Highlights (3 to 5 bullet points (maximum 85 characters including spaces per bullet point)

- Landscape position units (LSU) are adopted to identify priority management areas.
- A Markov chain-based surrogate model of $SWAT^+$ is proposed to identify PMAs.
- $SWAT^+$ is qualified to provide flow distribution matrix among LSUs and channels.
- LSU-based PMAs are more effective in distribution and cumulative load contributes.
- LSU-based PMAs have general applicability for various geographic environments.

Abstract

Priority Management Areas (PMAs) of a watershed are areas with high contributions to pollutant load of the assessment outlet such as the watershed outlet, and thus have high priorities in the decision-making of comprehensive watershed management. Existing types of spatial units used to identify PMAs are commonly based on subbasins, artificial geographic entities, and grid cells. However, these identification units cannot balance the general applicability to diverse geographic environments and the representation degree to spatial heterogeneity, which affects the effectiveness of PMAs. In this paper, we propose to adopt landscape positions along the hillslope to identify PMAs, which can be delineated by slope position units (e.g., upland, backslope, and valley). Landscape position units inherently have upstream-downstream relationships with each other and with channels. Therefore, their contributions to the assessment outlet can be quantified based on the propagation effects of hillslope routing processes and channel routing processes. The proposed method was implemented by SWAT^{+}, the restructured and enhanced version of the Soil and Water Assessment Tool, and validated by a comparative case study at a hilly watershed in southern China by identifying PMAs of total nitrogen with landscape position units and subbasin units, respectively. The results showed that the proposed PMAs based on landscape positions have more accurate distribution and contribute 68.34% of total nitrogen on 31.76% areas of the watershed, while subbasin-based PMAs contribute less (only 56.17%) on larger (39.66%) areas. The better effectiveness of landscape position units in identifying PMAs is mainly due to their better ability to represent hillslope processes and the spatial heterogeneity of underlying surface environments within subbasins.

Keywords: Priority Management Areas, Landscape positions, Spatial units, Pollutant load contribution, Best Management Practices, SWAT$^+$

1. Introduction

Priority Management Area (PMA) is a prioritizing area for management in the watershed which has a high pollutant production, and more importantly, a high contribution to the pollutant load of its direct or indirect downstream water bodies (Pionke et al., 2000; Chen et al., 2014). In the decision-making of comprehensive watershed management, PMAs are ideal spatial locations for implementing suitable Best Management Practices (BMPs) to effectively control ecological and environmental problems such as soil erosion and non-point source pollution (Shen et al., 2015; Tian et al., 2020; Guo et al., 2022). The spatial distribution of PMAs considerably impacts locations, areas, and effectiveness of configured BMPs and thus affects the cost-effectiveness of the BMP scenario (i.e., spatial configuration of multiple BMPs in the watershed) (Chiang et al., 2014; Qin et al., 2018; Wang et al., 2016; Zhu et al., 2021). Therefore, accurately identifying PMAs becomes a key issue for comprehensive watershed management (Chen et al., 2022).

The foremost step of identifying PMAs is to determine an appropriate type of spatial units as computing units for pollutant production and contribution to the assessment outlet such as the watershed outlet (hereafter referred to as identification units) (Dong et al., 2018; White et al., 2009). Identification units adopted in existing research are mainly based on three concepts, including subbasins (Shang et al., 2012; Chen et al., 2014; Shen et al., 2015; Dong et al., 2018), artificial geographic entities (Tian et al., 2020), and grid cells (Kovacs et al., 2012).

Subbasin represents a relatively closed and independent geographic unit that is linked to other subbasins through channels. Subbasin units are the most straightforward and frequently used identification units since they are delineated in most watershed modeling. In addition to directly utilizing subbasin units, researchers also use the combination of subbasins as identification units according to administrative regions (such as villages; Shang et al., 2012), for the benefit of making and implementing watershed management policies (Liu et al., 2019; Shang et al., 2012). However, a subbasin can be recognized and modeled as an integral of one or more levels of finer spatial units in order to better represent spatial heterogeneity within it, such as hillslopes, slope position units, landuse fields, and even grid cells. Therefore, it may be too coarse to use these subbasin-based identification units since the heterogeneity of pollutant sources and transportation processes within subbasins should be concerned (Qin et al., 2018; Wang et al., 2016).

Artificial geographic entities refer to artificial constructed and hydrologically connected geographic entities according to characteristics of a specific geographic environment (Ghebremichael et al., 2013), such as polders that developed in lowland plains with densely distributed rivers and lakes (Tian et al., 2020). Such spatial units have relative homogenous features in perspectives of physical geographic processes and/or anthropogenic activities. For example, a polder may contain agricultural land, irrigation channels, ponds, and even villages, that are enclosed by artificial dams to perform as a conservation area for flood and waterlogging. Although artificial geographic entities are quite appropriate to be used as identification units in corresponding geographic environments, they are not easy to be generalized as generally applicable identification units and applied widely.

Grid cells are commonly used spatial units with regular shapes in geographic modeling, whose underlying surface characteristics are considered to be homogeneous. Using watershed models that explicitly represent flow routings among grid cells, PMAs can be accurately identified (Kovacs et al., 2012). However, using gird cells may cause more fragmentized distributions of PMAs, which reduces the implementation efficiency and limits further applications (e.g., the PMA-based spatial optimization of BMPs).

Therefore, existing spatial units used for identifying PMAs still cannot balance the general applicability to diverse geographic environments and the representation degree to spatial heterogeneity. According to the previous analysis, proper identification units should: 1) not be related to a specific geographic environment, 2) be capable to represent the spatial heterogeneity of underlying surface characteristics, physical geographic processes, and/or anthropogenic activities inside the study area by a small number of units, and 3) have hydrologic connections among each other.

In this study, we propose to use landscape positions along hillslopes within each subbasin to identify PMAs. Landscape positions can be delineated by landform units (also refers to slope position units) that reflect the integrated effects of hillslope processes on topography and affect geographic processes on the surface meanwhile (Volk et al., 2007; Arnold et al., 2010; Miller and Schaetzl, 2015; Qin et al., 2018). Landscape position units are universality for most geographic environments (Wolock et al., 2004). Based on commonly used classification systems of slope positions (e.g., the divide, backslope, and valley units adopted by Arnold et al. (2010)), each subbasin only needs a few spatial units (e.g., three in Arnold et al. (2010)) to represent the spatial homogenous from the perspective of hillslope processes (Qin et al., 2018; Rathjens et al., 2016). Besides, landscape position units have inherent upstream-downstream relationships among each other, which have been considered in watershed modeling (Arnold et al., 2010; Bieger et al., 2019; Rathjens et al., 2015; Yang et al., 2002) and spatial optimization of BMPs (Qin et al., 2018; Zhu et al., 2019; Zhu et al., 2021). Thus, landscape position units meet the requirements to be used as identification units mentioned above.

The remaining sections of this paper are organized as follows. Section 2 introduces the proposed method of identifying PMAs based on landscape positions. Section 3 presents a comparative experimental design of using landscape position units and subbasin units respectively to identify PMAs of total nitrogen in a small hilly watershed of Southern China based on the same SWAT^{+} model, i.e., the restructured and enhanced version of the SWAT (Soil and Water Assessment Tool). Experimental results and discussion are given in Section 4, and conclusions in Section 5.

2. Method design

To identify PMAs at the landscape position unit level, two key issues should be addressed. The first is how to quantify pollutants released at landscape position units. The second is how to distinguish the pollutant load contribution of each landscape position unit to the assessment outlet, i.e., the residual amount of pollutant after transporting to its direct downstream channel and then transitioning in hierarchical channels before reaching the assessment outlet (Chen et al., 2014).

Generally, the pollutant load contribution cannot be directly found in the result of most watershed models. Instead, watershed models output the pollutant released from each simulation unit (e.g., HRU (Hydrologic Response Unit) in SWAT) or lumped unit (e.g., subbasin), as well as the flow in and out of substances of each channel. To fill this gap, Grimvall and Stålnacke (1996) proposed a Markov chain-based surrogate model to simulate pollutant transitions from upstream channels (subbasins) to the assessment outlet in a statistical way. Their basic idea is to analog pollutant transformation and transfer processes in hierarchical channels as the Markov process, where the transition matrix is determined by upstream-downstream relationships among channels and retention effects of the channel routing process. After a finite number of transitions (equal to the length of the longest branch in hierarchical channels), all pollutants from upstream subbasins reach the assessment outlet, and corresponding pollutant load contributions can thus be derived (Grimvall and Stålnacke, 1996).

Follow-up studies continued to consider the subbasin as a whole in the Markov chain-based model (Chen et al., 2014; Rankinen et al., 2016), including pollutant production at hillslopes and pollutant routing in the channel. If we can separate these two processes at landscape position units and in channels, respectively, the Markov chain-based model will be able to distinguish the pollutant contribution of each landscape position unit to the assessment outlet. Based on this basic idea, the proposed method aims at incorporating a watershed model that supports landscape position units as simulation units or lumped units to improve the Markov chain-based PMA identification method from the subbasin level to the landscape position unit level. Therefore, the Markov chain-based PMA identification method can be generalized as a method framework that supports hierarchical spatial units with explicit hydrological connection (i.e., upstream-downstream relationships) such as subbasins and landscape position units (Fig. 1).

2.1 Delineation and modeling of landscape position units in SWAT^{+}

As a restructured and enhanced version of the SWAT model, SWAT^{+} (Bieger et al., 2017, 2019) introduced a new type of spatial unit between subbasin unit and HRU named landscape position unit (LSU), the default including upland and floodplain (Fig. 2). That means the basic spatial discretization of a watershed in SWAT^{+} contains three types of nested spatial units as a hierarchy, i.e., subbasin, LSU, and HRU. Besides, SWAT^{+} also abstracts specific types of geographic entities as spatial units with locations and properties to participate in watershed modeling. For example, reservoirs or ponds within a subbasin are firstly generalized as a whole as one point in the channel which divides the channel into two parts, and then defined by the upstream part with additional properties such as storage capacity (Fig. 2). Hillslopes, LSUs, and HRUs will also be delineated accordingly, while two aquifer units remain unchanged (Fig. 2). These spatial units can enrich the flow routing network of SWAT^{+} and play important roles in the simulation of study areas with specific geographic environments, e.g., agricultural ecosystems with densely distributed ponds.

With the new spatial discretization scheme, $SWAT^+$ improved the representation of realistic hydrologic processes from hillslope to channel (Bieger et al., 2019). Instead of directly adding all released substances of HRUs (including water, sediment, pollutants, etc.) to the channel, $SWAT^+$ firstly lumps HRUs' outputs at the LSU level and then routes to other spatial units in two different methods. For surface runoff, the water from upland is distributed downstream into two portions, one directly added to the channel/pond/reservoir (e.g., 0.30 from LSU2 to the pond and 0.66 from LSU4 to the channel as shown in Fig. 2, hereafter referred to as channel collectively) and the other portion to floodplain as additional net precipitation to participate in the simulation, while the output from floodplain drains into the channel entirely (Fig. 2). The above-mentioned flow distribution ratio of surface runoff from upland is set by the area ratio of upland and hillslope by default and can be calibrated. The other method of flow routing from LSU to other spatial units is completely draining from upland to floodplain and from floodplain to channel, which is applicable for lateral flow in soils and groundwater recharge in aquifers (Fig. 2).

Therefore, with the flow routing network primarily constructed by HRU, LSU, and channel (Fig. 2), $SWAT^+$ is qualified to quantify pollutants released at landscape position units and corresponding transportation amounts to their direct channel.

2.2 Pollutant load contribution of landscape position units derived from a Markov chain-based surrogate model of $SWAT^+$

Based on the flow routing network and simulation results of $SWAT^+$, the key part of the Markov chain-based surrogate model can be determined, that is the transition matrix of pollutants through LSUs and channels. Then, with the lumped simulation results at LSUs as inputs, the Markov chain-based model can figure out the pollutant load contribution of each landscape position unit.

2.2.1 Transition matrix of pollutants based on flow routing network and retention effects of channel routing process

The transition matrix is constructed by flow distribution relationships from upstream units to downstream units and retention coefficients of channel routing processes (Chen et al., 2014). According to the spatial discretization scheme of SWAT$^+$ (see section 2.1), flow distribution relationships among LSUs and channels can be represented by an $n \times n$ matrix H (Eq. 1). Fig. 3 gives an example of the matrix H.

$$H(i,j)=\begin{cases} s, & \text{if LSU (floodplain) } j \text{ is adjacent downstream of LSU (upland) } i \\ 1-s, & \text{if CHA } j \text{ is direct downstream of LSU (upland) } i \\ 1, & \text{if CHA } j \text{ is adjacent downstream of CHA } i \text{ or LSU (upland) } i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where n is the total number of LSUs and channels in the watershed and s is the flow distribution ratio from upland to floodplain, for surface runoff, s is initially set by the area ratio of upland and hillslope, while for lateral flow and groundwater recharge, s equals 1 (Fig. 2). Each row represents flow distribution relationships of one spatial unit with its downstream units. The sum of all elements in one row equals 1 except the channel row where the assessment outlet is located (e.g., the 7th row in Fig. 3 when the outlet of channel 7 is the assessment outlet). To a given assessment outlet of channel k, there exists a smallest integer N_k to make $H^{N_k}=0$, that means after N_k times of transitions, pollutants from all upstream spatial units of channel k will reach the outlet.

The physical meaning of N_k is the longest routing length from uppermost spatial units to the outlet of channel k, e.g., N_7 equals 4 in Fig. 3.

The complicated channel routing process accounting for pollutant transformation and transfer processes can be simplified by a retention coefficient (i.e., removal capacity of pollutants) to be used as a surrogate calculation method (Chen et al., 2014; Grimvall and Stålnacke, 1996; Hejzlar et al., 2009). The landscape position unit is a lumped unit of pollutant sources calculated at HRUs and thus has no retention effect. The retention coefficient R is also represented by an $n \times n$ matrix as follows:

$$R = \begin{pmatrix} r_1 & 0 & \cdots & 0 \\ 0 & r_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & r_n \end{pmatrix} \tag{2}$$

where the ith diagonal element r_i denotes the retention coefficient of spatial unit i, for LSUs, r_i equals to 0, for channels, r_i can be calculated by simulation results of channels:

$$r_j = (\mathrm{Load}_{\mathrm{in}} - \mathrm{Load}_{\mathrm{out}})/\mathrm{Load}_{\mathrm{in}} \tag{3}$$

where $\mathrm{Load}_{\mathrm{in}}$ is the pollutant input to the channel j that including pollutant outputs of adjacent upstream channels and pollutant released from upstream LSUs; $\mathrm{Load}_{\mathrm{out}}$ is the pollutant output at the outlet of the channel j.

The transition matrix $\tilde{H}$ of the Markov chain-based model can be represented as follows and thus be used to simulate flow transitions of substances (e.g., water and pollutant) through the hierarchy of landscape position units and channels:

$$\tilde{H} = H\ (I - R) \tag{4}$$

where I is an identity matrix.

2.2.2 Calculation of pollutant load contribution

Except for the transition matrix, pollutant released from each LSU are primary input data for the Markov chain-based model as initial states. Since the channel acts as a receptor of pollutants, it has no self-generated pollutants. An $n \times 1$ matrix L is used to organize the input of pollutant sources:

$$L = (e_1,\ e_2,\ \cdots,\ e_i,\ \cdots,\ e_n)^{\mathrm{T}} \tag{5}$$

where e_i is the pollutant released from the spatial units i based on the simulation results of SWAT$^+$. Specifically, e_i is equal to 0 if i is a channel.

The pollutant load contribution of each spatial unit to a specific assessment outlet can be calculated by simple matrix calculations (Grimvall and Stålnacke, 1996):

$$E = \left(\tilde{H}_k\right)^{N_k} V_k * L \tag{6}$$

$$\tilde{H}_k(i, j) = \begin{cases} \tilde{H}(i, j), \text{ if } i \neq k \\ 1, \qquad \text{if } i = j = k \\ 0, \qquad \text{if } i = k \text{ and } j \neq k \end{cases} \tag{7}$$

$$V_k(i) = \begin{cases} 1, \text{ if } i = k \\ 0, \text{ otherwise} \end{cases} \tag{8}$$

where k represents the assessment outlet located channel and the corresponding modification from $\tilde{H}$ to $\tilde{H}_k$ implies the kth state is transformed to an absorbing state. V_k is an $n \times 1$ matrix for extracting the kth column of $\left(\tilde{H}_k\right)^{N_k}$, resulting the contribution rate of each unit. The * denotes element-wise multiplication.

Considering the interested pollutant may have various states that modeled in different watershed processes, the calculation of pollutant load contribution should be combined by all components calculated by different transition matrix and pollutant source matrix. For example, the total nitrogen considered in this study mainly includes the nitrate nitrogen (NO_3) and the organic nitrogen ($ORGN$). Therefore, the total nitrogen load contribution can be calculated as follows:

$$E_{TN} = E_{NO3-SURF} + E_{NO3-LAT} + E_{NO3-GW} + E_{ORGN} \quad (9)$$

$$E_{NO3-SURF} = \left(H_{SURF}(I - R_{NO3})_k\right)^{N_k} V_k * L_{NO3-SURF} \quad (10)$$

$$E_{NO3-LAT} = \left(H_{LAT}(I - R_{NO3})_k\right)^{N_k} V_k * L_{NO3-LAT} \quad (11)$$

$$E_{NO3-GW} = \left(H_{GW}(I - R_{NO3})_k\right)^{N_k} V_k * L_{NO3-GW} \quad (12)$$

$$E_{ORGN} = \left(H_{SURF}(I - R_{ORGN})_k\right)^{N_k} V_k * L_{ORGN-SURF} \quad (13)$$

where *SURF* denotes surface runoff, *LAT* denotes lateral flow, *GW* denotes groundwater recharge. H_{SURF}, H_{LAT}, and H_{GW} describe the flow distribution relationships among spatial units on surface runoff, lateral flow, and groundwater recharge, respectively. $L_{NO3-SURF}$, $L_{NO3-LAT}$, and L_{NO3-GW} are the amount of NO_3 released in surface runoff, lateral flow, and groundwater recharge, respectively; $L_{ORGN-SURF}$ is the amount of *ORGN* released in surface runoff.

2.2.3 PMA identification based on classification of pollution degrees

Once the pollutant load contribution of each landscape position unit is distinguished, a classification of pollution degrees can be adopted to identify different levels of PMAs such as high-, medium-, and low-contribution PMAs. The classification methods in existing studies include the standard deviation method, the Natural Breaks method, and the water quality control targets method (Chen et al., 2014; Giri et al., 2016), etc.

3. Experimental design

To illustrate the effectiveness of the proposed method, a comparative experimental study was design to identify PMAs of total nitrogen at landscape position level and subbasin level based on the same calibrated SWAT$^+$ model.

3.1 Study area and data

The Zhongtianshe watershed (~42 km^2), located in the south of Liyang City, Jiangsu Province, China (Fig. 4), is a typical hilly area situated at the upstream region of Lake Tai. The study area is represented as a subtropical monsoon climate. The average annual temperature is 15.5°C. The average annual precipitation is 1160 mm. The main soil type is yellow-red soil, a type of acidic soil that easy to be weathered. The main land use types are forest (77%), cropland (10%, primarily paddy field), orchard (3%), residential area (8%), and water area (2%). The watershed has frequent agriculture activities, and the cultivation of rice and wheat is the primary contribution to local non-point source pollution. Since the study area is on the drinking water source of Liyang, knowing the details of the pollution situation and take reasonable measures to control it becomes a vital issue for the local government (Shi et al., 2021).

The data of the study area for SWAT$^+$ modeling consists of Digital Elevation Model (DEM), land use types, soil types and properties, meteorological data, agricultural management practices and the observed flow and total nitrogen data at the watershed outlet. The detailed data description is shown in Table 1.

3.2 Modeling and calibration of the SWAT$^+$ model

A SWAT$^+$ model (version 59.3) was built to simulate the total nitrogen pollution in the study area. Since there are more than a hundred small ponds scattered in the study area, taking the representation of ponds into consideration in the model is very necessary. Based on the location and area of real ponds, six ponds were generalized in the watershed as shown in Fig. 4. Finally, a total of 15 subbasins, 41 LSUs, and 1260 HRUs were generated (Fig. 5).

Limited by the available observed data, we set the year of 2011 as a warm-up period, 2012–2013 and 2014–2015 as calibration and validation periods for flow modeling at the daily time step, respectively. The model performance of the total nitrogen was only calibrated by the 5-day monitoring data from 2014 to 2015 without validation.

The model performance was evaluated by Nash-Sutcliffe efficiency (NSE, Nash and Sutcliffe, 1970), percentage bias (PBIAS), root mean square error-standard deviation ratio (RSR), and R^2, as shown in Fig. 6 and Fig 7. The calibration of flow had an NSE, PBIAS, RSR, and R^2 of 0.48, 13.36%, 0.72, and 0.52, respectively. At the period of validation, the NSE, PBIAS, RSR, and R^2 were 0.52, 12.55%, 0.69, and 0.59, respectively. According to the criteria of monthly model performance proposed by Moriasi et al. (2007), the calibrated SWAT$^+$ model has an approximately satisfactory performance for flow modeling of the study area. For total nitrogen, the NSE, PBIAS, RSR, and R^2 of the calibration period were 0.27, -16.57%, 0.86, and 0.40, respectively. Considering a shorter time step may cause poorer model performance (Engel et al.

2007), and the simulation trend was quite consistent with the observed data (R^2=0.40), we believe the calibrated model is applicable for the validation of the proposed PMA identification method in this study.

3.3 Identification and evaluation of PMAs at LSU level and subbasin level

To evaluate the effectiveness of PMAs at the LSU level, we also identified PMAs at the subbasin level in the same study area based on the same calibrated $SWAT^+$ model.

The average annual total nitrogen of the calibration period (2014–2015) was used to calculate the TN load contribution with the watershed outlet set as the assessment outlet. The standard deviation classification method was adopted to classify the TN load contribution of spatial units into three classes (Table 2). In this study, high-contribution areas were identified as PMAs.

The comparison of PMAs identified at the LSU level and subbasin level is conducted from two perspectives, i.e., the spatial distribution and cumulative load contributions. The spatial distribution of PMAs is an intuitive way to qualitatively analyze the spatial consistency and difference from different units. The cumulative load contributions are used to quantitively compare the relationships between areas of PMAs and their total pollutant load contribution.

4. Experimental results and discussion

4.1 Spatial distribution of PMAs

Fig. 8 shows the ranking (labeled number in descending order) and classification of total nitrogen contribution at the LSU level and subbasin level, respectively. A total of 9 LSUs and 3 subbasins that classified as high-contribution areas are identified as PMAs.

Firstly, the classification maps of load contribution at both levels show a consistent spatial pattern. For example, low-contribution areas are almost identical, and the 2nd ranked subbasin (#2 in Fig. 8b) and its two LSUs (#2 and #3 in Fig. 8a) are all identified as PMAs.

Secondly, PMAs identified at the LSU level have a more accurate distribution and thus can represent the heterogeneity within subbasins to a certain extent. For example, two uplands (#12 and #15 in Fig. 8a) in high-contribution subbasins (#1 and #3 in Fig. 8b) are identified as medium-contribution LSU, while some floodplains (#6 and #7 in Fig. 8a) in medium-contribution subbasins (#5 and #8 in Fig. 8b) are identified as high-contribution LSU. Besides, comparing Fig. 8a with Fig. 4b, a relatively higher correlation of LSU-based PMAs with the distribution of the cropland (i.e., the main source of the local non-point source pollution) can be found, which is more reasonable.

Lastly, PMAs identified based on LSUs include not only floodplain located on the bottom of hillslopes and near channel but also uplands. With the consideration of generalized ponds in SWAT^{+}, one part of hillslope (floodplain #10 and upland #12 in

Fig. 8a) in the high-contribution subbasin #1 is excluded in high-contribution LSUs. These all proved that $SWAT^{+}$ is well qualified to characterize pollutants released at the LSU level and its transitions in the reconstructed routing network by LSUs and channels (including ponds). Therefore, the proposed PMA identification method at landscape position units using $SWAT^{+}$ is effective.

4.2 Cumulative load contribution

To quantitively evaluate the difference of PMAs identified at the LSU level and subbasin level, each type of spatial unit is ranked by load contribution in descending order and plotted in Fig. 9 with the cumulative area and load contribution calculated. As shown in Fig. 9a, LSU-based PMAs contribute 68.34% of total nitrogen on 31.76% of the watershed area, while subbasin-based PMAs only contribute 56.17% on as much as 39.66% areas. That means landscape position units are more effective to identify PMAs. Besides, it is clear that the cumulative area-contribution line of the LSU-based method in Fig. 9a is always higher than that of the subbasin-based method, proving the better effectiveness although based on different types of identification units.

From Fig. 9 we can recognize that there is no deterministic relationship between the area of the spatial unit and its pollutant load contribution. For example, LSU #1 contributes 11.97% of total nitrogen but ranks 17 in area, while subbasin #1 contributes 24.27% of total nitrogen with the 2^{nd} largest area (12.03% of the watershed). The curves in Fig. 9b and Fig. 9c indicate that the cumulative load contribution curve and cumulative area curve at the subbasin level have a more consistent variation trend than the LSU level. The comparison shows that the load contribution at the subbasin level is more dependent on the area. This is because the pollutant source of nitrogen is highly related to cropland in this study area and the identification of subbasin-based PMAs is ensured by the larger area, which in turn also illustrates that landscape position units have better representations of spatial heterogeneity of landuse than subbasins.

From both perspectives of the spatial distribution and the cumulative load contribution, identifying PMAs at the landscape positions performs better than subbasins. LSU-based PMAs have the merit of accounting for more pollutant load contribution with smaller areas and thus can be effectively utilized in the spatial configuration of BMPs for the watershed integrated management.

5. Conclusions

This paper proposes to use landscape position units (LSUs), derived from a universal type of spatial unit for most geographic environments, as identification units for priority management areas (PMAs). A Markov chain-based surrogate model of the SWAT^{+} model is proposed to distinguish the pollutant load contribution of each LSU to the assessment outlet and then identify PMAs according to a classification method. Experimental results show that landscape position units perform better effectiveness than widely used subbasins in identifying PMAs for their better ability to represent hillslope processes and the spatial heterogeneity of underlying surface environments within subbasins. Therefore, LSU-based PMAs are much more valuable in providing accurate locations to implement suitable best management practices for integrated watershed management.

The improved Markov chain-based PMA identification method can be regarded as a method framework. More types of spatial units with explicit upstream-downstream relationships may be proposed and validated for identifying PMAs with the support of proper watershed models. Besides, several issues may be worth attention in future research, for example, 1) how to consider various climate scenarios in determining retention effects of channel routing processes; 2) how a specific type of identification unit take effects on the identification of PMAs under different delineation methods; 3) how PMAs derived from different identification units affect the effectiveness and efficiency of spatial optimization of BMPs.

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Figure Captions

Fig. 1. Framework of the Markov chain-based PMA identification method using a hierarchy of hydrologically connected spatial units.

Fig. 2. Schematization of the spatial discretization scheme and hydrologic connections between spatial units implemented in SWAT$^+$. AQU, aquifer; CHA, channel; HRU, hydrologic response unit; LSU, landscape position unit; LAT, lateral flow; PND, pond; RES, reservoir; RHG, groundwater recharge; SUR, surface runoff; TOT, total outflow (specifically, for LSU, it equals to surface runoff plus lateral flow); and numbers represent flow distribution ratio from source unit to receiving unit (adapted from Bieger et al., 2017, 2019, and the source code of SWAT$^+$ version 59.3).

Fig. 3. Construction of flow distribution matrix *H* based on upstream-downstream relationships among landscape position units (LSUs) and channels and flow distribution ratios (s_1 and s_2) from upland to floodplain.

Fig. 4. DEM (a) and landuse map (b) of the Zhongtianshe watershed.

Fig. 5. Delineation of three types of spatial units in the SWAT$^+$ model of Zhongtianshe: (a) subbasin, (b) LSU, (c) HRU (take one subbasin as an example). Each color within the same subbasin in the map of HRU represents one unit, i.e., a particular combination of land use, soil type, and slope classification.

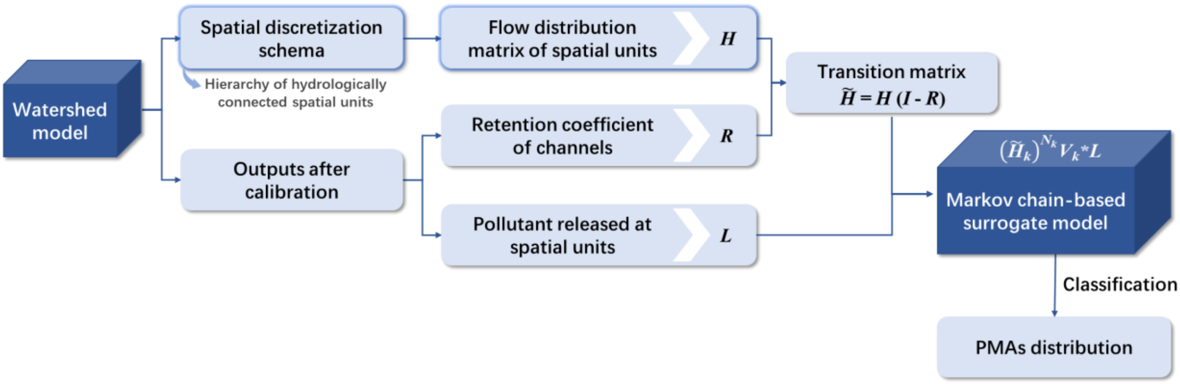
Fig. 6. Simulated and observed stream flow during calibration and validation periods.

Fig. 7. Simulated and observed total nitrogen (TN) at the calibration period.

Fig. 8. Ranking and classification of total nitrogen load contribution at (a) LSU (landscape position unit) level and (b) subbasin level. The labelled number is the ranked sequence of load contribution in descending order. High-contribution areas are identified as PMAs.

Fig. 9. Relationships between cumulative areas of spatial units and corresponding load contributions. Points in (a) present each spatial unit arranged in the descending order of load contribution. Detailed load contribution of landscape position units (LSUs) and subbasins are presented in (b) and (c), respectively.

Figure



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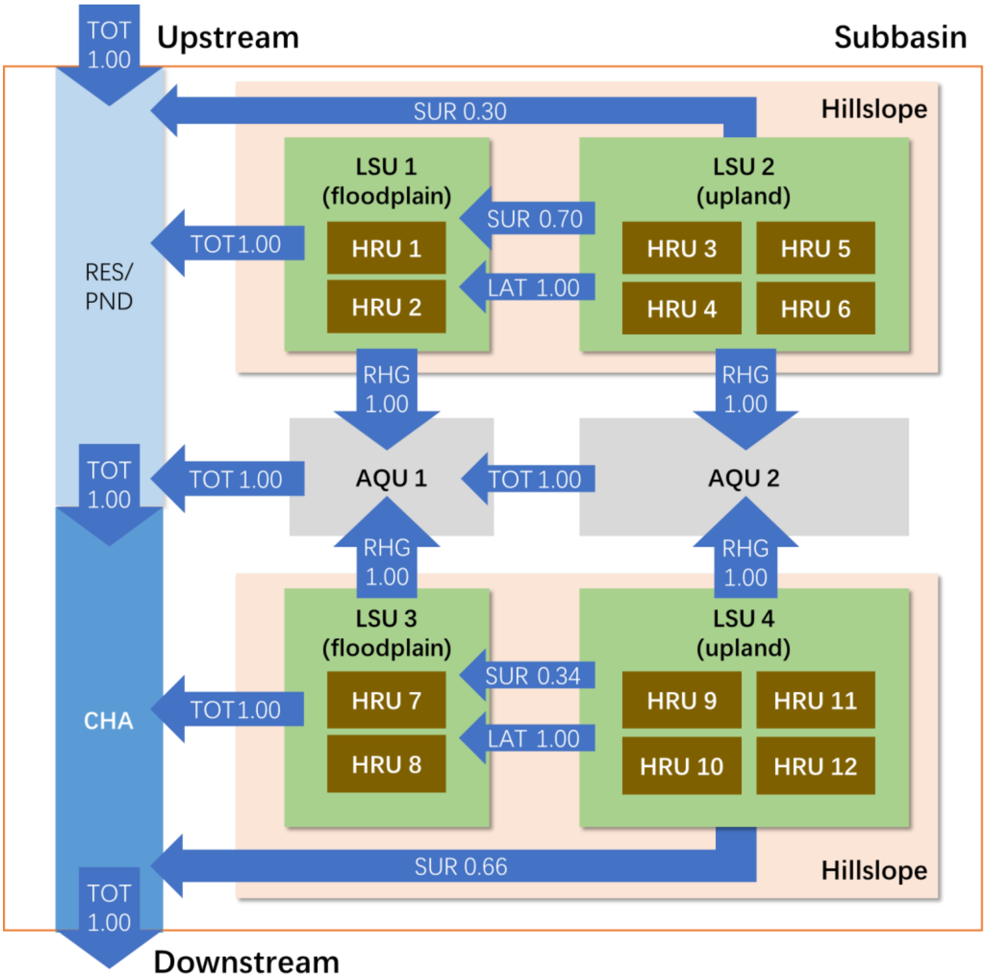

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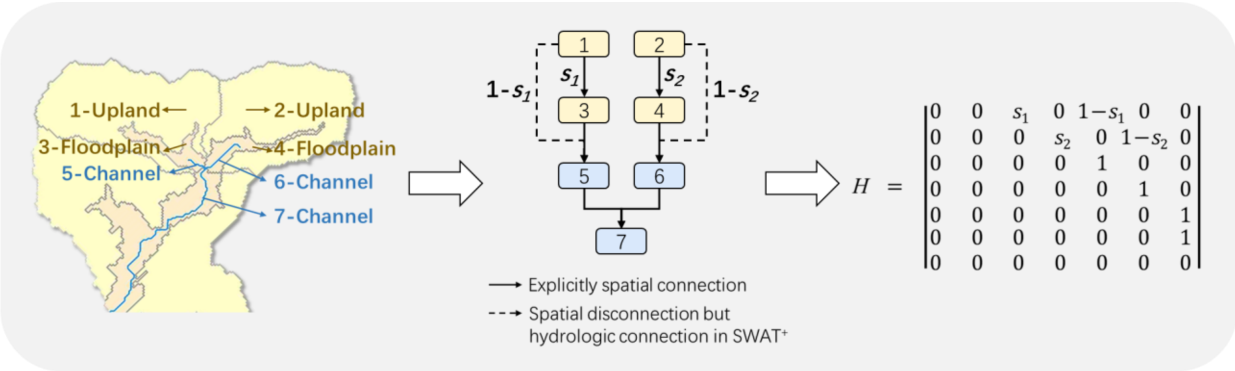

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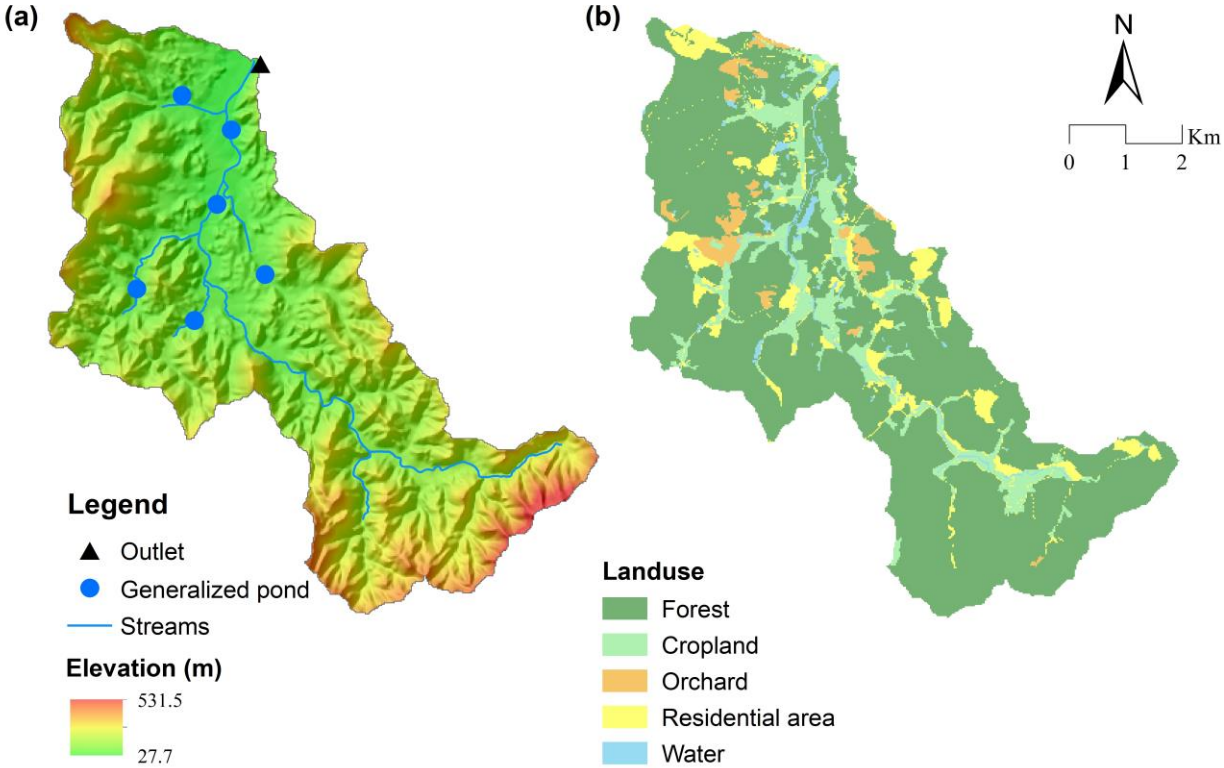

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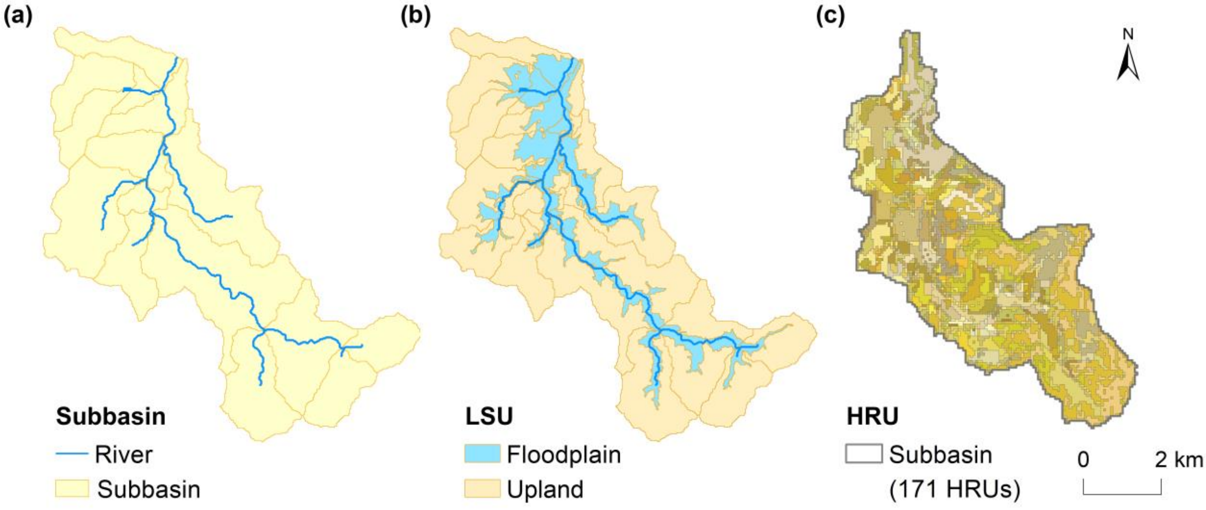

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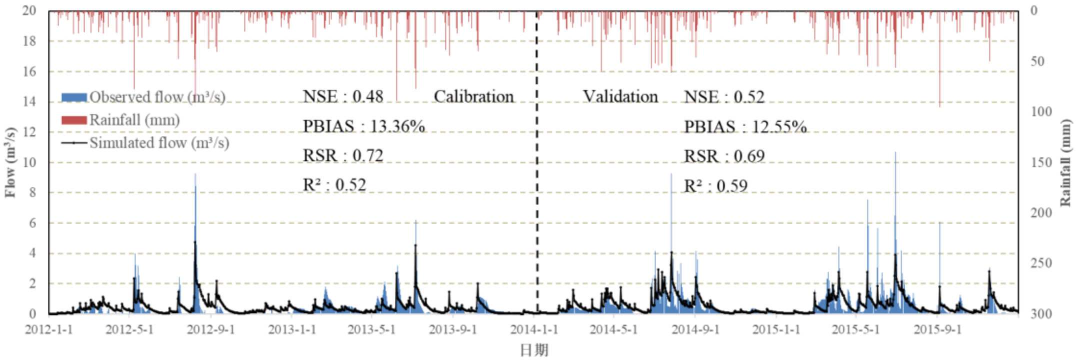
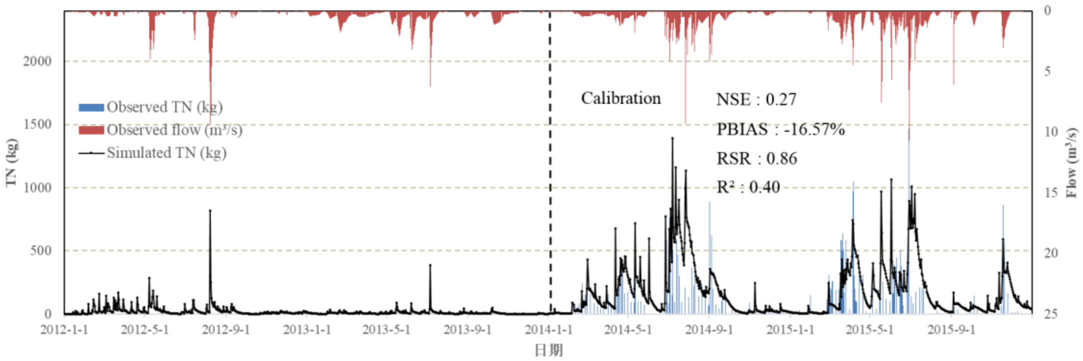


Fig. 6. Simulated and observed stream flow during calibration and validation periods.



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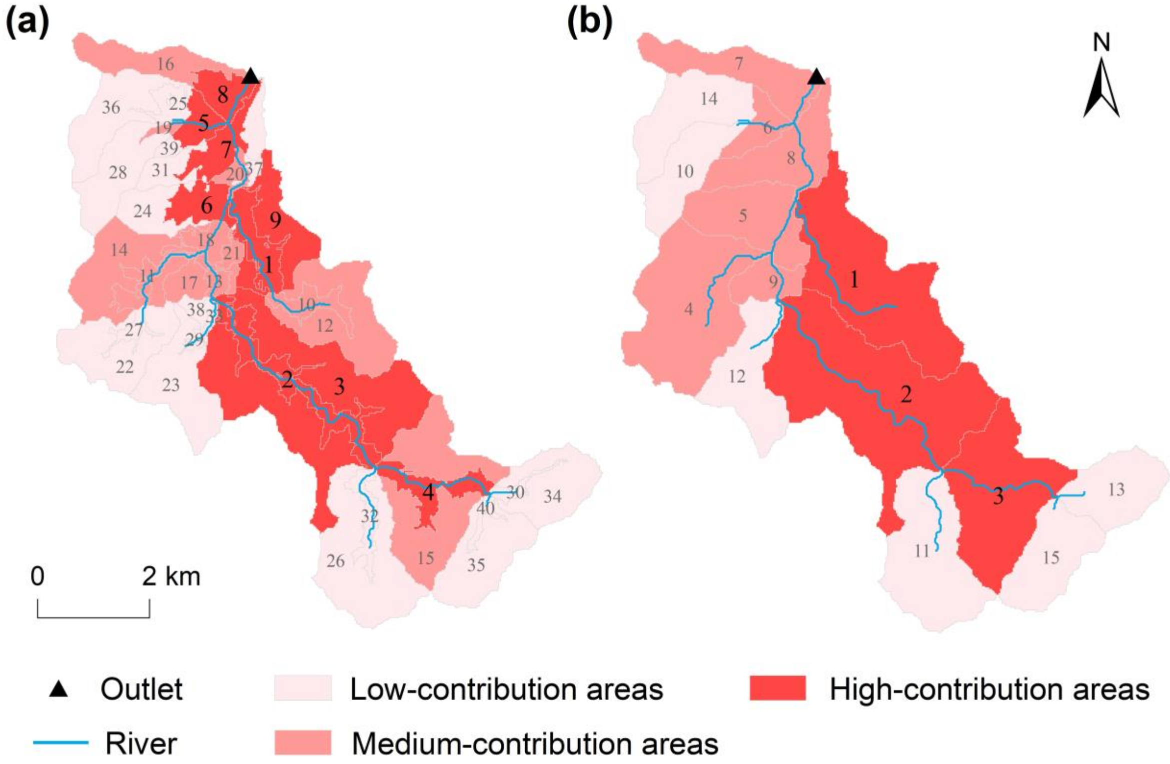

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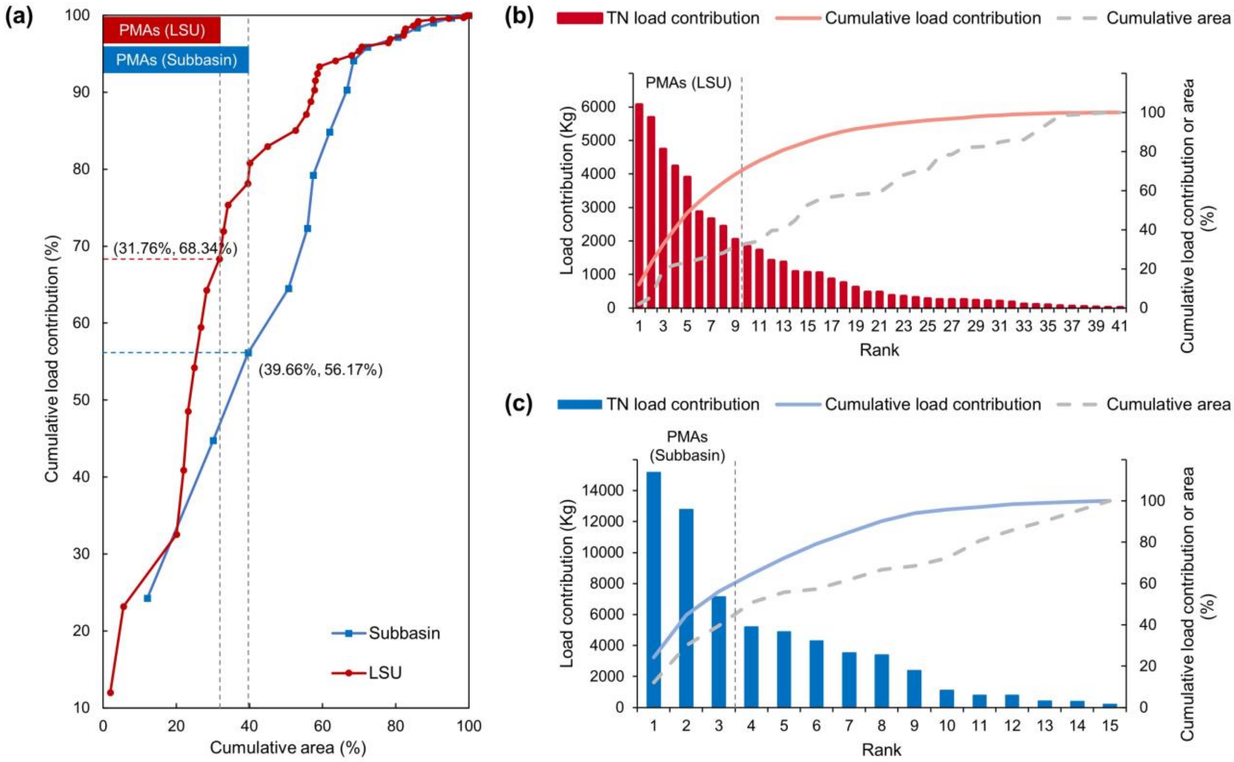

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Table

Table 1. Data description of the study area.

Data	Description
DEM	DEM with a resolution of 25 m
Land use	Manually interpreted from Google Earth image derived in 2015
Soil	Soil type map obtained from Soil Science Database of China and soil properties from field sampling
Meteorological data	Daily meteorological data (such as precipitation, temperature, humidity, wind speed and solar radiation) from 2011 to 2015 provided by China Meteorological Data Service Centre and Liyang meteorological station
Agricultural management practices	Cropping and irrigation schedule including crop types and fertilizer usage from field survey
Observed data at the outlet	Daily measured flow (2011─2015) and 5-day measured total nitrogen data (2014─2015) from the site-monitoring station at the watershed outlet

Table 2. Description of the standard deviation classification method used in this study.

Load contribution (x_i)	Level of load pollution
$(-\infty, \bar{x} - 0.5s)$	Low contribution
$(\bar{x} - 0.5s, \bar{x} + 0.5s)$	Medium contribution
$(\bar{x} + 0.5s, +\infty)$	High contribution

x_i denotes the pollutant load contribution of the spatial unit i; $\bar{x}$ and s denote the mean and the standard deviation of all the units' load contribution, respectively.