

Incorporating stakeholders' knowledge into assessing vulnerability to climatic hazards: application to the river basin management in Taiwan

Hung-Chih Hung · Ling-Yeh Chen

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Abstract There is a growing research interest on the transdisciplinary measurement of vulnerability to climatic hazards from the perspective of integrated river basin management. However, the incorporation of stakeholders' participation, local knowledge and locally spatial characteristics into the process of such vulnerability assessment is one of the challenges faced by decision-makers, especially in developing countries. This article proposes a novel methodology for assessing and communicating vulnerability to policymaking at the river basin level through a case study of Tachia River basin in Taiwan. The authors used a multicriteria decision analysis to develop an integrated vulnerability index applied to a participatory geographic information system (GIS) to map vulnerability to climatic hazards. Using a GIS-based spatial statistics technique and multivariate analysis, we test the degree to which vulnerabilities are spatially autocorrelated throughout the river basin, explain why clustering of vulnerable areas occurs in specific locations, and why some regions are particularly vulnerable. Results demonstrate that vulnerable areas are spatially correlated across the river basin. Moreover, exposure, biophysical sensitivity, land uses and adaptive capacity are key factors contributing to the formation of localized 'hot spots' of similarly and particularly vulnerable areas. Finally, we discuss how the findings provide direction for more effective approaches to river basin planning and management.

1 Introduction

A growing number of developing countries in Asia are expected to increase exposure and vulnerability to the impacts of climate change due to rapid urbanization and overdevelopment in hazard-prone areas (ISDR 2011; IPCC 2012). This has led to an impending challenge for

H.-C. Hung (✉)
Center for Land and Environmental Planning, National Taipei University, 151, University Road, San Shia, New Taipei City 23741, Taiwan
e-mail: hung@mail.ntpu.edu.tw

L.-Y. Chen
Department of Real Estate and Built Environment, National Taipei University, 151, University Road, San Shia, New Taipei City 23741, Taiwan
e-mail: smallwayne0322@gmail.com

disaster risk managers in many developing countries, because they lack sufficient technical skills and financial resources to tackle local vulnerabilities (FRRFD 2012). Thus, developing an effective mechanism to understand the vulnerability to climate-related (climatic) hazards, such as the assessment of which sectors, regions, or communities are most vulnerable and the factors that cause or exacerbate vulnerability, is becoming an important consideration to inform disaster policy and respond to climate changes (O'Brien et al. 2004a; Brooks et al. 2005).

To prepare and confront the potential impacts of climate change, many countries have implemented programs of integrated river basin management (RBM) (Hooijer et al. 2004; Engle and Lemos 2010). In Taiwan, for instance, the Taiwan Water Resources Agency has implemented an integrated RBM program that adopts the river basin as the management unit. This comprehensive program that incorporates the components of water supply management, agricultural irrigation, land-use planning with flood risk management, aims to enhance water supply efficiency, as well as to reduce disaster risks and climatic impacts. The integrated RBM program focuses on decentralization and societal participation in order to integrate diverse interests into water governance.

From an integrated RBM perspective, decision-makers are interested in identifying and assessing specific system vulnerability that will increase disaster risks. In the process of vulnerability assessment, the involvement of various stakeholders' concerns and their active participation for incorporating local knowledge into the identification of vulnerability is believed to be particularly critical (Leach et al. 2002; Engle and Lemos 2010). Community-based approaches give stakeholders a vital role in the identification of vulnerable areas for analysis and lead to effective planning and adaptation to climatic hazards (Krishnamurthy et al. 2011). This process integrates various local connections into planning and policy lines for risk reduction within the context of all river basins.

Vulnerability assessments have widely used geographic information system (GIS) as tools to identify hazards and create vulnerability or risk maps that can help stakeholders to understand the factors leading to vulnerability and its distribution within a given area (Wisner et al. 2004; Bernard and Ostländer 2008; Hung et al. 2013). Especially, GIS has been increasingly used in supporting community-based risk analysis by integrating various stakeholders' knowledge and participation into mapping process (Tran et al. 2009). But transdisciplinary and more inclusive approaches necessary for vulnerability assessment have received relatively little attention (Füssel and Klein 2006; Fuchs et al. 2011).

Advances in technology have increased the applicability of GIS-based approached on transdisciplinary studies, such as the incorporation of spatial statistics into GIS facilitates vulnerability assessment in identifying the clustered 'hot spots' of vulnerable communities. This technique has become a useful mechanism not only to communicate priorities of similarly vulnerable communities for disaster risk reduction, but also to enhance the understanding of where and why vulnerability occurs within particular areas.

This article proposes a novel methodology for the integrated assessment of vulnerability by combining multicriteria decision and multivariate analysis with a GIS-based spatial statistics analysis at the river basin level. To illustrate the proposed methodology, a case study is presented by an assessment of vulnerability to climatic hazards (especially typhoon and flood hazards) over the Tachia River basin in Taiwan. This research developed an integrated vulnerability index applied to a participatory GIS (PGIS) for generating vulnerability maps to climatic hazards. The process of assessment included an active participation of both experts and community members by incorporating their varying knowledge to assess and diagnose vulnerability. Spatial statistics and multivariate analysis were further used to characterize the geographic distribution and 'hot spots' of particularly vulnerable areas, and explain their determinants.

2 Vulnerability and assessments

2.1 Components of vulnerability

The concept of vulnerability has been broadly used in different research communities, such as socioeconomics, biophysics, ecology and climate change (Adger 2006; Gallopín 2006). The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as the degree to which a system is susceptible to and is unable to cope with adverse effects (IPCC 2007). This concept is also often used in the disaster risk management literature, which views vulnerability as the potential for loss and harm (Cutter et al. 2008). Nonetheless, a new emphasis on the vulnerability concept has more focused on the investigation of the system being stressed and its capacity to adapt (Adger 2006; Engle 2011).

In the climate change literature, vulnerability is generally described as a function of exposure, sensitivity and adaptive capacity (IPCC 2007), although it is also considered as susceptibility to suffer damage and loss (ISDR 2011). However, there is a need to more explicitly distinguish vulnerability factors when assessing vulnerability in practice and targeting support for risk management (Ionescu et al. 2005). For example, International Strategies Disaster Reduction (ISDR) (2011) classifies four groups of vulnerability factors that are related to the context of risk reduction and climate change: (1) physical, (2) socioeconomic, (3) external assistance, and (4) environmental and location factors.

Another intuitive approach to classify vulnerability factors is to distinguish biophysical from social (or socioeconomic) vulnerability (Eakin and Luers 2006; Füssel 2007). It contextualizes vulnerability as the result of an interaction between biophysical environment and social factors (Cutter et al. 2003; Turner et al. 2003). This interpretation of vulnerability is based on what O'Brien et al. (2004b) and Füssel (2007) refer to as a starting point or integrated approaches. One purpose of vulnerability assessments using this interpretation is to identify policies or measures that reduce vulnerability or risk. This can be achieved primarily by understanding the distribution and causes of vulnerability. Especially, vulnerability mapping can be used to characterize the spatial distribution pattern of vulnerability and provide an understanding of the factors that shape vulnerability (Metzger et al. 2005; O'Brien et al. 2004a).

2.2 Vulnerability assessment and river basin management

Integrated water resource management is defined as a process which promotes the coordinated development and management of water, land and related resources (GWP 2000). This definition suggests that RBM demands integrated approaches to link various sectors when dealing with the impacts of hazards and climate change. Vulnerability assessment is an important approach for river basin managers engaged in transdisciplinary and integrated analyses on the interaction between the properties of vulnerability and components of the systems of a specific river basin area (O'Brien et al. 2004b).

In the context of RBM, this study considers vulnerability as the interaction of exposure, biophysical, socioeconomic, land-use sensitivity and adaptive capacity. There is a need to integrate these components into the process of vulnerability assessment. The most notable existing studies on integrated approaches, such as the hazard-of-place model (Cutter et al. 2003, 2008) and the coupled vulnerability framework (Turner et al. 2003), provide useful methodologies to help accomplish such vulnerability research.

In order to achieve integration, decentralization of management and decision making to the river basin level, the incorporation of diversified stakeholders' participation and

indigenous knowledge into vulnerability assessments is one of the prerequisites of RBM (Ceccato et al. 2011). This is particularly crucial for strengthening the understanding of river basin contexts and communicating disaster vulnerability to stakeholders and policymakers. Therefore, numerous current studies have suggested that the combination of participatory mapping tools (such as PGIS) with integrated vulnerability assessments provides a useful initial step to help identify vulnerability and assist in RBM (McCall and Minang 2005; Tran et al. 2009).

3 Methods

An indicator-based assessment framework was developed with the goal of identifying composite indicators that could serve as proxies for attributes of vulnerability. This framework was applied using GIS tools to incorporate stakeholders' participation into a community-based assessment of vulnerability. In the process of assessment, we employed focus group meetings,¹ as well as interviewed experts, officers (who had participated in the policymaking process of RBM) and community members to incorporate key stakeholders' knowledge and participation into weighting indicators, mapping and assessing vulnerability.

3.1 Vulnerability indicators and hypotheses

The indicators used here were identified from literature and focus group discussion. An integrated assessment of vulnerability was then conducted across the study area at the community (village) level, which is the basic unit of local administration in Taiwan.

3.1.1 Exposure indicators

Exposure is seen as one of the major elements of vulnerability, although there are other views (Gallopín 2006). From an integrated assessment perspective, exposure is regarded as a physical factor of vulnerability, which refers to the extent to which properties of vulnerable system are in contact with hazards (Füssel 2007; Mehaffey et al. 2008). Here, the indicators for measuring exposure include averaged annual *rainfall*, and potential *debris flow torrents*. These two indicators are expected to have a positive relation to vulnerability.

3.1.2 Sensitivity indicators

Sensitivity is the most commonly used concept for describing vulnerability, reflecting of patterns of resource use, susceptibility, as well as the dependence of livelihoods on climate-sensitive activities (Smit and Wandel 2006; Eakin and Bojórquez-Tapia 2008). Sensitivity indicators consist of biophysical and social sensitivity, and social sensitivity can be further divided into land uses and socioeconomic sensitivity. We used two indicators: averaged *elevation* and *proximity to rivers* to measure biophysical sensitivity. The expectation is that either lower or higher elevations are more sensitive to threats from flooding, storms and/or debris flow torrents. The middle elevation areas are relatively less sensitive to climatic hazards than other areas. Thus, *elevation* has a 'V-shaped' relation to vulnerability. Distance

¹ The focus group consisted of six experts and officers from the fields of disaster management, city planning, civil engineering, climatology, and water management. The focus group meetings helped identify the framework of vulnerability indicators, the relationship between indicators and vulnerability, as well as the connections in the network of these indicators (Fig. 1).

or proximity often serves as an indicator that can measure the risk or sensitivity to climatic hazards (Balica et al. 2009; Hung and Wang 2011). Vulnerability is thus a function of proximity to rivers.

The indicators considered for describing socioeconomic sensitivity comprise *populations*, *social dependence*, *income*, *employment*, and *production values* of industries and services. *Employment* is expected to have a negative effect, *income* a ‘V-shaped’² and the other indicators a positive effect on vulnerability (Luers et al. 2003; Eakin and Luers 2006; Brouwer et al. 2007). Land use consists of four indicators: *urban*, *agricultural uses*, *sensitive areas*, and *road infrastructure* (Mehaffey et al. 2008). In general, larger scales of either *urban*, *agricultural uses* or *sensitive areas* have greater sensitivity to climatic hazards, and a positive relation to vulnerability. Provision of *road* or transportation infrastructure will be helpful for evacuation and disasters relief. But excessive *road infrastructure* can also encourage disproportionate land developments, agricultural and tourist activities to enter environmental sensitive areas, which would enhance vulnerability to hazards (Cutter et al. 2003). *Road infrastructure* is thus hypothesized to have a ‘V-shaped’ relation to vulnerability.³

3.1.3 Adaptive capacity indicators

Adaptive capacity is generally considered as the capacity to absorb impacts and to reduce losses resulting from potential hazards, which includes the ability to plan, prepare, facilitate, learn, and implement related strategies for reducing vulnerability (Klein et al. 2003). Recent research has emphasized the enhancement of coping, behavioral, and institutional capacities to improve adaptive capacity (Berman et al. 2012). Within the adaptive capacity indicators, *shelter*, *medical*, *police*, and *fire services* are the main facilities to support warning, evacuation, and emergency responses. These indicators reflect an area’s capabilities of coping with, preparedness, and recovery from disasters, and a negative linkage to vulnerability is expected.

From a behavioral perspective, community members’ ability of *access to resources*, *risk perceptions* and their appraisals of their ability to successfully adopt (self-efficacy) to hazards are the key factors that affect the willingness of residents to adopt adaptive strategies (Sharma et al. 2009). The expected effect of these behavioral indicators on vulnerability is negative. The evaluation of these factors was conducted by a random sampling of household interview for each village. Finally, those indicators considered to assess vulnerability are displayed in Table 1, along with their description, data sources, and referenced literature.

3.2 Weighting indicators

Once the indicators of vulnerability had been identified, the next step was to determine the weights for the indicators through the analytic network process (ANP). The ANP, proposed by Saaty (2004), is a novel method for evaluating and ranking indicators. It provides a general approach to deal with decisions, without making assumptions about the independence of higher level elements from lower level elements and about the independence within a level. The ANP extends the Analytic Hierarchy Process (AHP)⁴ to cases of dependence and feedback, and generalizes on the supermatrix approach constructed in the AHP.

² This implies that either lower or higher income areas are more sensitive to impacts of hazards. The middle income areas are thus relatively less sensitivity to hazards than other areas.

³ This assumption is particularly capable to reflect the natural circumstances of Tachia River basin, because large parts of the basin are composed of environmental sensitive areas.

⁴ The AHP with its independence assumptions within and between clusters and elements is a special case of the ANP.

Table 1 Indicators for assessing vulnerability to climatic hazards

Goal	Category	Indicator	Description	Data source	Literature
Vulnerability to climatic hazards	Exposure	Rainfall	Averaged annual rainfall (mm)	Central Weather Bureau, Taiwan	Füssel 2007; Mehaffey et al. 2008
		Debris flow torrents	Number of potential debris flow torrents and landslides	Council of Agriculture, Taiwan	
	Biophysical sensitivity	Proximity to rivers	Areas within 200 m from rivers (km ²)	Measured by GIS	Krishnamurthy et al. 2011; Eakin and Luers 2006
		Elevation	Average elevation (m)	Ministry of the Interior, Taiwan	
	Socioeconomic sensitivity	Populations	Population density (peoples/km ²)	Ministry of the Interior, Taiwan	Cutter et al. 2003; Eakin and Luers 2006;
		Social dependence	Number of people over age 65 and under age 6, and females	Ministry of the Interior, Taiwan	Scheuer et al. 2011
	Land uses	Income	Annual disposable household incomes (1000 NT\$)	DGBAST ^a	
		Employment	Number of employed people	DGBAST	
		Production values	Annual production values of industries and services (million NT\$)	DGBAST	
		Urban development	Areas of residential, commercial, industrial, educational and public land uses (km ²)	Land Use Investigation of Taiwan	Cutter et al. 2003; Mehaffey et al. 2008
		Agricultural uses	Areas of agricultural land uses (km ²)	Land Use Investigation of Taiwan	
		Sensitive areas	Environmental sensitive areas (km ²), e.g., flood plain, mountain slope reserve areas	Land Use Investigation of Taiwan	
Adaptive capacity	Road infrastructure	Areas of road infrastructure (km ²)	Ministry of the Interior, Taiwan		
	Shelters	Number of shelters	Measured by GIS	Sharma et al. 2009; Smit and Wandel 2006	
	Fire and police services	Number of fire and police manpower	Taichung City government		
	Medical services	Hospital beds	Taichung City government		
	Risk perceptions	Average levels of perceived residential risk to climate hazards (5-point Likert scale)	Questionnaire interviews		
	Access to resources	Average levels of ability of access to resources (5-point Likert scale)	Questionnaire interviews		
Adaptation appraisal	Adaptation appraisal	Average levels of residents evaluate their ability to perform adaptations successfully (5-point Likert scale)	Questionnaire interviews		

^a Directorate-general of budget, accounting statistics, Taiwan

We first organized indicators for vulnerability assessments into a three-level framework (Table 1). The top level corresponds to the overall goal of the analysis, which was to obtain the relative indicator weights associated with the concept of vulnerability. The second and third levels include five categories of indicators. A participatory method (focus group meetings) was applied to identify the interaction network between and within these categories of indicators.

The network connections shown in Fig. 1 indicate the outerdependence and interdependence between and within categories of indicators. It expresses that *exposure* influences both *adaptive capacity* and *land uses*, while it is affected by *biophysical sensitivity*. Moreover, *biophysical sensitivity* also affects *land uses*, and *land uses* alter *socioeconomic sensitivity*. Interdependence loops as shown in *exposure*, *socioeconomic sensitivity*, *land uses*, and *adaptive capacity*, implies that these indicators have feedback into the component itself. The 1–9 scale (i.e., 1=indifference, 9=absolute dominance) developed by Saaty was used to make pairwise comparisons between categories and indicators to construct the supermatrix (Gencer and Gürpınar 2007). An example of one of the pairwise comparison matrices can be provided as:

$$\mathbf{W} = \begin{matrix} c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \end{matrix} \begin{bmatrix} c_1 & c_2 & c_3 & c_4 & c_5 \\ 1 & 4 & 1 & 1 & 1/5 \\ 1/4 & 1 & 1/4 & 1/5 & 1/7 \\ 1 & 4 & 1 & 1 & 1/5 \\ 1 & 5 & 1 & 1 & 1/5 \\ 5 & 7 & 5 & 5 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} w \\ 0.135 \\ 0.041 \\ 0.135 \\ 0.141 \\ 0.548 \end{bmatrix} \tag{1}$$

where *c* is indicator; *w* is vector of resulting weights. Through nine experts⁵ pairwise comparisons and supermatrix operations, the mean values of experts’ comparisons were transformed into the weights that represent the relative importance of indicators with respect to the overall vulnerability.

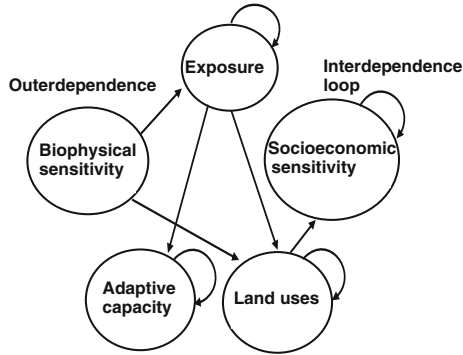
3.3 Integrated vulnerability index

Because the actual values from survey data for indicators contained incommensurate data (e.g., different scales or units), it is necessary to normalize all the data into a uniform [0, 1] scale with ratio properties. The normalized data was then transformed into an index for vulnerability through a value function (Table 2).

Several different forms of value function were derived in the data set according to weights of indicators, the types of variables, as well as their hypothetical relationships with the concept of vulnerability. Briefly, a binary value function was used for *sensitive areas*, indicating their presence increased, and absence decreased the vulnerability. We used categorical (or nominal) value functions for the following indicators: *risk perceptions*, *access to resources*, and *adaptive appraisal*. These value functions were derived by means of the ANP and under the assumptions about the relative contributions of specific values of indicator to vulnerability. For example, *risk perceptions* were classified into four degrees (from very low to very high) based on the residents’ perceived levels of risk to climatic hazards surveyed by a household interview.

⁵ These nine experts were organized separately from the abovementioned focus group. But the background was similar, which was also composed of experts and officers from the fields of city planning, engineering, climatology, as well as disaster and water management.

Fig. 1 Connections in the network of indicator categories for vulnerability assessment



The ‘V-shaped’ value functions imply that when the survey values of indicator are either lower or higher than a threshold value (assumed as the median of indicator’s survey values), the vulnerability is higher. The remaining indicators were represented by linear continuous value functions that were directly derived through the weights using the ANP. After determining the weights and value functions for each indicator, we used an additive approach to aggregate these weights with the indicators’ values to generate an integrated vulnerability index (InVI) for each village *i*. InVI is determined through the use of value functions to compute performance value y_{ij} for each village, as abovementioned:

$$\text{InVI}_i = \sum_{j=1}^m y_{ij} \tag{2}$$

The aim of PGIS is to involve stakeholders’ participation and their knowledge during the entire mapping and assessing process. Results of the estimated InVIs were thus processed and registered on GIS for each village to show the spatial distribution of vulnerability.

3.4 Spatial statistics analysis

The influence of social networks, proximity, and other spatial factors can cause vulnerable areas to unfold as clustered patterns or spatial analogues across regions, rather than randomly distributed (Hung and Wang 2011). These ‘hot spots’ of spatially correlated areas have important implications for the understanding of why and where the clustered areas are vulnerable. To obtain an overall picture for the degree of spatial dependency across areas, a Getis-Ord general *G* statistic was used to test autocorrelation in spatial distribution of vulnerability, and to measure whether vulnerable regions are clustered across areas. The Getis-Ord general *G* statistic value is commonly expressed as:

$$G = \frac{\sum_{i=1}^n \sum_{k=1}^n w_{ik} o_i o_k}{\sum_{i=1}^n \sum_{k=1}^n o_i o_k}, \forall i \neq k \tag{3}$$

where o_i and o_k are the variable values at a particular area *i* and *k* respectively; w_{ik} is a spatial weight for the linkage between area *i* and *k* (Getis and Ord 1992).

We employed the local indicator of spatial association (LISA) to identify and map the statistically significant similar vulnerability across the river basins (Anselin 1995). LISAs can test the extent of significant spatial clustering of similar values around individual areas. Identifying positively associated vulnerable areas is particularly important for river basin managers to detect ‘hot spots’ of areas in which risk management measures most need to be

Table 2 Weight and value function of vulnerability indicators

Category	Weight	Indicator	Mean (S.D.)	Weight	Value function
Exposure	0.38	Rainfall	2123(546)	0.20	$y=0.2x$
		Debris flow torrents	0.60(1..94)	0.18	$y=0.18x$
		Proximity to rivers	11.2(42.8)	0.13	$y=0.13x$
Biophysical sensitivity	0.20	Elevation	299 (385)	0.07	$y = \begin{cases} -0.58x + 0.14, & \text{if } x < 0.12 \\ 0.07, & \text{if } x = 0.12 \\ 0.07x + 0.07, & \text{if } x > 0.12 \end{cases}$
		Populations	181 (253)	0.01	$y=0.01x$
		Social dependence	1438(916)	0.02	$y=0.02x$
Socioeconomic sensitivity	0.09	Income	97.5(20.7)	0.02	$y = \begin{cases} -0.11x + 0.04, & \text{if } x < 0.21 \\ 0.02, & \text{if } x = 0.21 \\ 0.02x + 0.02, & \text{if } x > 0.21 \end{cases}$
		Employment	55(57)	0.02	$y=-0.02x+0.02$
		Production values	2.3(4.0)	0.02	$y=0.02x$
Land uses	0.22	Urban development	0.6(0.8)	0.05	$y=0.05x$
		Agricultural uses	1.3(1.7)	0.05	$y=0.05x$
		Sensitive areas	8.9(42.4)	0.07	$y = \begin{cases} 0.07x + 0.07, & \text{if } x > 0 \\ -0.07x + 0.07, & \text{otherwise} \end{cases}$
Adaptive capacity	0.11	Road infrastructure	0.1(0.1)	0.05	$y = \begin{cases} -0.42x + 0.1, & \text{if } x < 0.11 \\ 0.05, & \text{if } x = 0.11 \\ 0.05x + 0.05, & \text{if } x > 0.11 \end{cases}$
		Shelters	2.3(3.0)	0.01	$y=-0.01x+0.01$
		Fire and police services	251(64)	0.01	$y=-0.01x+0.01$
Risk perception	0.03	Medical services	278(366)	0.01	$y=-0.01x+0.01$
		Risk perception	2.2(0.7)	0.03	$y = \begin{cases} 0.03, & \text{if } x = \text{Very low risk} \\ 0.02, & \text{if } x = \text{Low risk} \\ 0.01, & \text{if } x = \text{High risk} \\ 0.006, & \text{if } x = \text{Very high risk} \end{cases}$

Table 2 (continued)

Category	Weight	Indicator	Mean (S.D.)	Weight	Value function
		Access to resources	2.6(0.6)	0.03	$y = \begin{cases} 0.03, & \text{if } x = \text{Very low} \\ 0.02, & \text{if } x = \text{Low} \\ 0.01, & \text{if } x = \text{High} \\ 0.006, & \text{if } x = \text{Very high} \end{cases}$
		Adaptation appraisal	2.0(0.8)	0.02	$y = \begin{cases} 0.02, & \text{if } x = \text{Very low} \\ 0.01, & \text{if } x = \text{Low} \\ 0.009, & \text{if } x = \text{High} \\ 0.005, & \text{if } x = \text{Very high} \end{cases}$

adopted to mitigate the potential impacts of climatic hazards. The local Moran’s I statistic is given by:

$$I_i = \frac{(z_i - \bar{z})}{s_z^2} \sum_{k=i}^n [w_{ik}(z_k - \bar{z})], \forall i \neq k \tag{4}$$

where \bar{z} is the mean intensity over observations; z_i and z_k are the intensity of observations i and k respectively; s_z^2 is the variance over all observations; w_{ik} is spatial weight for the linkage between observations i and k .

4 Assessments and analyses of integrated vulnerability

4.1 Tachia River basin

Tachia River is located in the central region of Taiwan (see Fig. 2). The river is 124 km long, making it the largest river in central Taiwan, with a total basin area of 1,236 km². A series of high-mountain (over 3,000 m above sea level) valleys, gorges and tablelands constitute the midstream and upstream reaches, and 90 % of the river basins are located in areas with steep slopes over 30°. Major portions of Tachia River basin are environmentally sensitive and highly exposed to the threats from climate-related hazards.

After the Chi-Chi catastrophic earthquake attacking central Taiwan in 1999, the geological contexts of Tachia River basin tend to more unstable. Subsequent heavy rainfall, typhoon or climatic extremes have frequently triggered serious landslides, debris flow torrents and flood disasters in the midstream and upstream areas. The downstream areas of Tachia River basin comprise a portion of Taichung Metropolis (the largest city in central

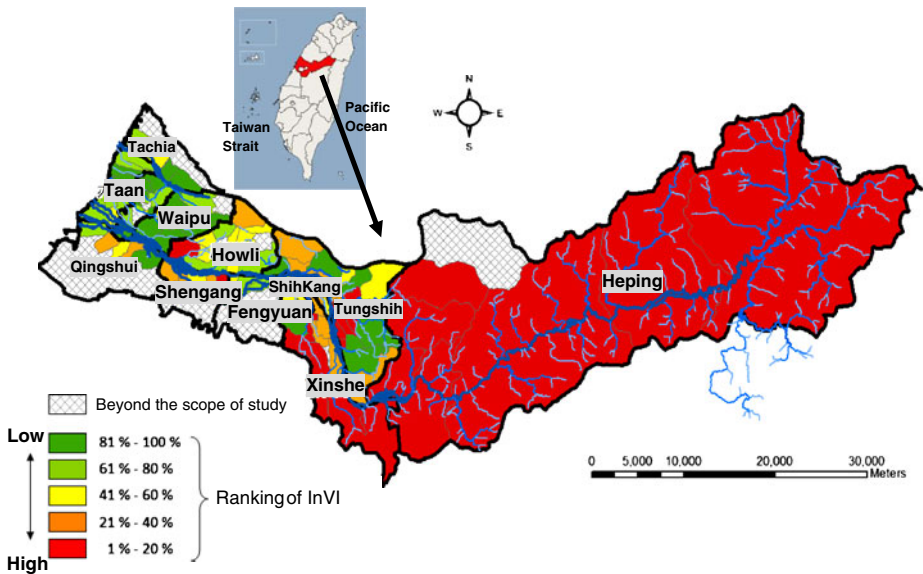


Fig. 2 Location and distribution of estimated integrated vulnerability indices throughout the Tachia River basin

Taiwan) and coastlines. These areas have widespread urbanization and overdevelopment, as well as agricultural and tourism activities, which increases the downstream basins exposure to various types of vulnerability under multiple climatic hazards.

4.2 Results of vulnerability assessments

4.2.1 Weights of indicators

Table 2 reports the weights obtained through the ANP for the indicators. Within the categories of indicators, the experts weighted relatively higher contributions of *exposure* and *biophysical sensitivity* to overall vulnerability. These results are similar to the risk-hazard approaches, emphasizing that hazard risks or impacts are primarily determined by the biophysical context and levels of exposure to hazards. Additionally, *land uses* were also weighted as important factors that influence vulnerability.

Among the indicators, *rainfall*, *debris flow torrents*, and *proximity to rivers* were assigned higher weights, while the experts gave relatively lower weights to the indicators related to adaptive capacity. Accordingly, the relative contribution of exposure and biophysical components to overall vulnerability is higher than residents' *risk perceptions*, *access to resources*, and their *adaptation appraisal* to climatic hazards.

4.2.2 Results of integrated vulnerability assessments

Figure 2 shows the spatial distribution of estimated InVI values associated with geopolitical boundaries of villages throughout the river basin. The estimated InVI values were divided into five levels (at 20 % intervals). We defined the villages of the top 20 % (or 80th percentile) of estimated InVI values for the entire study area as the most vulnerable, and those villages of the top 21–40 % (or 60th–79th percentiles) as the critically vulnerable areas.

The most vulnerable areas are almost all situated in the regions of middle and upper reaches of Tachia River. This spatial pattern approximately corresponds to historical experience with several typhoons attacking the study area in past years. For example, the Typhoon Mindulle, and Aere in 2004 and the Typhoon Haitang in 2005 all caused serious casualties, property damages, and agricultural losses in the areas that are consistent with the most and critically vulnerable areas identified in this study (Ministry of the Interior, Taiwan 2011).

Once the most vulnerable areas are delineated, river basin managers need to identify the determinants that cause these areas to be vulnerable. A subsequent scrutiny of the most vulnerable areas for the entire river basin was implemented through a spatial statistics analysis to provide further insight into how and why the combination of local attributes lent to specific spatial patterns and higher levels of vulnerability.

4.2.3 Geographical clustering of vulnerable area hotspots

Results of the Getis-Ord general G estimates indicate statistically significant positive spatial autocorrelation of areas on vulnerability for Tachia River basin. The estimated InVIs throughout the river basin show significantly high levels of spatial dependence with a Z -score of 1.76 ($p < 0.1$). The vulnerability components: exposure ($Z = 5.01$, $p < 0.01$), biophysical sensitivity ($Z = 5.73$, $p < 0.01$), and adaptive capacity ($Z = 2.45$, $p < 0.05$) also reveal significantly positive high levels of spatial clustering. These results disclose that the spatial patterns of local vulnerability across Tachia River are not dispersed randomly, but instead spatially correlated in certain regions within its basin.

Through the LISA analysis, Fig. 3 illustrates the distribution of ‘hot spots’ of locally clustered highly vulnerable areas across the river basin. Apart from some areas concentrated at the downstream regions,⁶ most of the significantly positive clustered vulnerable areas occur spatially in the midstream and upstream reaches. These clusters of vulnerable areas express highly positive correlation to the most vulnerable areas displayed in Fig. 2 (Spearman $\rho=0.52$, $p<0.01$). The presence of tightly packed, spatially-defined clusters of highly vulnerable areas suggests that local vulnerability may be linked by similar factors operating in specific regions. Identifying these factors is critical in particular for decision-makers to understand why and where vulnerable areas across the river basin tend to cluster, and to prioritize measures to remedy them.

4.2.4 Comparison of various types of vulnerable areas

Two sample independent *t*-tests allow us to recognize the major factors driving distribution variability of local vulnerability throughout the river basin, and explain why clusters of highly vulnerable areas occur in specific regions. We conducted two aspects of comparison between various types of vulnerable areas. First, a *t*-test was applied to compare the ‘hot spots’ of clustered vulnerable villages (top 5 % of local Moran’s *I* values for the entire study area) with the rest of the villages. Second, another test was used to compare the most vulnerable villages (top 20 % of the estimated InVI values) with the remaining ones.

Results show that both the ‘hot spots’ of clustered and the most vulnerable villages have significantly higher levels of average *rainfall*, *elevation*, more potential *debris flow torrents*, *landslides*, and *proximity to rivers* (Table 3). These factors will enhance exposure and biophysical sensitivity, and therefore increase vulnerability. The combination of these factors explains why the most vulnerable villages are mostly clustered in the midstream and upstream regions. *Low population* density and *employment* also contribute to this pattern of local autocorrelation because most clustered villages are situated in the high mountain regions which are not favorable for population agglomeration. This also provides a possible explanation for why the clustered villages have lower populations of *social dependence*. Furthermore, the most vulnerable villages also have lower levels of *employment* and *income* ($p<0.1$) compared to the remaining ones.

Land uses indicate as clear trend distinguishing the clustered and the most vulnerable from the remaining villages. Both the clustered and the most vulnerable villages have significantly more environmental *sensitive areas* and *road infrastructure*. The clustered and vulnerable villages tend to be more susceptible to hazards due to potentially urban, agricultural and tourist developments. Particularly, the linkage between *road* provision and vulnerability is consistent with the findings from existing vulnerability analysis (Cutter et al. 2003).

Adaptive capacity also plays a role in shaping both the clustered and the most vulnerable villages in the river basin. The residents for both the clustered and the most vulnerable villages perceive significantly higher levels of climatic hazard risks, although they have significantly lower levels of *medical*, *fire* and *police* services compared to the remaining villages. Moreover, the clustered villages have relatively lower ability of *access to resources* ($p<0.1$), while the most vulnerable villages appraise lower levels of ability to successfully adapt to hazards. Thus, the lower levels of emergency infrastructure provision, adaptation

⁶ Some villages in downstream regions were clustered highly vulnerable areas majorly due to their relatively more proximity to rivers and more social dependence, as well as lower risk perceptions and access to resources compared to other villages.

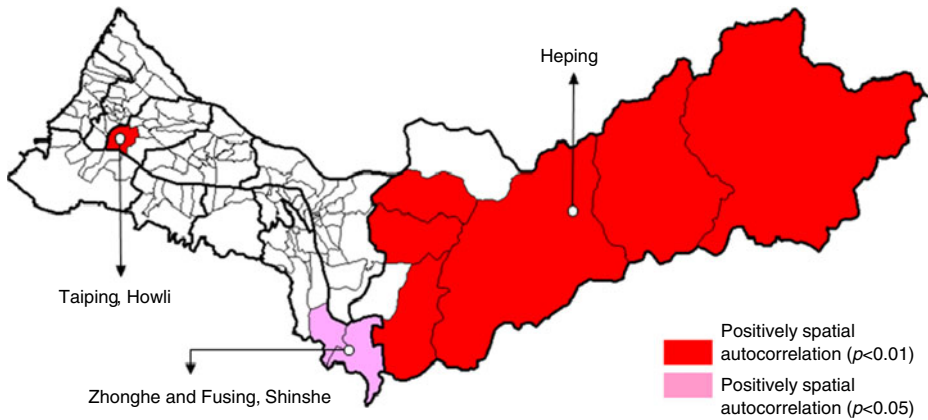


Fig. 3 LISA map of the vulnerability throughout the Tachia River basin

appraisal and access to resources would decrease coping capacity to hazards, and thus worsen vulnerability.

Table 3 Comparison of various types of most vulnerable areas

Indicator	Hot spots of clustered villages mean ($n=10$)	Remaining mean ($n=111$)	T -statistic	The most vulnerable villages mean ($n=25$)	Remaining mean ($n=96$)	T -statistic
Rainfall	2790 (470) ^a	2063 (513)	4.31 ^{***}	2728 (257)	1965 (490)	7.50 ^{***}
Debris flow torrents	4.80 (4.10)	0.23 (0.99)	9.39 ^{***}	2.04 (3.53)	0.23 (0.96)	4.47 ^{***}
Proximity to rivers	99.3 (122.6)	3.3 (3.1)	8.58 ^{***}	41.1 (89.4)	3.5 (3.0)	4.16 ^{***}
Elevation	1284 (759)	210 (137)	13.19 ^{***}	730 (656)	187 (131)	7.61 ^{***}
Populations	9 (18)	196 (259)	-2.28 ^{**}	219 (313)	170 (236)	0.85
Social dependence	893 (619)	1487 (925)	-1.99 ^{**}	1389 (1050)	1451 (883)	-0.30
Income	126 (344)	95 (193)	0.45	33.2 (46.9)	114.3(229.6)	-1.75 [*]
Employment	17 (8)	59 (58)	-2.26 ^{**}	29 (16)	62 (61)	-2.68 ^{***}
Urban development	0.36 (0.65)	0.58 (0.78)	-0.89	0.63 (1.06)	0.55 (0.68)	0.46
Agricultural uses	1.81 (3.41)	1.22 (1.45)	1.06	1.19 (2.60)	2.60 (1.36)	-0.27
Sensitive uses	95.2 (121.9)	1.1 (2.7)	8.47 ^{***}	38.48 (88.41)	1.20 (2.80)	4.17 ^{***}
Road infrastructure	0.35 (0.27)	0.12 (0.08)	6.50 ^{***}	0.18 (0.22)	0.12 (0.08)	1.98 ^{**}
Production values	0.67 (1.34)	2.42 (4.16)	-1.32	1.39 (3.71)	2.51 (4.09)	-1.24
Shelters	2 (2)	2 (3)	-0.74	2 (2)	2 (3)	-1.26
Fire and police services	207 (25)	255 (65)	-2.30 ^{**}	210 (47)	262 (63)	-3.76 ^{***}
Medical services	4 (3)	302 (372)	-2.58 ^{***}	104 (132)	323 (393)	-2.74 ^{***}
Risk perceptions	2.90 (0.32)	2.18. (0.65)	3.46 ^{***}	2.88(0.44)	2.07 (0.60)	6.27 ^{***}
Access to resources	2.31 (0.48)	2.60 (0.65)	-1.89 [*]	2.64(0.49)	1.53	0.46
Adaptation appraisal	1.70 (0.48)	2.00 (0.79)	-1.18	1.68 (0.48).	2.05 (0.81)	-2.19 ^{**}

^a Standard deviation in parentheses; * : $p<0.1$; ** : $p<0.05$; *** : $p<0.01$

Several studies have suggested that mainstreaming adaptation to vulnerability reduction appears to be most effective if undertaken in combination with institutional and coping capacity improvement in policy-making processes (Smit and Wandel 2006; Berman et al. 2012). Based on our findings, adaptive strategies should improve emergency infrastructure, risk communication, and community support linkages to external governance institutions in the clustered and the most vulnerable villages to reduce vulnerability (Hung 2009).

5 Conclusions

The experience from recent typhoons and floods suggests that flood risk management should adopt river basins as the management unit, and should seek to integrate locally social, biophysical contexts, and various stakeholders' knowledge into the process of risk management. A better understanding of vulnerability distribution and which factors lead to higher vulnerability can provide guidance for decision-making in preparing and dealing with the impacts of climate change.

This article provides a novel approach to assess the vulnerability to climatic hazards at the river basin level. Our methods construct an indicator framework to capture the diverse and often incommensurate nature of vulnerability attributes, the differential importance and the interdependence between and within these attributes. We used focus group meetings and interviews to incorporate the participation and knowledge of experts and community members into the process of vulnerability assessments. An integrated vulnerability index was integrated with a PGIS to generate a vulnerability map that is easily understood and can be helpful in communicating local knowledge to the stakeholders of climatic risk management. Additionally, we combined spatial statistics and multivariate analysis to disclose the geographical distribution and 'hot spots' of vulnerable areas to river basin managers, and to explain why these areas are particularly vulnerable.

In the Tachia River case, given the fact that particularly vulnerable areas are clustered in the river basin, a targeted strategy of policymaking may be more necessary for the integrated RBM. Policies to reduce climatic hazard risks or vulnerabilities should first focus on the areas that are the most vulnerable and spatially clustered. In this regard, the priority of areas for vulnerability reduction will focus on the upstream, midstream and some hot spots among the downstream reaches. Land-use planning policies (such as regulation, relocation, and building codes) in combination of adaptation policies (such as emergency plan, infrastructure improvement) as well as natural resource protection could help reduce vulnerability of these areas.

While this study proposes initial insights into the spatial patterns of vulnerability to climatic hazards, additional research is needed to more fully consider the interaction between climatic hazards and vulnerability, for example a systematic examination of the impacts of climatic extremes and sea-level changes on various vulnerability components and their interactions. Our assumptions of different types of value functions to reflect the relationship between indicators and vulnerability concept are probably arbitrary, but they do provide a basis for future work on how overall vulnerability is affected by each individual factor. This work can be valuable not only for identifying the linkage between vulnerability and its components, but also for quantifying vulnerability. More in-depth empirical and field research should be conducted across various river basins to compile a more complete understanding of the thresholds beyond which a river environment is vulnerable.

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