Upstream to downstream: a multiple-assessment-point approach for targeting non-point-source priority management areas at large watershed scale

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Abstract: The identification of priority management areas (PMAs) is essential for the control of non-point source (NPS) pollution, especially for a large-scale watershed. However, previous studies have typically focused on small-scale catchments adjacent to specific assessment points; thus, the interactions between multiple river points remain poorly understood. In this study, a multiple-assessment-point PMA (MAP-PMA) framework was proposed by integrating the upstream sources and the downstream transport aspects of NPS pollution. Daning River watershed was taken as a case study in this paper, which has demonstrated that the integration of the upstream input changes was vital for the final PMAs map, especially for downstream areas. Contrary to conventional wisdom, this research recommended that the NPS pollutants could be best controlled among the upstream high-level PMAs when protecting the water quality of the entire watershed. The MAP-PMA framework provided a more cost-effective tool for the establishment of conservation practices, especially for a large-scale watershed.

Keywords: Priority management area; Multiple assessment points; Non-point source pollution; Upstream-downstream relationship; Integrated modeling

1. Introduction

Unlike point source pollution, nonpoint source (NPS) pollution varies greatly at multiple spatial and temporal scales, making it difficult and costly to identify and alleviate (Kovacs et al., 2012; Squillace and Thurman, 1992). As widely accepted concepts, priority management areas (PMAs) are defined as those areas where the risk potential of certain pollutants exceeds local loss tolerance or contributes more pollutant to the nearby water body (Carpenter et al., 1998; Ghebremichael et al., 2013). Many successes of the NPS control efforts have been reported based on PMAs (Ghebremichael et al., 2010; Kovacs et al., 2012; Setegn et al., 2009; Strauss et al., 2007; Tripathi et al., 2003; White et al., 2009; Whitehead et al., 2007; Yeghiazarian et al., 2006; Zhou and Gao, 2011). Today, the targeting of watershed PMAs has been integrated as an inherent part of large-scale watershed management programs, such as the Total Maximum Daily Load (TMDL) (Savage and Ribaudo, 2013;Sahoo et al., 2013; White et al., 2009).

As a geographically connected unit, a watershed can be broken into a distinct stream network and corresponding sub-watersheds (Gerard-Marchanti et al., 2006; Liu and Weller, 2008; Miller et al., 2013). A river assessment point, where water quality is sampled and evaluated, is usually designed as the key variable in assessing and protecting water quality within a river network (Lee et al., 2012). A typical assessment point is placed at the outlet of a key sub-watershed or tributary, a specific location of interest, or other key physical boundary, such as the downstream node of a stream segment (Brown and Barnwell, 1987; Lee et al., 2012). Despite the potential advantages of watershed-scale PMAs, watershed management programs and related funds currently focus on high-pollutant-loss areas that are of small scale or within a specific district. This idea is derived from the land resource perspective, which brings local collaborators into the cost share programs. However, from a water quality perspective, the scientific basis of these watershed management programs have long been questioned because these approaches cannot address the water quality at multiple assessment points, especially for large-scale watersheds.

Previous studies have demonstrated the impact of those sensitive areas on the water quality at certain assessment points. For example, Meybeck (1998) reported that most PMAs of nitrogen (N) were located along small agricultural streams, while the loss potential of phosphorus (P) was higher when adjacent to the watershed outlet. However, the impacts of these spatial units on the water quality vary greatly among multiple assessment points. Böhlke and Denver (1995) found that there was a decreasing impact of the drainage areas from upstream to downstream in the Atlantic Coastal Plain, USA. Alexander et al. (2000) analyzed the monitoring data collected from 374 river assessment points in the USA, and their results showed the P loss declined from the main channel to the tributary. Prasad et al. (2005) further demonstrated that multiple river assessment points integrated the source and transport aspects of NPS pollution at the watershed scale. These studies have improved our understanding of the spatial variability of PMAs at the catchment scale (Hefting et al., 2006). However, the nature of the interactions among those multiple river points still remains poorly understood. The relationship between the upstream and downstream assessment points has yet to be developed for those large-scale watersheds (Horton, 1945; Kang et al., 2008; Meynendonckx et al., 2006; Rodriguez-Iturbe and Rinaldo, 1997).

One solution is to identify those sensitive areas responsible for disproportionate load contributions to the pollutant fluxes at multiple river assessment points (Behera and Panda, 2006). The aim of this paper is to establish a multiple-assessment-point PMA (MAP-PMA) framework for a more cost-effective allocation of PMAs. In this new framework, the respective impacts of each spatial unit on multiple assessment points were considered instead of those deterministic areas adjacent to a specific river point. An innovative approach is presented here, which integrates the response of downstream water quality to the corresponding variation of upstream inputs.

2. Materials and Methods

2.1. Study watershed description

The Daning river watershed (108°44′-110°11′E, 31°04′-31°44′N), which located in the north-east part of the Three Gorges Reservoir Area (TGRA), China, was selected as the study area. The drainage area of this watershed is 2,422 km^2, and the geological formation is dominated by mountains (95%) and low hills (5%), with elevations ranging from 2588 m in the north to 200 m in the south. In this watershed, the headwater areas are characterized by high relief and valley gradients, which are conducive to the transport of NPS pollutants. The middle and low catchments exhibit low-gradient alluvial channels bounded by agricultural areas. The local climate is temperate and humid, with an average annual precipitation of 1,124 mm. The land cover types that dominate the watershed are forest (65.8%), agricultural area (22.2%), and grassland (11.4%).

In the TGRA, point source pollution is insignificant owing to the absence of large sewage systems and strict regulations. However, NPS pollution remains largely unregulated and accounts for a large share of the pollutant release into eutrophic water bodies (Wu and Zheng, 2013). Eutrophication, in terms of algae blooms, has increased eightfold in the TGRA since 1990, and a particular emphasis has been placed on NPS-P. In our previous studies (Gong et al., 2011; Shen et al., 2012; Shen et al., 2013), the upstream areas of the Wuxi station (labeled as AP-1 in this research) have served as a study area. For the purpose of comparison, both of the upstream areas of AP-1 and the watershed outlet (labeled as AP-2) were selected as the study area (Fig. 2a), and the targeting results were based on the load contributions of each sub-watershed to the P fluxes at AP-1 and AP-2.

2.2 The MAP-PMA framework

The MAP-PMA framework, which integrates the interactions between multiple river points from upstream to downstream, is shown in Fig. 1. The upstream PMAs are first identified based on the required load reduction at the upstream assessment point. Then, the downstream PMAs are identified by the variations of pollutant fluxes at the downstream river point. In the end, each required load reduction is separated into its origin sources to reach a specific frequency of water quality target at multiple assessment points.

2.2.1 The targeting of upstream PMAs

In **Step 1**, the river network information was extracted from a digit elevation map (DEM) using the hydrology module of ArcGIS. As shown in Fig. 2a, AP-1 and AP-2 were placed at the outlets of sub-watershed No. 67 and 80, respectively. Traditionally, the upstream pollutant inputs are assumed to transport semi-systematically downstream. In the MAP-PMA framework, this classical continuum idea was replaced by a hierarchical idea, in which the river network is divided into smaller river sections between multiple assessment points (Brierley and Fryirs, 2011; Miller et al., 2012; Miller et al., 2013). Each river section represents a homogeneous spatial unit, which associated with a specific assessment point within the river network.

In **step 2**, a multi-level PMAs (ML-PMAs) approach, recommended by our previous study, was used successively for each river section through the river network. The ML-PMA approach, which integrates both watershed and river processes, was proposed by integrating a watershed model, a stream model and a Markov chain method. The detailed processes involve the following three steps.

Step 2-1: The watershed processes were simulated using the Soil Water Assessment Tool (SWAT) (Arnold et al., 1998). In our previous studies (Shen et al., 2012; Shen et al., 2013; Shen et al., 2008, 2010), the SWAT model was applied in the Daning River watershed to quantify the pollutant loads release from each sub-watershed. In this research, the flow and P yields were obtained from our constructed SWAT model.

Step 2-2: The in-stream processes for each river section were simulated by the Qual2kw (Brown and Barnwell, 1987). For loose modeling, the SWAT results were used as model inputs to the river process model (Wu et al., 2006). More information about these two models and the calibration processes can be obtained from our related studies (Shen et al., 2012; Shen et al., 2013; Shen et al., 2008, 2010). Following model calibration (Gong et al., 2011; Shen et al., 2012; Shen et al., 2013), a 10-year modeling period was performed to isolate climate change and land use change.

Step 2-3: Lastly, the total pollutant fluxes at certain assessment point were separated, in terms of their origin sub-watersheds, by the Markov matrix calculation provided by Grimvall and Stalnacke (1996). In this respect, those upstream sub-watersheds were characterized and ranked based on their load contributions to the water quality at certain assessment points. Compared to the required water quality standard of China (GB3838-2002), the total phosphorus (TP) concentration '<0.1 mg/l' was considered as the water quality target for both AP-1 and AP-2. Thereafter, those multiple levels of PMAs were corresponded to the upgrading of the frequency of this water quality target. More details about the ML-PMA approach can be found in our previous study.

2.2.2 The targeting of downstream PMAs

Following **step 2**, after allocating the required load reductions among the upstream sub-watersheds, the water quality at the upstream assessment point was assumed to reach the required level. In **steps 3 and 4**, the concept of 'connectivity', mentioned by Hooke (2003), was used to refer to the response of the pollutant fluxes at the nearby downstream point to the variation of upstream inputs (Buchanan et al., 2013). In this respect, the response of the downstream pollutant fluxes was quantified based on the variation of the upstream inputs if these two assessment points were hydrologically connected. Assume the flow, pollutant load and concentration during the baseline period can be marked as $q_1, ..., q_j, ... q_k$, $load_1, ..., load_j, ... load_k$, and $c_1, ..., c_j, ... c_k$, respectively, for each assessment point. To reach the water quality target, the load reduction requirement at each river point was calculated as $\Delta E_1, ..., \Delta E_j, ..., \Delta E_k$, which can be expressed as follows:

$$\Delta E_j = 31.54 \times (C_j q_j - C_{js} q_{js}) \tag{1}$$

where ΔE_j represents the required load reduction at assessment point e_i (t/year), q_i and C_i represent the flow (m^3/s) and water quality (mg/l), respectively, during the baseline period, and q_{js} and C_{js} represent the required water quality target (mg/l) and the corresponding flow (m^3/s) , respectively. Over a long period, the flow volume can be assumed to stay unaffected so equation 1 becomes:

$$\Delta E_i = 31.54 \times (C_i - C_{is}) q_i \tag{2}$$

If $C_i < C_{js}$, ΔE_j is defined as 0. In this respect, there is no further load reduction requirement at the downstream assessment point. In **step 2**, the river retention potentials between each pair of assessment points were quantified based on the method given by Grimvall and Stalnacke (1996) and expressed by the following matrix:

$$Z=\begin{pmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1k} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{k1} & \alpha_{k2} & \cdots & \alpha_{kk} \end{pmatrix} \quad (3)$$

where each matrix element represents the river retention potential between e_i and e_j, which integrates the river transport aspects of NPS pollution. Thereafter, the responds of pollutant fluxes at the nearby downstream point to the variation of upstream inputs can be quantified as follows:

$$\Delta E'_{j+1} = 31.54 \times \sum_{j=1}^{m} \alpha_j \times \Delta E_j \quad (4)$$

where $\Delta E'_{j+1}$ represents the variation of downstream pollutant fluxes (t/year), and m represents the number of its upstream tributaries.

In the **following steps**, the value of $\Delta E'_{j+1}$ was compared to the required load reduction at the nearby downstream assessment point. If $\Delta E'_{j+1} \geq \Delta E_{j+1}$, the changed water quality can be assumed to have reached the required water quality target. For a more effective allocation of those downstream PMAs, no further load reductions are needed, and thus the downstream sub-watersheds are identified as the low-level PMAs. Otherwise, if $\Delta E'_{j+1} < \Delta E_{j+1}$, the load reduction requirement at this point is $\Delta E_{j+1} - \Delta E'_{j+1}$. Thereafter, those multi-level PMAs were re-identified based on this changed load reduction requirement. Finally, the MAP-PMA framework determined whether there were any more downstream assessment points. If there were any other assessment points, this algorithm proceeded to the next nearby downstream point. If there were not, this algorithm terminated. Contrary to conventional wisdom, the multiple levels of PMAs for a given large watershed or a complex river network are allocated from upstream to downstream.

3. Results and Discussion

3.1 The comparison between multiple- and single- assessment points results

Based on the framework of MAP-PMAs, the ranking result of each sub-watershed could be obtained, which provided the basis of multiple-levels PMAs. In this section, the targeting results of multiple- and single- assessment points PMAs are compared. As shown in Table 1, the TP concentration over the period of 2000-2009 ranges from 0.07 to 0.27 mg/l at AP-1 and 0.07 to 0.17 mg/l at AP-2. Therefore, the required TP load reductions were quantified as 16.43, 30.29, 50.00, and 64.12% at AP-1 and 7.02, 23.21, 29.66, and 43.99% at AP-2, respectively. The current frequency of water quality target was approximately 60%, so five range values, in terms of <70%, 70-80%, 80-90%, 90-100% and 100% frequency, were used to illustrate the multiple levels of PMAs. To reach each frequency of water quality target, the load reductions at AP-1 were quantified as 101, 263, 453, and 610 tons. Likewise, the variations of TP fluxes at AP-2 were 96-148, 168-259, 300-463, and 378-582 tons during the period of 2000-2009. Specifically, if the water quality was targeted as 100% at AP-1, the frequency of this target at AP-2 increased from 60% to 100% as well. Conversely, if the water quality targets were set as 70, 80, and 90% at AP-1, the required load reduction at AP-2 leveled off from 23.21% in 2000, 29.66% in 2002, and 43.99% in 2003 to 12.07, 18.00, and 32.36%, and 3.71, 9.26, and 23.64%, and 0.00, 0.00, and 7.65%. This result demonstrated that the upstream water quality had a great impact on the downstream pollutant fluxes. Therefore, the interactions between these river assessment points identified by the MAP-PMA integrate the upstream sources and the downstream transport aspects of the NPS pollution at the watershed scale.

As shown in Fig. 2b, the targeting results for AP-1 showed that a total 15.06, 15.29, 23.66, 20.05, and 10.13% of the upstream areas of AP-1 were identified as the 1st-, 2nd-, 3rd-, 4th-, 5th-level PMAs, respectively. These multiple levels of PMAs disproportionately contributed 25.90, 20.94, 27.04, 19.40 and 6.72% of the TP fluxes at AP-1. On the aspect of spatial distribution, high-level PMAs were distributed among the areas adjacent to AP-1 and the Houxi River. Specifically, sub-watersheds No. 69-80 were not included in the targeting results of AP-1 because these sub-watersheds were located along the downstream of AP-1. Conversely, as shown in Fig. 2c, these sub-watersheds were identified as high-level PMAs for AP-2 because of their geographic locations adjacent to AP-2. This result indicated that there was a declining trend of load contribution of upstream areas from upstream to downstream assessment points, while the impact of those downstream sub-watersheds increased among multiple river points. The corresponding level PMAs for AP-2 accounted for 7.59, 12.58, 10.69, 19.23, and 50.91% of the total area and 14.48, 16.73, 13.23, 18.32, and 37.24% of the total TP fluxes.

On the aspect of the MAP-PMAs, the level of each downstream sub-watershed increased as the water quality target increased from 60% to 100% at AP-1. As shown in Table 2, if the upstream water quality was targeted as 100%, sub-watershed No. 68-80 were identified as 5th-level PMAs, indicating that there was no further required load reduction at AP-2. If the upstream water quality target was approximately 90%, sub-watersheds No. 70 and 74-78 leveled off from 1st-level PMAs to 4th-level PMAs, while the remaining sub-watersheds were identified as 5th-level PMAs. This could be considered an important insight suggested by the MAP-PMA framework. Compared to the single point results, the interactions between upstream and downstream points are very helpful for a more cost-effective allocation of watershed PMAs, especially for those downstream areas. Furthermore, if the upstream water quality was targeted as 70% or 80%, there were no 1st-level and 5th-level PMAs among the downstream areas. This result indicated a maximum frequency of water quality target existed at the downstream river point (90% at AP-2) if the pollutant removal potential at the upstream point was below a certain threshold. This could be considered another important insight provided by the MAP-PMA framework. In general, the pollutant removal potential is usually below a specific threshold due to local economic or technical constraints (Domingo et al., 2007; Massoud et al., 2006; Sharpley et al., 1999; Sun et al., 2010; Zhang et al., 2009). From the economic point of view, to control the NPS pollution among multiple assessment points, emission trading is recommended as a more effective approach by producing a legal right of NPS pollution discharge and trading it as a commodity between upstream and downstream areas (Crutchfield et al., 1994).

3.2 The comparison between the MAP-PMA and traditional targeting approach

In this research, the MAP-PMA framework was based on a hierarchical idea, and the respective impacts of each spatial unit were separated from upstream to downstream. Comparatively, using the classical continuum idea, multiple assessment points were treated as an entirety by the traditional approach, and the identifying of PMAs generally focused on the highest impact of each spatial unit (Hefting et al., 2006). As shown in Fig. 2e, the corresponding levels of the traditional PMAs accounted for 50.00, 18.75, 13.75, 6.25, and 11.25% of the total number and 39.38, 26.37, 10.22, 8.55, and 15.13% of the total area of the Daning watershed. Clearly, the proportion of high-level MAP-PMAs was less than that of the traditional PMAs, while the percentile of low-level MAP-PMAs was much higher.

On the aspect of spatial distribution, no dramatic variations of PMAs were observed among the upstream areas adjacent to AP-1. This was because the river transport process stayed almost unaffected in the adjacent regions of AP-1. Conversely, there was great variation between the MAP-PMAs and traditional PMAs among the downstream areas. This can be explained by the fact that the MAP-PMA focused on the pollutant load actually reaching those multiple assessment points. First, there was a general trend of reduced agricultural areas from upstream to downstream in the Daning watershed. This trend implied reduced P loss potentials among those downstream areas because agricultural lands generally induce a greater impact on the export of P than other land uses (Whitehead et al., 2007; Gong et al., 2011; Shen et al., 2012; Shen et al., 2013). Second, the upstream P concentration have been diluted during the transport process because of the long hydrological residence time within the downstream river network (Arheimer and Brandt, 2000; Bae and Ha, 2006; Zhou and Gao, 2011). The P depletion and P consumption by phytoplankton is also important during the downstream in-stream transport. In this sense, traditional PMAs appeared to have higher loss potentials relative to certain assessment points. However, as indicated by Table 2, the upstream P fluxes were rarely translated to the nearby downstream assessment points. Therefore, those traditional PMAs are questionable because the adoption of the classical continuum idea hindered the documenting of the upstream input changes, especially with respect to limited time and resource constraints.

As shown in Fig. 2d, it is possible to delineate those sensitive areas from high to low through the MAP-PMA framework. Among the high-level MAP-PMAs, there is more opportunity to reduce a much larger quantity of the NPS pollutant transported to multiple assessment points. Therefore, it is more effective to implement Best Management Practices (BMPs) in these high-level PMAs. Contrary to the conventional wisdom that BMPs are more effective adjacent to the watershed outlet (Hefting et al., 2006), it is demonstrated that more high-level MAP-PMAs are distributed among the adjacent areas of the upstream river point. In this sense, it is recommended that the NPS pollutant could be best controlled among the upstream high-level PMAs adjacent to AP-1, and also by preventing the P exports from the downstream areas to protect the water quality of the entire watershed.

4. Conclusions

In this research, a MAP-PMA framework was proposed for aiding the targeting of PMAs, especially for large-scale watersheds. Compared to single assessment point results, the MAP-PMA framework integrated the upstream inputs and the downstream transport aspects of NPS pollution at the watershed scale. Based on the results obtained from this research, the integration of the upstream input changes was vital for the final PMAs map, especially for a more cost-effective allocation of those downstream PMAs. From this study, a maximum frequency of water quality target existed at the downstream river point if the pollutant removal potential at the upstream point was below a certain threshold. Contrary to the conventional wisdom, it is recommended that the NPS pollutant could be best controlled among the upstream high-level PMAs in protecting the water quality of the entire watershed.

The major error of the MAP-PMA may come from the selection process of multiple assessment points. In this research, the existing water quality monitoring stations were chosen as multiple assessment points where such were available. However, these stations were designed as a monitoring network for point source pollution and may not refer to the perspective of the NPS pollution. Therefore, by the aid of the MAP-PMA, the resolution of the current monitoring network should be improved. It is believed that the optimal design of the monitoring network, together with the MAP-PMA framework, would provide a valuable tool for effectively allocating state funds for the establishment of conservation practices where they are needed.

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Table 1 The TP load reduction requirements at the Wuxi station and the watershed outlet during the period of 2000 to 2009

Period	Rainfall (mm)	AP-1			AP-2		
		Load (t)	Concentration (mg/l)	Exceed	Load (t)	concentration (mg/l)	Exceed
2000	1111	952	0.27	64.12%	1329	0.13	23.21%
2001	728	642	0.08	0%	804	0.11	7.02%
2002	1082	871	0.14	30.29%	1162	0.14	29.66%
2003	1444	865	0.20	50%	1156	0.17	43.99%
2004	1028	618	0.12	16.43%	782	0.07	0%
2005	1193	787	0.09	0%	986	0.09	0%
2006	790	669	0.07	0%	842	0.08	0%
2007	1254	723	0.09	0%	909	0.09	0%
2008	1257	699	0.09	0%	884	0.08	0%
2009	1240	680	0.09	0%	875	0.08	0%

AP-1 represents the Wuxi station, AP-2 represents the watershed outlet

Table 2 The targeting results based on the MAP-PMAs in the Daning Watershed

Sub-watershed	Load (t)	Cumulative load (%)	Cumulative area (%)	The targeting results				
				60%	70%	80%	90%	100%
76	421	0.04%	0.01%	1st	2nd	2nd	4th	5th
78	27748	2.44%	0.86%	1st	2nd	2nd	4th	5th
77	441	2.47%	0.88%	1st	2nd	2nd	4th	5th
70	43095	6.20%	2.41%	1st	2nd	2nd	4th	5th
74	34153	9.15%	3.72%	1st	2nd	3rd	4th	5th
75	5749	9.65%	4.00%	1st	2nd	3rd	4th	5th
79	52010	14.15%	7.24%	2nd	2nd	3rd	5th	5th
68	61654	19.48%	11.11%	2nd	2nd	4th	5th	5th
80	30135	22.09%	13.01%	2nd	3rd	4th	5th	5th
72	45054	25.98%	15.92%	3rd	3rd	4th	5th	5th
73	4926	26.41%	16.25%	3rd	3rd	4th	5th	5th
69	9745	27.25%	16.93%	4th	4th	4th	5th	5th

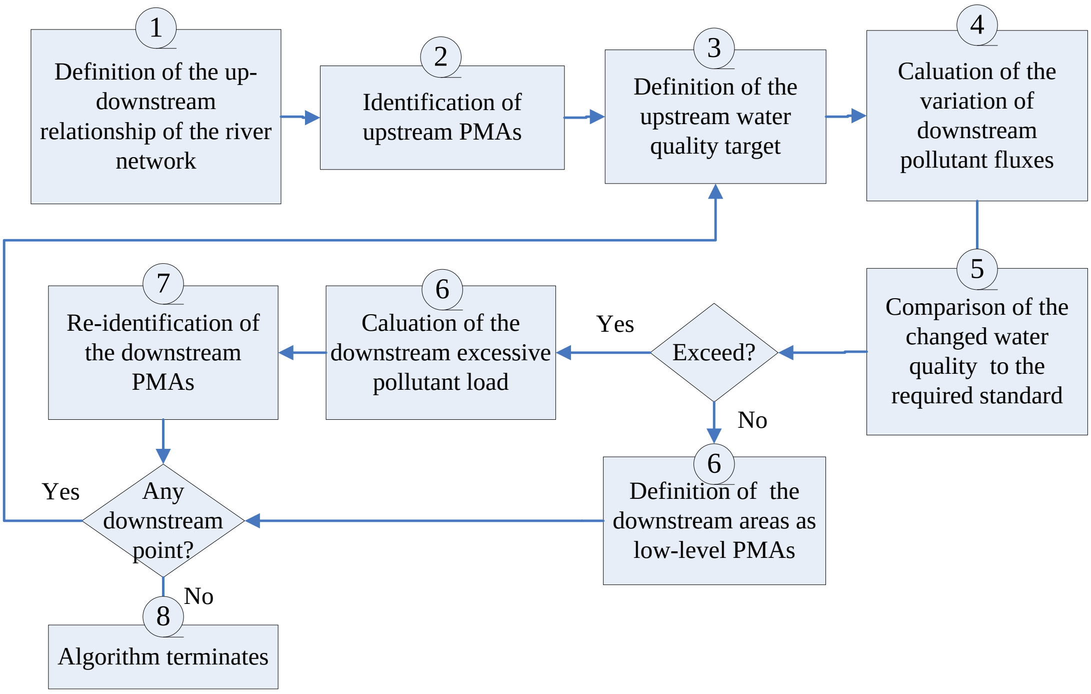

Fig. 1 The framework of the MAP-PMA

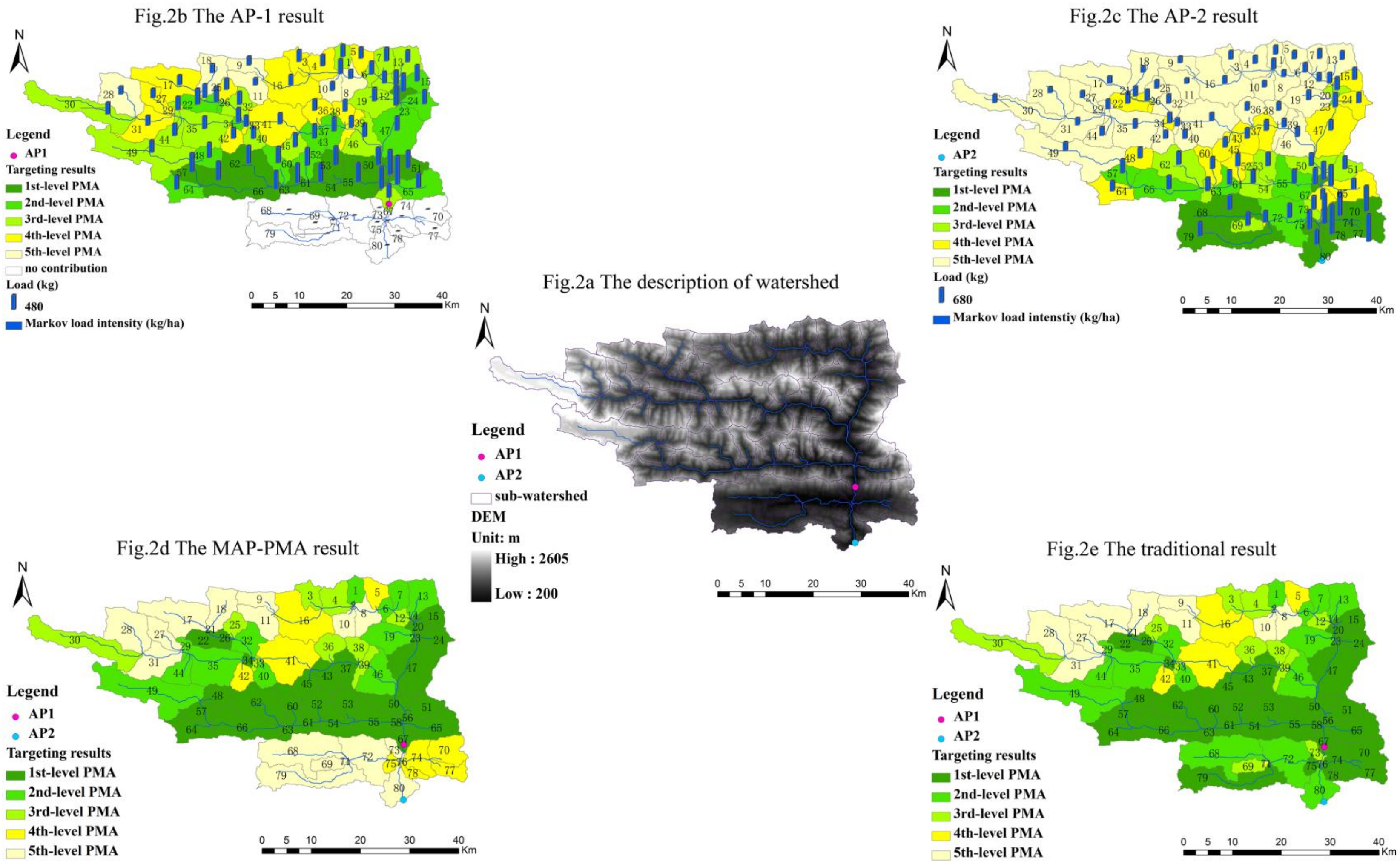

Fig. 2 The targeting results of the MAP-PMA, the AP-1, the AP-2, and traditional approach