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Using multiple-criteria decision-making techniques for eco-environmental vulnerability assessment: a case study on the Chi-Jia-Wan Stream watershed, Taiwan

Pi-Hui Huang · Jing-Shyan Tsai · Wen-Tzu Lin

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Abstract The Chi-Jia-Wan Stream watershed, located in the area of the upstream Da-Chia River in central Taiwan, is famous for slopeland agriculture and the land-locked salmon. Improper agricultural activities have caused apparent ecosystem vulnerability and sensitivity. In this study, a system that combined three watershed-based environmental indicators with multiple-criteria decision-making techniques, the Analytical Hierarchy Process, and the Preference Ranking Organization METHod for Enrichment Evaluations was developed to assess eco-environmental vulnerability. The composite evaluation index system was set up including sediment, runoff, and nutrient factors. Supported by geographic information system and K-means clustering and taking the subwatershed as the evaluation unit, the vulnerability is classified into four levels: potential, low, moderate, and high. The evaluated results show that 8.82% of subwatersheds (six subwatersheds) are in the moderately and highly vulnerable zones. These subwatersheds represent vertical-belt distribution, mainly concentrated in the right side of the studied area and near the riparian zone along the Chi-Jia-Wan Stream. The exploited farmland in the moderately and highly vulnerable zones is about 142.21 ha, occupying 75.38% of the total farmland in the studied watershed. These seriously vulnerable zones that have caused degradation in the quality of the eco-environment should be treated with more best management practices for eco-environmental rehabilitation. Additionally, the proposed model can effectively evaluate the eco-environmental vulnerability grade for reference in policy planning and ecological restoration in this area.

Keywords Eco-environmental vulnerability · Analytical Hierarchy Process (AHP) · Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE)

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Introduction

Ecological environment quality is the basis of sustainable development. The assessment of eco-environment quality is useful to find out the current condition of sustainable development for the related policy planning of eco-environment protection (Xiong et al. 2007; Lin et al. 2008c). In the past few decades, the exploitation of slopeland in Taiwan has resulted in excessive, inappropriate, and illegal land uses. Nonpoint source pollutants such as sediments, pesticides, and organic residues from slopeland agriculture have been proven to be the major causes of water quality degradation (Lin et al. 2004).

Habitat fragmentation, landscape ecology changes, soil erosion, and water quality degradation are common eco-environmental impacts caused by natural disasters or human disturbances. Many researchers have focused on eco-environmental vulnerability evaluation using remotely sensed data and the geographic information system (GIS) coupled with environmental models or methods (Plummer 2000; Li et al. 2006), ecosystem restoration and/or evaluation (Mitsch 2005; Boesch 2006; Mitsch and Day 2006; Fink and Mitsch 2007; Hernandez and Mitsch 2007), vegetation restoration (Roovers et al. 2005; Lin et al. 2006), and multiple-criteria decision-making techniques (Li et al. 2007; Xiong et al. 2007; Lin 2008). These exploited lands belong to eco-environmentally sensitive areas where appropriate best management practices (BMPs) are needed for ecological rebuilding.

Due to the long-term use of improper agricultural activities, the exploited lands have become one of the most vulnerable eco-environmental sites in the Chi-Jia-Wan Stream watershed. The objective of this study is to assess the eco-environmental vulnerability grade using watershed-based environmental indicators coupled with multiple-criteria decision-making techniques and K-means clustering. Firstly, three disaster indicators for the evaluation of eco-environmental vulnerability, including sediment, runoff, and nutrients, were calculated using digital elevation models (DEMs) and remotely sensed data. Then, multiple-criteria decision-making techniques, the analytical hierarchy process (AHP), the Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE), and K-means clustering were employed to assess the eco-environmental vulnerability grade for reference in policy planning and ecological restoration in this area.

Multiple-Criteria Decision Making can assist policy makers in evaluating and selecting a suitable strategy from among some feasible plans based on each plan's unique features. Current frequently used evaluation methods include (1) value-focused approaches such as the weighted sum method (Janssen 1996) or AHP (Saaty 1977) and (2) outranking methods such as PROMETHEE (Brans et al. 1986) or ELimination Et Choix Traduisant la REalité (Roy 1991). Numerous researchers have integrated the above-mentioned methods with GIS, remote sensing (RS), and environmental evaluation models for environmental management and monitoring as well as ecological or habitat evaluation issues (Chou et al. 2007; Xiong et al. 2007; Ascough et al. 2008). The fuzzy algorithms or gray relational analysis method can be applied to uncertain information decision making and can also be used in environmental management (Strobl et al. 2007; Lin et al. 2008a, b, c, d). In this study, based on the decision-making algorithms, GIS and RS compatibility, available software, and applications in this study field, AHP and PROMETHEE are therefore employed to evaluate the environmental vulnerability.

Materials and methods

Study area

The Chi-Jia-Wan Stream watershed (area 7,403.20 ha, altitude 1,693–3,873 m, average slope 71 %, average precipitation 2,246 mm/year, annual mean temperature 15.8°C) is located in the area of the upstream Da-Chia River in Taichung County, Taiwan (Fig. 1). The area lies between latitudes 24° 20′ 43″ N and 24° 26′ 36″ N and between longitudes 121° 13′ 46″ E and 121° 19′ 48″ E. The geological data from Taiwan's Central Geological Service show that the rock formations occurring in the target area are the Da-Tong-Shan and Gan-Gou Paleocene stratifications, chiefly formed by slate, shale, gravel, rock, and

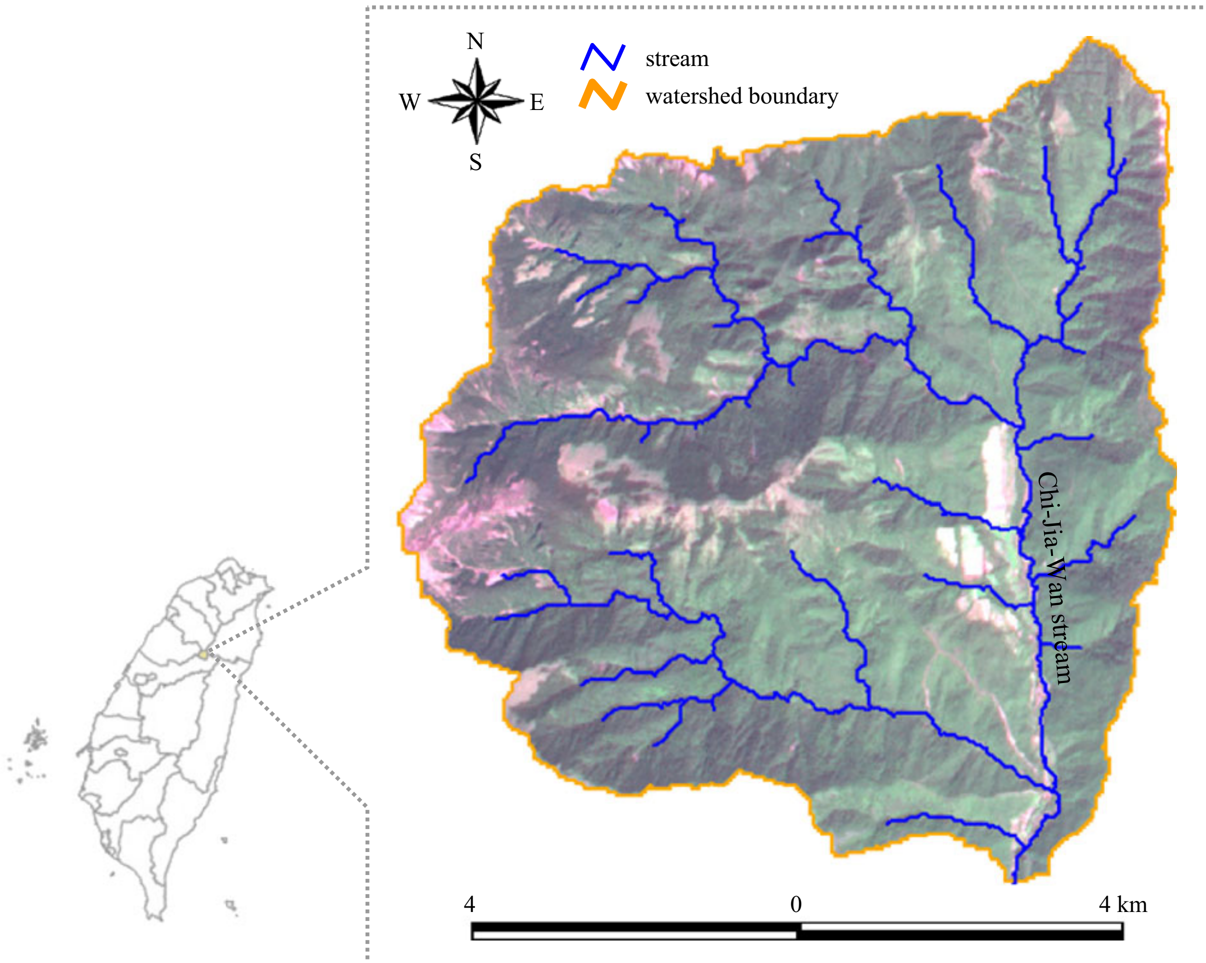


Fig. 1 Site of study area

sandstone. The soils contain a high percentage of sand and minor silt and clay. Since 1961, Wu-Ling Farm development projects have utilized lands near the Chi-Jia-Wan Stream in the upstream Techi Reservoir watershed in central Taiwan. The slope of these lands is steep, which speeds up runoff. Agricultural development of these slopes for fruit trees and vegetables has deeply impaired the habitat of land-locked salmon (*Oncorhynchus masou formosanus*).

Materials

This study aimed to assess the eco-environmental vulnerability of the Chi-Jia-Wan Stream watershed, combining the concepts of natural disaster factors, watershed-based environmental models, and multiple-criteria decision-making techniques. The selected disaster factors for eco-environmental vulnerability assessment were on the basis of researches carried out in the past few decades on the studied watershed. Watershed analyses include flow direction calculation, drainage network extraction, and watershed delineation. Environmental digital data consist of DEMs (grid size 40 m) from Taiwan's Agriculture and Forest Aviation Measurement Institution and a 20-m high-resolution Satellite Pour l'Observation de la Terre (SPOT) image taken on 12 October 2000 from the Center for

Space and Remote Sensing Research, National Central University. The weight and priority of eco-environmental vulnerability factors were quantified using multiple-criteria decision-making techniques. The system architecture has been developed as watershed analysis software (Lin et al. 2008b). Some important algorithms used in the developed system are watershed modeling analysis, satellite image analysis, sediment yield estimation, storm-water runoff simulation, and watershed information statistics. A study flow chart representing the relations among these parameters, models, and methods is shown in Fig. 2.

Watershed analysis and land use interpretation

A modified method proposed by Chou et al. (2004) was chosen to calculate the depressionless flow directions for improving dead-end problems in depressions and flat areas. The suitable stream networks in the studied watershed were extracted by the headwater-tracing method proposed by Lin et al. (2008b), which is different from the constant-threshold method for extracting drainage networks. By tracing the flow paths from headwaters to the outlet, the stream networks can be delineated, as shown in Fig. 3. The accurate headwaters, the channel initiation points, were

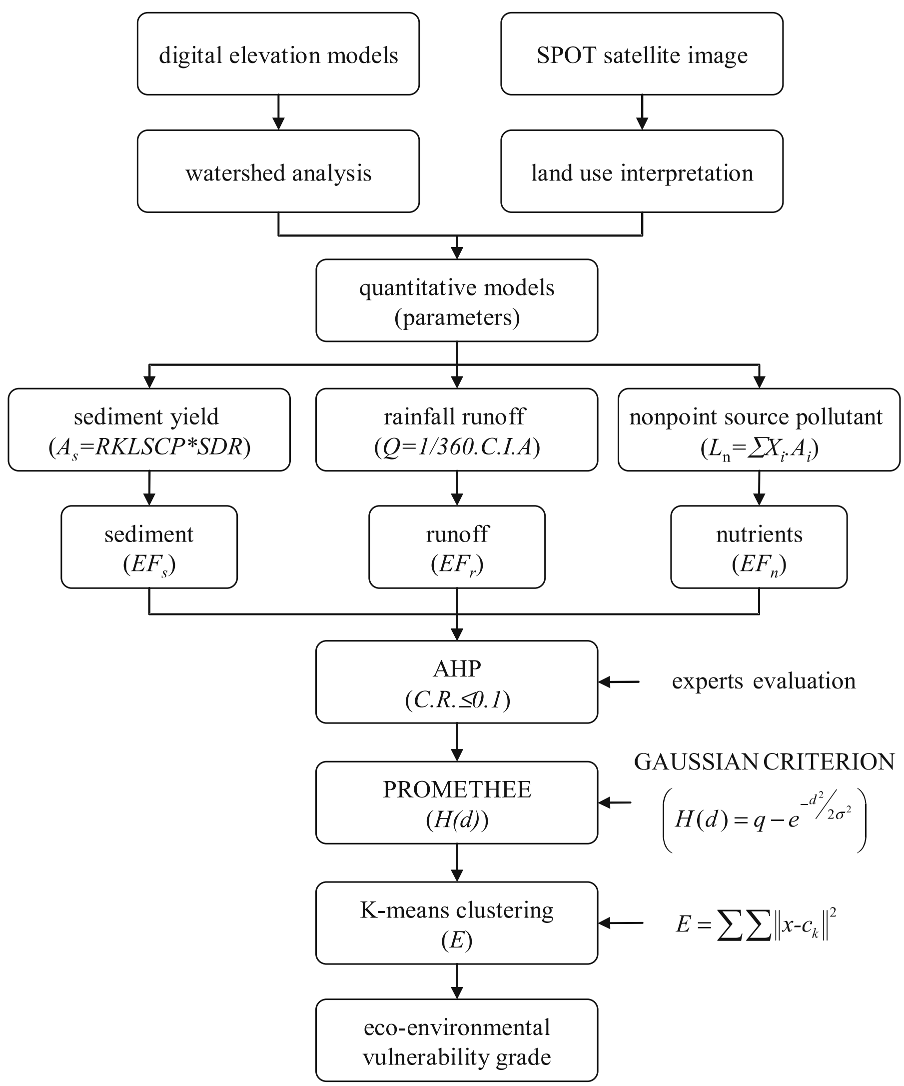


Fig. 2 Illustration of the study flow chart

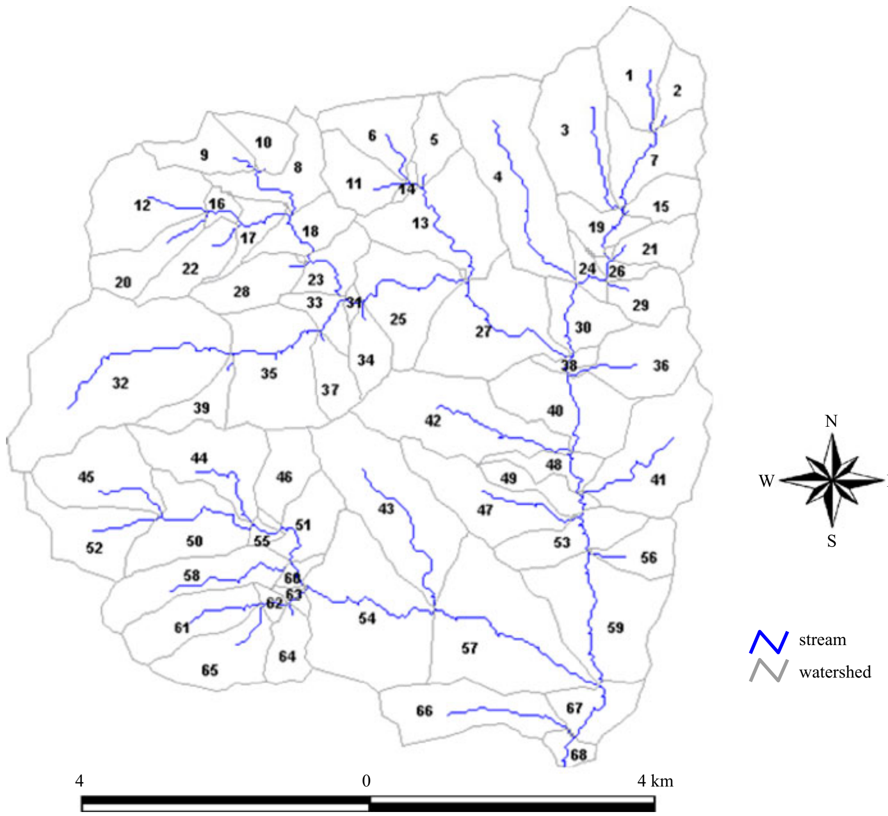


Fig. 3 The delineated subwatersheds and stream networks in the studied area

obtained from topographic maps. In the studied area, there are 68 subwatersheds (Fig. 3) delineated based on the user requirement technique. The automated watershed delineation was preformed based on a large-scale topographic map which is characterized by blue lines and contour lines. The obtained stream headwater origins were used to extract channel networks fitting real topography using the headwater-tracing algorithm (Lin et al. 2008b). Based on the derived channel networks, the confluent point for each tributary was used to delineate the upstream subwatershed using the outlet-tracing algorithm (Lin et al. 2008b).

In the studied watershed, five primary land uses (water, forest, grass, landslide, and farmland) were interpreted from SPOT imagery from a former study (Lin et al. 2008d), as shown in Fig. 4. Forest covers 95.91% (7,100.28 ha) of the watershed area. The cultivated land is concentrated on the right riverbank along the stream.

Modeling the factors of eco-environmental vulnerability

In mountainous watersheds, there have been several hillslope disasters, such as sediments, surface runoff, landslide, debris flow, and nonpoint source pollution. The more vulnerable the assessed eco-environment, the more disastrous conditions occurred. Due to improper agricultural activities in the Chi-Jia-Wan Stream watershed, there has been a large number of researchers focused on soil loss, water pollution, and/or BMPs (Ding and Cheng 1979; Wong and Lee 1991; Chang et al. 1996; Lin 1998; Lin et al. 2002a, 2004, 2008d). During the rainfall season, a tremendous amount of sediments, fertilizer, and pesticides was flushed into channels by concentrating surface runoff, which severely deteriorates the water quality of the downstream river and reservoir. Therefore, three disaster factors, slopeland sediment, surface runoff, and nonpoint source pollutant,

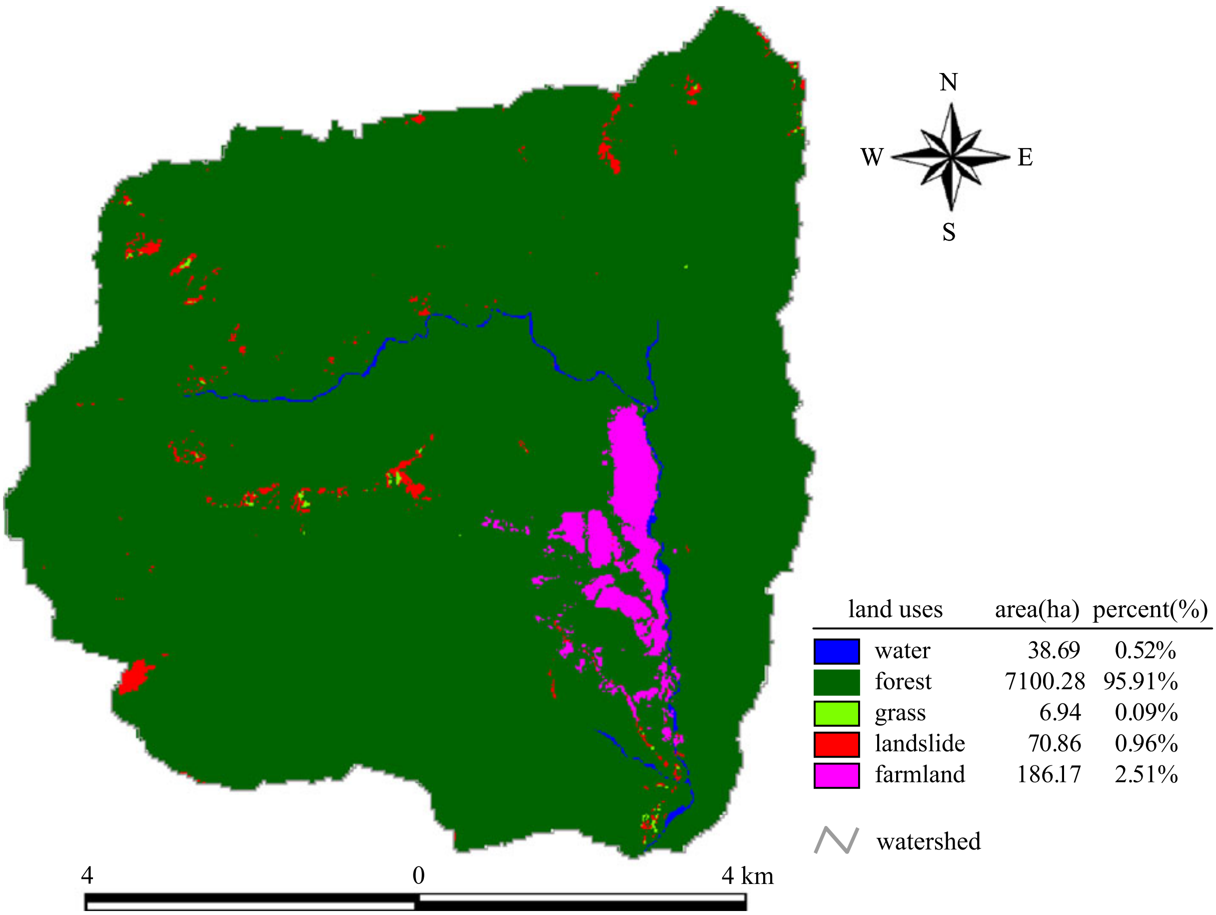


Fig. 4 Spatial distribution of land uses in the studied watershed

were selected to assess the eco-environmental vulnerability.

Sediment yield prediction

Soil loss was estimated using a watershed-based soil erosion model based on the modified Universal Soil Loss Equation (USLE) coupled with the sediment delivery ratio and GIS technique (Young et al. 1989; Kinnell 2001; Lin et al. 2002b). The USLE is expressed as follows:

$$A = RKLSCP$$

where A is the average annual soil loss (tons/ha per year); R is the rainfall erosivity factor (MJ/ha/mm/h); K is the soil erodibility factor (tons/MJ/h/mm); L is the slope length factor; S is the slope steepness factor; C is the cover management factor, and P is the supporting practice factor.

The R value can be checked on the Taiwan rainfall erosivity map given by Huang (1979). The monograph of Taiwan's K values was interpolated or measured from county soil surveys by sampling more than 113 sites (Wann 1984). This study employed the method by Lin et al. (2002b) for calculating the L factor. The S factor can be evaluated by combining the L factor for each land cell (Wischmeier and Smith 1978). Land use and management are represented by CP factors and can be inferred using RS combined with ground truthing. The SPOT image of the studied watershed was classified into five land cover types, including water, forest, grass, landslide, and farmland. Lin

(1995) verified the cover management factor for Taiwan's upstream watershed and suggested that C values for a variety of land covers are water (0), forest (0.01), grass (0.05), landslide (1.0), and farmland (0.39). Because artificial erosion control practices are nearly absent, a P factor is assigned to each land cell with a value of 1.0 in the studied watershed.

The amount of sediment delivery from upland to the stream or watershed outlet can be determined by multiplying the soil erosion rates against a delivery ratio. The relationship is given by

$$L_s = \sum (\mathrm{As})_i \times \mathrm{SDR}_i$$

where L_s is the total amount of upland sediment delivered to the perennial stream (tons/year); As is the annual soil loss (tons/year) for a given cell, and SDR_i is the upland sediment delivery ratio of the cell i. It can be expressed in nondimensional terms as:

$$SDR = \frac{S_Y}{T}$$

where S_Y is the sediment yield (mass/area/time) at the watershed outlet or point of interest, and T is the total soil loss (mass/area/time) defined as the total eroded sediment of the watershed. The average erosion depth (D_{ero}) for a watershed can be calculated as:

$$D_{ero}\,(\mathrm{cm}) = \frac{L_s\,(\mathrm{ton})}{W_a\,(\mathrm{ha}) \times 10^4\left(\mathrm{m}^2/\mathrm{ha}\right) \times 10^{-2}\,(\mathrm{m/cm}) \times 1.4\left(\mathrm{ton/m}^3\right)}$$

where L_s is the total amount of sediment delivered to the perennial stream (tons/year); W_a is the watershed area (ha).

Rainfall runoff simulation

Chou (2002) proposed an improved hydrograph simulation from a rational method that combines rational formula, watershed delineation theory, and GIS technique to calculate peak discharge for the upstream watershed. The improved rational method is based on raster data, and the discharge for each spatially distributed grid can be written as:

$$Q_i = \frac{1}{360} C_i I_i A_i$$

where Q_i is the discharge for a specific grid (m^3/s); A_i is the grid area (ha); I_i is the calculated rainfall intensity (mm/h), and C_i is the distributed runoff coefficient derived from satellite imagery (dimensionless). The synthetic discharge from the total grids in this watershed can be obtained by:

$$Q_i = \sum_{i=1}^{n} \frac{1}{360} C_i I_i A_i$$

Normally, rainfall intensity can be obtained from an intensity–duration–frequency curve (Patra 2001); the general form is given as:

$$I = \frac{K \cdot T^a}{(t_c + b)^n}$$

where I is rainfall intensity (cm/h); T is the return period (years), and t_c is the concentration time (h), which can be calculated based on using t_0 (time for overland flow in hours), and t_s (time for channel flow in hours), $t_c = t_0 + t_s$; K, a, b, and n are the watershed's constants.

The normalized difference vegetation index (NDVI) is one of the most popular methods for monitoring vegetation conditions. It has been reported that multitemporal NDVI is useful for classifying land cover and the dynamics of vegetation (Birky 2001; Lin et al. 2008a; Chou et al. 2009). NDVI can be expressed as (Justice et al. 1985):

$$\mathrm{NDVI} = \frac{\mathrm{DN}_{nir} - \mathrm{DN}_r}{\mathrm{DN}_{nir} + \mathrm{DN}_r}$$

where DN_{nir} is the brightness of the near-infrared waveband and DN_r is the brightness of the visible red waveband. The higher the NDVI value, the better is the photosynthesis activity.

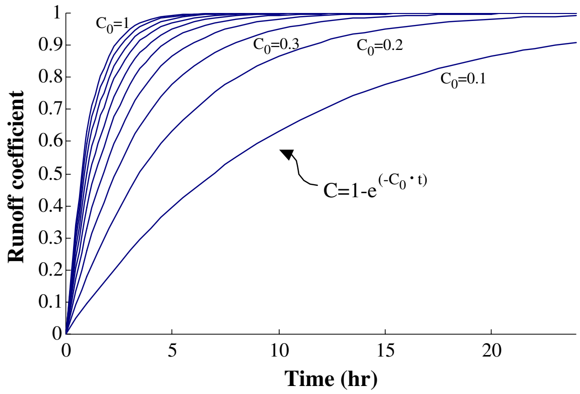


Fig. 5 The time-varying runoff coefficient C

The time-varying runoff coefficient can be derived based on the concept of initial runoff coefficient (C_0) from NDVI by SPOT data analysis ($C_0 = (1 - NDVI)/2$) and Horton's infiltration equation $f(t) = f_c + (f_0 - f_c) \cdot e^{-kt}$, where $f(t)$ is an infiltration rate as a function of time in centimeter per hour; f_c is the ultimate infiltration rate in centimeter per hour; f_0 is the initial infiltration rate in centimeter per hour; k is the recession constant per hour, and t is time in hours. The conceptual formula for the time-varying runoff coefficient can be expressed as:

$$C = \left(1 - e^{C_0 t}\right)^n$$

where C_0 is the initial coefficient; t is the time after rainfall, and n reflects the watershed complicated reactions. Under an ideal condition, n is assumed to be 1, with the runoff coefficient C in Fig. 5 illustrating an upside-down shape of Horton's infiltration curve. Figure 5 also shows the different initial runoff coefficients C_0, with the time increasing, soil moisture reaching saturated condition, and the runoff coefficient C tending towards a constant value.

Nonpoint source pollutant estimation

Nonpoint source pollution is a type of pollution that does not come from a single source or point. In most of Taiwan's watersheds, nonpoint source pollution occurs mainly through stormwater runoff. Nonpoint source pollutants such as sediments, pesticides, and organic residues from slopeland agriculture have been proven to be the major causes of water quality degradation (Lin et al. 2004). Widely used methods of estimating nonpoint source pollution include the nutrient export coefficient method, the directly measured method, and the model simulating method (Johnes and O'Sullivan 1989; Wanielista and Yoursef 1992; Chang et al. 1996; Endreny and Wood 2003). In these methods, the nutrient export coefficient is the rate at which nitrogen or phosphorus is exported from each land use type in the river basin. It is suitable for generating reasonable estimates of annual nutrients loading, especially for total nitrogen (TN) and total phosphorus (TP), simply from a watershed's land cover data. The annual nutrient loading for each land use can be expressed as:

$$L_\mathrm{n} = \sum_{i=1}^{n} X_i \cdot A_i$$

where L_n is the annual nutrient loading for each land use (kg); X_i is the unit load of the ith land use; A_i is the area of the ith land use in the watershed, and n is the number of land uses in the watershed.

The export coefficient values of nutrients for each land use pattern in the studied area were estimated as listed in Table 1 (Chang et al. 1996; Lin 2003). The values were used to calculate the annual nutrient loading for each subwatershed.

Multiple-criteria decision-making techniques

Analytic hierarchy process

The AHP is a multiple-criteria decision-making method proposed by Saaty (1977). AHP is a powerful decision-making technique that enables decision makers to structure a complex problem in the form of a simple hierarchy and to evaluate a large

Table 1 The export coefficient values of nutrients for each land use pattern

Land use pattern	*TN* (kg/ha per year)	*TP* (kg/ha per year)
Forest	3.00	0.20
Grass	0.74	0.20
Bared soil	26.00	4.00
Farmland	26.00	5.33

number of quantitative and qualitative factors in a systematic manner under multiple conflicting criteria. Each step is described as follows:

Step 1. Establishing the hierarchic structure

The overall evaluation of a goal breaks down a complex problem into a number of evaluative factors and structures the factors into a hierarchical form. In this study, the hierarchy was structured in Fig. 6. The goal (level 1) is the eco-environmental vulnerability assessment. The evaluative factors (level 2) for the goal are sediment (EF_s), runoff (EF_r), and nutrients (EF_n). The corresponding quantitative indices are the average erosion depth (D_{ero}), runoff coefficient (C), and annual nutrient loading (L).

Step 2. Establishing the comparison matrix

The pairwise comparison is performed with a judgment scale (Table 2). Generally, the nine-point scale is used because the qualitative distinctions are meaningful in practice. The ability to make qualitative distinctions is represented well by the five possible points: equal, moderate, strong, very strong, and extreme (Saaty 1980). Each pairwise comparison assigns a numerical value to the pair according to the relative importance of the two factors. The $n \times n$ pairwise comparison matrix, $A = [a_{ij}]$, is mathematically expressed as follows:

$$A = \begin{bmatrix} 1 & a_{12} & \ldots & a_{1n} \\ 1/a_{12} & 1 & \ldots & \\ \vdots & \vdots & \vdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \ldots & 1 \end{bmatrix}$$

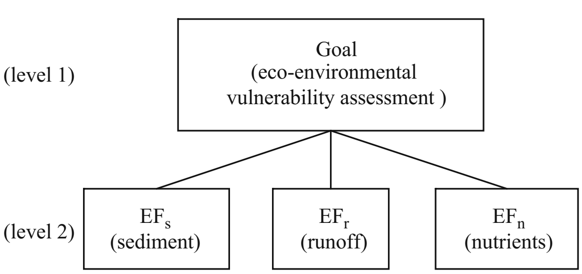


Fig. 6 Hierarchy for eco-environmental vulnerability assessment

Table 2 Judgments and definitions for the pairwise comparison

Judgment of importance	Definition
1	Two factors are equally important
3	One is moderately important compared to the other
5	One is strongly important compared to the other
7	One is very strongly important compared to the other
9	One is extremely important compared to the other
2, 4, 6, 8	The intermediate values of the neighboring two scales

where n is the number of evaluative factors, and a_{ij} is the relative weight determined by the pairwise comparison to quantify the relative importance of the ith evaluative factor with respect to the jth evaluative factor ($i, j = 1, 2, 3, ..., n$).

Step 3. Calculating the weights of evaluative factors in each group

If matrix A is not a nonzero vector, the matrix can be computed by using the following mathematical expression:

$$Aw = \lambda_{\max} w \quad \text{and} \quad \sum_{i=1}^{n} w_i = 1$$

where $w = [w_1\ w_2\ \cdots\ w_n]^T$, the weights of evaluative factors in each group; $\lambda_{\max}$ is the largest eigenvector of the matrix A. If the pairwise comparison matrix is perfectly consistent, then $\lambda_{\max} = n$ and the consistency ratio (CR) is 0.

Step 4. Measuring the consistency of the pairwise comparison matrix

The consistency of the matrix A is evaluated by the consistency ratio (CR), and w is accepted if $CR \leq 0.1$. The CR is measured by the ratio of the consistency index (CI) to the random index (RI). The expression is as follows:

$$CR = \frac{CI}{RI}$$

where $CI = (\lambda_{\max} - n) / (n - 1)$, and RI is the average of CI values of the randomly generated

Table 3 Random index

Size (n)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.54	1.56	1.57	1.58

pairwise comparison matrix. The values of RI are described in Table 3. The pairwise comparison has obvious inconsistencies and might not yield meaningful results when CR > 0.1 (Saaty 1980; Kinoshita 2000).

Step 5. Calculating global weights of each evaluative factor

The global weights of each evaluative factor in a level of the hierarchy relative to a whole level directly above can be obtained by multiplying all weights on the pass from the top of the hierarchy to the level.

The Preference Ranking Organization METHod for Enrichment Evaluations

The PROMETHEE method presented by Brans et al. (1984) is an iterative multiple-criteria decision-making technique designed to handle qualitative and discrete alternatives. For a complex eco-environment system with multiobjective problems, it is appropriate to apply the PROMETHEE technique. Based on PROMETHEE outranking flow calculation, three watershed-based disaster factors (EF_s, EF_r, and EF_n) coupled with the derived weights from the AHP algorithm were proposed to assess the priority of eco-environmental vulnerability for watershed restoration planning.

In this study, the PROMETHEE II method was chosen to quantify and determine the priority of eco-environmental vulnerability. The method PROMETHEE II is a popular decision method that has been successfully applied in the selection of the final solution of convex multiobjective optimization problems. It is based on the concept of an outranking relation, which is a binary relation defined between every pair (a, b) of alternatives. If a is preferred to b, then a outranks b. The method PROMETHEE II extends this classical PROMETHEE approach by modeling the decision maker's preferences through a preference function $H(d)$ (Parreiras and Vasconcelos 2007). The calculation steps of the PROMETHEE method are described as follows:

1. Establishing an alternatives and criterion matrix

If the studied area is delineated with n watersheds, there will be n alternatives $(a_1, a_2, ..., a_n)$. Usually, the calculated annual nutrient loading consists of TN and TP. Therefore, each watershed has four evaluative factors (EF_s, EF_r, $EF_{n,TP}$, and $EF_{n,TN}$). The evaluative function can be written as $f_1(.)$, $f_2(.)$, $f_3(.)$, and $f_4(.)$. The alternatives and criterion can be expressed as an n-by-4 matrix $\vec{T}$.

$$\vec{T} = \begin{vmatrix} f_1(a_1) & f_2(a_1) & f_3(a_1) & f_4(a_1) \\ f_1(a_2) & f_2(a_2) & f_3(a_2) & f_4(a_2) \\ \cdots & \cdots & \cdots & \cdots \\ f_1(a_n) & f_2(a_n) & f_3(a_n) & f_4(a_n) \end{vmatrix}$$

2. Selecting a preference function $(H(d))$

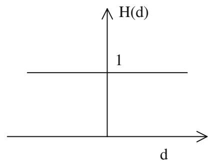
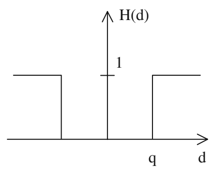
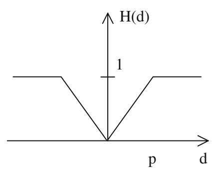
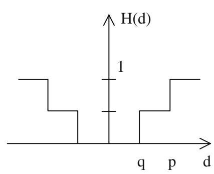
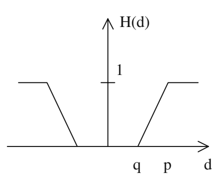
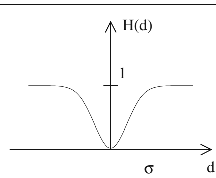
The evaluative difference between the ith watershed and the other watersheds can be expressed as an n-by-4 matrix $\vec{d_i}$.

$$\vec{d_i} = \begin{vmatrix} d_1(a_i, a_1) & d_2(a_i, a_1) & d_3(a_i, a_1) & d_4(a_i, a_1) \\ d_1(a_i, a_2) & d_2(a_i, a_2) & d_3(a_i, a_2) & d_4(a_i, a_2) \\ \cdots & \cdots & \cdots & \cdots \\ d_1(a_i, a_n) & d_2(a_i, a_n) & d_3(a_i, a_n) & d_4(a_i, a_n) \end{vmatrix}$$

where $d(a_i, a_n) = f(a_i) - f(a_n)$.

Brans et al. (1984) presented the shape of the six possible types of generalized criteria to assist the decision maker with this selection, as shown in Table 4. He pointed out that the GAUSSIAN criterion was selected most by users for practical applications, especially for continuous data. Because of the criteria containing continuity, the GAUSSIAN criterion was chosen for evaluation.

Table 4 The shape of the six possible types of generalized criteria

Generalized criterion type	Preference function($H(d)$)
Type I : USUAL CRITERION $H(d)=\begin{cases}0 & d=0\\ 1 & \lvert d\rvert>0\end{cases}$	
Type II : U-SHAPE CRITERION $H(d)=\begin{cases}0 & \lvert d\rvert\le q\\ 1 & \lvert d\rvert>q\end{cases}$	
Type III : V-SHAPE CRITERION $H(d)=\begin{cases}\frac{\lvert d\rvert}{p} & \lvert d\rvert\le p\\ 1 & \lvert d\rvert>p\end{cases}$	
Type IV : LEVEL CRITERION $H(d)=\begin{cases}0 & \lvert d\rvert\le q\\ \frac{1}{2} & q<\lvert d\rvert\le p\\ 1 & \lvert d\rvert>p\end{cases}$	
Type V : V-SHAPE CRITERION WITH INDIFFERENCE CRITERION $H(d)=\begin{cases}0 & \lvert d\rvert\le q\\ \frac{\lvert d\rvert-q}{p-q} & q<\lvert d\rvert\le p\\ 1 & \lvert d\rvert>p\end{cases}$	
Type VI : GAUSSIAN CRITERION $H(d)=1-e^{-d^2/2\sigma^2}$	

In the six-type function, $H(d)=1-e^{-\frac{d^2}{2\sigma^2}}$, σ is a parameter of Gaussian distribution and defined as the threshold value between the indifferent and strict preference areas. The evaluative difference in the ith watershed compared with the other watersheds can be expressed as an n-by-4 matrix $\vec{H}_i$.

$$\vec{H}_i=\begin{vmatrix} 1-e^{\frac{d_1(a_i,a_1)}{2\sigma}} & 1-e^{\frac{d_2(a_i,a_1)}{2\sigma}} & 1-e^{\frac{d_3(a_i,a_1)}{2\sigma}} & 1-e^{\frac{d_4(a_i,a_1)}{2\sigma}}\\ 1-e^{\frac{d_1(a_i,a_2)}{2\sigma}} & 1-e^{\frac{d_2(a_i,a_2)}{2\sigma}} & 1-e^{\frac{d_3(a_i,a_2)}{2\sigma}} & 1-e^{\frac{d_4(a_i,a_2)}{2\sigma}}\\ \ldots & \ldots & \ldots & \ldots\\ 1-e^{\frac{d_1(a_i,a_n)}{2\sigma}} & 1-e^{\frac{d_2(a_i,a_n)}{2\sigma}} & 1-e^{\frac{d_3(a_i,a_n)}{2\sigma}} & 1-e^{\frac{d_4(a_i,a_n)}{2\sigma}} \end{vmatrix}$$

3. Calculating the preference index (π)

For each pair of alternatives, the preference index $\pi(d)$ can be written as:

$$\pi\,(d)=\sum_{j=1}^{2} w_j H_j\,(d)$$

where w_j, $j=1,2,3,4$ are weights associated with each criterion. In this study, the weights are based on the calculated result of AHP in which the third and fourth evaluative factors ($EF_{n,\mathrm{TP}}$ and $EF_{n,\mathrm{TN}}$) have the same weights (half the weight of EF_n). The weights can be expressed as a 1-by-4 matrix $\vec{w}$.

$$\vec{w}=\begin{vmatrix} w_1 & w_2 & w_3 & w_4 \end{vmatrix}$$

The preference index of the ith cell compared with the other cells can be written as:

$$\pi_i=\vec{H}_i\cdot\vec{w}\cdot\vec{S}$$

where $\vec{S}$ is an n-by-1 scalar matrix ($\vec{S}=\begin{vmatrix}1\\1\\\ldots\\1\end{vmatrix}$).

4. Calculating the outranking flow (ϕ)

According to the above preference index (π), the outranking flow for the ith cell can be written as:

$$\phi_i=\sum_{i=1}^{n}\pi_i$$

From the outranking flow calculation, the watershed that has a larger outranking flow has more serious eco-environmental vulnerability.

Table 5 The analyzed results of eco-environmental vulnerability indicators

Watershed no.	Watershed area (ha)	D_{ero} (mm)	C	$L_n(TP)$ (kg/ha per year)	$L_n\ (TN)$ (kg/ha per year)
1	118.24	0.48	0.21	0.30	3.62
2	55.20	0.57	0.27	0.31	3.65
3	188.96	0.59	0.20	0.28	3.51
4	282.40	0.45	0.19	0.23	3.20
5	54.56	0.55	0.22	0.22	3.13
6	98.56	0.66	0.22	0.24	3.22
7	123.68	0.45	0.23	0.21	3.08
8	97.28	0.39	0.26	0.20	3.00
9	69.76	0.58	0.25	0.20	3.00
10	57.44	0.24	0.29	0.20	3.00
11	83.20	0.27	0.24	0.20	3.00
12	173.76	3.27	0.27	0.35	3.93
13	200.48	0.43	0.21	0.20	3.02
14	9.12	0.53	0.23	0.20	3.00
15	51.84	0.31	0.26	0.20	3.00
16	19.36	0.75	0.27	0.20	3.00
17	44.32	0.73	0.27	0.21	3.08
18	71.04	0.39	0.26	0.21	3.05
19	58.24	0.51	0.21	0.20	3.00
20	80.32	1.08	0.30	0.28	3.49
21	63.20	0.43	0.29	0.20	3.00
22	77.12	0.44	0.28	0.27	3.42
23	63.84	0.55	0.26	0.20	3.00
24	27.52	0.40	0.22	0.20	2.98
25	154.40	0.68	0.28	0.23	3.17
26	18.56	0.49	0.22	0.20	3.00
27	228.80	0.59	0.26	0.21	3.01
28	84.32	0.23	0.24	0.27	3.44
29	62.88	0.49	0.25	0.20	3.00
30	78.24	0.61	0.21	0.20	2.94
31	8.48	0.62	0.28	0.19	2.89
32	461.12	1.27	0.32	0.24	3.23
33	41.12	0.39	0.30	0.20	2.94
34	52.96	0.38	0.29	0.21	3.07
35	201.92	0.34	0.31	0.20	3.00
36	130.72	0.25	0.18	0.20	3.00
37	51.52	0.19	0.28	0.22	3.14
38	17.12	8.36	0.24	1.48	8.58
39	52.64	0.28	0.30	0.23	3.21
40	163.68	1.11	0.24	1.54	8.97
41	212.16	0.73	0.17	0.21	3.05
42	226.08	2.69	0.17	0.67	5.23
43	269.12	0.62	0.15	0.27	3.42
44	152.32	0.78	0.24	0.32	3.74
45	150.08	0.56	0.32	0.20	3.00
46	78.08	1.01	0.18	0.31	3.65
47	149.12	4.49	0.17	1.07	6.90
48	50.08	4.40	0.23	2.70	14.14
49	51.20	4.94	0.23	3.16	16.18
50	145.60	0.44	0.29	0.20	3.00
51	82.88	0.44	0.25	0.20	3.00
52	125.92	0.73	0.31	0.21	3.09
53	99.36	3.67	0.23	1.11	7.07

Table 5 (continued)

Watershed no.	Watershed area (ha)	D_{ero} (mm)	C	$L_n(TP)$ (kg/ha per year)	$L_n(TN)$ (kg/ha per year)
54	312.32	0.50	0.23	0.20	3.00
55	11.68	0.72	0.28	0.20	3.00
56	62.24	0.50	0.18	0.20	3.00
57	315.68	1.24	0.21	0.36	3.80
58	137.44	2.04	0.23	0.48	4.69
59	229.76	3.11	0.23	0.65	5.00
60	16.16	0.97	0.25	0.20	3.00
61	113.60	0.42	0.23	0.20	3.00
62	13.12	0.72	0.23	0.20	3.00
63	11.04	0.29	0.23	0.20	3.00
64	52.80	0.67	0.24	0.20	3.00
65	115.84	0.39	0.24	0.22	3.10
66	156.16	0.72	0.14	0.22	3.09
67	76.32	0.57	0.22	0.26	3.26
68	25.92	3.01	0.22	0.11	1.30

Eco-environmental vulnerability grade using K-means clustering

In this study, eco-environmental vulnerability is classified into four levels, defined as potential, light, moderate, and high levels, using unsupervised K-means clustering. The K-means algorithm is an iterative clustering method which divides the data into a number of clusters by minimizing an error function which can be expressed as (Vesanto and Alhoniemi 2000):

$$E = \sum_{k=1}^{C} \sum_{x \in Q_k} \|x - c_k\|^2$$

where x is the outranking flow calculated using the PROMETHEE technique. C is the number of clusters; in this study, $C = 4$. Q_k is the kth cluster and c_k is the center of cluster k.

Results and discussion

Analysis of eco-environmental vulnerability indicators

The estimated sediment yields and average annual depths derived from the 1.4-tons/m^3 bulk density calculation of the topsoil for the studied subwatersheds are summarized in Table 5. Because the bare surface is easily eroded during rainfall or typhoon events, there are ten watersheds (nos. 12, 38, 42, 47, 48, 49, 53, 58, 59, and 68) of soil loss belonging to the highly eroded area ($D_{ero} \geq 2$ mm). Overlaid with the classified land uses, the results show that watersheds (nos. 38, 42, 47, 48, 49, 53, and 59) were overused by improper agricultural activities, as listed in Table 6. Watershed no. 38 has the maximum erosion depth of up to 8.36 mm.

In this study, the rainfall–runoff simulation for each watershed was carried out using the rainfall data from the climate station of the Taiwanese Central Weather Bureau. The runoff coefficient C for each watershed was calculated as shown in Table 5. Seven watersheds (nos. 20, 32, 33, 35, 39, 45, and 52) have larger runoff coefficients ($C \geq 0.3$). Watershed nos. 32 and 45 have the maximum runoff coefficients of up to 0.32. These subwatersheds were mainly distributed on the left side of

Table 6 The statistics of farmland areas in subwatersheds

Watershed no.	Watershed area W_a (ha)	Farmland F_a (ha)	F_a/W_a (%)
27	228.80	0.88	0.38
38	17.12	4.28	25.01
40	163.68	42.95	26.24
41	212.16	0.27	0.13
42	226.08	16.88	7.46
47	149.12	23.72	15.91
48	50.08	24.48	48.89
49	51.20	29.30	57.22
53	99.36	17.48	17.60
57	315.68	7.14	2.26
59	229.76	18.80	8.18

Table 7 The outranking flow and level of eco-environmental vulnerability

Watershed no.	Outranking flow (ϕ)	Level	Watershed no.	Outranking flow (ϕ)	Level
1	−8.601	Potential	35	3.984	Light
2	0.303	Light	36	−14.567	Potential
3	−10.308	Potential	37	0.054	Light
4	−12.630	Potential	38	44.851	High
5	−8.258	Potential	39	3.025	Light
6	−7.957	Potential	40	35.094	Moderate
7	−7.099	Potential	41	−15.128	Potential
8	−2.910	Potential	42	4.877	Light
9	−4.247	Potential	43	−16.515	Potential
10	1.336	Light	44	−3.701	Potential
11	−6.068	Potential	45	5.310	Light
12	9.884	Light	46	−12.002	Potential
13	−9.976	Potential	47	24.619	Moderate
14	−7.127	Potential	48	48.063	High
15	−3.010	Potential	49	48.936	High
16	−0.952	Light	50	1.594	Light
17	−0.870	Light	51	−4.393	Potential
18	−2.828	Potential	52	4.549	Light
19	−9.912	Potential	53	33.260	Moderate
20	4.885	Light	54	−7.158	Potential
21	1.583	Light	55	0.502	Light
22	0.982	Light	56	−14.263	Potential
23	−2.741	Potential	57	−6.254	Potential
24	−8.632	Potential	58	4.364	Light
25	0.726	Light	59	12.895	Light
26	−8.516	Potential	60	−3.635	Potential
27	−2.655	Potential	61	−7.242	Potential
28	−5.303	Potential	62	−6.906	Potential
29	−4.341	Potential	63	−7.403	Potential
30	−9.867	Potential	64	−5.607	Potential
31	0.219	Light	65	−5.746	Potential
32	7.125	Light	66	−17.770	Potential
33	2.783	Light	67	−7.917	Potential
34	1.628	Light	68	−6.419	Potential

the Chi-Jia-Wan Stream. The runoff coefficient is the ratio of runoff to precipitation, which can be used to assess the water conservation capacity in the watershed. The higher the vegetation cover, the better is the water conservation capacity. A watershed with a larger runoff coefficient may cause runoff-related disasters.

The calculated values for the nonpoint source pollutants are listed in Table 5. Nonpoint source pollution is mainly from agricultural lands in the study area; there are six watersheds of TP and TN nutrients (nos. 38, 40, 47, 48, 49, and 53) with higher export coefficient values. Watershed no. 49 has the maximum export coefficient values of TP and TN of up to 3.16 kg/ha per year and 16.18 kg/ha per year, respectively. These watersheds with agricultural activities are located near the riparian zone. Nonpoint source pollutants such as sediments, pesticides, and organic residues are easily eroded into the river channel through storm-water runoff, degrading the water quality.

The study results indicate that the highly eroded watersheds with higher runoff coefficient and export coefficient values belong to vulnerable eco-environment zones, easily impacting the river ecosystem. Ecotechnology methods should be applied to protect vulnerable eco-environment zones. According to the study results for each subwatershed vulnerability, suitable BMPs can be implemented at the top priority sites based on their own characteristics. The BMPs include the following: (1) soil and water conservation measures such as engineering foundations and grass ditches are required for the initial stage of treatment of environmentally sensitive areas to reduce debris hazards; (2) reafforestation is suggested for the overused tillage areas for its direct environmental benefits; and (3) an appropriate width of vegetation buffer strip is recommended for riparian areas to prevent water pollution from fertilizers or pesticides.

Assessment of eco-environmental vulnerability grade using AHP and PROMETHEE

In this research, we invited experts with ecological, land management, and soil and water conservation backgrounds to assess the relative importance of each evaluative factor. Based on these experts' evaluations, the pairwise comparison matrix is established. The calculated weights for evaluative factors EF_s, EF_r, and EF_n are 0.154, 0.222, and 0.624, respectively. The calculated λ_{max}, CI, RI, and CR are 3.0130, 0.0065, 0.58, and 0.0112, respectively. When $CR \leq 0.10$, it means that the consistence of this matrix is acceptable. The evaluated result indicates that water pollution was crucial to ecological issues rather than runoff and sediment. The reason is that water quality degradation may impact the endangered fish, *O. masou formosanus*, which exist in their habitat. Therefore, EF_n has the highest weight. Runoff transports harmful substances and solids that will influence the river ecosystem. EF_r has the second highest weight. Comparing EF_n and EF_r, EF_s is less important because the forest is the major land cover pattern and may intercept sediments. However, the topsoil of the minor bare surface and farmland may still be easily eroded into streams.

The degree of eco-environmental vulnerability was calculated using the PROMETHEE

Fig. 7 The spatial distribution of eco-environmental vulnerability grades

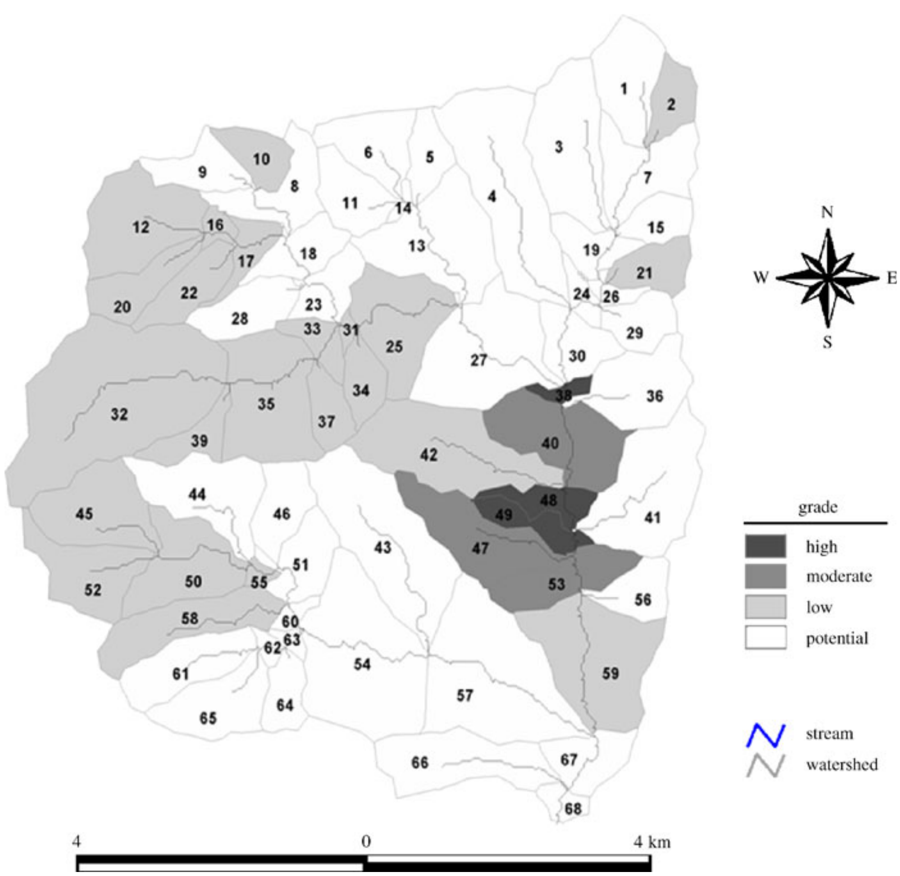


Table 8 The statistics on eco-environmental vulnerability level

Eco-environmental vulnerability level	Watershed		Clustering center of ϕ
	Number	Percentage	
Potential	39	57.35	−7.836
Light	23	33.82	3.078
Moderate	3	4.41	30.991
High	3	4.41	47.283

algorithm coupled with the weights obtained from AHP, as listed in Table 7. Then, the vulnerable zone in the studied area was classified into four levels using K-means clustering. The clustering centers for potential, low, moderate, and high vulnerability are −7.836, 3.078, 30.991, and 47.283, respectively. The spatial distributions for different eco-environmental vulnerability levels are shown in Fig. 7. From Table 8, the potential vulnerability zone has proportionally the largest area, accounting for 57.35% (39 subwatersheds); the low vulnerability zone accounts for 33.82% (23 subwatersheds); the moderate vulnerability zone accounts for 4.41% (three subwatersheds), and the high vulnerability zone also accounts for only 4.41% (three subwatersheds). The subwatersheds in the high vulnerability zone are nos. 38, 48, and 49. The subwatersheds in the moderate vulnerability zone are nos. 40, 47, and 53. These six subwatersheds present apparent vertical-belt distribution, mainly concentrated in right-hand side parts of the studied area and the riparian zone along the Chi-Jia-Wan Stream. The land along the streamside was developed as farmland with an area of 142.21 ha (occupying 76.38% of the total farmland). Because nonpoint source pollutants from slopeland agriculture have been proven to cause water pollution and affect river ecosystems, these seriously vulnerable zones should be reafforested for eco-environmental restoration.

Conclusions

Monitoring and assessment of eco-environmental vulnerability are important tasks for decision making and policy planning in a vulnerable ecosystem area. This study proposed a system that combined three watershed-based environmental indicators with multiple-criteria decision-making techniques, AHP, and PROMETHEE, for eco-environmental vulnerability assessment. The evaluated results show that slopeland agriculture with potential pollution sources has caused apparent ecosystem vulnerability and sensitivity. Information on the analyzed seriously vulnerable zones can be provided to the authorities as BMPs for eco-environmental rehabilitation in this area are needed.

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