B., & Eppstein, M. J. (2013). Minimization of cost, sediment load, and sensitivity to climate change in a watershed management application. *Environmental Modelling & Software, 50*, 158–168.

Choi, J. Y. (2008). Nonpoint source pollution management for the multipurpose dam watersheds. *Water Science and Technology, 57*(11), 1835–1841.

Dixon, B., & Earls, J. (2012). Effects of urbanization on streamflow using SWAT with real and simulated meteorological data. *Applied Geography, 35*(1), 174–190.

Duchemin, M., & Hogue, R. (2009). Reduction in agricultural non-point source pollution in the first year following establishment of an integrated grass/tree filter strip system in southern Quebec (Canada). *Agriculture, Ecosystems & Environment, 131*(1), 85–97.

Eghball, B., & Power, J. F. (1999). Composted and noncomposted manure application to conventional and no-tillage systems: Corn yield and nitrogen uptake. *Agronomy Journal, 91*(5), 819–825.

Fu, B. J., Meng, Q. H., Qiu, Y., Zhao, W. W., Zhang, Q. J., & Davidson, D. A. (2004). Effects of land use on soil erosion and nitrogen loss in the hilly area of the Loess Plateau, China. *Land Degradation & Development, 15*(1), 87–96.

Gao, C., & Zhang, T. L. (2010). Eutrophication in a Chinese context: Understanding various physical and socio-economic aspects. *Ambio, 39*(5–6), 385–393.

Gassman, P. W., Sadeghi, A. M., & Srinivasan, R. (2014). Applications of the SWAT model special section: Overview and insights. *Journal of Environmental Quality, 43*(1), 1–8.

Ghebremichael, L. T., Veith, T. L., & Hamlett, J. M. (2013). Integrated watershed-and farm-scale modeling framework for targeting critical source areas while maintaining farm economic viability. *Journal of Environmental Management, 114*, 381–394.

Guertal, E. A. (2009). Slow-release nitrogen fertilizers in vegetable production: A review. *HortTechnology, 19*(1), 16–19.

Guo, W. X., Fu, Y. C., Ruan, B. Q., Ge, H. F., & Zhao, N. N. (2014). Agricultural non-point source pollution in the Yongding river basin. *Ecological Indicators, 36*, 254–261.

Guto, S. N., Pypers, P., Vanlauwe, B., de Ridder, N., & Giller, K. E. (2011). Tillage and vegetative barrier effects on soil conservation and short-term economic benefits in the Central Kenya highlands. *Field Crops Research, 122*, 85–94.

Kaini, P., Artita, K., & Nicklow, J. W. (2012). Optimizing structural best management practices using SWAT and genetic algorithm to improve water quality goals. *Water Resources Management, 26*(7), 1827–1845.

Kaplowitz, M. D., & Lupi, F. (2012). Stakeholder preferences for best management practices for non-point source pollution and stormwater control. *Landscape and Urban Planning, 104*(3), 364–372.

Karlen, D. L., Dinnes, D. L., Jaynes, D. B., Hurburgh, C. R., Cambardella, C. A., Colvin, T. S., et al. (2005). Corn response to late-spring nitrogen management in the Walnut Creek watershed. *Agronomy Journal, 97*(4), 1054–1061.

Kirsch, J., Kirsch, A., & Arnold, J. (2002). Predicting sediment and phosphorus loads in the rock river basin using SWAT. *Transactions of the ASAE, 45*(6), 1757–1769.

Lamba, J., Thompson, A. M., Karthikeyan, K. G., Panuska, J. C., & Good, L. W. (2016). Effect of best management practice implementation on sediment and phosphorus load reductions at subwatershed and watershed scale using SWAT model. *International Journal of Sediment Research, 31*(4), 386–394.

Lam, Q. D., Schmalz, B., & Fohrer, N. (2011). The impact of agricultural Best Management Practices on water quality in a North German lowland catchment. *Environmental Monitoring and Assessment, 183*(1–4), 351–379.

Lee, M., Park, G., Park, M. J., Park, J. Y., Lee, J. W., & Kim, S. J. (2010). Evaluation of non-point source pollution reduction by applying Best Management Practices using a SWAT model and QuickBird high resolution satellite imagery. *Journal of Environmental Sciences, 22*(6), 826–833.

Lee, J. G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J. X., Shoemaker, L., et al. (2012). A watershed-scale design optimization model for stormwater best management practices. *Environmental Modelling & Software, 37*, 6–18.

Liu, Z. A., Yang, J. P., Yang, Z. C., & Zou, J. L. (2012). Effects of rainfall and fertilizer types on nitrogen and phosphorus concentrations in surface runoff from subtropical tea fields in Zhejiang, China. *Nutrient Cycling in Agroecosystems, 93*(3), 297–307.

Liu, R. M., Zhang, P. P., Wang, X. J., Chen, Y. X., & Shen, Z. Y. (2013). Assessment of effects of best management practices on agricultural non-point source pollution in Xiangxi River watershed. *Agricultural Water Management, 117*, 9–18.

Logan, T. J. (1993). Agricultural best management practices for water pollution control: Current issues. *Agriculture, Ecosystems & Environment, 46*(1–4), 223–231.

Ma, Y. H., Xie, X. Y., Ma, Z. W., Wang, G. L., Sun, X. W., Hu, S. B., et al. (2012). Nitrogen and phosphorus runoff from garden plots in Anhui Province. *Journal of Soil and Water Conservation, 26*(3), 12–17 (In Chinese).

Meng, Q. H., Fu, B. J., Tang, X. P., & Ren, H. C. (2008). Effects of land use on phosphorus loss in the hilly area of the Loess Plateau, China. *Environmental Monitoring and Assessment, 139*(1–3), 195–204.

Mostaghimi, S., Park, S. W., Cooke, R. A., & Wang, S. Y. (1997). Assessment of management alternatives on a small agricultural watershed. *Water Research, 31*(8), 1867–1878.

Murphy, P. N. C., Ogilvie, J., Meng, F. R., & Arp, P. (2008). Stream network modelling using lidar and photogrammetric digital elevation models: A comparison and field verification. *Hydrological Processes, 22*(12), 1747–1754.

Nagumo, T., Yosoi, T., & Aridomi, A. (2012). Impact of agricultural land use on N and P concentration in forest-dominated tea-cultivating watersheds. *Soil Science and Plant Nutrition, 58*(1), 121–134.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—a discussion of principles. *Journal of Hydrology, 10*(3), 282–290.

NBSC. (2014). *China statistical year book*. Beijing: National Bureau of Statistics of China.

Ng, S. L., Cai, Q. G., Ding, S. W., Chau, K. C., & Qin, J. (2008). Effects of contour hedgerows on water and soil conservation, crop productivity and nutrient budget for slope farmland in the Three Gorges Region (TGR) of China. *Agroforestry Systems, 74*(3), 279–291.

Noellsch, A. J., Motavalli, P. P., Nelson, K. A., & Kitchen, N. R. (2009). Corn response to conventional and slow-release nitrogen fertilizers across a claypan landscape. *Agronomy Journal, 101*(3), 607–614.

Ongley, E. D., Zhang, X. L., & Tao, Y. (2010). Current status of agricultural and rural non-point source pollution assessment in China. *Environmental Pollution, 158*(5), 1159–1168.

Prescott, J. A. (1940). Evaporation from a water surface in relation to solar radiation. *Transactions of the Royal Society of South Australia, 64*(1), 114–118.

Ramos, M. C., & Martınez-Casasnovas, J. A. (2004). Nutrient losses from a vineyard soil in Northeastern Spain caused by an extraordinary rainfall event. *Catena, 55*(1), 79–90.

Ruan, J. Y., Ma, L. F., & Shi, Y. Z. (2013). Potassium management in tea plantations: Its uptake by field plants, status in soils, and efficacy on yields and quality of teas in China. *Journal of Plant Nutrition and Soil Science, 176*(3), 450–459.

Ruan, J. Y., Wu, X., Shi, Y. Z., & Ma, L. F. (2001). Nutrient input and evaluation of fertilization efficiency in typical tea areas of China (in Chinese) *Soils and Fertilizers, 5*, 9–13.

Ruiz, J. J., Diaz-Mas, L., Perez, F., & Viguria, A. (2013). Evaluating the accuracy of DEM generation algorithms from UAV imagery. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-1/W2*, 2013 UAV-g2013, 4 – 6 September, Rostock, Germany.

Schilling, K. E., & Wolter, C. F. (2009). Modeling nitrate-nitrogen load reduction strategies for the Des Moines River, Iowa using SWAT. *Environmental management, 44*(4), 671–682.

Schuol, J., Abbaspour, K. C., Srinivasan, R., & Yang, H. (2008). Estimation of freshwater availability in the West African sub-continent using the SWAT hydrologic model. *Journal of Hydrology, 352*(1), 30–49.

Sharpley, A. N. (1997). Rainfall frequency and nitrogen and phosphorus runoff from soil amended with poultry litter. *Journal of Environmental Quality, 26*(4), 1127–1132.

Shaviv, A., & Mikkelsen, R. L. (1993). Controlled-release fertilizers to increase efficiency of nutrient use and minimize environmental degradation-a review. *Nutrient Cycling in Agroecosystems, 35*(1), 1–12.

Shenk, G. W., Wu, J., & Linker, L. C. (2012). Enhanced HSPF model structure for Chesapeake Bay watershed simulation. *Journal of Environmental Engineering, 138*(9), 949–957.

Shen, Z. Y., Qiu, J. L., Hong, Q., & Chen, L. (2014). Simulation of spatial and temporal distributions of non-point source pollution load in the three Gorges reservoir region. *Science of the Total Environment, 493*, 138–146.

Strauch, M., Lima, J. E. F. W., Volk, M., Lorz, C., & Makeschin, F. (2013). The impact of Best Management Practices on simulated streamflow and sediment load in a Central Brazilian catchment. *Journal of Environmental Management, 127*, S24–S36.

Sun, Y., Tong, S., & Yang, Y. J. (2016). Modeling the cost-effectiveness of stormwater best management practices in an urban watershed in Las Vegas Valley. *Applied Geography, 76*, 49–61.

Sun, B., Zhang, L., Yang, L., Zhang, F., Norse, D., & Zhu, Z. (2012). Agricultural non-point source pollution in China: Causes and mitigation measures. *Ambio, 41*(4), 370–379.

Tan, M. L., Ficklin, D. L., Dixon, B., Yusop, Z., & Chaplot, V. (2015). Impacts of DEM resolution, source, and resampling technique on SWAT-simulated streamflow. *Applied Geography, 63*, 357–368.

Tokuda, S., & Hayatsu, M. (2001). Nitrous oxide emission potential of 21 acidic tea field soils in Japan. *Soil Science and Plant Nutrition, 47*(3), 637–642.

Tolson, B. A., & Shoemaker, C. A. (2007). Cannonsville reservoir watershed SWAT2000 model development, calibration and validation. *Journal of Hydrology, 337*(1), 68–86.

Tuppad, P., Kannan, N., Srinivasan, R., Rossi, C. G., & Arnold, J. G. (2010). Simulation of agricultural management alternatives for watershed protection. *Water Resources Management, 24*(12), 3115–3144.

Udawatta, R. P., Motavalli, P. P., Garrett, H. E., & Krstansky, J. J. (2006). Nitrogen losses in runoff from three adjacent agricultural watersheds with claypan soils. *Agriculture, Ecosystems & Environment, 117*(1), 39–48.

Ullrich, A., & Volk, M. (2009). Application of the Soil and Water Assessment Tool (SWAT) to predict the impact of alternative management practices on water quality and quantity. *Agricultural Water Management, 96*(8), 1207–1217.

Vaché, K. B., Eilers, J. M., & Santelmann, M. V. (2002). Water quality modeling of alternative agricultural scenarios in the US corn belt. *JAWRA Journal of the American Water Resources Association, 38*(3), 773–787.

Van Liew, M. W., Arnold, J. G., & Bosch, D. D. (2005). Problems and potential of autocalibrating a hydrologic model. *Transactions of the ASAE, 48*(3), 1025–1040.

Wang, X., He, F. H., & Zhang, X. (2013). Optimization of best management practices for non-point source pollution in Danjiangkou Reservoir Basin. *China Environmental Science, 33*(7), 1335–1343.

Wechsler, S. P. (2007). Uncertainties associated with digital elevation models for hydrologic applications: A review. *Hydrology and Earth System Sciences, 11*(4), 1481–1500.

Wu, Y. Z., Li, Y., Fu, X. Q., Liu, X. L., Shen, J. L., Wang, Y., et al. (2016). Three-dimensional spatial variability in soil microorganisms of nitrification and denitrification at a row-transect scale in a tea field. *Soil Biology and Biochemistry, 103*, 452–463.

Wu, S., Li, J., & Huang, G. H. (2008). A study on DEM-derived primary topographic attributes for hydrologic applications: Sensitivity to elevation data resolution. *Applied Geography, 28*(3), 210–223.

Xi, Y. G., Chen, R. B., Li, G. P., Wang, H., Xu, X., Wei, Q., et al. (2010). Surface runoff in tea gardens on slope land in Taihu Lake region. *Journal of Ecology and Rural Environment, 26*(4), 381–385 (In Chinese).

Xu, F., Dong, G. X., Wang, Q. R., Liu, L. M., Yu, W. W., Men, C., et al. (2016). Impacts of DEM uncertainties on critical source areas identification for non-point source pollution control based on SWAT model. *Journal of Hydrology, 540*, 355–367.

Yang, G. X., & Best, E. P. H. (2015). Spatial optimization of watershed management practices for nitrogen load reduction using a modeling-optimization framework. *Journal of Environmental Management, 161*, 252–260.

Yang, X. Y., Jiang, G. M., Luo, X. Z., & Zheng, Z. (2012). Preliminary mapping of high-resolution rural population distribution based on imagery from google earth: A case study in the lake tai basin, eastern China. *Applied Geography, 32*(2), 221–227.

Yen, H., Jeong, J. . k., Feng, Q. Y., & Deb, D. (2015). Assessment of input uncertainty in SWAT using latent variables. *Water Resources Management, 29*(4), 1137–1153.

Zhai, X. Y., Zhang, Y. Y., Wang, X. L., Xia, J., & Liang, T. (2014). Non-point source pollution modelling using Soil and Water Assessment Tool and its parameter sensitivity analysis in Xin'anjiang catchment, China. *Hydrological Processes, 28*(4), 1627–1640.

Zhang, P. P., Liu, R. M., Bao, Y. M., Wang, J. W., Yu, W. W., & Shen, Z. Y. (2014). Uncertainty of SWAT model at different DEM resolutions in a large mountainous watershed. *Water Research, 53*, 132–144.

Zvomuya, F., Rosen, C. J., Russelle, M. P., & Gupta, S. C. (2003). Nitrate leaching and nitrogen recovery following application of polyolefin-coated urea to potato. *Journal of Environmental Quality, 32*(2), 480–489.