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 (PMAs).
- 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 contribution.
- LSU-based PMAs have general applicability for various geographic environments.

Identification of watershed priority management areas based on landscape positions: an implementation using SWAT^{+}

Abstract

Priority management areas (PMAs) of a watershed are areas with high contributions to the pollutant load of the assessment outlet, such as the watershed outlet, and thus, have high priority in the decision-making of comprehensive watershed management. Existing spatial units used to identify PMAs are commonly based on three concepts including subbasins, artificial geographic entities, and grid cells. However, these identification units cannot balance the general applicability to diverse geographic environments and the representation degree of spatial heterogeneity, which impacts the effectiveness of the PMAs. This study proposes adopting landscape positions along the hillslope as identification units of PMAs, which can be represented 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 and channel routing processes. The proposed method was implemented using a restructured and enhanced version of the Soil and Water Assessment Tool (SWAT^{+}), and an improved Markov chain-based surrogate model. Two watersheds, one in China and one in the USA, with different geographic characteristics were selected to separately conduct the comparative experiments to identify PMAs at the landscape position and the subbasin levels. The results showed that PMAs based on landscape positions have more accurate spatial distribution and require less area for the future configuration of management practices to achieve the same management goal as PMAs based on subbasins. 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. The proposed method can be implemented by other watershed models that support landscape position units or different types of spatial units with explicit upstream-downstream relationships within subbasins.

Keywords: Priority management areas; Landscape positions; Spatial units; Pollutant load contribution; Best Management Practices; $SWAT^+$

1. Introduction

The 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 (Chen et al., 2014). This concept is similar to the critical source area (CSA), which is more commonly used to identify highly polluted areas (Pionke et al., 2000; White et al., 2009) but usually does not emphasize propagation effects from upstream to downstream in the watershed, which is essential in the decision-making of comprehensive watershed management. Priority management areas 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 identification of PMAs can be regarded as the first step in the spatial configuration of BMPs for comprehensive watershed management, where factors affecting actual management decisions, such as investment plans, stakeholders' willingness, environmental goals, and BMP effectiveness, could be considered. The spatial distribution of PMAs considerably affects the locations, areas, and effectiveness of the configured BMPs, affecting the cost-effectiveness of the BMP scenario (i.e., the 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, the accurate identification of PMAs is a key issue for comprehensive watershed management (Chen et al., 2022).

The foremost step in identifying PMAs is to determine an appropriate type of spatial units as a computing unit for pollutant production and contribution to the assessment outlet, such as the watershed outlet (hereafter referred to as the identification units) (Dong et al., 2018; White et al., 2009). The identification units adopted in existing research are mainly based on three concepts: 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).

The subbasin represents a relatively closed and independent geographic unit that is linked to other subbasins through channels. Subbasin units are the most straightforward and most frequently used identification units because they are delineated and modeled 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 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 because the heterogeneity of pollutant sources and transportation processes within the subbasins should be considered (Qin et al., 2018; Wang et al., 2016).

Artificial geographic entities refer to artificially constructed and hydrologically connected geographic entities based on the 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 relatively homogeneous features from the 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 serve as conservation areas for flood and waterlogging. Although artificial geographic entities are appropriate for use as identification units in the corresponding geographic environments, they are not easy to be generalized as generally applicable identification units and are widely applied.

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

Therefore, the existing spatial units used for identifying PMAs cannot balance the general applicability to diverse geographic environments and the representation degree of spatial heterogeneity. According to the previous analysis, proper identification units should (1) be broadly available and not be limited to a specific geographic environment; (2) be capable of representing 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.

This study proposes the use of landscape positions along hillslopes within each subbasin to identify PMAs. Landscape positions can be delineated by landform units (also referred to as slope position units) that reflect the integrated effects of hillslope processes on topography and affect geographic processes on the surface (Volk et al., 2007; Arnold et al., 2010; Miller and Schaetzl, 2015; Qin et al., 2018). Landscape position units are universality in 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 needs only a few spatial units (e.g., three) to represent the spatial homogeneity from the perspective of hillslope processes (Qin et al., 2018; Rathjens et al., 2016). In addition, 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 for use as identification units mentioned above.

This study proposes a PMA identification method based on landscape position units exemplified by SWAT^{+} (i.e., the restructured and enhanced version of the Soil and Water Assessment Tool) and evaluates the effectiveness of the proposed method by comparing it to widely used subbasin units. The remainder of this paper is organized as follows: Section 2 introduces the proposed method; and Section 3 presents a comparative experimental design of using landscape position and subbasin units to identify PMAs of total nitrogen in two watersheds with different geographic characteristics. The experimental results and discussion are presented in Section 4, and the conclusions are presented in Section 5.

2. Method design

To identify PMAs at the landscape position unit level, two key issues must be addressed. The first is the quantification of 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, that is, the residual amount of pollutant after being transported to its direct downstream channel and then transitioning in hierarchical channels before reaching the assessment outlet (Chen et al., 2014).

Generally, the contribution of the pollutant load cannot be directly determined from the results of most watershed models. Instead, watershed models output the pollutant released from each simulation unit (e.g., the hydrologic response unit [HRU] in SWAT) or lumped unit (e.g., subbasin), as well as the flow of substances in and out 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 (one channel for each subbasin) to the assessment outlet in a statistical manner. Their basic idea is to use analog pollutant transformation and transfer processes in hierarchical channels as a Markov process, in which, the transition matrix is determined by the upstream-downstream relationships among channels and the 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, thus, the corresponding pollutant load contributions can be derived (Grimvall and Stålnacke, 1996).

Follow-up studies continued to adopt the subbasin unit in the Markov chain-based model (Chen et al., 2014; Rankinen et al., 2016), which includes pollutant production at hillslopes and pollutant routing in the channel. The transition matrix of the Markov chain-based model can be improved to represent both landscape position and channel units. Therefore, if we can separate these two processes in landscape position units and channels, the improved 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 to incorporate a watershed model that supports landscape position units as simulation 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 one or more types of hierarchical spatial units with explicit hydrological connections (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 the subbasin unit and HRU named the landscape position unit (LSU), which includes the uplands and floodplains

(Fig. 2). This means that the basic spatial discretization of a watershed in $SWAT^+$ contains three types of nested spatial units as a hierarchy: subbasin, LSU, and HRU. In addition, $SWAT^+$ 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 first generalized as one point in the channel that divides the channel into two parts, and then defined by the upstream part with additional properties such as storage capacity (Fig. 2). The hillslopes, LSUs, and HRUs are also delineated accordingly, while the 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, such as, agricultural ecosystems with densely distributed ponds.

With the new spatial discretization scheme, $SWAT^+$ improved the representation of realistic hydrologic processes from hillslopes to channels (Bieger et al., 2019). Instead of directly adding all released substances of HRUs (including water, sediment, and pollutants) to the channel, $SWAT^+$ first lumps HRUs' outputs at the LSU level and then routes to other spatial units using two different methods. The first method involves completely draining from the upland to the floodplain and from the floodplain to the channel, which is applicable for lateral flow in soils and groundwater recharge in aquifers (Fig. 2). The second method distributes water from the upland to the channel/pond/reservoir by a constant ratio (e.g., 0.30 from LSU2 to the pond and 0.66 from LSU4 to the channel, as shown in Fig. 2; hereafter 'channel/pond/reservoir' is referred to as channel collectively) and the rest to the floodplain as additional net precipitation to participate in the simulation. The output from the floodplain drains entirely into the channel (Fig. 2). SWAT$^+$ provides two ways to determine this ratio: the user-specified global value for all upland units in the watershed and the area ratio of each upland to its floodplain. The area ratio method has been proven to be more realistic in representing the connectivity than the fixed ratio for the entire watershed (Bieger et al., 2019) and is therefore adopted in this study.

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 the corresponding transportation amounts to their direct channels.

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. Subsequently, using the lumped simulation results at LSUs as inputs, the Markov chain-based model can determine 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 using flow distribution relationships from upstream to downstream units and the retention coefficients of channel routing processes (Chen et al., 2014). According to the spatial discretization scheme of SWAT$^+$

(see Section 2.1), the flow distribution relationships among the LSUs and channels can be represented by an $n \times n$ matrix H (Eq. 1). Fig. 3 shows an example of the matrix H.

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

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 = 1 (Fig. 2). Each row represents the flow distribution relationships of a spatial unit with its downstream units. The sum of all elements in one row equals 1, except for 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). For a given assessment outlet of channel k, there exists a smallest integer N_k to make $H^{N_k} = 0$, which means that after N_k 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 the uppermost spatial units to the outlet of channel k, for example, $N_7 = 4$ in Fig. 3.

The complicated channel routing process accounting for pollutant transformation and transfer processes can be simplified by using a retention coefficient (i.e., removal capacity of pollutants) 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, thus, has no retention effect. The retention coefficient R is also represented by an $n \times n$ matrix, as follows:

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

Where the ith diagonal element r_i denotes the retention coefficient of spatial unit i; for LSUs, r_i = 0; and for channels, r_i can be calculated using the simulation results of channels:

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

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

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

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

where I is an identity matrix.

2.2.2 Calculation of pollutant load contribution

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

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

where e_i is the pollutant released from spatial units i based on the simulation results of

SWAT$^+$. Specifically, $e_i = 0$, if i is a channel.

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

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

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

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

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

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

$$E_{TN} = E_{NO3-SURF} + E_{NO3-LAT} + E_{NO3-GW} + E_{ORGN} \tag{9}$$

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

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

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

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

where *SURF* denotes the surface runoff, *LAT* denotes the lateral flow, *GW* denotes the groundwater recharge; H_{SURF}, H_{LAT}, and H_{GW} describe the flow distribution relationships among the spatial units of surface runoff, lateral flow, and groundwater recharge, respectively; $L_{NO3\text{-}SURF}$, $L_{NO3\text{-}LAT}$, and $L_{NO3\text{-}GW}$ are the amounts of NO_3 released in surface runoff, lateral flow, and groundwater recharge, respectively; and $L_{ORGN\text{-}SURF}$ 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 natural breaks method, standard deviation method, and water quality control targets method (Chen et al., 2014; Giri et al., 2016).

3. Experimental design

To illustrate the effectiveness of the proposed method, a comparative experimental study was designed to identify the PMAs of total nitrogen at the landscape position and subbasin levels based on the same calibrated SWAT$^+$ model. The same experimental design was used in two watersheds to evaluate the applicability of the method under different geographic characteristics (e.g., topographical, climatic, hydrological, and ecological conditions), that is, the Zhongtianshe Watershed (~42 km^2) in southern China and the Willow River Watershed (~212 km^2) in western Wisconsin, USA (Fig. 4).

3.1 Study areas and data

The Zhongtianshe Watershed, located in the south of Liyang City, Jiangsu Province, China, is a typical hilly area situated in the upstream region of Lake Tai. The study area is characterized by a subtropical monsoon climate. The average annual temperature is 15.5°C and the average annual precipitation is 1160 mm. The main soil type is yellow-red soil, which is a type of acidic soil that is easily weathered. The main land use types were forests (77%), croplands (10%, primarily paddy fields), orchards (3%), residential areas (8%), and water areas (2%). The watershed experiences frequent agricultural activities, and the cultivation of rice and wheat is the primary contributor to local non-point source pollution. Because the study area is on the drinking water source of Liyang, knowing the details of the pollution situation and taking reasonable measures to control is a vital issue for the local government (Shi et al., 2021).

The Willow River, located in western Wisconsin, USA, is a tributary of the St. Croix River. It is classified as the Central Wisconsin Undulating Till Plain based on a report by the environmental protection agency (EPA, 2020), and is characterized as relatively flat compared to the Zhongtianshe watershed. The area has a continental climate with high evapotranspiration, an average annual temperature of 11.8°C, and an average annual precipitation of 788 mm. The soils are predominantly silt loams with moderately well-drained characteristics. The main land use types were grasslands

(45%), forests (27%), croplands (18%), residential areas (6%), and wetlands (3%). Watershed crops are dominated by corn-silage, soybeans, and alfalfa, resulting in non-point source pollution and relatively poor water quality. As the headwater of the popular Willow River State Park and attractive trout fishing destinations, the watershed has been the focus of non-point source pollution control for decades (Almendinger and Murphy, 2007).

The input data of the study areas for SWAT$^+$ modeling consisted of a digital elevation model (DEM), land use types, soil types and properties, meteorological data, agricultural management practices, and observed data at the watershed outlet. Detailed descriptions of the data for the two watersheds are presented in Table 1.

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

Two SWAT$^+$ models (version 59.3) were built to simulate the total nitrogen pollution in each study area. A total of 15 subbasins, 41 LSUs, and 1260 HRUs were generated in the Zhongtianshe Watershed, while 19 subbasins, 131 LSUs, and 7245 HRUs were generated in the Willow River Watershed (Fig. 5).

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

For the Willow River watershed, the model had a 2-year warm-up period. The calibration period ranged from 1 January 2012 to 31 July 2014, and the validation period was from 1 October 2010 to 31 December 2011, respectively. The available daily ammonia and organic nitrogen were combined to calibrate and validate the nitrogen modeling.

Model performance was evaluated using the Nash–Sutcliffe efficiency (NSE, Nash and Sutcliffe, 1970), percentage bias (PBIAS), root mean square error-standard deviation ratio (RSR), and R^2, as listed in Table 2. According to the criteria of monthly model performance proposed by Moriasi et al. (2007), calibrated SWAT$^+$ models have approximately satisfactory performance for flow modeling in both study areas. For nitrogen, considering that a shorter time step may cause poorer model performance (Engel et al. 2007), and that the simulation trend (shown in R^2) was quite consistent with the observed data, we believe that both calibrated models are 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 the PMAs at the LSU level, PMAs were also identified at the subbasin level in the same study area based on the same calibrated SWAT$^+$ model and the original Markov chain-based surrogate model.

The average annual total nitrogen modeled during the calibration period was used to identify the PMAs, with the watershed outlet set as the assessment outlet. The natural break method was adopted to classify the nitrogen load contribution of the spatial units into three classes, and high-contribution areas were identified as PMAs.

The comparison of PMAs identified at the LSU and subbasin levels was conducted from two perspectives, the spatial distribution and cumulative load contributions. The spatial distribution of PMAs is an intuitive way to qualitatively analyze the spatial consistency and differences between different units. The cumulative load contributions were used to quantitatively compare the relationships between the areas of PMAs and their total pollutant load contribution.

4. Experimental results and discussion

4.1 Spatial distribution of PMAs

In the Zhongtianshe Watershed, five LSUs and two subbasins, classified as high-contribution areas, were identified as PMAs (Fig. 6). There was a relatively consistent spatial correlation between the two levels. For example, one subbasin was identified as PMA at both levels, that is, subbasin S2 in Fig. 6b and its two LSUs, L2 and L3 in Fig. 6a. PMAs identified at the LSU level had a more accurate spatial distribution because of the inherent characteristics of the LSUs that can represent the spatial heterogeneity within subbasins. Considering the retention effect of ponds and reservoirs in SWAT^{+}, the upstream part of the subbasin may have a distinctive load contribution compared to the downstream part. For example, in the subbasin S1 in Fig. 6b, the upstream part constituted by floodplain L10 and upland L12 in Fig. 6a were identified as medium-contribution areas, while the downstream floodplain L1 was the high-contribution area. In addition, most LSU-based PMAs were floodplains in the Zhongtianshe Watershed. This may be because that the cropland in the study area is mostly distributed along the valley plain, which is a direct cause of local non-point source pollution. These results also prove that SWAT^{+} is well suited for characterizing pollutants released at the LSU level and their transitions in the reconstructed routing network by LSUs and channels (including ponds).

In the Willow River Watershed, two LSUs and two subbasins, classified as high-contribution areas, were identified as PMAs (Fig. 7). It was similar at both the LSU and subbasin levels where the northeast areas of the watershed were identified as low contribution areas, owing to the upstream pollution predominantly reduced by the ponds and wetlands along the main channel. Although the results identified at the two levels had similar spatial distributions, the subbasin-based PMAs covered larger areas than the LSU-based PMAs, which may result in additional screening work or more investment in watershed management decision-making. In contrast, the LSU-based PMAs were the upland areas within the subbasins, that is, uplands L1 and L2 (Fig. 7a) within two subbasins (Fig. 7b). The medium-contribution areas identified at the LSU level were also more specific and detailed than the areas identified at the subbasin level. Therefore, it is clear that LSU-based results can provide a finer identification than subbasin-based results in the Willow River Watershed.

In addition, for the Willow River Watershed, LSUs belonging to subbasin L2 in Fig. 7b were not identified as PMAs but as contribution areas below medium-contribution areas. This shows that the application of detailed spatial units could decompose the aggregation of the pollutant load within a subbasin in a relatively realistic representation, although subbasin S2 contributed a high pollutant load as the result of the largest subbasin in the watershed.

Overall, LSU-based PMAs have improved the accuracy of identification from the perspective of spatial distribution compared with subbasin-based PMAs. It is also proven that the proposed PMA identification method at landscape position units using SWAT$^+$ is effective and applicable to different watersheds.

4.2 Cumulative load contribution

To quantitatively evaluate the difference in PMAs identified at the LSU and subbasin levels for each case study, each type of spatial unit was ranked by load contribution in descending order and plotted in Figs. 8 and 9, with the cumulative area and load contribution calculated.

In the Zhongtianshe Watershed, LSU-based PMAs contributed 48.6% of the total nitrogen in 23.3% of the watershed area, whereas subbasin-based PMAs only contributed 44.7% in as much as 30.1% of the area (Fig. 8a). This means that landscape position units are more effective in identifying the PMAs. Moreover, the cumulative area-contribution line of the LSU-based method in Fig. 8a was always higher than that of the subbasin-based method, proving its better effectiveness, although based on different types of identification units.

In the Willow River Watershed, LSU-based PMAs contributed 31.7% of the total nitrogen in 5.9% of the watershed area, whereas subbasin-based PMAs contributed 54.9% of the total nitrogen in 21.5% of the area (Fig. 9a). It is not convincing to simply use these numbers to compare the effectiveness of the two levels in this watershed. However, the line in Fig. 9a shows that the LSU-based PMAs almost always covered less area than the subbasin-based PMAs under the same cumulative contribution. In general, the results revealed that there would be less work on the reduction of pollution at the LSU level if the local government wanted to control the pollution to a certain extent.

Furthermore, there was no deterministic relationship between the area of the spatial unit and its pollutant load contribution. For example, LSU L1 in the Zhongtianshe Watershed contributed 12.0% of the total nitrogen but ranked 17 in area, while subbasin S1 contributed 24.3% of the total nitrogen with the 2nd largest area (Fig. 8). In the Willow River Watershed, LSU L1 contributed 16.8% of total nitrogen with the 2nd largest area, and subbasin S1 contributed 31.7% of total nitrogen which has the 2nd largest area of all subbasins (Fig. 9).

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

5. Conclusions

This study proposes the use of landscape position units (LSUs), derived from a universal type of spatial unit for most geographic environments, as identification units for priority management areas (PMAs). An improved Markov chain-based surrogate model of the $SWAT^+$ model was implemented to distinguish the pollutant load contribution of each LSU to the assessment outlet and then identify the PMAs according to a classification method. Experimental results show that landscape position units are more effective than widely used subbasins in identifying PMAs because of their superior ability to represent hillslope processes and the spatial heterogeneity of underlying surface environments within subbasins. Therefore, LSU-based PMAs are much more valuable for providing accurate locations for implementing suitable BMPs 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 to identify PMAs with the support of proper watershed models. In addition, several issues may be worth attention in future research such as 1) how to consider various climate scenarios to determine the retention effects of channel routing processes; 2) how to better quantify the hydrological connectivity among landscape positions and channels and its effects on PMA identification;3) how a specific type of identification unit affects the identification of PMAs under different delineation methods; 4) how the modeling accuracy and precision of the same or different watershed models affects PMA identification; and 5) how PMAs derived from different identification units impact the effectiveness and efficiency of the spatial optimization of BMPs.

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Table

Table 1. Data description of the study areas for building SWAT+.

	Zhongtianshe Watershed	Willow River Watershed
DEM	DEM with a resolution of 25 m from Provincial Geomatics Centre of Jiangsu	DEM with a resolution of 30 m from National Elevation Data, USGS
Land use	Manually interpreted from Google Earth image derived in 2015	Land use map from National Land Cover Data (NLCD, 2011 Edition), USGS
Soil	Soil type map obtained from Soil Science Database of China and soil properties from field sampling	Soil dataset from the Soil Survey Geographic database (SSURGO), U.S. Department of Agriculture-Natural Resource Conservation Service
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	Daily meteorological data from 2008 to 2014 provided by Climate Forecast System Reanalysis dataset, U.S. National Centers for Environmental Prediction
Agricultural management practices	Cropping and irrigation schedule including crop types and fertilizer usage from field survey	Crop rotations, tillage practices and fertilizer usage collated from Almendinger and Murphy (2007)
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	Daily flow and ammonia plus organic nitrogen data (from 1 October 2010 to 31 July 2014) measured at the monitoring station by USGS (no. 05341687)

Table 2. The SWAT+ model performance of the two watersheds.

			NSE	PBIAS	RSR	R^2
Zhongtianshe Watershed	Calibration	Flow	0.48	13.36%	0.72	0.52
		Nitrogen	0.27	-16.57%	0.86	0.40
	Validation	Flow	0.52	12.55%	0.69	0.59
		Nitrogen	–	–	–	–
Willow River Watershed	Calibration	Flow	0.48	-28.82%	0.72	0.51
		Nitrogen	0.37	3.97%	0.79	0.39
	Validation	Flow	0.34	-58.16%	0.81	0.47
		Nitrogen	0.25	-128.73%	0.87	0.54

Figure

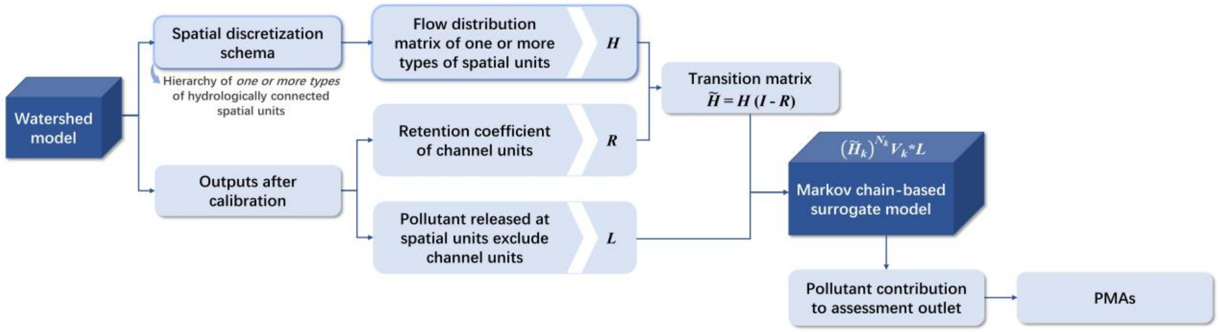

Fig. 1. Generalized framework of the Markov chain-based PMA identification method using a hierarchy of one or more types of hydrologically connected spatial units.

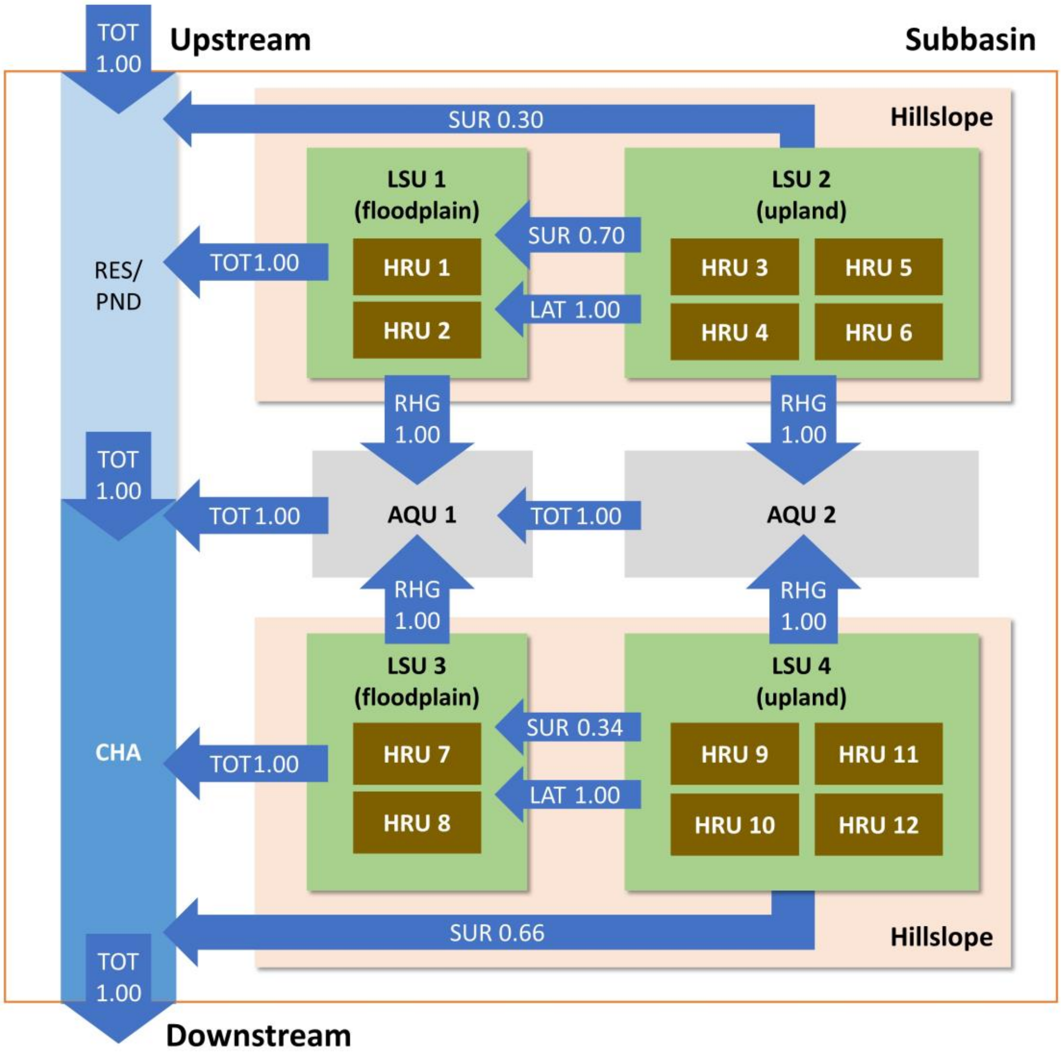

Fig. 2. **Schematic of the spatial discretization scheme and hydrologic connections between spatial units implemented in SWAT^{+}. AQU, aquifer; CHA, channel; HRU, hydrologic response unit; LSU, landscape position unit; LAT, lateral flow; PND, pond; RES, reservoir; RHG, groundwater recharge; SUR, surface runoff; TOT, total outflow (specifically, for LSU, it equals to surface runoff plus lateral flow); and numbers represent flow distribution ratio (values less than 1.0 are presented for example) from source unit to receiving unit (adapted from Bieger et al., 2017, 2019, and the source code of SWAT^{+} version 59.3).**

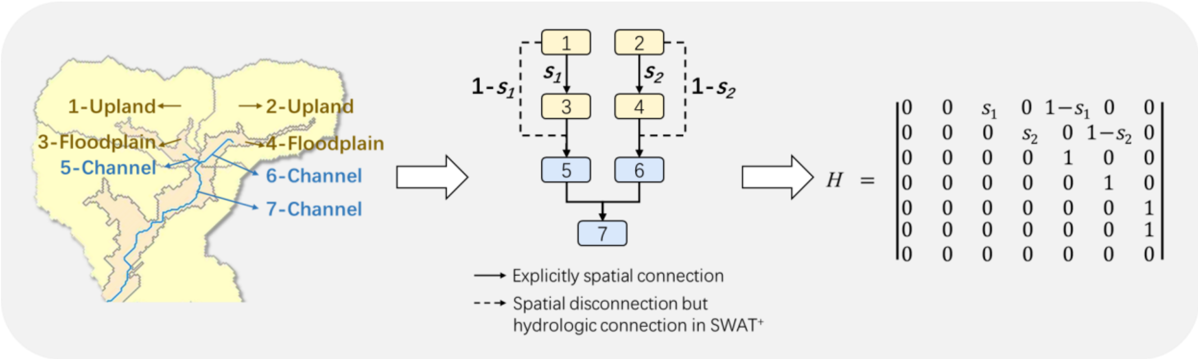

Fig. 3. Example of constructing flow distribution matrix *H* based on upstream-downstream relationships among landscape position units (LSUs) and channels and flow distribution ratios from upland to floodplain (e.g., s_1 and s_2 in different subbasins).

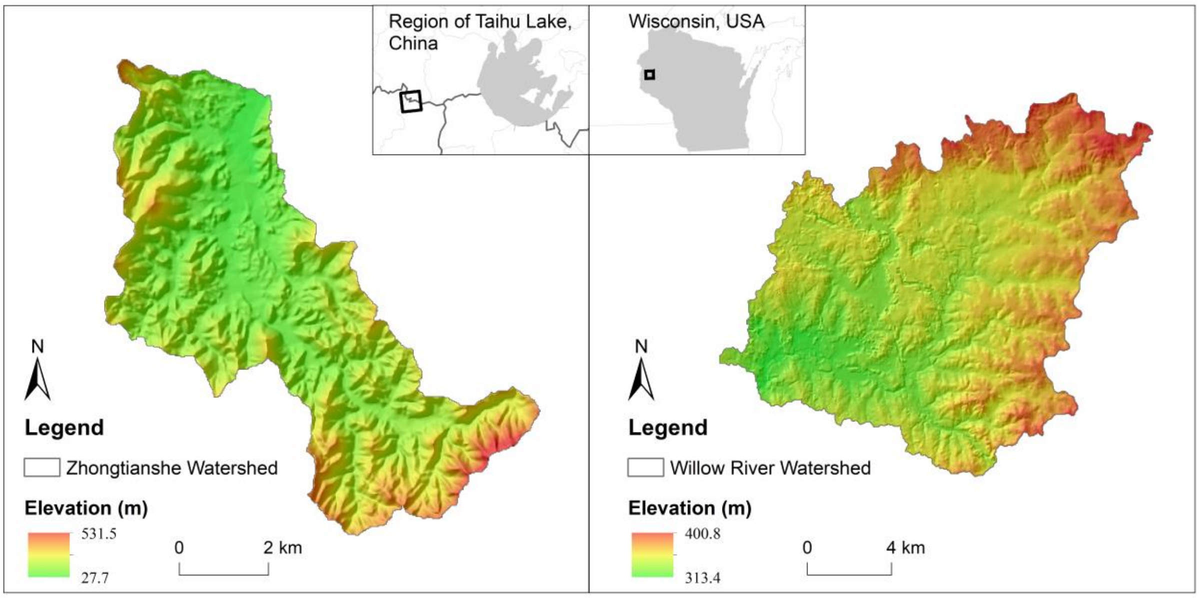

Fig. 4. Overview of the Zhongtianshe and Willow River Watersheds.

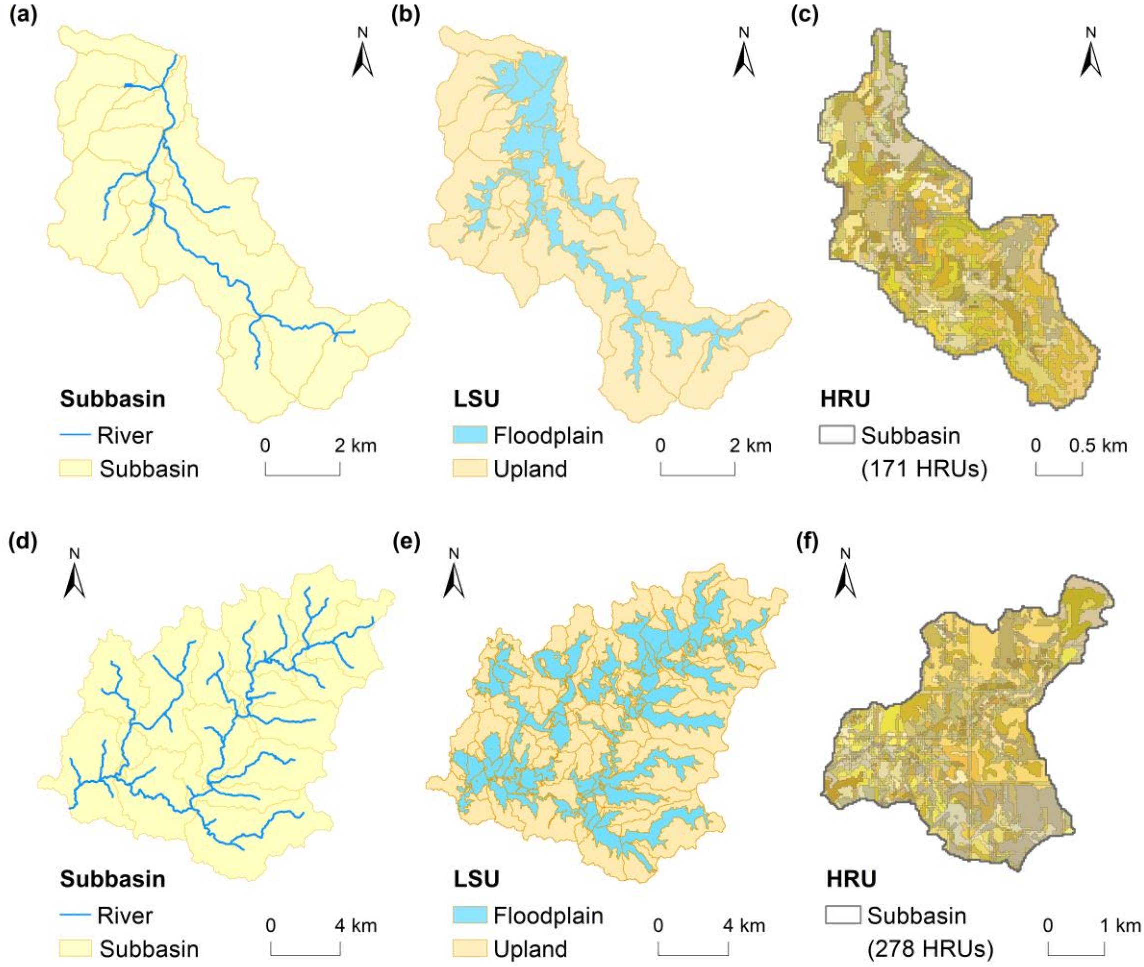

Fig. 5. Delineation of three types of spatial units in the SWAT^{+} model of the Zhongtianshe Watershed: (a) subbasin, (b) LSU, (c) HRU (take one subbasin as an example) and the Willow River Watershed: (d) subbasin, (e) LSU, (f) HRU (take one subbasin as an example). Each color within the same subbasin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

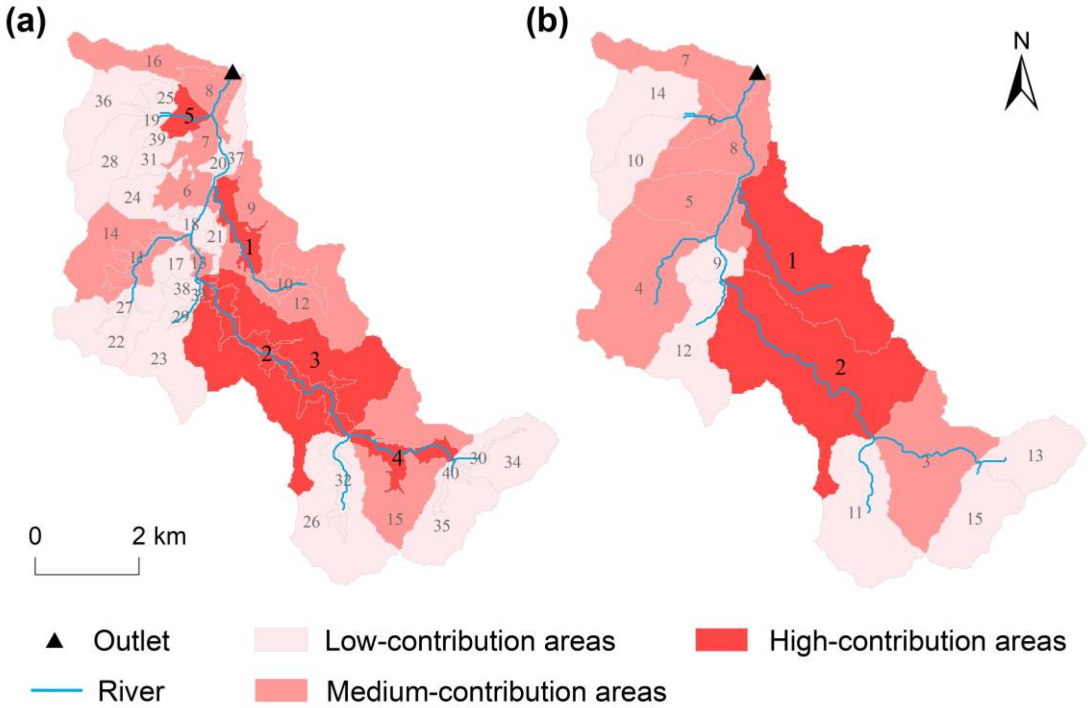

Fig. 6. Ranking and classification of nitrogen load contribution at the (a) LSU (landscape position unit) and (b) subbasin levels in the Zhongtianshe Watershed. The labelled number is the ranked sequence of load contribution in descending order. High-contribution areas are identified as PMAs.

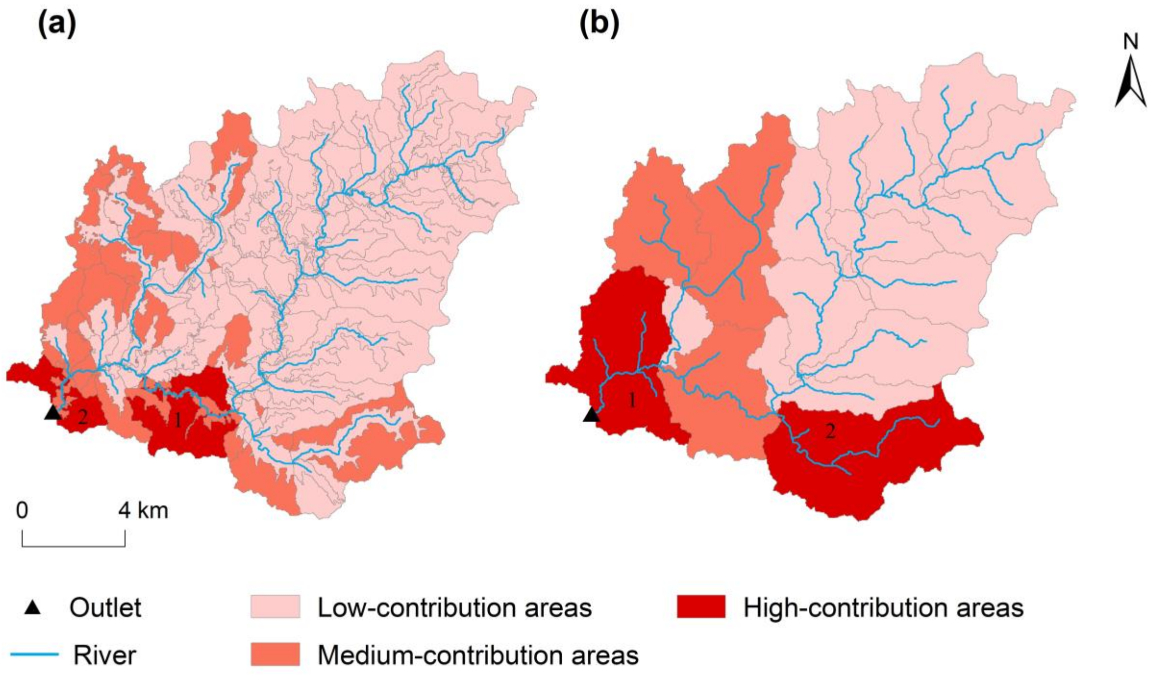

Fig. 7. Ranking and classification of total nitrogen load contribution at the (a) LSU (landscape position unit) and (b) subbasin levels in the Willow River Watershed. High-contribution areas are identified as PMAs, which are ranked and labelled by load contribution.

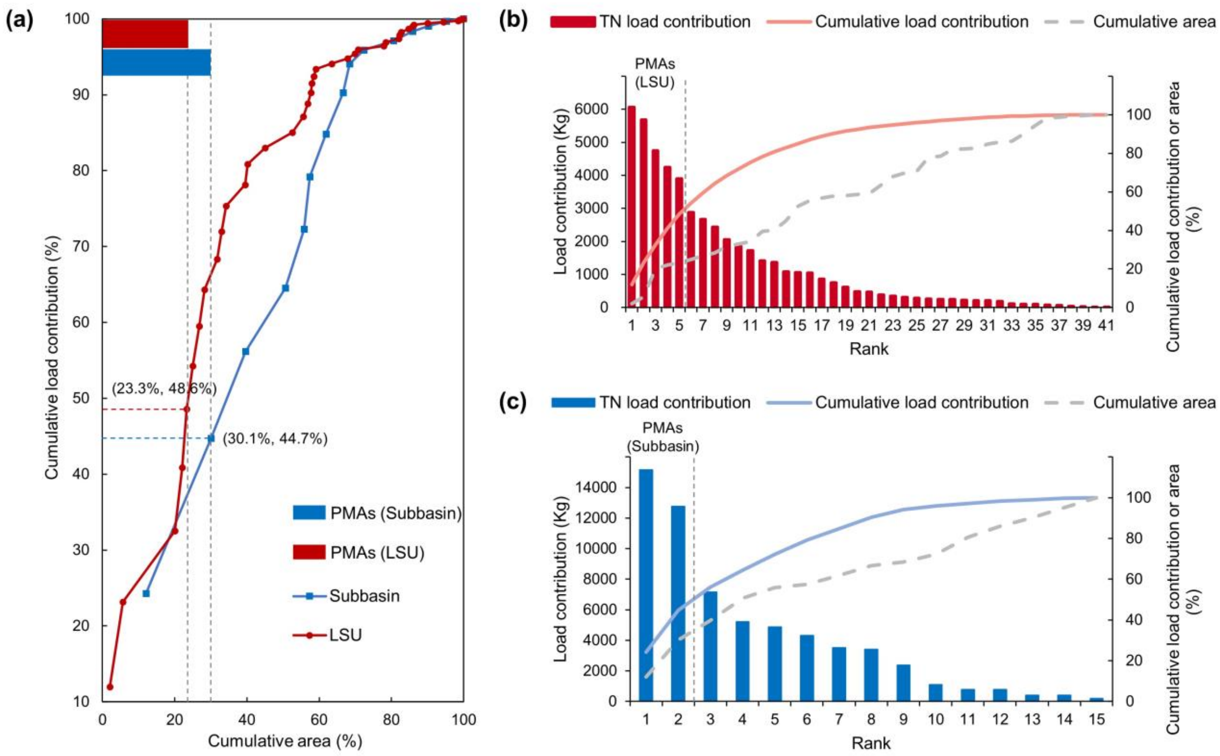

Fig. 8. Relationships between cumulative areas of spatial units and corresponding load contributions in the Zhongtianshe Watershed. (a) each point represents a spatial unit arranged in the descending order of load contribution. Detailed load contribution of landscape position units (LSUs) and subbasins are presented in (b) and (c), respectively.

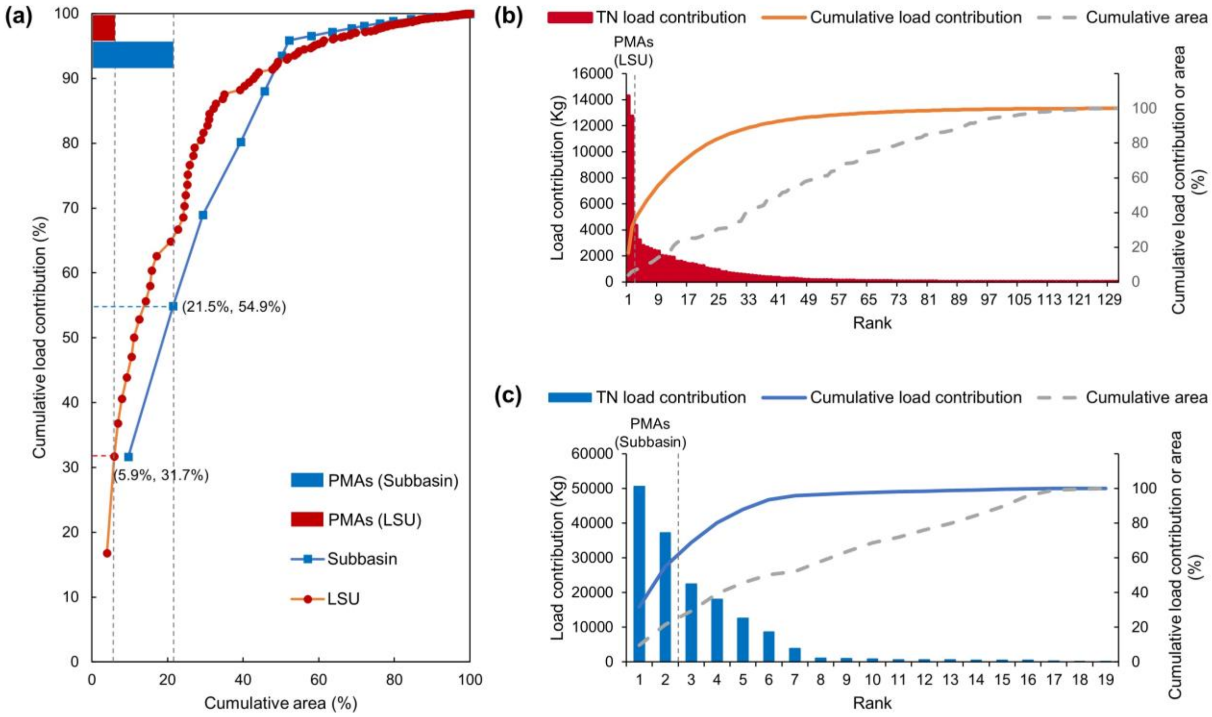

Fig. 9. Relationships between cumulative areas of spatial units and corresponding load contributions in the Willow River Watershed. (a) each point represents a spatial unit arranged in the descending order of load contribution. Detailed load contribution of landscape position units (LSUs) and subbasins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