Ecological Indicators 146 (2023) 109919

Contents lists available at ScienceDirect

Ecological Indicators

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

A framework for identifying priority areas through integrated eco-environmental risk assessment for a holistic watershed management approach

Hualin Li [a], Shouhong Zhang [a,b,c], Jianjun Zhang [a,b,c,*], Wenlong Zhang [a], Zhuoyuan Song [a], Peidan Yu [a], Chenxin Xie [a]

[a] School of Soil and Water Conservation, Beijing Forestry University, Beijing 100083, China
[b] National Station for Forest Ecosystem Research in Ji County, Ji County, Shanxi 042200, China
[c] Beijing Engineering Research Center of Soil and Water Conservation, Beijing 100083, China

A R T I C L E I N F O

Keywords:
Integrated watershed management
Priority management areas
Integrated eco-environmental risk assessment framework
Risk zoning
Socio-economic system

A B S T R A C T

Identifying priority management areas (PMAs) through assessing integrated eco-environmental risk (IER) of watersheds is vital for efficient integrated watershed management (IWM). However, there is a lack of effective tools to support IWM. A novel framework, which couples the analytical network process with the mean-square deviation decision method to quantify reciprocal feedbacks between ecosystems and socio-economic systems for assessing IER, was developed to identify PMAs for IWM through a case study in the upper Beiyun River watershed, China. The results show that water pollution, water resources, soil loss, hazards (i.e., floods, debris flows, collapses, and landslides), and vegetation degradation are noticeable environmental problems in the watershed. Water pollution, floods, and vegetation degradation risks are high in the southeast plain areas and low in the northwest mountainous areas of the watershed, while the other eco-environmental risks are opposite that of the three risks. The soil loss is mainly dominated by negligible class with a mean of 10.87 ($t \cdot km^{-2} \cdot yr^{-1}$). The weights of water pollution risk and socio-economic indicator for IER are 0.2906 and 0.1837, respectively. It indicates that water pollution control is crucial for IWM, and socio-economic systems have a significant impact on IER. The PMAs, which are identified as zones with extremely high IER values, account for 6.46 % (72.91 km^2) of the watershed. They are centrally distributed in the southeastern areas with high risks of both water pollution and vegetation degradation caused by large population density. The framework provides an effective tool to assess IER and identify PMAs for IWM.

1. Introduction

Watersheds are social-ecological systems where humans and other organisms interact with the physical environment and each other (Mosaffaie et al., 2021), and provide many ecosystem services such as nutrient cycles, energy transfer, water supply, carbon storage, and habitats (Lu et al., 2018). Watersheds are considered as the most effective units for managing the complex relationships among the water-land-air-plant-human nexus to support regional sustainable development (Li et al., 2018; RazaviToosi and Samani, 2019). Healthy watersheds play a vital role in ensuring the sustainability of social-economic systems and improving the well-being of humans (Ervinia et al., 2019; Moradi and Limaei, 2018). Healthy watersheds have high reliability and resilience, which suggests that watersheds must be restored and controlled a healthy level through integrated eco-environmental risk assessment for implementing effective watershed restoration and management (Duan et al., 2022). These restored watersheds could be reduced the impact of climate change and human activities on watershed ecosystems and sustainable development (Liu et al., 2020a). However, many watersheds are degrading or have the potential to become impaired because of climate change, urbanization, and the rapid development of industry, agriculture and tourism (Lerch et al., 2015; Sanches Fernandes et al., 2018; Zhang et al., 2022). Consequently, there are various environmental problems in many watersheds, which have resulted in forgone watershed ecosystem service functions.

To restore degraded ecological functions, integrated watershed

* Corresponding author.
E-mail address: zhangjianjun@bjfu.edu.cn (J. Zhang).

https://doi.org/10.1016/j.ecolind.2023.109919
Received 11 November 2022; Received in revised form 11 January 2023; Accepted 14 January 2023
Available online 20 January 2023

management (IWM) is increasingly adopted in many regions around the world (Mekonnen et al., 2021; Šatalová and Kenderessy, 2017). IWM is a holistic method to optimize the complex interactions between ecosystems and socio-economic systems for ensuring sustainable development (Arteaga et al., 2020; Kang and Park, 2015). For instance, the Rhine River was regarded as “a dead river” in the 1970 s because of severe eco-environmental problems resulting from rapid industrialization and population growth (Dieperink, 2000). With the implementation of an IWM program called the Rhine action plan, the ecological functions of the Rhine River watershed gradually recovered (Wang et al., 2016). It has been reported that the Poyang Lake watershed has experienced serious environmental problems, such as water pollution and soil loss, due to the rapid increase in population since the 1980 s (Liu et al., 2015). After the implementation of the IWM, the ecosystem of the Poyang Lake watershed was improved (Chen et al., 2005). Teka et al. (2020) indicated that implementing IWM could effectively reduce soil loss rates and increase people’s incomes in the Gule watershed. Brombal et al. (2018) showed that the environmental conditions of the Lihu watershed were improved and that the regional economy increased because of IWM. However, these outcomes were achieved through significant investments in resources, time, and manpower due to a lack of proper methods in IWM, leading to low cost-effectiveness and efficiency of IWM (Mosaffaie et al., 2021; Sun et al., 2016). It is still a challenge to improve the efficiency of IWM for watersheds with limited resources.

In order to improve the efficiency of IWM, priority management areas (PMAs) should be identified by considering as many eco-environment problems as possible or assessing integrated eco-environmental risk (IER) within watersheds (Evenson et al., 2021; Wang et al., 2016). PMAs are defined as relatively small yet sensitive areas with maximum potential eco-environmental problems. Previous studies have shown that deploying IWM measures in PMAs is of obvious significance for the economic viability and overall effectiveness of IWM (Huang et al., 2015; Shrestha et al., 2021). This is because the selection and configuration of IWM measures require consideration of the investment of both construction and maintenance, and the implementation of IWM measures across entire watersheds is economically and logistically unfeasible (Shen et al., 2015; Chen et al., 2022). Once the PMAs are identified, measurement systems can be efficiently determined for IWM, especially in regions with limited resources. For instance, Zou et al. (2021) identified PMAs for hazard management, and indicated that the PMAs are mainly distributed in regions with high altitudes and large slopes. Wu and Chen (2012) combined the SWAT model with the classical sediment transport method to identify PMAs for reducing soil loss. Chen et al. (2022) identified PMAs for non-point source pollution (NSP) management by using the SWAT model in the Daning River watershed. However, most of the previous studies only assessed a single problem (risk) to identify PMAs for watershed management, such as water pollution (Liu et al., 2018; Zhong et al., 2020), soil loss (Bekele et al., 2022; Liu et al., 2020b), desertification (Abuzaid and Abdelatif, 2022; Karavitis et al., 2020), hazards (Chen and Li, 2020; Zou et al., 2021), and vegetation degradation (Sun et al., 2020; Zhumanova et al., 2018). None of these previous studies identified PMAs through assessing integrated eco-environmental problems (risks) to support efficient IWM.

Previous studies have focused on a single problem to manage watersheds. For instance, Zuo et al. (2022) used the SWAT model to identify PMAs of water pollution and assess the impacts of precipitation on the identification of PMAs. Guo et al. (2022) reported that PMA identification of water pollution will help to improve the scientific configuration of IWM. Wu et al. (2022) integrated the SWAT model and entropy weight method to identify PMAs, and these areas should be implemented BMPs to reduce the environmental impact of soil loss. Yu et al. (2021) reported that PMA identification of soil loss for implementing watershed conservation practices can reduce investment and disturbance. Sobhani et al. (2017) analyzed different scenarios of management strategies through assessing the desertification sensitivity map. Turkes et al. (2017) used the analytical hierarchy process model to assess desertification vulnerability and risk. Only a few previous studies have assessed the multiple environmental risks for watershed management from the perspective of subjective consciousness. Karageorgis et al. (2005) used the driver-pressure-state-impact-response (DPSIR) framework to assess environmental pressures and risks driving climate change and socioeconomic development. Wang et al. (2006) used an interval fuzzy multi-objective watershed management model to assess healthy watersheds and solve an IWM problem in the Lake Qionghai watershed. Water pollution, water supply, forest coverage, tourism, and soil loss were fully interpreted for optimal planning of management strategies. Parkes et al. (2010) used the watershed governance prism method to explore integrated governance for social-ecological systems, water, and health. Bremer et al. (2021) investigated the PMAs for groundwater recharge and drinking water protection in Hawai’i Island.

In addition, some studies focused on the relationships between the ecological environment in watersheds and socio-economic development. Alvarado et al. (2021) reported that the ecological footprint is an integrated index for assessing environmental problems because it evaluates the impact of both climatic change and human activities, and this study explored the effect of both natural resources rents and economic complexity on the ecological footprint in Latin America. Khan et al. (2022) explored the impact of economic expansion, clean energy, and trilemma energy balance on environmental sustainability. Xie et al. (2022) explored the impact of the forestry resources obtained from IWM on socio-economic development. Although the methods of IWM have been highlighted in several studies, the optimal method should be explored because of the complexity of watershed management. For instance, the interpretive structural modeling (ISM), the analytical hierarchy process (AHP) method, the analytical network process (ANP), the expert scoring method, the coefficient variation method (CVM), and data envelopment analysis, are used to assess the watershed environmental risk (RazaviToosi and Samani, 2019; Alilou et al., 2019; Alamanos et al., 2020). A multi-objective optimization algorithm (e.g., genetic algorithm, non-dominating sort genetic algorithm, and string pareto evolutionary algorithm) is applied to the optimization design of best management practices for efficient watershed management (Liu et al., 2019). The life cycle assessment method is used to assess the efficiency of governance measurement systems for IWM (Mostashari-Rad et al., 2020; Nabavi-Pelesaraei et al., 2017).

Unlike previous studies, this study diagnoses the possible environmental problems in a watershed based on the natural environment and socio-economic data, and then different environmental risks are quantitatively assessed to establish an indicator system including both eco-environmental risks and socio-economic factors. The weights of both potential eco-environmental risks and socio-economic factors are determined to assess the IER of watersheds. The IER is classified into different levels to identify PMAs for IWM. The novelty of this study is to develop a framework to quantitatively identify PMAs through assessing IER for efficient IWM. The framework considers reciprocal feedbacks between ecosystems and socio-economic systems of watersheds by coupling the analytical network process with the mean-square deviation decision method. It is applied in the upper Beiyun River watershed which has been experiencing both ecological civilization construction and rapid urbanization. The results provide insights into quantitatively assessing IER of watersheds and identifying PMAs for efficient IWM.

2. Materials and methods

2.1. Framework development

Eco-environmental risk refers to the combined effect of the probability and consequence of events or activities induced by natural causes or human activities, which have adverse effects on the ecological environment. The integrated eco-environmental risk assessment (IERA) framework is developed to quantitatively identify PMAs through assessing IER within watersheds. As shown in Fig. 1, the steps of the framework are as follows. (1) Natural environment and socio-economic data are collected to diagnose the possible environmental problems within watersheds. (2) An indicator system including both eco-environmental risks and socio-economic factors is established. (3) The weights of both potential eco-environmental risks and socio-economic factors are determined to assess the IER of watersheds. (4) The IER is classified into different levels to identify PMAs for IWM. (5) The integrated measure systems could be selected and configured in PMAs. The framework could also be used to identify PMAs for a single environmental risk (e.g., water pollution), and to support the selection of control measures for this specific environmental risk.

2.1.1. Step 1. Qualitative analysis of watershed characteristics

The characteristics of different watersheds vary greatly as they are affected by many factors such as climate, human activities, hydrology, geology, soil, and vegetation characteristics (Elmes and Price, 2019; Qiu et al., 2021). Therefore, based on the collected data (e.g., rainfall, soil, water quality, vegetation, topography, lithology, and land use) of a watershed, the watershed characteristics must be analyzed to diagnose the possible eco-environmental risks, such as water pollution, hazards, desertification, water resources, vegetation degradation, and soil loss. In addition to these eco-environmental risks, the socio-economic system should also be considered because there is a strong relationship between ecosystems and socio-economic systems (Nguyen et al., 2016; Whitehead et al., 2018). For instance, regions with high incomes are more capable of eco-environmental risk control, while rapid population growth will increase pressure on ecosystems (Lopes et al., 2022; Mosaffaie et al., 2021).

2.1.2. Step 2. Establishing eco-environmental risk and socio-economic indicator system

Based on Step 1, the possible eco-environmental risks and socio-economic factors of watersheds are selected to establish an indicator system. The indicator system is listed and explained as follows (Fig. 2).

Water pollution: is one of the major challenges for watershed management as it has a fundamental impact on water ecosystems and public health (Ma et al., 2020; Wang et al., 2022). The influence of water quality is mainly categorized as point source pollution (PSP) and non-point source pollution (NSP). According to the national pollution source census manual of China, empirical models (e.g, export coefficient model) are applied to calculate water pollution (i.e., PSP and NSP) as shown in Appendix A.

Vegetation degradation: vegetation provides important ecological services and resources and plays an important role in the ecosystem (Chen et al., 2020; Isabel et al., 2020; Sun et al., 2020). It is necessary to assess vegetation quality for vegetation management (e.g., replanting, thinning, updating, and density control of vegetation). The assessment method can be found in Appendix A.

Water resource: is regarded as the leading, fundamental, and controlling factor of socio-economy development, and is the key element linking environmental protection, food production, energy development, and safe water supply (Bai et al., 2022; Zuo et al., 2021). Water yield is crucial since it provides water resources for people and other natural resources (Li et al., 2021a; Sun et al., 2019). The integrated valuation of ecosystem services and trade-offs (InVEST) model is applied to assess water yield as shown in Appendix A.

Soil loss: is a common form of land degradation with many negative influences, such as degrading soil structure, weakening soil fertility,

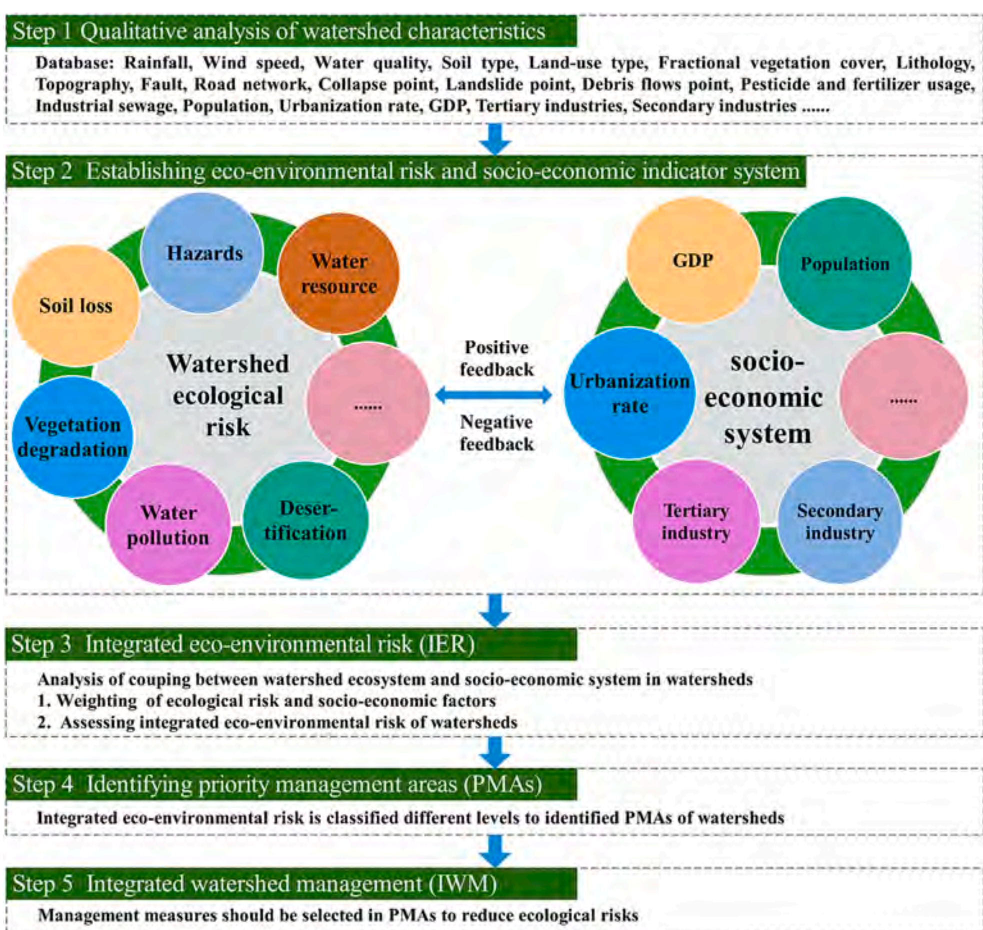

Fig. 1. Schematic diagram of integrated eco-environmental risk assessment (IERA) framework for integrated watershed management.

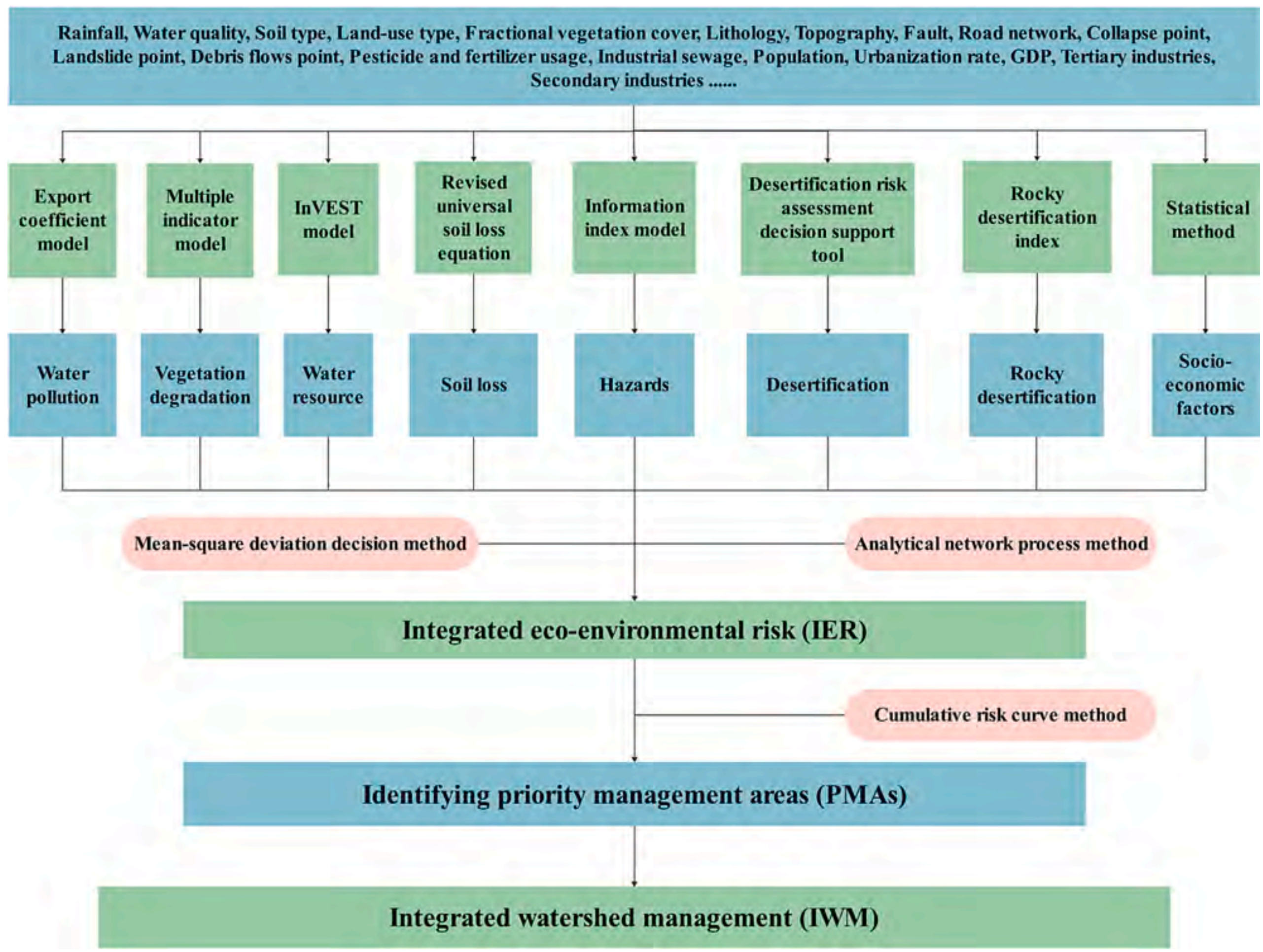

Fig. 2. Technology roadmap of integrated eco-environmental risk assessment (IERA) framework.

decreasing water availability, silting up rivers and reservoirs, and losing economy (Bouamrane et al., 2021; Kayet et al., 2018). The Revised Universal Soil Loss Equation is used to evaluate soil loss, referring to Appendix A.

Hazards: such as collapses, landslides, floods, and debris flows damage to water conservancy facilities and construction of traffic arteries, restricting local socio-economic development (Chen and Li, 2020; Zou et al., 2021). Previous research showed that thousands of hazards (e.g., collapses, landslides, floods, and debris flows) occur in China every year, and 9933 people died from hazards from 2001 to 2010 (excluding approximately 25,000 deaths from the Wenchuan earthquake) (Qiang et al., 2019). The calculation method is applied to assess hazards, as shown in Appendix A.

Socio-economic factors: socio-ecological systems of watersheds are complex and demonstrate reciprocal feedbacks between humans and nature (Nguyen et al., 2016; Whitehead et al., 2018). Due to the rapid development of the economy and industry, urbanization, and the rapid rise of population, the watershed ecosystem has collapsed, leading to economic, social, and cultural losses. On the contrary, the key environmental problem risks are used to assess and identify IER for restoring healthy watersheds, it will be led to diverse societal benefits (Leslie et al., 2015; Lopes et al., 2022). Thus, the impacts of socio-economic systems on watershed ecosystems should be nested in the IERA framework. According to the Pressure-State-Response (PSR) theory, the positive or negative impacts of socio-economic systems on watershed ecosystems are considered in the IERA framework (Hazbavi et al., 2020; Mosaffaie et al., 2021). Taking previous studies (Duan et al., 2021; Ferguson et al., 2017; Mosaffaie et al., 2021) as references, it is assumed that gross domestic product (GDP) and tertiary industry have positive impacts on watershed ecosystems, while population density, secondary industry, and urbanization rate have negative impacts on watershed ecosystems.

Additionally, the framework should also consider desertification (or rocky desertification) in watersheds with severe desertification (or rocky desertification) as it affects the local ecological environment, forestry production, agricultural activities, food security, etc. (Abuzaid and Abdelatif, 2022; Jiang et al., 2014). The desertification risk assessment decision support tool is used to assess the desertification risk, as shown in Karavitis et al. (2020). In addition, the evaluation of rocky desertification risk refers to ref. Zhang et al. (2021).

2.1.3. Step 3. Integrated eco-environmental risk (IER)

With the outputs from Step 2, the values of both possible eco-environmental risks and socio-economic factors are standardized through the max–min standardization method for eliminating the dimension impact caused by different ranges and units of these values (Li et al., 2022). The IER is then assessed by the weighted average of both possible eco-environmental risks and socio-economic factors within a watershed as shown in Eq. (1).

$$I = \sum_{i=1}^{n} a_i \cdot R_i \pm \sum_{j=1}^{n} b_j \cdot S_j \tag{1}$$

where I represents the IER of watersheds, a_i is the weight of the i-th kind of eco-environmental risk, R_i is the i-th risk, b_j is the weight of the j-th socio-economic factor, S_j is the j-th socio-economic indicator, and $\pm$ represents the positive or negative feedbacks between the socio-economic factors and the watershed ecosystems.

The weights of the eco-environmental risks and the socio-economic factors are determined by coupling the analytical network process (ANP) method with the mean-square deviation decision (MDD) method. The ANP method is based on multi-criteria decision-making (MCDM) theory, and it can be used to determine the weights of dependent indicators. Previous studies have shown that the method considers relationships among indicators of both socio-economic factors and eco-environmental risks in a more appropriate manner than other MCDM methods (e.g., the analytical hierarchy process (AHP) method, expert scoring method, coefficient variation method (CVM), and data envelopment analysis (DEA)) (Azareh et al., 2019; Sajedi-Hosseini et al., 2018). Details of the principles and computation steps of the ANP method are presented in Alilou et al. (2018) and Saaty (1996).

In the ANP method, a supermatrix of pairwise comparisons among indicators, which is used to calculate the relative weights of indicators, is generated by the expert scoring method (RazaviToosi and Samani, 2019). To avoid subjective error resulting from the expert scoring method, the MDD method can be used to replace the expert scoring method for building the supermatrix of pairwise comparisons to calculate the weights of indicators. The computation formulas and steps of the MDD can be found in Li et al. (2021b). In this study, the weights of the eco-environmental risks and socio-economic factors are determined for obtaining IER by using the MDD-ANP method.

2.1.4. Step 4. Identifying priority management areas (PMAs)

On the basis of Step 3, the obtained IER could be classified into five levels to identify PMAs of watersheds using the cumulative risk curve method. Details of the cumulative risk curve method are presented in Li et al. (2022).

2.1.5. Step 5. Integrated watershed management (IWM)

With the outputs from Step 4, management measures, such as soil erosion control, water purification, peak flow reduction, and disaster prevention practices, could be selected and configured in PMAs to reduce eco-environmental risks.

2.2. Case study

The IERA framework is applied in the upper Beiyun River watershed which has been experiencing both ecological civilization construction and rapid urbanization in the past four decades. The watershed is located in northwest Beijing, China, and its area is approximately 1130 km^2 (Fig. 3). The Dongsha River, Beisha River, and Nansha River are the three tributaries of the watershed. It is located in a warm temperate monsoon climate zone with cold and dry winter, hot and rainy summer, and four distinct seasons. The average annual rainfall ranges from 463 to 598 mm, and the annual average temperature ranges from 10 to 12 ℃ (Li et al., 2022).

3. Results

3.1. Qualitative analysis of watershed characteristics

The dataset of the upper Beiyun River watershed is collected and presented in Fig. B1 and Tables C1, 2. According to observed water quality data from 2018 to 2019 (Table C2), the total nitrogen (TN) and total phosphorus (TP) concentrations ranged from 1.72 mg·L^{-1} to 16.03 mg·L^{-1} and 0.06 mg·L^{-1} to 5.51 mg·L^{-1}, respectively. This indicated that the water was contaminated to varying levels, and the spatial distribution characteristics of water pollution risk should be investigated to improve water quality. The domestic waste disposal rate has reached 99.99 % based on the Beijing Statistical Yearbook, and there are no factories that may be a source of point source pollution(PSP) in the upper Beiyun River watershed. Therefore, the spatial distribution of non-point source pollution (NSP) is assessed to control water pollution in this watershed. The vegetation of the watershed has changed significantly because of urbanization and the implementation of policies (e.g., Ecological Civilization Construction, Grain for Green Program) in the past four decades (Li et al., 2022). Therefore, it is also necessary to evaluate vegetation quality. Rainfall is the most significant source of water recharge in the watershed, and the average annual rainfall changed from 463 mm to 598 mm from 1980 to 2020. Water yield should be evaluated to manage water resources. Moreover, approximately 80 % of the rainfall occurred between June and August, and the slope of the watershed is large and ranges from 0° to 87°. Therefore, soil

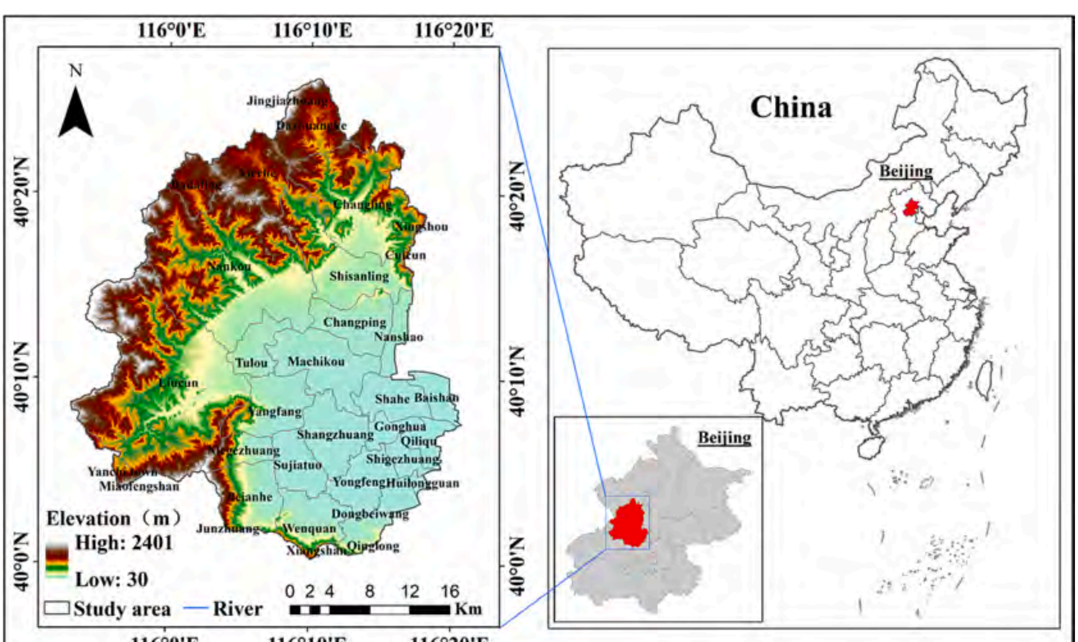

Fig. 3. Location of the upper Beiyun River watershed.

loss may occur in the watershed. Based on the hazard datasets provided by the Beijing Changping District Water Authority, hazards (i.e., debris flows, floods, collapses, and landslides) occurred occasionally in the watershed (Fig. B1). Meanwhile, tertiary industry (TI), population density (PD), secondary industry (SI), and gross domestic product (GDP) of the watershed are selected to quantitatively represent the socio-economic system.

3.2. Assessing eco-environmental risks and socio-economic factors

3.2.1. Non-point source pollution

The spatial distribution characteristics of non-point source pollution (NSP) in the upper Beiyun River watershed of 2019 are shown in Fig. 4. Generally, the high-value zones of both TN and TP, which are zones giving the maximum potential contribution to water pollution, are distributed in the southeastern plain zones. This is appropriate because most of these zones are densely populated or cultivated and may generate amounts of pollution. As shown in Fig. 4a, b, the highest values of TN and TP are estimated as 37.29 kg·pixel^{-1}·yr^{-1} (pixel size = 30 m × 30 m) and 1.88 kg·pixel^{-1}·yr^{-1}, respectively. On the other hand, the low-value zones of both TN and TP, which are zones exerting the minimum potential contribution to water pollution, are mostly located in the northwestern mountainous zones. The land-use types in these zones are mainly forest and pasture lands characterized by low anthropogenic modification and low pollution potential.

3.2.2. Vegetation degradation

Fig. 5a illustrates the spatial distribution characteristics of the vegetation ecological quality (VEQ) risk in the watershed. The high-value areas of VEQ risk, where vegetation management (e.g., replanting, thinning, updating, and density control of vegetation) should be implemented to improve the vegetation quality, are distributed in the southeastern plain areas. This is because most of these regions are urban land, cultivated land, and rural residential land, which are characterized by high population density and frequent human activities. It implies that the vegetation of these areas needs to be controlled for improving the ecological function of vegetation. In contrast, the low-value areas of VEQ risk are located in the northwestern mountainous areas with green spaces. It is worth noting that there are several sporadic high values in the northwest mountainous areas, which may be caused by the abnormal values from the MYD17A3HGF product dataset.

3.2.3. Water yield

The spatial distribution characteristics of water yield in the upper Beiyun River watershed are shown in Fig. 5b. The low-value regions of water yield are located in the northwestern mountainous areas. It is reasonable because most of these zones are forests, pasture, and orchard lands which are characterized by high rates of both evapotranspiration and soil infiltration. On the contrary, the high-value regions of water yield are distributed in the southeastern plain areas with built-up land (i.e., industrial land, rural residential land, and urban land). This is appropriate because the impervious surface leads to the reduction of evapotranspiration and the increase of surface runoff. It indicates that water yield will increase due to the increase in built-up land under the same rainfall conditions. As shown in Fig. 5b, the water yield is relatively low, and changes from 262.29 mm·pixel^{-1} to 566.86 mm·pixel^{-1}. It is fundamentally related to rainfall since rainfall is the most significant source of water recharge in the upper Beiyun River watershed.

3.2.4. Soil loss

According to the classification standard of soil erosion (SL190-2007) of China, the soil loss of the watershed is mainly dominated by negligible class with a mean of 10.87 t·km^{-2}·yr^{-1}, and 69.81 % of the watershed area is in the negligible class of soil loss (Table 1). Fig. 5c presents the spatial distribution characteristics of soil loss. The high-value areas of soil loss are mostly distributed in the northwestern mountainous areas with large slopes and relatively low vegetation coverage. In contrast, the soil loss rates are low in the southeastern plain areas where the main

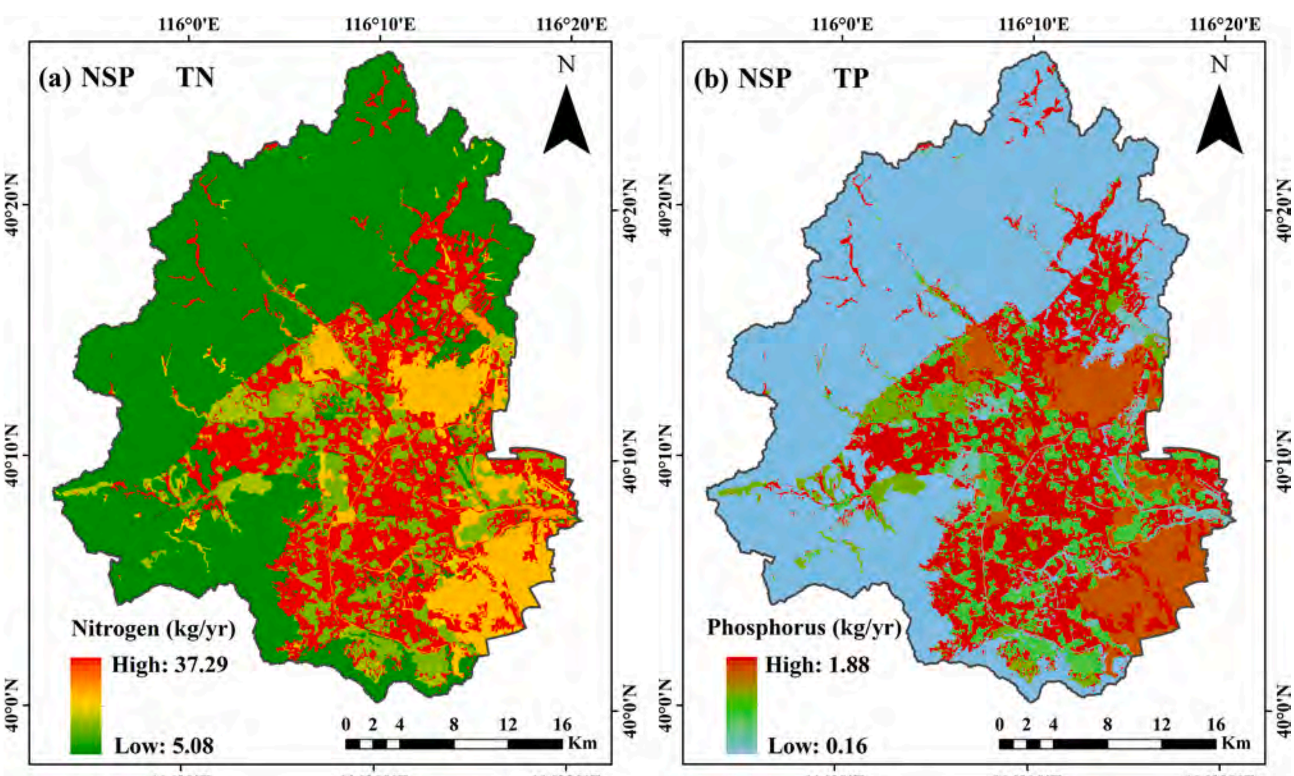

Fig. 4. Spatial distributions of both total nitrogen (TN) and total phosphorus (TP) of non-point source pollution (NSP) in the upper Beiyun River watershed. (a) TN release from NSP, (b) TP release from NSP.

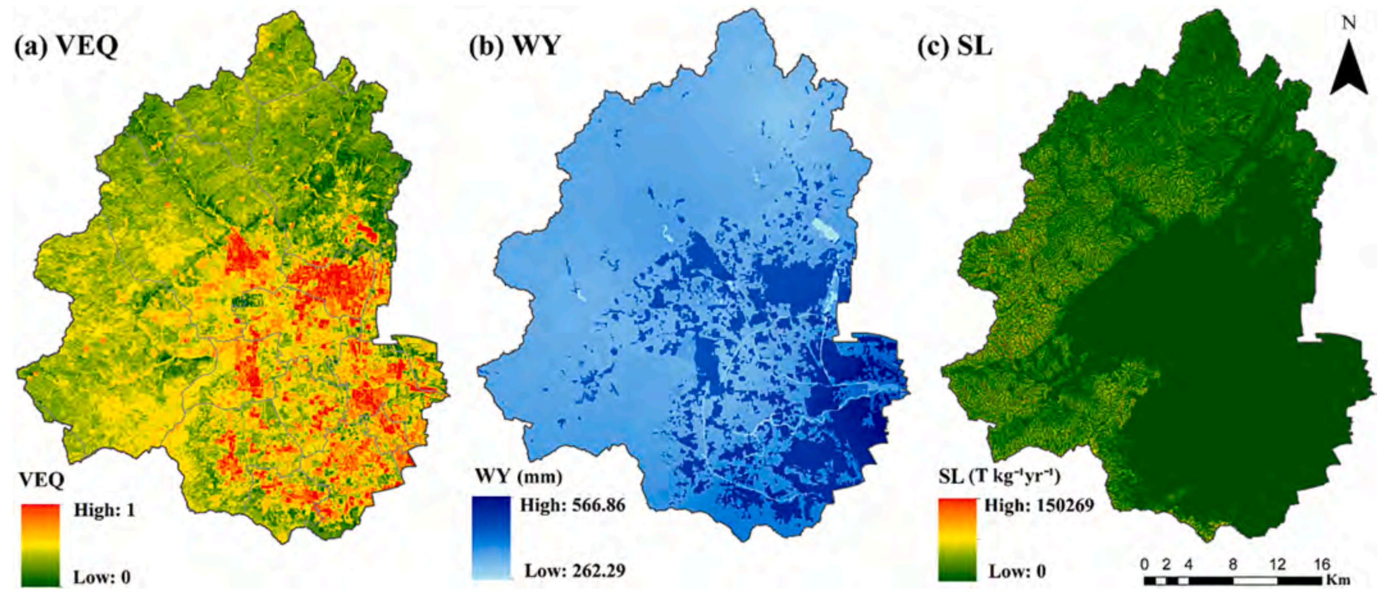

Fig. 5. Vegetation ecological quality (a), water yield (b), and soil loss (c) of the upper Beiyun River watershed in 2019.

Table 1
Soil loss rate of the upper Beiyun River watershed in 2019.

Class ($t{\cdot}km^{-2}{\cdot}yr^{-1}$)	Intensity class	Mean ($t{\cdot}km^{-2}{\cdot}yr^{-1}$)	Percent area (%)
0–200	Negligible	10.87	69.81
200–2500	Low	1148.35	6.49
2500–5000	Medium	3821.47	10.01
5000–8000	High	6303.93	9.13
> 8000	Extremely high	11229.62	4.56
Total	———	1552.35	100

land-use types are built-up lands. This is reasonable because the terrain of these regions is flat and the area percentage of impervious surfaces in these regions is larger than that in the northwestern mountainous areas.

3.2.5. Hazards

The spatial distribution characteristics of hazard risks (i.e., floods, debris flows, collapses, and landslides) in the watershed are presented in Fig. 6. The high values of flood risks are located in the southeastern plain areas (e.g., Changping, Huilongguan, Shigezhuang, Yongfeng) with built-up land (Fig. 6a). Impervious surface leads to the reduction of evapotranspiration and the increase of surface runoff, thereby the possibility of flooding increases. However, the high-value areas of the other types of hazards (i.e., debris flows, collapses, and landslides) are located in the northwestern mountainous areas. It is fundamentally related to the spatial distributions of slope (Fig. B1.c) and lithology (Fig. B1.f). In addition, with the soft rocky masses and main faults in these regions, intense tectonic activity and many loose deposits promote the occurrence of hazards. It could be inferred that the three hazards (i.e., debris flows, collapses, and landslides) occur frequently in the northwestern mountainous areas with slopes between 25° and 87° based on the spatial distributions of slope (Fig. B1.c). On the contrary, the low-value areas for debris flows, collapses, and landslides (excluding flood risks) are mostly distributed in the southeastern areas which are characterized by gentle slopes (0°– 6°), a large share of impervious surfaces, and no faults. As demonstrated in Fig. 6b–d, the spatial distribution characteristics of debris flows, collapses, and landslides are quite similar, but with relatively minor differences. For instance, the medium-risk areas of both collapses and debris flows are located in the southwestern mountainous regions of the watershed, whereas most of these areas are under the high-risk class of landslides (Fig. 6d).

3.2.6. Socio-economic factors

The spatial distribution characteristics of the socio-economic factors in the upper Beiyun River watershed are shown in Fig. 7. The high-value areas of the four indicators of the socio-economic system (i.e., PD, GDP, TI, and SI) are all located in the southeastern plain areas, which are the core zones for human habitation with a large population and economy. As shown in Fig. 7a, b, the spatial distribution characteristics of PD are consistent with those of GDP. The values of PD change from 0.02 person·pixel^{-1} to 12.19 person·pixel^{-1} (Fig. 7a), and the total population of Changping town is the largest (317 584 person). The values of GDP range from 900 RMB·pixel^{-1} to 605 400 RMB·pixel^{-1} (Fig. 7b), and the GDP value of Changping town is the largest (1 577.41 million RMB). On the other hand, the spatial distribution characteristics of TI are consistent with those of SI (Fig. 7c, d). The extremely high values of both TI and SI are located in the southeastern plain areas, such as Wenquan, Shangzhuang, and Sujiatuo town. The values of TI and SI in the watershed change from 0.06 million RMB·pixel^{-1} to 2.51 million RMB·pixel^{-1} and from 0.23 million RMB·pixel^{-1} to 2.83 million RMB·pixel^{-1}, respectively.

3.3. Assessing IER

Fig. 8a presents the weights of both socio-economic factors and eco-environmental risks. The weights of total nitrogen, total phosphorus, vegetation ecological quality, soil loss, population density, water yield, collapses, debris flows, landslides, floods, secondary industry, tertiary industry, and gross domestic product are 0.1453, 0.1453, 0.1360, 0.1346, 0.1210, 0.0911, 0.0526, 0.0502, 0.0334, 0.0278, 0.0232, 0.0222, and 0.0173, respectively. The weight of water pollution is larger (0.2906) than the other indicators, i.e., socio-economic indicator (0.1837), hazards (i.e., debris flows, collapses, floods, and landslides) (0.1640), vegetation ecological quality (0.1360), soil loss (0.1346), and water resource (0.0911). This indicates that water pollution control is crucial for managing the watershed ecosystem, and the socio-economic systems have a significant impact on the IER in the watershed and determine the economic capacity for IWM.

The spatial distribution characteristics of IER in the upper Beiyun River watershed are shown in Fig. 8b. Generally, the high-value zones of IER are mainly located in southeastern areas because most of these regions are urban land, cultivated land, and rural residential land which are characterized by high risks of both pollution and vegetation degradation. Surprisingly, the extremely high-value zones (0.53–0.67) of IER

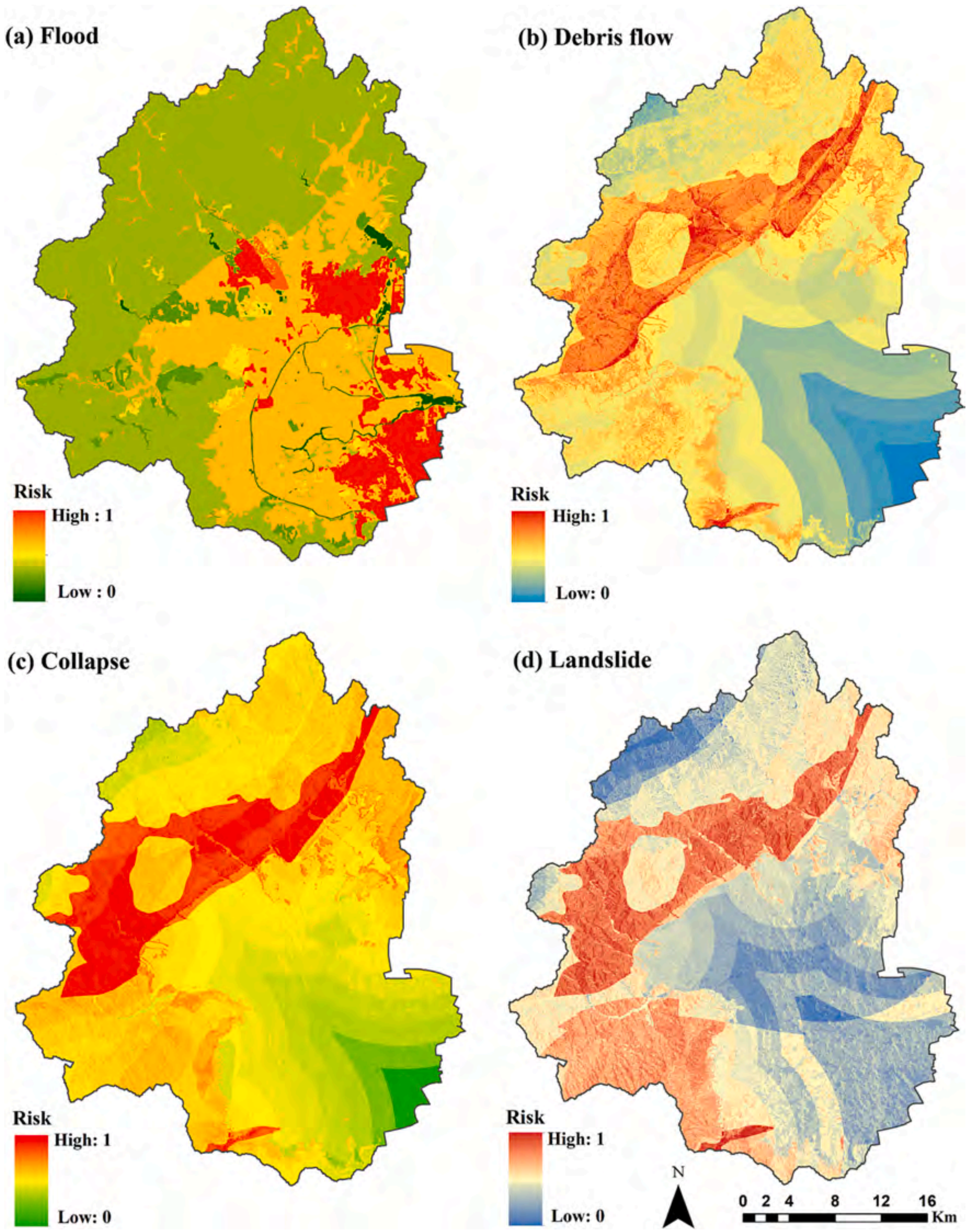

Fig. 6. Hazard risks in the upper Beiyun River watershed. (a) flood, (b) debris flow, (c) collapse, and (d) landslide.

are mostly distributed in Changping town with the highest risks of water pollution caused by the largest population density. On the contrary, the extremely low-value zones of IER are mainly located in the northern areas (e.g., Dazhuangke, Jingjiazhuang, Badaling, Yanchi, and Miaofengshan) because most of these regions are green spaces that are characterized by low population density, anthropogenic modification, and pollution risk. It is worth noting that the low-value zones of IER are mainly located in the northwestern mountainous areas, which are under the extremely high-risk class of debris flows, collapses, and landslides.

3.4. Identifying PMAs

The spatial distribution characteristics of the PMAs of the watershed are presented in Fig. 9a. Generally, the PMAs are centrally distributed in southeastern areas which are characterized by high risks of water pollution, vegetation degradation, and flood. It should be noted that most of the PMAs appear in Changping town, which is located in the southeastern plain areas of the watershed. It is reasonable that the land-use types in the PMAs are built-up lands with high risks of both water pollution and vegetation degradation caused by the largest population density (12.19 person·pixel^{-1}). It is important to highlight that although

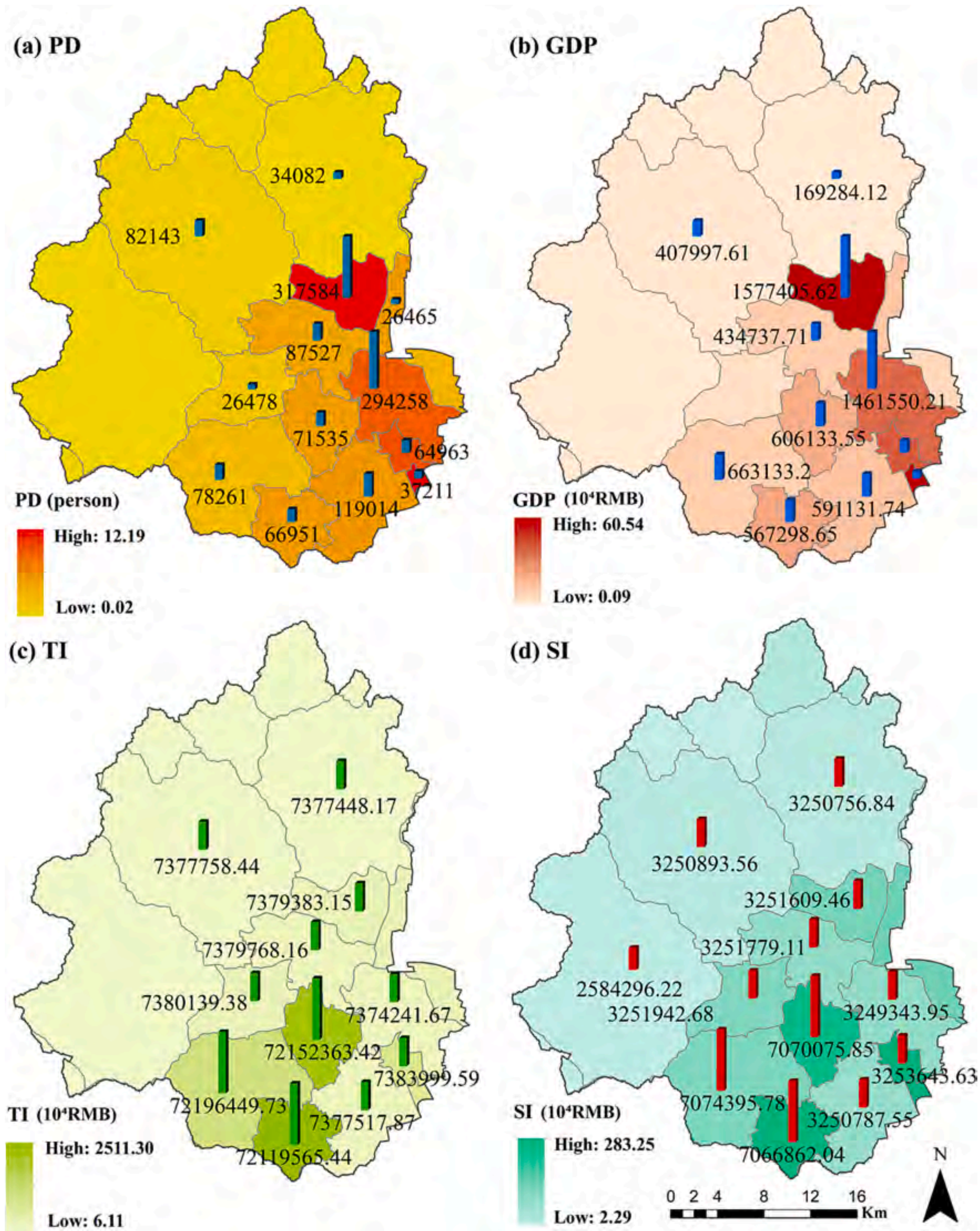

Fig. 7. Spatial distributions of socio-economic factors in 2019. (a) population density (PD), (b) gross domestic product (GDP), (c) tertiary industry (TI), and (d) secondary industry (SI).

the water resources scarcity (Fig. 5b), soil loss risk (Fig. 5c), debris flows (Fig. 6b), collapses (Fig. 6c), and landslides (Fig. 6d) in the northwestern mountainous areas of the watershed are higher than that in the south-eastern plain areas, the PMAs are centrally distributed in southeastern areas because of the total weight of water pollution, vegetation ecological quality, and flood risks is higher (0.4544) than the total weight (0.3619) of the other eco-environmental risks. This implies that it is necessary to take into account the relative weights of risk indicators, as the weights of indicators also have a significant effect on the results of IER and thus the identification of PMAs. As shown in Fig. 9b, the average area percentages of PMAs (i.e., extremely high-risk), high-risk, medium-risk, low-risk, and extremely low-risk zones are 6.46 % (72.91 km^2), 13.28 % (149.85 km^2), 18.64 % (210.43 km^2), 21.95 % (247.74 km^2), and 39.67 % (447.69 km^2), respectively.

Overall, watersheds are considered as the most effective units to support regional sustainable development. Many watersheds are degrading or have the potential to become impaired because of climate change and human activities. To restore degraded ecological functions of watersheds, IWM is increasingly adopted in many regions around the world. PMAs should be identified by considering as many eco-environment problems as possible or assessing integrated to improve the efficiency of IWM. However, most of the previous studies only

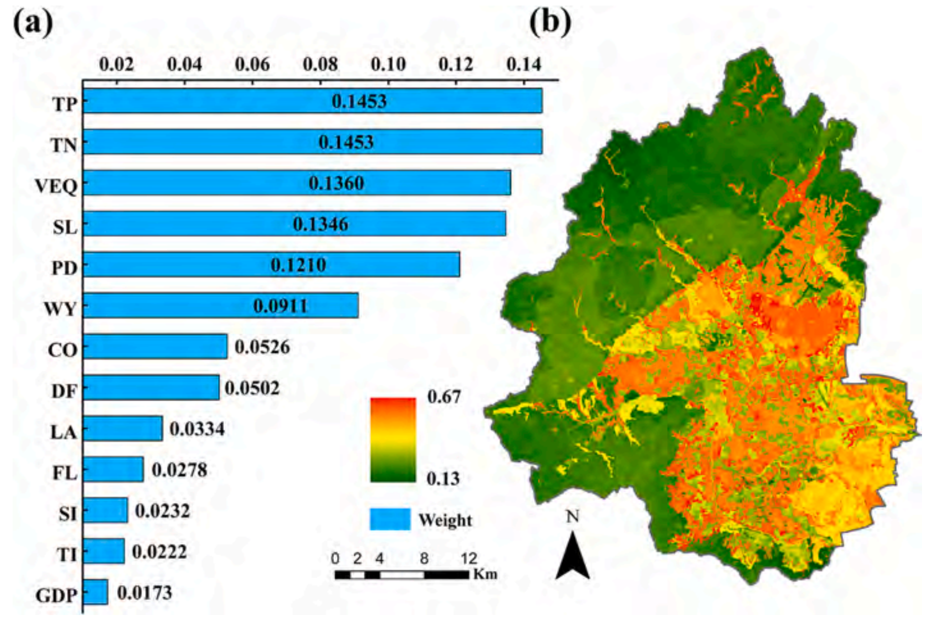

Fig. 8. (a) Weights of indicators and (b) spatial distributions of integrated eco-environmental risk in the upper Beiyun River watershed. TP, total phosphorus; TN, total nitrogen; VEQ, vegetation ecological quality; SL, soil loss; PD, population density; WY, water yield; CO, collapse; DF, debris flow; LA, landslide; LF: flood; SI, secondary industry; TI, tertiary industry; GDP, gross domestic product.

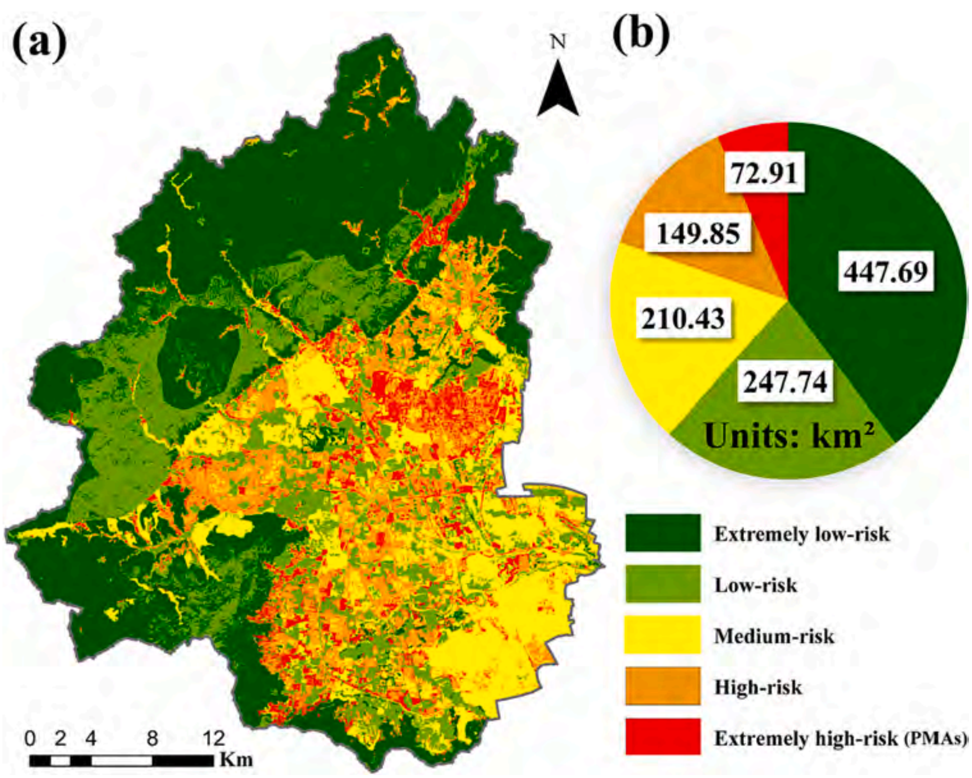

Fig. 9. (a) Identification of priority management areas (PMAs) in the upper Beiyun River watershed and (b) area percentage of PMAs.

assessed a single problem (risk) to identify PMAs for watershed management. None of these previous studies identified PMAs through assessing integrated eco-environmental problems (risks) to support efficient IWM. In addition, this study considers reciprocal feedbacks between ecosystems and socio-economic systems of watersheds by coupling the analytical network process with the mean-square deviation decision method. The novelty of this study is to develop a framework to quantitatively identify PMAs through assessing IER for efficient IWM through a case study in the upper Beiyun River watershed, China.

In this case study, there are five noticeable environmental problems, including water pollution, water resources scarcity, soil loss, hazards, and vegetation degradation based on the natural environment and socio-economic data of the upper Beiyun River watershed. The water pollution was contaminated to varying levels using the export coefficient model, and the regions of the southeastern plain areas should be implemented to improve the vegetation quality since these regions have been experiencing rapid urbanization. The water yield is relatively low using the InVEST model, and changes from 262.29 mm·pixel^{-1} to 566.86 mm·pixel^{-1}. It is fundamentally related to rainfall since rainfall is the most significant source of water recharge in the upper Beiyun River watershed. According to the classification standard of soil erosion (SL190-2007) of China, the soil loss of the watershed is mainly dominated by negligible class with a mean of 10.87 t·km^{-2}·yr^{-1}. For hazards, the high-value areas of the debris flows, collapses, and landslides are located in the northwestern mountainous areas. Through the analytical network process with the mean-square deviation decision method, the weight of water pollution for the IER is the largest (0.2906), indicating that water pollution control is crucial for IWM in the upper Beiyun River watershed. The weight of socio-economic systems is 0.1837, suggesting that the socio-economic systems have a significant impact on the IER and determine the economic capacity for IWM. The PMAs, which are identified as zones with extremely high IER values, account for 6.46 % (72.91 km^2) of the watershed. They are centrally distributed in the southeastern areas with high risks of both water pollution and vegetation degradation caused by large population density. In this case study, our results may provide a scientific reference for efficient watershed management through identifying PMAs. The best management practices should be selected and configured to reduce eco-environmental risks for restoring watershed ecosystem service functions in the upper Beiyun River watershed. The framework provides insights into quantitatively assessing IER of watersheds and identifying PMAs for efficient IWM. With flexible structure, the framework has the potential to be applicable in various watersheds to identify PMAs through assessing IER for efficient IWM.

4. Discussion

4.1. Advantages of the IERA framework

The framework was developed to identify PMAs through assessing integrated eco-environmental problems for IWM. Compared with previous studies in the IWM (Akhbari and Grigg, 2014; Lee and Chung, 2007; Lopes et al., 2022; Wang et al., 2006), the framework comprehensively identified possible environmental problems such as water pollution (i.e., PSP and NSP), soil loss, desertification, rocky desertification, hazards (e.g., collapses, landslides, floods, and debris flows), and vegetation degeneration to assess IER of watersheds. Therefore, the framework can be more widely used for IWM than previous methods (Baloch and Tanik, 2008; Biswas et al., 2012; Karageorgis et al., 2005). Theoretically, the framework is applicable to various watersheds, which have different natural environments and socio-economic characteristics. In addition, the framework can also be used to identify PMAs for a single environmental risk (e.g., water pollution, soil loss, hazards, or vegetation degradation), and to support the selection of control measures for this specific environmental risk.

The socio-economic system and the watershed ecosystem are inseparably linked in a symbiotic relationship (Whitehead et al., 2018). For instance, Berger et al. (2021) reported that socio-economic factors have a significant impact on water quality and quantity. Leslie et al. (2015) found that a healthy watershed ecosystem can increase the income and well-being of people. In previous studies, the impacts of socio-economic systems on land management (Brymer et al., 2016), ecological service value (Chen et al., 2021), watershed health (Parkes et al., 2010), water resource management (Akhbari and Grigg, 2015; Almaarofi et al., 2017), and flood management (Ahmadisharaf et al., 2016) have been extensively investigated. However, the impacts of socio-economic systems on IER of watersheds are still lacking. In this study, the positive or negative feedbacks between watershed socio-economic systems and ecosystems were nested in the IERA framework. As shown in Fig. 8, the results of this study demonstrated that the socio-economic system affected the IER of the upper Beiyun River watershed and eco-environmental risks. This result was consistent with the findings of previous studies (Lopes et al., 2022; RazaviToosi and Samani, 2019).

Previous studies have shown that it is vital to precisely determine the weights of indicators as the values of indicator weights will affect the output results of the investigation (Azareh et al., 2019). As shown in Fig. 9, the weights of indicators had a significant effect on the assessment result of IER, and thus they could also impact the identification of PMAs for IWM. Therefore, it is critical to select a proper methodology for calculating the weights of indicators. In this study, to ensure that interactions of indicators were correctly expressed in the assessment of IER, a robust technique (i.e., ANP) was used to describe the interdependency among indicators of both socio-economic factors and eco-environmental risks. Previous studies have shown that the ANP method considers the relationship among indicators in a more appropriate manner than other MCDM methods (e.g., DEA, AHP, and CVM) (Azareh et al., 2019; Sajedi-Hosseini et al., 2018). Moreover, successful applications of the ANP method have been confirmed by (Alilou et al., 2018; Alilou et al., 2019). In the ANP method, a supermatrix of pairwise comparisons among indicators, which is used to calculate the relative weights of indicators, is generated by expert scoring. However, uncertainties and subjective errors are always associated with the expert scoring method (Kanani-Sadat et al., 2019). In this study, the MDD method was used to replace the expert scoring method and avoid subjective errors and uncertainties. We apply a couplet method in order to avoid subjective errors and uncertainties and provide more information of the advantage of this approach in the outcomes of research and in the establishment of PMAs.

4.2. Limitations

Although the IERA framework has several advantages as discussed in Section 4.1, there are also some limitations need to be improved. The framework for quantitative assessment of IER requires considerable computational power and time, and it requires the collection of massive datasets. In this study, the eco-environmental risks of the watershed were assessed based on a relatively simple method. For instance, the export coefficient model, which is recognized as an empirical model, was applied to assess the NSP risk. Although the export coefficient model has been widely applied to evaluate NSP, the evaluated pollutant concentrations may not match the actual pollutant concentrations (Wang et al., 2020; Zhang et al., 2020). These empirical models may not be capable of investigating the intrinsic mechanism of migration and transformation of pollutants (Li et al., 2022; Shen et al., 2015). In future studies, mechanistic models (e.g., AnnAGNPS model, SWMM model, and SWAT model) can be used for the assessment of NSP. In addition, the net primary productivity (NPP) values were extracted from the MYD17A3HGF product dataset to assess the vegetation ecological quality. As shown in Fig. 5a, there were several sporadic high values in the northwest mountainous areas, which may have been caused by the abnormal values of the MYD17A3HGF product dataset. For future studies, the NPP can be calculated by using the Carnegie-Ames-Stanford Approach (CASA) model to improve the accuracy of assessing vegetation ecological quality (Cheng et al., 2020).

To ensure the generality and performance of the framework, the upper Beiyun River watershed, which has been experiencing both ecological civilization construction and rapid urbanization, was taken as an example for identifying PMAs by assessing IER. According to the characteristics of the watershed, it may be affected by water pollution, soil loss, hazards, and vegetation degradation. Other kinds of eco-environmental risks (e.g., desertification, rocky desertification) are not assessed because these risks may not occur in the watershed. More watersheds, where various eco-environmental risks (e.g., desertification, rocky desertification, hazards, soil loss, water pollution, and vegetation degradation) may occur, could be selected to demonstrate the applicability of this framework in the future. Furthermore, due to the lack of alternatives, we adopted a simplified and generalized derivation of social fitness as reciprocal feedbacks between socio-economic systems and watershed ecosystems. Despite such limitations, the framework is capable of identifying PMAs through assessing IER for efficient IWM.

4.3. Future work

The limitations of the study presented in Section 4.2 need to be further improved, for example, various watersheds could be selected to demonstrate the applicability of this framework. More importantly, given the advantages of the framework, an interactive user platform could be developed to improve its generalizability and applicability for efficient IWM in the future. The platform may consist of input, output, and decision interfaces, and it could be developed using advanced technologies such as big data, virtual reality, and artificial intelligence to provide powerful functions. For example, big data technology not only plays an important role in data acquisition, storage, and analytics but also provides data for the IERA framework (Li et al., 2018). Virtual reality is applied to create a digital watershed that can be virtually handled and visualized in the configuration of IWM measures. In terms of functions, the platform can be used to select optimized measures for adapting to future climate change (Wang et al., 2016b). In the platform, users are able to adjust their management strategies to more effectively meet existing and new governance issues by evaluating the efficiency of IWM measurement systems. More importantly, the platform can recommend and select the best management strategies for efficient IWM to achieve the goal of sustainable development.

5. Conclusion

This study developed a novel framework to quantitatively identify priority management areas (PMAs) for efficient integrated watershed management (IWM) through assessing integrated eco-environmental risk (IER) of watersheds. This framework was applied and tested in the upper Beiyun River watershed of Beijing, China. The results showed that there are five noticeable environmental problems (i.e., water pollution, water resources, soil loss, hazards, and vegetation degradation) in this watershed. The high-risk regions of both water pollution and vegetation degradation are located in the southeastern plain areas, which are covered by urban land, cultivated land, and rural residential land. The water yield changes from 262.29 mm·pixel^{-1} to 566.86 mm·pixel^{-1}, and the soil loss is mainly dominated by negligible class with a mean of 10.87 (t·km^{-2}·yr^{-1}). Debris flows, collapses, and landslides occur frequently in the northwestern mountainous areas with large slopes between 25° and 87°, while the high-risk regions of floods are distributed in the southeastern plain areas. The weight of water pollution for the IER is the largest (0.2906), followed by the weights of socio-economic indicator (0.1837), hazards (0.1640), vegetation degradation (0.1360), soil loss (0.1346), and water resources (0.0911), indicating that water pollution control is crucial for IWM in the watershed. It also implies that the socio-economic systems have a significant impact on the IER and determine the economic capacity for IWM. The PMAs, which are identified as zones with extremely high IER values, account for 6.46 % (72.91 km^2) of the watershed. They are centrally distributed in the southeastern areas with high risks of both water pollution and vegetation degradation caused by large population density. With flexible structure, the framework has the potential to be applicable in various watersheds to identify PMAs through assessing IER for efficient IWM.

The eco-environmental risks of the watershed were assessed based on a relatively simple method because the framework for quantitative assessment of IER requires considerable computational power and time, and it requires the collection of massive datasets. We should collect massive data using big data technology, and choose an optimal and accurate assessment method to assess various environmental risks and identify PMAs for IWM. In addition, to ensure the generality and performance of the framework, more watersheds, where various eco-environmental risks (e.g., desertification and rocky desertification) may occur, could be selected to demonstrate the applicability of the framework in the future. The management strategies, which are designed based on PMAs with historical data, may not have the adaptive capacity to adequately address climate change. IWM will need to consider the influence of climate change to ensure that watersheds continue to serve their ecological functions. Importantly, the framework can also be used to identify PMAs for a single environmental risk (e.g., water pollution, soil loss, hazards, or vegetation degradation), and to support the selection of control measures for this specific environmental risk.

PMA identification is only the first step in this study, the best management practices should be selected and configured to reduce eco-environmental risks for restoring watershed ecosystem service functions in the next step. More importantly, the optimization design of best management practices using a multi-objective optimization algorithm (e.g., genetic algorithm, non-dominating sort genetic algorithm, string pareto evolutionary algorithm, and multi-objective shuffled frog leaping algorithm) are essential for efficient watershed management in the future.

Secondly, based on the optimization design of best management practices, the efficiency of governance measure systems for IWM is assessed through the life cycle assessment method to adjust their management strategies to more effectively meet existing and new governance issues. Lastly, developing the best management strategies to achieve the goals of sustainability in relation to land and water resource use, the ecosystem of watersheds, the ecological economy, and human health and well-being.

Thirdly, an interactive user platform could be developed to improve its generalizability and applicability for efficient IWM in the future. The platform could be developed using advanced technologies (e.g., big data, virtual reality, and artificial intelligence) to provide powerful functions. The platform can recommend and select the best management strategies for efficient IWM to achieve the goal of sustainable development.

CRediT authorship contribution statement

Hualin Li: Formal analysis, Methodology, Visualization, Writing – original draft. **Shouhong Zhang:** Data curation, Software, Writing – review & editing. **Jianjun Zhang:** Conceptualization, Methodology. **Wenlong Zhang:** Data curation, Software. **Zhuoyuan Song:** Data curation, Software. **Peidan Yu:** Data curation, Software. **Chenxin Xie:** Data curation, Software.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This research was funded by the National Natural Science Foundation of China (52279001), the National Key Research and Development Program of China (2022YFF1303101), and the Fundamental Research Funds for the Central Universities (2021BLRD04).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.109919.

References

Abuzaid, A.S., Abdelatif, A.D., 2022. Assessment of desertification using modified MEDALUS model in the north Nile Delta. Egypt. Geoderma 405, 115400. https://doi.org/10.1016/j.geoderma.2021.115400.

Ahmadisharaf, E., Kalyanapu, A.J., Chung, E.S., 2016. Spatial probabilistic multi-criteria decision making for assessment of flood management alternatives. J. Hydrol., 533, 365-378. https://doi.org/:10.1016/ j.jhydrol.2015.12.031.

Akhbari, M., Grigg, N.S., 2014. Water management trade-offs between agriculture and the environment: a multiobjective approach and application. J. Irrig. Drain. Eng., 140(8), 05014005. https://doi.org/: 10.1061/(asce)ir.1943-4774.0000737.

Akhbari, M., Grigg, N.S., 2015. Managing water resources conflicts: modelling behavior in a decision tool. Water Resour. Manage. 29 (14), 5201–5216. https://doi.org/10.1007/s11269-015-1113-9.

Alamanos, A., Latinopoulos, D., Loukas, A., Mylopoulos, N., 2020. Comparing two hydro-economic approaches for multi-objective agricultural water resources planning. Water Resour. Manage. 34 (14), 4511–4526. https://doi.org/10.1007/s11269-020-02690-6.

Alilou, H., Nia, A.M., Keshtkar, H., Han, D.W., Bray, M., 2018. A cost-effective and efficient framework to determine water quality monitoring network locations. Sci. Total Environ. 624, 283–293. https://doi.org/10.1016/j.scitotenv.2017.12.121.

Alilou, H., Rahmati, O., Singh, V.P., Choubin, B., Pradhan, B., Keesstra, S., et al., 2019. Evaluation of watershed health using Fuzzy-ANP approach considering geo-environmental and topo-hydrological criteria. J. Environ. Manage. 232, 22–36. https://doi.org/10.1016/j.jenvman.2018.11.019.

Almaarofi, H., Etemad-Shahidi, A., Stewart, R.A., 2017. Strategic Evaluation Tool for surface water quality management remedies in drinking water catchments. Water 9 (10), 738. https://doi.org/:10.3390/, w9100738.

Alvarado, R., Tillaguango, B., Dagar, V., Ahmad, M., Işık, C., Méndez, P., et al., 2021. Ecological footprint, economic complexity and natural resources rents in Latin America: Empirical evidence using quantile regressions. J. Clean. Prod. 318, 128585 https://doi.org/10.1016/j.jclepro.2021.128585.

Arteaga, J., Ochoa, P., Fries, A., Boll, J., 2020. Identification of priority areas for integrated management of semiarid watersheds in the Ecuadorian Andes. J. Am. Water Resour. Assoc. 56 (2), 270–282. https://doi.org/10.1111/1752-1688.12837.

Azareh, A., Sardooi, E.R., Choubin, B., Barkhori, S., Shahdadi, A., Adamowski, J., et al., 2019. Incorporating multi-criteria decision-making and fuzzy-value functions for flood susceptibility assessment. Geocarto Int. 36 (11), 1–21. https://doi.org/10.1080/10106049.2019.1695958.

Bai, X., Jin, J., Zhou, R., Wu, C., Zhou, Y., Zhang, L., et al., 2022. Coordination evaluation and obstacle factors recognition analysis of water resource spatial equilibrium system. Environ. Res. 210, 112913 https://doi.org/10.1016/j.envres.2022.112913.

Baloch, M.A., Tanik, A., 2008. Development of an integrated watershed management strategy for resource conservation in Balochistan Province of Pakistan. Desalination, 226(1-3), 38-46. https://doi.org/: 10.1016/j.desal.2007.02.098.

Bekele, D.A., Gella, G.W., Ejigu, M.A., 2022. Erosion risk assessment: A contribution for conservation priority area identification in the sub-basin of Lake Tana, north-western Ethiopia. Int. Soil Water Conserv. 10 (1), 46–61. https://doi.org/10.1016/j.iswcr.2021.04.010.

Berger, E., Bossenbroek, L., Beermann, A.J., Schafer, R.B., Znari, M., Riethmuller, S., et al., 2021. Social-ecological interactions in the Draa River Basin, southern Morocco: Towards nature conservation and human well-being using the IPBES framework. Sci. Total Environ. 769 (1), 144492 https://doi.org/10.1016/j.scitotenv.2020.144492.

Biswas, S., Vacik, H., Swanson, M.E., Haque, S.M.S., 2012. Evaluating integrated watershed management using multiple criteria analysis-a case study at Chittagong Hill Tracts in Bangladesh. Environ. Monit. Assess. 184 (5), 2741–2761. https://doi.org/10.1007/s10661-011-2148-x.

Bouamrane, A., Bouamrane, A., Abida, H., 2021. Water erosion hazard distribution under a Semi-arid climate Condition: Case of Mellah Watershed. North-eastern Algeria. Geoderma 403, 115381. https://doi.org/10.1016/j.geoderma.2021.115381.

Bremer, L.L., DeMaagd, N., Wada, C.A., Burnett, K.M., 2021. Priority watershed management areas for groundwater recharge and drinking water protection: A case study from Hawai'i Island. J. Environ. Manage. 286, 111622 https://doi.org/10.1016/j.jenvman.2020.111622.

Brombal, D., Niu, Y., Pizzol, L., Moriggi, A., Wang, J., Critto, A., et al., 2018. A participatory sustainability assessment for integrated watershed management in urban China. Environ. Sci. Policy 85, 54–63. https://doi.org/10.1016/j.envsci.2018.03.020.

Brymer, A.L.B., Holbrook, J.D., Niemeyer, R.J., Suazo, A.A., Wulfhorst, J.D., Vierling, K. T., et al., 2016. A social-ecological impact assessment for public lands management: application of a conceptual and methodological framework. Ecol. Soc. 21 (3) https://doi.org/10.5751/es-08569-210309.

W. Chen Y. Li GIS-based evaluation of landslide susceptibility using hybrid computational intelligence models Catena 195 2020 104777 https://doi.org/:10.1016/j.catena.2020.104777.

Chen, D.S., Pan, Y.Q., Jin, X.L., Du, H.Y., Li, M.C., Jiang, P.H., 2021. The delineation of ecological redline area for catchment sustainable management from the perspective of ecosystem services and social needs: A case study of the Xiangjiang watershed, China. Ecol. Indic., 121, 107130. https://doi.org/:10.1016/ j.ecolind.2020.107130.

Chen, L., Li, J., Xu, J., Liu, G., Wang, W., Jiang, J., et al., 2022. New framework for nonpoint source pollution management based on downscaling priority management areas. J. Hydrol. 606, 127433 https://doi.org/10.1016/j.jhydrol.2022.127433.

Chen, X.Y., Wang, L.Y., Cai, J.M., Zhou, X.N., Zheng, J., Guo, J.G., et al., 2005. Schistosomiasis control in China: the impact of a 10-year World Bank Loan Project (1992–2001). Bull. World Health Organ. 83 (1), 43–48.

Chen, Y., Wang, W., Guan, Y., Liu, F., Zhang, Y., Du, J., et al., 2020. An integrated approach for risk assessment of rangeland degradation: A case study in Burqin County, Xinjiang. China. Ecol. Indic. 113, 106203 https://doi.org/10.1016/j.ecolind.2020.106203.

Cheng, W., Xi, H., Sindikubwabo, C., Si, J., Zhao, C., Yu, T., et al., 2020. Ecosystem health assessment of desert nature reserve with entropy weight and fuzzy mathematics methods: A case study of Badain Jaran Desert. Ecol. Indic. 119, 106843 https://doi.org/10.1016/j.ecolind.2020.106843.

Dieperink, C., 2000. Successes in the international cooperation in the rhine catchment area. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere 25 (3), 341–347. https://doi.org/10.1016/S1464-1909(00)00024-1.

Duan, T., Feng, J., Zhou, Y., Chang, X., Li, Y., 2021. Systematic evaluation of management measure effects on the water environment based on the DPSIR-Tapio decoupling model: A case study in the Chaohu Lake watershed, China. Sci. Total Environ., 801, 149528. https://doi.org//10.1016/j.scitotenv.2021. 149528.

Duan, T., Feng, J., Chang, X., Li, Y., 2022. Watershed health assessment using the coupled integrated multistatistic analyses and PSIR framework. Sci. Total Environ. 847, 157523 https://doi.org/10.1016/j.scitotenv.2022.157523.

Elmes, M.C., Price, J.S., 2019. Hydrologic function of a moderate-rich fen watershed in the Athabasca Oil Sands Region of the Western Boreal Plain, northern Alberta. J. Hydrol. 570, 692–704. https://doi.org/10.1016/j.jhydrol.2018.12.043.

Ervinia, A., Huang, J.L., Huang, Y.L., Lin, J.Y., 2019. Coupled effects of climate variability and land use pattern on surface water quality: An elasticity perspective and watershed health indicators. Sci. Total Environ. 693, 133592 https://doi.org/10.1016/j.scitotenv.2019.133592.

Evenson, G.R., Kalcic, M., Wang, Y.-C., Robertson, D., Scavia, D., Martin, J., et al., 2021. Uncertainty in critical source area predictions from watershed-scale hydrologic models. J. Environ. Manage. 279, 111506 https://doi.org/10.1016/j.jenvman.2020.111506.

Ferguson, J.M., Reichert, B.E., Fletcher, R.J., Jr., Jager, H.I., 2017. Detecting population-environmental interactions with mismatched time series data. Ecology, 98(11), 2813-2822. https://doi.org/:10.1002/ecy. 1966.

Guo, Y., Wang, X., Melching, C., Nan, Z., 2022. Identification method and application of critical load contribution areas based on river retention effect. J. Environ. Manage. 305, 114314 https://doi.org/10.1016/j.jenvman.2021.114314.

Hazbavi, Z., Sadeghi, S.H., Gholamalifard, M., Davudirad, A.A., 2020. Watershed health assessment using the pressure-state-response (PSR) framework. Land Degrad. Dev. 31 (1), 3–19.

Huang, J.J., Lin, X., Wang, J., Wang, H., 2015. The precipitation driven correlation based mapping method (PCM) for identifying the critical source areas of non-point source pollution. J. Hydrol. 524, 100–110. https://doi.org/10.1016/j.jhydrol.2015.02.011.

Isabel, N., Holliday, J.A., Aitken, S.N., 2020. Forest genomics: Advancing climate adaptation, forest health, productivity, and conservation. Evolutionary Applications, 13(1), 3-10. https://doi.org/:10.1111/eva. 12902.

Jiang, Z.C., Lian, Y.Q., Qin, X.Q., 2014. Rocky desertification in Southwest China: Impacts, causes, and restoration. Earth-Sci. Rev. 132, 1–12. https://doi.org/10.1016/j.earscirev.2014.01.005.

Kanani-Sadat, Y., Arabsheibani, R., Karimipour, F., Nasseri, M., 2019. A new approach to flood susceptibility assessment in data-scarce and ungauged regions based on GIS-based hybrid multi criteria decision-making method. J. Hydrol. 572, 17–31. https://doi.org/10.1016/j.jhydrol.2019.02.034.

Kang, M.G., Park, S.W., 2015. An adaptive watershed management assessment based on watershed investigation data. Environ. Manage. 55 (5), 1006–1021. https://doi.org/10.1007/s00267-014-0442-4.

Karageorgis, A.P., Skourtos, M.S., Kapsimalis, V., Kontogianni, A.D., Skoulikidis, N.T., Pagou, K., et al., 2005. An integrated approach to watershed management within the DPSIR framework: Axios River catchment and Thermaikos Gulf. Reg. Environ. Change 5 (2–3), 138–160.

Karavitis, C.A., Tsesmelis, D.E., Oikonomou, P.D., Kairis, O., Kosmas, C., Fassouli, V., et al., 2020. A desertification risk assessment decision support tool (DRAST). Catena 187, 104413. https://doi.org/10.1016/j.catena.2019.104413.

Kayet, N., Pathak, K., Chakrabarty, A., Sahoo, S., 2018. Evaluation of soil loss estimation using the RUSLE model and SCS-CN method in hillslope mining areas. Int. Soil Water Conserv. 6 (1), 31–42. https://doi.org/10.1016/j.iswcr.2017.11.002.

Khan, I., Zakari, A., Zhang, J., Dagar, V., Singh, S., 2022. A study of trilemma energy balance, clean energy transitions, and economic expansion in the midst of environmental sustainability: New insights from three trilemma leadership. Energy 248, 123619. https://doi.org/10.1016/j.energy.2022.123619.

Lee, K.S., Chung, E.-S., 2007. Development of integrated watershed management schemes for an intensively urbanized region in Korea. J. Hydro-environ. Res., 1(2), 95-109. https://doi.org/:10.1016/j.jher.2007.07. 004.

Lerch, R.N., Baffaut, C., Kitchen, N.R., Sadler, E.J., 2015. Long-term agroecosystem research in the Central Mississippi River Basin: Dissolved nitrogen and phosphorus transport in a High-Runoff-Potential Watershed. J. Environ. Qual. 44 (1), 44–57. https://doi.org/10.2134/jeq2014.02.0059.

Leslie, H.M., Basurto, X., Nenadovic, M., Sievanen, L., Cavanaugh, K.C., Cota-Nieto, J.J., et al., 2015. Operationalizing the social-ecological systems framework to assess sustainability. Proc. Natl. Acad. Sci. U. S. A. 112 (19), 5979–5984. https://doi.org/10.1073/pnas.1414640112.

Li, X., Cheng, G.D., Lin, H., Cai, X.M., Fang, M., Ge, Y.C., et al., 2018. Watershed system model: The essentials to model complex human-nature system at the River Basin Scale. J. Geophys. Res. Atmos. 123 (6), 3019–3034. https://doi.org/10.1002/2017jd028154.

Li, G., Jiang, C., Zhang, Y., Jiang, G., 2021a. Whether land greening in different geomorphic units are beneficial to water yield in the Yellow River Basin? Ecol. Indic. 120.

Li, H., Zhang, J., Zhang, Y., Chang, G., Shi, D., Xu, W., et al., 2021b. Analysis of spatial-temporal variation characteristics of potential non-point source pollution risks in the Upper Beiyun River Basin using different weighting methods. Environmental, 202010225 Science 42 (6), 2796–2809. https://doi.org/10.13227/j.hjkx.
Li, H., Zhang, J., Zhang, S., Zhang, W., Zhang, S., Yu, P., et al., 2022. A framework to assess spatio-temporal variations of potential non-point source pollution risk for future land-use planning. Ecol. Indic. 137, 108751 https://doi.org/10.1016/j.ecolind.2022.108751.
Liu, G.W.C., Chen, L., Wei, G.Y., Shen, Z.Y., 2019. New framework for optimizing best management practices at multiple scales. J. Hydrol. 578 https://doi.org/10.1016/j.jhydrol.2019.124133.
Liu, B., Wang, M., Chen, T., Tseng, P., Sun, Y., Chiang, A., et al., 2020a. Establishment and implementation of green infrastructure practice for healthy watershed management: Challenges and perspectives. Water-Energy Nexus 3, 186–197. https://doi.org/10.1016/j.wen.2020.05.003.
Liu, W., Wei, X., Fan, H., Guo, X., Liu, Y., Zhang, M., et al., 2015. Response of flow regimes to deforestation and reforestation in a rain-dominated large watershed of subtropical China. Hydrol. Process. 29 (24), 5003–5015. https://doi.org/10.1002/hyp.10459.
Liu, B., Xie, Y., Li, Z., Liang, Y., Zhang, W., Fu, S., et al., 2020b. The assessment of soil loss by water erosion in China. Int. Soil Water Conserv. 8 (4), 430–439. https://doi.org/10.1016/j.iswcr.2020.07.002.
Liu, J., Zhenyao, S.Y., Yan, T.Z., Yang, Y.C., 2018. Source identification and impact of landscape pattern on riverine nitrogen pollution in a typical urbanized watershed, Beijing. China. Sci. Total Environ. 628, 1296–1307. https://doi.org/10.1016/j.scitotenv.2018.02.161.
Lopes, T.R., Folegatti, M.V., Zolin, C.A., Moura, L.B., Oliveira, R.K., Fraga, L.S., et al., 2022. Multicriterial analysis for the identification of key areas to improve the management in Piracicaba River Basin. Brazil. J. Hydrol. Eng. 27 (1), 02146. https://doi.org/10.1061/(asce)he.1943-5584.0002146.
Lu, S.B., Shang, Y.Z., Li, W., Wu, X.H., Zhang, H.B., 2018. Basic theories and methods of watershed ecological regulation and control system. J. Water Clim. Chang. 9 (2), 293–306.
Ma, T., Sun, S., Fu, G.T., Hall, J.W., Ni, Y., He, L.H., et al., 2020. Pollution exacerbates China's water scarcity and its regional inequality. Nat. Commun. 11 (1), 1–9. https://doi.org/10.1038/s41467-020-14532-5.
Mekonnen, M., Abeje, T., Addisu, S., 2021. Integrated watershed management on soil quality, crop productivity and climate change adaptation, dry highland of Northeast Ethiopia. Agricultural Systems 186, 102964. https://doi.org/10.1016/j.agsy.2020.102964.
Moradi, S., Limaei, S.M., 2018. Multi-objective game theory model and fuzzy programing approach for sustainable watershed management. Land Use Policy, 71, 363-371. https://doi.org/:10.1016/j.landusepol. 2017.12.008.
Mosaffaie, J., Salehpour Jam, A., Tabatabaei, M.R., Kousari, M.R., 2021. Trend assessment of the watershed health based on DPSIR framework. Land Use Policy, 100, 104911. https://doi.org/:10.1016/j.landusepol. 2020.104911.
Mostashari-Rad, F., GhasemiMobtaker, H., Taki, M., Ghahderijani, M., Saber, Z., Chau, K.-W., et al., 2020. Data supporting midpoint-weighting life cycle assessment and energy forms of cumulative exergy demand for horticultural crops. Data in Brief 33, 106490. https://doi.org/10.1016/j.dib.2020.106490.
Nabavi-Pelesaraei, A., Bayat, R., Hosseinzadeh-Bandbafha, H., Afrasyabi, H., Chau, K.-W., 2017. Modeling of energy consumption and environmental life cycle assessment for incineration and landfill systems of municipal solid waste management - A case study in Tehran Metropolis of Iran. J. Clean. Prod. 148, 427–440. https://doi.org/10.1016/j.jclepro.2017.01.172.
Nguyen, V.M., Lynch, A.J., Young, N., Cowx, I.G., Beard, T.D., Taylor, W.W., et al., 2016. To manage inland fisheries is to manage at the social-ecological watershed scale. J. Environ. Manage. 181, 312–325. https://doi.org/10.1016/j.jenvman.2016.06.045.
Parkes, M.W., Morrison, K.E., Bunch, M.J., Hallstrom, L.K., Neudoerffer, R.C., Venema, H.D., et al., 2010. Towards integrated governance for water, health and social-ecological systems: The watershed governance prism. Global Environmental Change-Human and Policy Dimensions 20 (4), 693–704. https://doi.org/10.1016/j.gloenvcha.2010.06.001.
Qiang, Z., Peng, C., Jing, H.C., Yu, L.A., Sl, C., 2019. Regional risk assessment of debris flows in China—An HRU-based approach. Geomorphology, 340, 84-102. https://doi.org/:10.1016/j.geomorph.2019.04. 027.
Qiu, C., Su, L., Zou, Q., Geng, X., 2021. A hybrid machine-learning model to map glacier-related debris flow susceptibility along Gyirong Zangbo watershed under the changing climate. Sci. Total Environ. 818, 151752 https://doi.org/10.1016/j.scitotenv.2021.151752.
RazaviToosi, S.L., Samani, J.M.V., 2019. A fuzzy group decision making framework based on ISM-FANP-FTOPSIS for evaluating watershed management strategies. Water Resour. Manage. 33 (15), 5169–5190. https://doi.org/10.1007/s11269-019-02423-4.
Saaty, T.L., 1996. Decision making with dependence and feedback: The analytic network process. International 95 (2), 129–157. https://doi.org/10.1007/0-387-33987-6.
Sajedi-Hosseini, F., Choubin, B., Solaimani, K., Cerda, A., Kavian, A., 2018. Spatial prediction of soil erosion susceptibility using a fuzzy analytical network process: Application of the fuzzy decision making trial and evaluation laboratory approach. Land Degrad. Dev., 29(9), 3092-3103. https://doi.org/: 10.1002/ldr.3058.
Sanches Fernandes, L.F., Fernandes, A.C.P., Ferreira, A.R.L., Cortes, R.M.V., Pacheco, F.A.L., 2018. A partial least squares – Path modeling analysis for the understanding of biodiversity loss in rural and urban watersheds in Portugal. Sci. Total Environ., 626, 1069-1085. https://doi.org/:10.1016/j.scitotenv. 2018.01.127.
Šatalová, B., Kenderessy, P., 2017. Assessment of water retention function as tool to improve integrated watershed management (case study of Poprad river basin, Slovakia). Sci. Total Environ. 599–600, 1082–1089. https://doi.org/10.1016/j.scitotenv.2017.04.227.
Shen, Z.Y., Zhong, Y.C., Huang, Q., Chen, L., 2015. Identifying non-point source priority management areas in watersheds with multiple functional zones. Water Res., 68, 563-571. https://doi.org/:10.1016/j.watres. 2014.10.034.
Shrestha, N.K., Rudra, R.P., Daggupati, P., Goel, P.K., Shukla, R., 2021. A comparative evaluation of the continuous and event-based modelling approaches for identifying critical source areas for sediment and phosphorus losses. J. Environ. Manage. 277, 111427 https://doi.org/10.1016/j.jenvman.2020.111427.
Sobhani, A., Asgari, H.R., Noura, N., Owonegh, M., Sakieh, Y., 2017. Application of land-use management scenarios to mitigate desertification risk in northern Iran. Environ. Earth Sci. 76 (17), 1–15. https://doi.org/10.1007/s12665-017-6945-6.
Sun, S., Wang, Y., Liu, J., Cai, H., Wu, P., Geng, Q. et al., 2016. Sustainability assessment of regional water resources under the DPSIR framework. J. Hydrol., 532, 140-148. https://doi.org/:10.1016/j.jhydrol. 2015.11.028.
Sun, F.Y., Mejia, A., Che, Y., 2019. Disentangling the contributions of climate and basin characteristics to water yield across spatial and temporal scales in the Yangtze River Basin: A combined hydrological model and boosted regression approach. Water Resour. Manage., 33(10), 3449-3468. https://doi.org/: 10.1007/s11269-019-02310-y.
Sun, Q., Liu, W., Gao, Y., Li, J., Yang, C., 2020. Spatiotemporal variation and climate influence factors of vegetation ecological quality in the Sanjiangyuan National Park. Sustainability 12 (16), 6634. https://doi.org/10.3390/su12166634.
Teka, K., Haftu, M., Ostwald, M., Cederberg, C., 2020. Can integrated watershed management reduce soil erosion and improve livelihoods? A study from northern Ethiopia. Int. Soil Water Conserv. 8 (3), 266–276. https://doi.org/10.1016/j.iswcr.2020.06.007.
Tuerkes, M., Oztas, T., Tercan, E., Erpul, G., Karagoz, A., Dengiz, O., et al., 2020. Desertification vulnerability and risk assessment for Turkey via an analytical hierarchy process model. Land Degrad. Dev. 31 (2), 205–214. https://doi.org/10.1002/ldr.3441.
Wang, W., Chen, L., Shen, Z., 2020. Dynamic export coefficient model for evaluating the effects of environmental changes on non-point source pollution. Sci. Total Environ. 747, 141164 https://doi.org/10.1016/j.scitotenv.2020.141164.
Wang, G., Mang, S., Cai, H., Liu, S., Zhang, Z., Wang, L. et al., 2016. Integrated watershed management: evolution, development and emerging trends. J. For. Res., 27(5), 967-994. https://doi.org/:10.1007/ s11676-016-0293-3.
Wang, R., Cai, C., Zhang, J., Sun, S., Zhang, H., 2022. Study on phosphorus loss and influencing factors in the water source area. Int. Soil Water Conserv., 10(2), 324-334. https://doi.org/:10.1016/j.iswcr.2021.07. 002.
Wang, L.J., Meng, W., Guo, H.C., Zhang, Z.X., Liu, Y., Fan, Y.Y., 2006. An interval fuzzy multiobjective watershed management model for the Lake Qionghai watershed. China. Water Resour. Manage. 20 (5), 701–721. https://doi.org/10.1007/s11269-005-9003-1.
Whitehead, P.G., Jin, L., Macadam, I., Janes, T., Sarkar, S., Rodda, H.J.E. et al., 2018. Modelling impacts of climate change and socio-economic change on the Ganga, Brahmaputra, Meghna, Hooghly and Mahanadi river systems in India and Bangladesh. Sci. Total Environ., 636, 1362-1372. https://doi.org/: 10.1016/j.scitotenv.2018.04.362.
Wu, Y., Chen, J., 2012. Modeling of soil erosion and sediment transport in the East River Basin in southern China. Sci. Total Environ. 441, 159–168. https://doi.org/10.1016/j.scitotenv.2012.09.057.
Wu, L., Liu, X., Chen, J.L., Li, J.F., Yu, Y., Ma, X.Y., 2022. Efficiency assessment of best management practices in sediment reduction by investigating cost-effective tradeoffs. Agric. Water Manage. 265, 107546 https://doi.org/10.1016/j.agwat.2022.107546.
Xie, M., Irfan, M., Razzaq, A., Dagar, V., 2022. Forest and mineral volatility and economic performance: Evidence from frequency domain causality approach for global data. Resources Policy 76, 102685. https://doi.org/10.1016/j.resourpol.2022.102685.
Yu, D., Dong, X.H., Xie, P., Wei, C., Liu, J., Hu, X.N., et al., 2021. Prioritization of critical source areas for soil and water conservation by using a one-at-a-time removal approach in the upper Huaihe River basin. Land Degrad. Dev. 32 (3), 1513–1524. https://doi.org/10.1002/ldr.3814.
Zhang, X., Yi, Y., Yang, Z., 2020. Nitrogen and phosphorus retention budgets of a semiarid plain basin under different human activity intensity. Sci. Total Environ., 703, 134813. https://doi.org/:10.1016/j.scitotenv. 2019.134813.
Zhang, C., Khan, I., Dagar, V., Saeed, A., Zafar, M.W., 2022. Environmental impact of information and communication technology: Unveiling the role of education in developing countries. Technol. Forecast. Soc. Change 178, 121570. https://doi.org/10.1016/j.techfore.2022.121570.
Zhang, J., Liu, M.L., Liu, X.N., Luo, W.Q., Wu, L., Zhu, L.H., 2021. Spectral analysis of seasonal rock and vegetation changes for detecting karst rocky desertification in southwest China. Int. J. Appl. Earth Obs. 100, 102337 https://doi.org/10.1016/j.jag.2021.102337.
Zhong, S., Chen, F., Xie, D., Shao, J., Yong, Y., Zhang, S., et al., 2020. A three-dimensional and multi-source integrated technology system for controlling rural non-point source pollution in the Three Gorges Reservoir Area. China. J. Clean. Prod. 272 (15), 122579 https://doi.org/10.1016/j.jclepro.2020.122579.
Zhumanova, M., Moennig, C., Hergarten, C., Darr, D., Wrage-Moennig, N., 2018. Assessment of vegetation degradation in mountainous pastures of the Western Tien-Shan, Kyrgyzstan, using eMODIS NDVI. Ecol. Indic. 95, 527–543. https://doi.org/10.1016/j.ecolind.2018.07.060.

Zou, Q., Jiang, H., Cui, P., Zhou, B., Jiang, Y., Qin, M.Y. et al., 2021. A new approach to assess landslide susceptibility based on slope failure mechanisms. Catena, 204, 105388. https://doi.org/:10.1016/j.catena. 2021.105388.
Zuo, Q., Guo, J., Ma, J., Cui, G., Yang, R., Yu, L., 2021. Assessment of regional-scale water resources carrying capacity based on fuzzy multiple attribute decision-making and scenario simulation. Ecol. Indic. 130, 108034 https://doi.org/10.1016/j.ecolind.2021.108034.
Zuo, D., Han, Y., Gao, X., Ma, G., Xu, Z., Bi, Y., et al., 2022. Identification of priority management areas for non-point source pollution based on critical source areas in an agricultural watershed of Northeast China. Environ. Res. 214, 113892 https://doi.org/10.1016/j.envres.2022.113892.