Establishing Disaster Resilience Indicators for Tan-sui River Basin in Taiwan

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Accepted: 10 December 2012/Published online: 27 December 2012 © Springer Science+Business Media Dordrecht 2012

Abstract A major trend in disaster management is to build resilience for sustainable development. Resilience is defined as the ability which may be learned from previous disaster experiences to make the system more stable than before through absorbing and adapting the changes caused by the disaster. In this paper, enhancing disaster resilience in a river basin is studied and regarded as an important operation process to achieve sustainability of urban area. The measurement of disaster resilience can be used as a potential environmental disaster diagnosis of previous urban planning policy strategies, and is a required foundation for drafting future spatial and urban planning policies. This paper proposes an application that combines fuzzy Delphi and analytic network process techniques in order to establish a set of disaster resilience indicators for a re-developed urban area in Tan-sui River Basin (Taiwan). By incorporating expert opinion, a priority index is calculated for each studied disaster resilience indicator. And, an enhanced resilience indicator evaluation methodology, which reflects interdependencies among evaluation dimensions using an integrated approach, is suggested in this paper. The results show that the main influences on satisfaction are: (1) factors of the management institute of basin, (2) financial capability, (3) conservation of water resource, (4) environmentally sensitive area, and (5) conservation of slope area. Overall, these main influences (five resilience indicators) show future directions for sustainable development in Tan-sui River Basin.

Keywords Resilience indicator · Tan-sui river basin · Taiwan · Fuzzy Delphi · Analytic network process

1 Introduction

Typhoon and flood are the most frequent and extreme natural hazards in Taiwan. There is an average of 4.04 typhoons each year over the last ten decades, resulting in loss of life and

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property damage. Disaster management burdens local governments. With the location and characteristics of hazardous areas, river basin will be a more appropriate spatial scale for risk management and research. A major trend in disaster management is to build resilience for sustainable development. Resilience is commonly defined as "when a dynamic system face to the extreme impact, the system has an ability to absorb and adapt the change, to cushion the system to become more stable, to self-organization, to learn from previous disaster experience." Thus enhancing disaster resilience in river basin is an important operation process to achieve sustainable development in urban areas. The measurement of disaster resilience can be used as a potential environmental disaster diagnosis as well as a required foundation in urban spatial planning. This paper proposes an application that combines fuzzy Delphi method (FDM) and analytic network process (ANP) technique to establish a set of disaster resilience indicators for a re-developed urban area in Tan-sui River Basin (Taiwan). A priority index is calculated for each studied disaster resilience indicators by incorporating expert opinion.

A number of studies in the social science and environmental planning literature have suggested that the measurement of disaster diagnosis needs to consider both objective measures of environmental phenomena and subjective measures of human responses (e.g., Anderson 1995; King 2001). And, both measures are part of multi-attribute decision analysis in nature. Several studies (e.g., Chen and Liu 2007; Cheng and Lin 2002; Chang and Wang 2006; Lee and Li 2006) show that the FDM can effectively identify critical attributes from a pool of evaluated attributes. However, there usually exist interdependent relationships among dimensions—goal, criteria, and alternatives—in the evaluation process (Chan and Huang 2004; Maclaren 1996). Thus the ANP method which is designed to specifically handle interdependencies among dimensions (i.e. attributes and indicators) can be used to transform a subjective, qualitative, and mutually influential problem to an objective and quantitative model of problem solving and decision making (see Chen et al. 2005; Lee and Kim 2001; Sarkis 2003).

The prioritization of disaster resilience indicators means to identify potential indicators related to an organization's processes, procedures, and operating environment, and among them, to select those indicators that are most important to the general public and that would allocate resources effectively. To select an indicator mix is difficult because the selection process involves multiple factors, such as project risk, public goals, and limited resources. The prioritization problem is therefore a multi-criteria decision making problem. When conducting the prioritization, it is necessary to obtain group opinion in order to understand the interdependent relationships between indicators. And, an expert interview is normally used to collect group opinion. Keeney and Raiffa (1976) propose a mathematical method to determine the utility function of decision-maker. The utility function represents a decisionmaker's level of satisfaction with different options. Mathematical programming is basically static optimization, consisting of different models such as linear programming, goal programming, dynamic programming, and game theory (Reza et al. 1988). Goal Programming (GP) is designed to deal with problems involving multiple conflicting objectives (Lee 1972). Yet, GP lacks a systematic approach to set priorities and trade-offs between objectives and criteria (Reza et al. 1988). This drawback is even more evident in the following three situations: (1) when the prioritization takes into consideration of both tangible and intangible factors, (2) when the prioritization involves interdependent factors, and (3) when the prioritization requires inputs from a group of people. In order to overcome this problem, the ANP technique which is developed by Saaty (1996) is commonly used to set priorities for objectives and to determine trade-offs between them.

Several studies have compiled a variety of dimensions and indicators that influence the resilience factors of a disaster (e.g., Norris et al. 2008; Cutter et al. 2008), and the relevant measurement and evaluation models should tackle multi-attribute decision making problems in nature. To solve this type of problem, it is necessary to set a simple and clear goal. And, this goal needs to be integrated into objectives and criteria. Methodologies frequently used include: ranking technique (Buttoud 2000), scoring (Spencer et al. 1998), AHP (Roper-Low and Sharp 1990), TOPSIS (Kim et al. 1997), multivariable analysis method (Martin 1998), and mathematical models—goal programming, dynamic programming, and zero–one goal programming (Wey and Wu 2007). However, these methodologies cannot effectively apply the abstract concept of sustainable development related to disaster resolution and prevention in practice nor handle the inter-relationships among factors.

In recent years, studies have suggested that the fundamentals of evaluation model development is to identify and establish evaluation factors, indicators, or criteria (see Andrews and Carroll 2001; Bell and Morse 2004; Spangenberg 2002). However, there usually exist interdependencies among evaluation factors in real-world practice (Weber et al. 1990). Moreover, a linear-hierarchical structure or a single direction circular path cannot represent relationships among evaluation factors in the model framework. As there are mutual influences and interdependencies among evaluation factors, their relationships should be expressed as a network structure. Accordingly, this study adopts the ANP modeling technique developed by Saaty (1996) in order to solve a network problem.

The disaster resilience indicators prioritization techniques introduced in the aforementioned studies are useful, but these prioritization technologies only consider independent disaster resilience indicators or evaluation criteria. Considering indicator interdependent properties reduces costs and generates benefits to organizations. Unfortunately, there are numerous interdependent cases to be considered in real-world subset selection problems. That is, when carrying out disaster resilience indicators, large amounts of resources will need to be shared from different disaster resilience applications. However, disaster resilience indicators are interdependent to each other.

This paper proposes a methodology which combines the fuzzy Delphi Method (FDM) and the analytic network process (ANP) technique to effectively prioritize a group of interdependent disaster resilience indicators. In order to reflect interdependent properties in the prioritization with multiple criteria, both the ANP technique and the group expert interview are used in this paper. Moreover, using Tan-Sui River Basin (Taiwan) as an example, the paper demonstrates the effectiveness of proposed methodology in prioritizing disaster resilience indicators.

2 Indicator Evaluation and Selection Problem

Several methodologies have been introduced to help organizations make good indicator selection decisions (Anadalingam and Olsson 1989; Czajkowski and Jones 1986). Existing methodologies on selection of indicators range from single-criteria cost/benefit analysis to multiple criteria scoring models and ranking methods, or subjective committee evaluation methods (Horwitch and Thietart 1987; Ringuest and Graves 1989; Weingarther 1966).

Buss (1983) attempts to provide an alternative approach to indicator selection with a ranking technique. This technique does not solve problems requiring resource feasibility and indicator interdependence. In addition, methods such as ranking, scoring, and AHP are not designed to solve problems having resource feasibility, optimization requirements, or indicator interdependence constraints. Nonetheless, these methods are popular for dealing

with real-world problems because they are simple and easy to implement. On the other hand, it is common to use a mathematical model, such as goal programming, dynamic programming, or Linear 0–1 programming, to solve more complicated optimization problems. (Dantzig 1958; Ringuest and Graves 1989; Schniederjans and Kim 1987). And, these methodologies assume criteria or indicators are independent.

Many real-world problems have an interdependent property among criteria and indicators (Saaty 1996). Beneficial interdependencies occur when the full benefits to the organization derived from implementing two related projects increase due to their synergistic effects (King and Scherem 1978). Recently, Sanathanam and Kyparisis (1996) propose a nonlinear programming model that considers interdependencies. The authors introduce a model to solve problems involving project interdependences. But they do not consider multiple indicators or evaluation criteria. In addition, an expert group discussion should be used in designing evaluation because the evaluation result is likely to be biased if only one or two decision-makers are involved to determine the indicator or the degree of interdependence in a project (such as building a disaster resilience system). In reality, it is more appropriate to consider multiple criteria in the selection of interdependent disaster resilience indicators. However, to the best of the authors' knowledge, there is no study that takes into account both multiple criteria and interdependence relationships in prioritizing disaster resilience indicators. In this paper, the prioritization of disaster resilience indicators considers the influences of both interdependent relationships and multiple criteria when ranking indicators.

Previously, Saaty and Takizawa (1986) develop a matrix manipulation approach for solving a network with dependent criteria alternatives. Lee and Kim (2000) integrate the ANP technique into a ZOGP model to solve an information system project selection problem. Their model considers interdependencies among evaluation criteria and a set of possible candidate projects. Similarly, Meade and Presley (2002) use the ANP technique to aid the selection of feasible projects in a research and development environment. Although these methods are designed to help organizations make good project selection decisions, there is no study that introduces a methodology for the disaster resilience indicator selection problem that involves multiple criteria and interdependence relationships. Accordingly, in this paper, a group consisting of high-ranking public officials and consultants in the field of disaster resilience is invited to participate in a discussion regarding the establishment of disaster resilience indicators for Tan-Sui River Basin (Taiwan). The fuzzy Delphi method (Murray et al. 1985; Ishikawa et al. 1993) is then used to screen the collected expert opinion. Finally, in order to account for both interdependent relationships and multiple criteria, the ANP technique is utilized to prioritize indicators.

3 Proposed Model: Integrate Fuzzy Delphi and ANP

The fuzzy Delphi method (Ishikawa et al. 1993; Murray et al. 1985) is a systematic procedure for evoking expert group opinion. The fuzzy Delphi method is also used to determine the degree of interdependence. The information obtained from the fuzzy Delphi method is then incorporated into the ANP technique. The objective of this paper is to propose an integrated approach for solving the interdependent disaster resilience indicator prioritization problem. Thus, in this paper, an improved prioritization methodology reflecting interdependencies among candidate indicators using FDM and ANP is suggested.



Fig. 1 Research flow chart

The proposed integrated model for making the best disaster resilience indicator selection is based on the evaluation of qualitative indicator information using the fuzzy Delphi method and the Analytic Network Process technique. Figure 1 shows the research flow chart of this study. In the flow chart, the dimensions and possible impact factors (PIFs) for disaster are identified based on relevant literature review and their characteristics. Next, the critical disaster resilience indicators are screened and determined by FDM. After constructing the evaluation network using the ANP, we can calculate the weights of critical disaster resilience indicators. The final ranking of disaster resilience indicators are then generated.

3.1 Fuzzy Delphi Method (FDM)

Since its inceptive development at Rand Corporation by Helmer and Dalkey (Dalkey and Helmer 1963; Helmer 1966), the traditional Delphi method has been widely accepted as an effective forecasting tool and used in a wide range of applications. The traditional Delphi method is a structured process which utilizes a series of anonymous questionnaires or rounds to gather and to provide information. The process continues until expert opinions come into group consensus (Chu and Hwang 2008; Keeney et al. 2001). The method has been considered as a reliable qualitative research method with potential for use in problem solving, decision making, and group consensus reaching in a wide variety of areas (Chu and Hwang 2008; Graham et al. 2003; Wey and Wu 2007). Although the method has provided much merit, but as with many other survey techniques, the problems of ambiguity and uncertainty still exist. The problem not only may exist in the survey question, but also in the response (Chang et al. 2000; Wey and Wu 2007).

Moreover, in order to prevent expert judgment from the influence of extreme values, Ishikawa et al. (1993) incorporate the fuzzy theory into the Delphi Method. The authors utilize the concepts of cumulative frequency distribution and fuzzy integral to integrate expert opinions and their outcomes to create fuzzy sets. The fuzzy Delphi method has been applied to perform time series prediction and obtained appropriate criteria for expert judgment. Whereas, Hsu and Yang (2000) treat the minimum and maximum values of

experts' scores as triangular end caps and then use the geometric mean as the centre of the triangular membership function. This paper applies the gray interval to examine the convergent cognition of all experts and utilizes the possible range of the minimum and maximum values to obtain model results.

To deal with the uncertainty of experts' subjective opinions effectively, Murray et al. (1985) first apply the fuzzy theory to the traditional Delphi Method. Ishikawa et al. (1993) employ the cumulative frequency distribution function and the fuzzy integration to integrate experts' estimation into fuzzy numbers, and utilize the 'gray zone', the intersection of the fuzzy numbers, to develop the Max–Min fuzzy Delphi method and the fuzzy Delphi method via fuzzy integration (FDMFI).

Thereafter, Chang et al. (1995) and Chang and Wang (2006) extend the fuzzy number to the triangular fuzzy numbers (TFNs) and the asymmetric bell-shaped fuzzy numbers (ABFNs) to acquire the similarity degree among tolerable scope to select the critical factors from a list of PIFs. Moreover, Cheng (2001) and Hsiao (2006), based on the study of Ishikawa et al. (1993), use TFNs to combine experts' cognitions and apply gray zone test to examine whether the cognitions have reached convergence. Hence, FDM can combine participants' viewpoints more objectively and reasonably. This paper applies FDM, based on Zheng (2001) and other works (Chang and Wang 2006; Cheng 2001; Hsiao 2006; Ishikawa et al. 1993), to find critical evaluation criteria and indicators. The proposed procedure is provided as follows:

- Step 1. Collect all possible impact factors (PIFs): $U = \{u_i, i=1, 2, ..., n\}$, where u_i is a possible impact factor i.
- Step 2. Collect estimated score of each factor u_i from each expert. The score is denoted as S^i by T experts, $S^i = (C_t^i, O_t^i)$, i = 1, 2, ..., n. C_t^i is the lowest score of the th expert to the ith factor, called "the most conservative cognition value"; O_t^i is the highest score, called "the most optimistic cognition value," and both C_t^i and O_t^i are in a range from 1 to 10 (Chang and Wang 2006; Zheng 2001).
- Step 3. Calculate the minimum, geometric mean and maximum values of C_t^i and O_t^i for each factor. A group average is calculated for both C_t^i and O_t^i , and any abnormal value which is not in the rang of two standard deviations is eliminated (Cheng 2001). Next, calculate the minimum C_L^i (O_L^i), the geometric mean (GM) C_M^i (O_M^i), and the maximum C_U^i (O_U^i) of C_t^i (O_t^i).
- Step 4. Establish the TFNs. The TFN for the most conservative cognition value is $C^i = (C_L^i, C_M^i, C_U^i)$, and the TFN for the most optimistic cognition value is $O^i = (O_L^i, O_M^i, O_U^i)$. The overlap section of the two TFNs is called the gray zone, as shown in Fig. 2 (Cheng 2001; Hsiao 2006; Ishikawa et al. 1993).
- Step 5. Inspect the consensus among experts' opinions. The gray zone of each factor is used to calculate "the important degree of consensus" G^i by Eq. (1), and the higher value of G^i , the higher significance of u_i .

$$G^{i} = \{Y|\mu_{F^{i}(x)}(y)\}$$
(1)

- (1) If there is no overlap between the two TFNs $(C_U^i \le O_L^i)$, i.e. no gray zone of vague relationship exists, the experts all converge towards the same opinion (Cheng 2001; Zheng 2001), and let $G^i = (C_M^i + O_M^i)/2$ (Zheng 2001).
- (2) If there is overlap between the two TFNs $(C_U^i > O_L^i)$, i.e. the gray zone (Z^i) exists:



Fig. 2 Two triangular fuzzy numbers

(a) If $Z^i \leq M^i$, where $Z^i = C_U^i - O_L^i$ and $M^i = O_M^i - C_M^i$, G^i is calculated by Eqs. (2) and (3).

$$F^{i}(x_{j}) = \left\{ \int_{x} \left\{ \min\left[C^{i}(x_{j}), O^{i}(x_{j})\right] \right\} dx \right\}, \quad j \in U$$
(2)

$$G^{i} = \left\{ x_{j} | \max \mu_{F^{i}}(x_{j}) \right\}, \quad j \in U$$
(3)

- (b) If $Z^i > M^i$, a discrepancy exists between the opinions of the experts. Repeat *Step 2* to *Step 5* until a convergence is reached. Relevant discussions of the gray zone test approach can be found in the studies of Ishikawa et al. (1993) and Hsiao (2006).
 - Step 6. Extract critical evaluation criteria from U. Compare G^i with the threshold value (S). If $G^i \ge S$, select factor *i*; and if $G^i < S$, eliminate factor *i* (Dzeng and Wen 2005; Zheng 2001). In general, the threshold value is determined subjectively by the decision-maker (Dzeng and Wen 2005; Kuo and Chen in press).

Similar to the study of Hsu and Yang (2000), the geometric mean value is more suitable to deal with the empirical study carried out in this paper. This is because, in order to establish a set of disaster resilience indicators for a re-developed urban area in Tan-sui River Basin (Taiwan), the proposed methodology needs to consider factors, such as resource feasibility, optimization requirements, and indicator interdependence constraints. The methodology also needs to take into account multiple criteria and interdependence relationships in prioritizing a set of possible candidate indicators. Budescu et al. (1986) address that the geometric mean calculation is more correct and meaningful, especially for variables that are related to each other. Also, both Dong et al. (2008) and Herman and Koczkodaj (1996) show that to apply the geometric mean in a group of dependence numbers is more reasonable than any other calculation method.

In summarizing these approaches, the FDM may provide the following advantages in addition to that of traditional Delphi methods: (1) it enables us to process the fuzziness in relation to the forecast item and the information contents of the respondents, instead of being merely crisp estimates as with the traditional Delphi method. (2) individual attributes of the experts may be elucidated because of the fuzzy forecasts utilized and thus preserved.



Fig. 3 a Linear hierarchy and b nonlinear network

3.2 Analytic Network Process

Analytic Network Process (ANP) is a generalization of analytic hierarchy process by replacing hierarchies with networks (Saaty 1996, 2005) and by allowing more complex interrelationships (e.g., interdependence and feedback) in a network system. ANP enhances the function of AHP to develop a complete model that can incorporate interdependent relationships among elements from different levels or within levels, which are assumed to be uncorrelated in AHP (Cheng and Li 2007). ANP has been widely used in MADA problems in various fields such as environment management, multi-dimension forecast, strategic decision, project selection, product planning, and so on (Chung et al. 2005; Wu and Lee 2007).

Figure 3 depicts structures and the corresponding supermatrix between a hierarchy and a network. A node represents a component (or cluster) with elements inside it; a straight line/or an arc denotes the interactions between two components; and a loop indicates the inner dependence of elements within a component (Sarkis 2002).

When the elements of a component *Node*¹ depend on another component *Node*², this relation is represented with an arrow from component *Node*¹ to *Node*². The corresponding supermatrix of the hierarchy with three levels of clusters is also shown: where w_{21} is a vector that represents the impact of the *Node*¹ on the *Node*²; W_{32} is a matrix that represents the impact of the *Node*² on each element of the *Node*³; and **I** is the identity matrix. As shown in the Figure, a hierarchy is a simple and special case of a network.

ANP is a general theory of relative measurement used to derive composite-priority-ratio scales from individual-ratio scales that represent relative influence of factors that interact with respect to control criteria (Niemiraa and Saaty 2004). Through the "supermatrix", which is composed of matrices of column priorities, the ANP framework catches the consequence of dependence/feedback within and among components. A standard supermatrix form is as follows (Saaty and Vargas 1998):

Let the components of a network system be C_k , k = 1,..., N, and let each component k has n_k elements, denoted by $e_{k1}, e_{k2}, ..., e_{kn_k}$. The influence of a set of elements belonging to a component on any element in another component can be represented as a priority matrix (\mathbf{W}_{ij}) by applying pairwise comparisons in the same way as in AHP. \mathbf{W}_{ij} shows the influence of the elements in the i_{th} component to the elements in the *j*th component, and vice versa. In addition, if there is no influence, then $\mathbf{W}_{ij} = 0$ (Huang et al. 2005; Yu and Tzeng 2006). The process of ANP is described as follows (Meade and Sarkis 1998; Saaty 1996):

- Step 1. Model construction and problem structuring. The problem should be stated clearly by decision makers and be decomposed into a rational system like a network, which represents the relationship of feedback or interdependence among the components. An example (Momoh and Zhu 1998) is shown in Fig. 4.
- Step 2. Pairwise comparisons matrices and priority vectors. Like AHP, decision elements at each component are compared pairwisely with respect to their importance towards their control criterion, and the components themselves are also compared pairwisely with respect to their contribution to the goal (Chung et al. 2005b). The relative importance values are determined with a scale of 1–9, and an eigenvector can be obtained. Consistency index (CI) and consistency ratio (CR) are calculated next (Saaty 1996). If an inconsistent judgment is found, the part of the pairwise comparison must be performed



Fig. 4 Network example

again. For the example in Fig. 4, the criteria are interrelated among themselves and W_{22} indicates the interdependency; and W_{21} is a matrix that represents the impact of the goal on the criteria, W_{32} is a matrix that represents the impact of criteria on each of the alternatives (Momoh and Zhu 1998).

Step 3. Supermatrix formation. To generate global priorities in a system with interdependent influences, the obtained local priority vectors and matrices from *Step 2* are entered in a matrix to form a "supermatrix" as follows:

$$W = \frac{Goal}{Criteria} \begin{bmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I \end{bmatrix}$$
(5)

where "I" is the identity matrix, and entries of zeros correspond to those elements that have no influence. After forming the supermatrix, a weighted supermatrix is derived by transforming all columns sum to unity, i.e. like the concept of Markov chain for ensuring column stochastic (Huang et al. 2005). Next, in order to achieve a convergence on the importance weights, the weighted supermatrix is raised to limiting powers by Eq. (6) to obtain the limit supermatrix (Saaty 1996; Yu and Tzeng 2006), which shows the long-term stable weighted values (Chung et al. 2005) and the global priority weights. A detailed mathematical process can be found in the study of Saaty (1996).

$$\lim_{k \to \infty} \mathbf{W}^{2k+1} \tag{6}$$

Step 4. Selection of best alternatives. If the supermatrix formed in Step 3 covers the whole network, the priority weights of alternatives can be found in the column of alternatives-to-goal in the limit supermatrix (Sarkis 2003).

The process for solving the interdependent disaster resilience indicator prioritization problem is summarized as follows: In order to consider interdependence, the first step is to identify key indicators and check for interdependent relationships among the indicators. Next is to determine the degree of impact or influence between the indicators. For example, the decision maker will respond to questions such as: "In comparing indicators A and B, on the basis of cost reduction, which indicator is preferred?" The responses are presented numerically, scaled on the basis of Saaty's 1–9 scale (Saaty 1980, 1996) with reciprocals, in a project comparison matrix. The final step is to determine the overall prioritization of these disaster resilience indicators.

4 Selection of Tan-sui River Basin Disaster Resilience Indicators

To illustrate the use and advantage of the combined fuzzy Delphi and ANP model in prioritizing a set of candidate disaster resilience indicators, an empirical example, called "Disaster Resilience Indicators Planning and Evaluation of Tan-sui River Basin of Taipei," is used. The specific empirical example concerned the Tan-sui River Basin of Taipei is shown in Fig. 5. The basin is located in the north of Taiwan and covers the Taipei Metropolitan Area, which is the economic, political and cultural center of Taiwan. The





Tan-sui River Basin has been suffering from more frequent extreme natural disasters such as typhoon and flood for the past decades. This problem involves issues of population, transportation and natural disaster preparedness. In an effort to solve such urban disaster issues, the Taipei City Hall seeks to alleviate the problem by means of building a disaster resilience indicator prioritization system in order to effectively allocate government resources. A project is implemented to select key indicators for improving the urban disaster prevention strategy in Tan-sui River Basin.

4.1 Critical Disaster Resilience Indicators

The proposed modeling process in Sect. 3 has been applied to Tan-sui River Basin of Taipei city in Taiwan. Taipei City has deliberated on reaching an optimal solution, for the best disaster resilience indicators within their limited resources, from some considered disaster resilience dimensions and indicators.

This paper first considers practical viewpoints from different fields such as urban planning and design, disaster prevention, community and property management, as well as combines the characteristics of local development units and dwelling users. Five dimensions that influence the Tan-sui River Basin disaster resilience are summarized as follows.

Since 1990 s, the concept of disaster resilience has emerged as a popular issue to the problem of urban sustainable development especially for a rapidly growing population (Handmer and Dovers 1996). Studies have focused on the sustainability issue of disaster resilience (e.g., Holling et al. 1995; Klein et al. 1998; Adger 2000; Buckle et al. 2001; Carpenter et al. 2001; Fiksel 2003; McManus et al. 2007). In particular, these studies have focused on the definition and the possible utilization of disaster resilience, and related policy and careful stewardship of natural resources on operation and development. However, the operation process must be based on future human safety to establish indicators/

criteria for integration and self-discipline, and for reference in measurement and decision evaluation.

Disaster resilience has been studied in various countries. These study results have reported in the literature (Mayunga 2007; Rose 2004; Bruneau et al. 2003; Jing 2008). For example, Mayunga (2007) proposes several types of disaster resilience including socialeconomic capital, manpower resource capital, physical construction capital, and naturalenvironment capital. Whereas, Bruneau et al. (2003) suggest that a typical and ideal disaster resilience should be defined in four dimensions: (1) technical, (2) organization, (3) social, and (4) economic. Jing (2008) lists five dimensions to further explore and enhance the disaster resilience concept: (1) environment resilience, (2) economic resilience, (3) organization and decision-making resilience, (4) social resilience, and (5) science and technology resilience. In a famous study by McManus et al. (2007), resilience indicators for sustainable development are defined under four dimensions: environment, economy, organization and resources, and technology and operation. Moreover, Carpenter et al. (2001) claim that a resilience should contain the following principles: environmental safety, economic improvement, build environment enhancement, and institutional capacity. Hence, the research focus has shifted from abstract and extensive core concept discussion of overall large-scale environment to the reflection of cognition to actual and concrete area. The focus moreover is emphasized on the exhibition of fundamental concerns on residential security and disaster reliance, social and economic impact, and environment management. For most studies concerning questionnaire analyses and group discussions, the studies establish core indicators including parent dimensions (environment, society, economy and institution) and children indicators (e.g., disaster prevention plans, public facilities, etc.).

In order to determine critical evaluation criteria (i.e. PIFs), the authors consider the following areas based on literature review: urban planning/design, built environment planning, construction planning, community management. The authors also consider a combined characteristic parameter obtained by combining the agency development unit and the actual demand and interaction of dwelling users. Accordingly, five dimensions influencing the disaster resilience are summarized as follow: science and technical (ST), built-environment (BE), organizations and institutes (OI), social-economic (SE), and natural-environment (NE). Each dimension is defined in the following way. Science and Technical (ST) is based on both the relief and rescue capabilities and the forecasts and preparedness capacities. Built-Environment (BE) targets the life-support system and the infrastructure capability. In addition, BE contains the spatial structure of urban and regional areas in the Tan-sui River Basin. Organizations and Institutes (OI) generally refers to hardware and software plans developed in order to prevent disaster shocks. OI also possesses management capacities and institutions to deal with disaster outbreak. Social-Economic (SE) considers the social and economic capability for emergency response and recovery. And, it includes the local government financial capacity to cope with typhoon and flood disasters. Lastly, for Natural-Environment (NE), it focuses on the high potential areas of land slide, flooding, and other hazards. NE also includes water conservation areas and field slope for conservation plans. This paper studies the content and nature covered in each dimension, as well as analyzes and summarizes the PIFs that are simple, understandable and representative of each dimension.

Prioritizing all disaster resilience indicators on the basis of five resilience dimensions deems to be important for Tan-sui River Basin's future development. The Tan-sui River Basin planning agency proposes to establish an indicator in an attempt to evaluate five disaster resilience dimensions. As a typical urban problem, there are multiple indicators for

comparing different basin performances: these include both quantitative and qualitative elements. Furthermore, there are five resilience dimensions for this evaluation problem, e.g., (1) Science and Technical (ST), (2) Built-Environment (BE), (3) Organizations and Institutes (OI), (4) Social-Economic (SE), and (5) Natural-Environment (NE). Each dimension weight is evaluated with respect to these resilience dimensions by evaluators and specialist teams consisting of authorities in the corresponding fields. These teams report their evaluation for each dimension by assigning a pairwise comparison cardinal number score. The higher the score, the better the evaluation performance.

Followed by the five disaster resilience dimensions, to achieve the validity and practicality of evaluation, this research studies the content and nature covered in each dimension, and analyzes and summarizes PIFs that are simple, understandable and representative of each dimension. The number of PIFs under ST, BE, OI, SE, NE is 2, 2, 3, 3 and 3, respectively. These 13 disaster resilience indicators (PIFs) are described in Table 1.

After obtaining PIFs, this research adopts a face-to-face survey to collect opinions of six experts in the fields of urban planning and design, disaster prevention, community and property management, as well as local development units. Next, the FDM is applied to integrate expert opinions on the importance of PIFs, and the most decisive factors are extracted. Experts are asked to assign a score from 1 to 10, with a larger number for higher importance, to a PIF, and the value is used as a reference benchmark. Then, experts need to fill in the most conservative cognition value and the most optimistic cognition value according to the benchmark, i.e. C_t^i and O_t^i . Subsequently, the geometric mean of all $C_t^i(O_t^i)$ of each PIF is calculated, and the extreme values of C_t^i and O_t^i that are not in the range of

Dimension	Indicator	Description		
(ST) Science and technical	ST1. Rescue capabilityST2. Accuracy of weather forecasts	Relief and rescue capability The forecasts and preparedness capacities.		
(BE) Built	BE1. Public facilities	Life-support systems and infrastructures capability		
environment	BE2. Spatial structure of land use	Spatial structures of the urban areas and regional areas in the river basin		
(OI) Organizations and institutes	OI1. Disaster prevention plans	Developed the hardware and software plans to prevent the disaster shocks		
	OI2. River basin management organizations	The management capacity and institute to face the disaster		
	OI3. Resource distribution capability	Water resources distribution and regulation capability		
(SE) Social	SE1. Vulnerable population	Elder, low income, and hospitalized population		
economic	SE2. Individual capability	Social and economic capability for emergency response and recovery		
	SE3. Government's financial capability	Local government financial capacity to cope with the typhoon and flood disaster		
(NE) Natural environment	NE1. Environmentally sensitive area	High potential areas of land slide, flooding, and other hazard		
	NE2. Water resource conservation	Areas of water conservation plan		
	NE3. Slope area conservation	Areas of slope conservation plan		

 Table 1
 Description of disaster resilience indicators



Fig. 6 Interdependences among five dimensions

two standard deviations are eliminated. If there is no elimination in the operation process, it implies that there is no extreme cognition among experts. Finally, the minimum, the geometric mean and the maximum of $C_t^i(O_t^i)$ are calculated to establish TFNs. Finally, the gray zone test is conducted, and "the important degree of consensus", G^i , is calculated.

The AHP technique introduced by Saaty is applied to a problem without considering the interdependence properties among dimensions. However, there exists interdependence relationships among the identified dimensions in disaster resilience indicator prioritization problem. Generally, if we promote a disaster resilience area the ability of Science and Technology, the performance of Built-Environment will be increased in hereafter operations. Similarly, in order to increase the Social-Economics, we will have to increase clerical operations. Likewise, in order to increase clerical operations, we will increase the understandings of Natural-Environment. Accordingly, there exists interdependence relationships among these dimensions, that is, the ST dimension influences BE, OI, NE, and SE dimensions; the NE dimension influences OI, BE and SE dimensions; the BE dimension influences the NE dimension (see Fig. 6).

In order to check network structure or relationship in considered dimensions or candidate indicator, we need to have group discussion because the type of network or relationship depends on the decision makers' judgment.

4.2 Proposed Resilience Indicator Evaluation Model

This research bases on the extraction results by FDM in Sect. 4.1 and invites eight experts with practical experiences in urban disaster planning and prevention, construction development, ecology engineering, governmental urban planning/design, and building management to carry out group discussion and evaluation meeting. In the process, the network structure of ANP is focused and constructed first, and the experts seek for consensus on possible interdependence or feedback of components among goal level, dimension level and indicator level. After that, objects to be evaluated are added to establish the complete evaluation model.

In order to determine the weights of the degree of influence among the dimensions, we showed the procedure using the matrix manipulation based on Saaty's supermatrix and his nine scales. More importantly, all these data were collected by a group discussion to avoid the unilateral decision based upon one individual's subjective judgment. Figure 7 demonstrates the standard network for our empirical example.

Furthermore, this transformed network and corresponding supermatrix representations are shown in Fig. 8. The algorithm presented in Sect. 3 is applied to determine the importance ratings within each level by pairwise comparisons. The application is stated in stepwise form as given below. Note that the data of example used in this paper are based on Saaty's nine scales (Saaty 1980, 1996):

Step 1: To compare the resilience dimensions, one responds to this question: Which dimension should be emphasized more in a disaster resilience indicator, and how much more? By pairwise comparing all pairs with respect to the five resilience dimensions, we will obtain the following data via AHP method like (*ST*, *BE*, *OI*, *SE*, *NE*) = (0.090, 0.269,



Fig. 7 Proposed model structure



Fig. 8 Network structure and supermatrix notation

0.177, 0.070, 0.394), assuming that there is no interdependence among them. This data means only relative weight without considering independence among dimensions. We defined the weight matrix of dimension as $W_I = (ST, BE, OI, SE, NE) = (0.090, 0.269, 0.177, 0.070, 0.394)$. For the W_I matrix, which is obtained from the AHP, CI = 0.0620 and CR = 0.0554, respectively. The values of CI and CR show the consistency for pairwise comparisons.

Step 2: Again, by assuming that there is no interdependence among the thirteen indicators, (ST1, ST2, BE1, BE2, OI1, OI2, OI3, SE1, SE2, SE3, NE1, NE2, NE3), they are compared with respect to each criterion yielding the column normalized weight with respect to each criterion, as shown in Table 2.

The second row in Table 2 shows the degree of relative importance for each criterion, and the data of third row are normalized to sum to one for each dimensions. We defined the weight matrix of thirteen indicators for dimension ST as

W_2	ST	BE	OI	SE	NE
ST1	9	3	7	7	3
ST2	9	3	7	7	7
BE1	7	9	7	5	7
BE2	3	9	5	7	5
<i>OI1</i>	5	7	9	7	7
<i>OI2</i>	5	7	9	7	5
OI3	7	5	9	5	7
SE1	5	3	7	9	5
SE2	7	7	7	9	5
SE3	3	5	7	9	5
NE1	7	7	5	5	9
NE2	7	7	5	5	9
NE3	7	7	5	5	9
ST1	0.111	0.038	0.079	0.080	0.036
ST2	0.111	0.038	0.079	0.080	0.084
BE1	0.086	0.114	0.079	0.057	0.084
BE2	0.037	0.114	0.056	0.080	0.060
<i>OI1</i>	0.062	0.089	0.101	0.080	0.084
<i>OI2</i>	0.062	0.089	0.101	0.080	0.060
<i>OI3</i>	0.086	0.063	0.101	0.057	0.084
SE1	0.062	0.038	0.079	0.103	0.060
SE2	0.086	0.089	0.079	0.103	0.060
SE3	0.037	0.063	0.079	0.103	0.060
NE1	0.086	0.089	0.056	0.057	0.108
NE2	0.086	0.089	0.056	0.057	0.108
NE3	0.086	0.089	0.056	0.057	0.108
	W_{21}	W ₂₂	W ₂₃	W_{24}	W ₂₅

Table 2Column eigenvectorswith respect to each criterion

	0.111
	0.111
	0.086
	0.037
	0.062
	0.062
$W_{21} =$	0.086
	0.062
	0.086
	0.037
	0.086
	0.086
	0.086

Step 3: we consider the interdependences among dimensions. When we prioritize disaster resilience indicators, we cannot examine only one criterion. We need to examine the impacts of all dimensions on each criterion by using pairwise comparisons. In Table 3, we obtain six sets of weights through an expert group interview. The table shows the impact degree of five resilience dimensions while accounting for dependences within themselves. For example, the ST's degree of relative impact for BE is 0.105 and the NE's degree of relative impact for OI is 0.187 (Table 4).

We define the interdependence weight matrix of resilience dimensions as

$$W_3 = \begin{bmatrix} 0.540 & 0.105 & 0.233 & 0.243 & 0.236 \\ 0 & 0.349 & 0.087 & 0 & 0.108 \\ 0.297 & 0.249 & 0.258 & 0.162 & 0.142 \\ 0.163 & 0.116 & 0.233 & 0.319 & 0.087 \\ 0 & 0.181 & 0.187 & 0.276 & 0.427 \end{bmatrix}$$

Due to space limitations, the data among interdependent resilience dimensions' degree of relative impact for each dimension individually are shown in Tables 5, 6, 7, 8, 9 (see "Appendix 1").

Step 4: we deal with interdependence among the indicators with respect to each criterion and defined the weight matrices as W_{41} , W_{42} , W_{43} , W_{44} , and W_{45} . An illustration of the question to which one must respond is: with respect to the satisfaction of the resilience dimensions, resilience dimension 1 (ST), with indicator, which indicator contributes more

<i>W</i> ₃	ST	BE	OI	SE	NE
ST	0.540	0.105	0.233	0.243	0.236
BE	0.000	0.349	0.087	0.000	0.108
OI	0.297	0.249	0.258	0.162	0.142
SE	0.163	0.116	0.233	0.319	0.087
NE	0.000	0.181	0.187	0.276	0.427

 Table 3 Relative impact degree of resilience dimension

Table 4Disaster resilienceindicators: aggregate prioritiesand ranking	Criteria	Aggregate priorities	Aggregate ranking
	ST1. Rescue capability (C1)	0.027	13
	ST2. Accuracy of weather forecasts (C2)	0.033	12
	BE1. Public facilities (C3)	0.040	10
	BE2. Spatial structure of land use (C4)	0.035	11
	OI1. Disaster prevention plans (C5)	0.064	7
	OI2. River basin management organizations (C6)	0.172	1
	OI3. Resource distribution capability (C7)	0.072	5
	SE1. Vulnerable population (C8)	0.065	6
	SE2. Individual capability (C9)	0.058	8
	SE3. Government's financial capability (<i>C10</i>)	0.055	9
	NE1. Environmentally sensitive area (C11)	0.165	2
	NE2. Water resource conservation (C12)	0.122	3
	NE3. Slope area conservation (C13)	0.093	4

to the action of indicator 1 to resilience dimension 1 and how much more? In this way, the data are shown in Tables 10, 11, 12, 13 and 14 (see "Appendix 2").

 $W_{41} =$

0.027	0.030	0.071	0.026	0.087	0.053	0.008	0.009	0.014	0.009	0.039	0.025	0.031
0.027	0.030	0.071	0.077	0.087	0.053	0.013	0.015	0.014	0.045	0.028	0.025	0.031
0.009	0.010	0.024	0.077	0.010	0.159	0.013	0.015	0.014	0.009	0.028	0.025	0.019
0.027	0.010	0.008	0.026	0.029	0.159	0.013	0.015	0.014	0.015	0.028	0.025	0.019
0.009	0.010	0.071	0.026	0.029	0.032	0.038	0.015	0.041	0.015	0.065	0.018	0.031
0.080	0.091	0.024	0.026	0.146	0.159	0.191	0.306	0.205	0.227	0.196	0.368	0.283
0.133	0.091	0.071	0.077	0.029	0.032	0.038	0.044	0.041	0.045	0.039	0.025	0.019
0.133	0.091	0.071	0.077	0.087	0.023	0.038	0.044	0.123	0.045	0.039	0.041	0.031
0.080	0.091	0.071	0.077	0.029	0.032	0.038	0.015	0.041	0.045	0.039	0.041	0.031
0.133	0.030	0.118	0.077	0.087	0.032	0.038	0.044	0.041	0.045	0.039	0.041	0.031
0.133	0.212	0.165	0.179	0.087	0.159	0.191	0.219	0.205	0.227	0.196	0.123	0.283
0.133	0.152	0.118	0.128	0.204	0.053	0.191	0.131	0.123	0.136	0.196	0.123	0.094
0.080	0.091	0.118	0.128	0.087	0.053	0.191	0.131	0.123	0.136	0.065	0.123	0.094

	$W_{42} =$												
	0.026	0.030	0.035	0.032	0.086	0.053	0.008	0.009	0.014	0.009	0.038	0.024	0.027]
	0.026	0.030	0.035	0.097	0.086	0.053	0.013	0.015	0.014	0.045	0.027	0.024	0.027
	0.026	0.030	0.035	0.097	0.029	0.159	0.013	0.015	0.014	0.015	0.038	0.024	0.082
	0.026	0.010	0.012	0.032	0.029	0.159	0.013	0.015	0.014	0.015	0.038	0.040	0.082
	0.009	0.010	0.035	0.032	0.029	0.032	0.038	0.015	0.041	0.015	0.064	0.017	0.027
	0.078	0.091	0.035	0.032	0.143	0.159	0.191	0.306	0.205	0.225	0.192	0.362	0.246
	0.130	0.091	0.106	0.097	0.029	0.032	0.038	0.044	0.041	0.045	0.038	0.024	0.016
	0.130	0.091	0.106	0.097	0.086	0.023	0.038	0.044	0.123	0.045	0.038	0.040	0.027
	0.078	0.091	0.106	0.097	0.029	0.032	0.038	0.015	0.041	0.045	0.038	0.040	0.027
	0.130	0.030	0.106	0.097	0.086	0.032	0.038	0.044	0.041	0.045	0.038	0.040	0.027
	0.130	0.212	0.176	0.161	0.086	0.159	0.191	0.219	0.205	0.225	0.192	0.121	0.246
	0.130	0.152	0.176	0.097	0.200	0.053	0.191	0.131	0.123	0.135	0.192	0.121	0.082
	0.078	0.091	0.035	0.032	0.086	0.053	0.191	0.131	0.123	0.135	0.064	0.121	0.082
1	$W_{42} =$												
	Г0.024	0.030	0.035	0.030	0.026	0.053	0.013	0.008	0.014	0.008	0.030	0.020	0.0217
	0.024	0.030	0.035	0.091	0.026	0.053	0.021	0.013	0.014	0.040	0.021	0.020	0.021
	0.024	0.030	0.035	0.091	0.077	0.159	0.021	0.013	0.014	0.013	0.030	0.020	0.064
	0.024	0.010	0.012	0.030	0.026	0.159	0.021	0.013	0.014	0.013	0.030	0.034	0.064
	0.073	0.091	0.035	0.091	0.077	0.032	0.193	0.117	0.041	0.040	0.150	0.101	0.191
	0.073	0.091	0.035	0.030	0.385	0.159	0.322	0.274	0.205	0.201	0.150	0.302	0.191
	0.122	0.091	0.106	0.091	0.026	0.032	0.064	0.039	0.041	0.121	0.150	0.101	0.064
	0.122	0.091	0.106	0.091	0.026	0.023	0.064	0.039	0.123	0.040	0.030	0.034	0.021
	0.073	0.091	0.106	0.091	0.077	0.032	0.064	0.013	0.041	0.040	0.030	0.034	0.021
	0.122	0.030	0.106	0.091	0.077	0.032	0.021	0.039	0.041	0.040	0.030	0.034	0.021
	0.122	0.212	0.176	0.152	0.077	0.159	0.064	0.196	0.205	0.201	0.150	0.101	0.191
	0.122	0.152	0.176	0.091	0.077	0.053	0.064	0.117	0.123	0.121	0.150	0.101	0.064
	0.073	0.091	0.035	0.030	0.026	0.053	0.064	0.117	0.123	0.121	0.050	0.101	0.064
u	-												
Г	44 - 0.023	0.030	0.035	0.030	0.021	0.045	0.013	0.010	0.013	0.010	0.029	0.020	0.021
	0.023	0.030	0.035	0.000	0.021	0.045	0.015	0.010	0.013	0.017	0.021	0.020	0.021
	0.023	0.030	0.035	0.001	0.021	0.135	0.021	0.017	0.013	0.017	0.021	0.020	0.021
	0.023	0.050	0.035	0.031	0.004	0.135	0.021	0.017	0.022	0.017	0.029	0.020	0.004
	0.023	0.010	0.012	0.050	0.021	0.135	0.021	0.017	0.022	0.017	0.029	0.004	0.004
	0.070	0.091	0.035	0.091	0.004	0.027	0.195	0.050	0.022	0.050	0.144	0.101	0.191
	0.070	0.091	0.055	0.050	0.519	0.155	0.522	0.150	0.005	0.149	0.144	0.502	0.191
	0.110	0.091	0.106	0.091	0.021	0.027	0.064	0.050	0.065	0.149	0.144	0.101	0.064
	0.110	0.152	0.100	0.091	0.004	0.045	0.004	0.050	0.005	0.050	0.029	0.034	0.021
	0.116	0.152	0.106	0.091	0.191	0.135	0.064	0.050	0.065	0.050	0.048	0.034	0.021
	0.116	0.091	0.106	0.091	0.064	0.045	0.021	0.050	0.065	0.050	0.048	0.034	0.021
	0.116	0.212	0.176	0.152	0.064	0.135	0.064	0.249	0.195	0.149	0.144	0.101	0.191
	0.116	0.152	0.176	0.091	0.064	0.045	0.064	0.150	0.195	0.149	0.144	0.101	0.064
L	0.070	0.091	0.035	0.030	0.021	0.045	0.064	0.150	0.195	0.149	0.048	0.101	0.064

I	$V_{45} =$												
	0.022	0.030	0.033	0.030	0.021	0.037	0.013	0.008	0.014	0.008	0.023	0.020	0.023
	0.022	0.030	0.033	0.091	0.021	0.037	0.021	0.014	0.014	0.040	0.023	0.020	0.038
	0.022	0.030	0.033	0.091	0.064	0.112	0.021	0.014	0.014	0.013	0.033	0.020	0.038
	0.022	0.010	0.011	0.030	0.021	0.112	0.021	0.014	0.014	0.013	0.033	0.034	0.113
	0.067	0.091	0.033	0.091	0.064	0.022	0.193	0.127	0.041	0.040	0.055	0.101	0.113
	0.067	0.091	0.033	0.030	0.319	0.112	0.322	0.297	0.205	0.201	0.055	0.302	0.113
	0.111	0.091	0.099	0.091	0.021	0.022	0.064	0.042	0.041	0.121	0.164	0.101	0.113
	0.111	0.091	0.099	0.091	0.021	0.016	0.064	0.042	0.123	0.040	0.055	0.034	0.038
	0.067	0.091	0.099	0.091	0.064	0.022	0.064	0.014	0.041	0.040	0.033	0.034	0.038
	0.111	0.030	0.099	0.091	0.064	0.022	0.021	0.042	0.041	0.040	0.033	0.034	0.038
	0.156	0.212	0.165	0.152	0.191	0.335	0.064	0.127	0.205	0.201	0.164	0.101	0.113
	0.111	0.152	0.165	0.091	0.064	0.037	0.064	0.127	0.123	0.121	0.164	0.101	0.113
	0.111	0.091	0.099	0.030	0.064	0.112	0.064	0.127	0.123	0.121	0.164	0.101	0.113

Step 5: We now obtain the interdependence priorities of the resilience dimensions by synthesizing the results from Steps 1 to 3 as follows:

$$w_{c} = W_{3} \times w_{1} = \begin{bmatrix} 0.540 & 0.105 & 0.233 & 0.243 & 0.236 \\ 0 & 0.349 & 0.087 & 0 & 0.108 \\ 0.297 & 0.249 & 0.258 & 0.162 & 0.142 \\ 0.163 & 0.116 & 0.233 & 0.319 & 0.087 \\ 0 & 0.181 & 0.187 & 0.276 & 0.427 \end{bmatrix} \\ \times \begin{bmatrix} 0.090 \\ 0.269 \\ 0.178 \\ 0.070 \\ 0.393 \end{bmatrix} = \begin{bmatrix} 0.228 \\ 0.152 \\ 0.207 \\ 0.144 \\ 0.269 \end{bmatrix}$$

Thus we have $W_c = (ST, BE, OI, SE, NE) = (0.228, 0.152, 0.207, 0.144, 0.269).$

Step 6: The priorities of the Indicators W_p with respect to each of the five resilience dimensions are given by synthesizing the results from Steps 2 and 4 as follows:

	0.033	
	0.036	
	0.027	
	0.027	
	0.031	
	0.176	
$W_{P1} = W_{41} \times W_{21} =$	0.056	
	0.069	
	0.051	
	0.059	
	0.183	
	0.138	
	0.107	

	[0.033
	0.042
	0.050
	0.041
	0.031
	0.168
$W_{P2} = W_{42} \times W_{22} =$	0.054
	0.068
	0.054
	0.060
	0.176
	0.136
	L0.087 J
	[0.024]
	0.031
	0.048
	0.037
	0.092
	0.195
$W_{P3} = W_{43} \times W_{23} =$	0.076
	0.062
	0.056
	0.053
	0.151
	0.106
	0.072
	ך 0.022 ס
	0.028
	0.043
	0.033
	0.078
	0.147
$W_{P4} = W_{44} \times W_{24} =$	0.083
	0.069
	0.088
	0.063
	0.155
	0.120
	0.090

	0.022
	0.030
	0.038
	0.037
	0.083
	0.169
$W_{P5} = W_{45} \times W_{25} =$	0.087
	0.060
	0.053
	0.048
	0.161
	0.113
	0.103

We define the matrix W_2 by grouping together the above five columns: $W_2 = (W_{p1}, W_{p2}, W_{p3}, W_{p4}, W_{p5})$. That is,

	0.033	0.033	0.024	0.022	0.022
	0.036	0.042	0.031	0.028	0.030
	0.027	0.050	0.048	0.043	0.038
	0.027	0.041	0.037	0.033	0.037
	0.031	0.031	0.092	0.078	0.083
	0.176	0.168	0.195	0.147	0.169
$W_2 =$	0.056	0.054	0.076	0.083	0.087
	0.069	0.068	0.062	0.069	0.060
	0.051	0.054	0.056	0.088	0.053
	0.059	0.060	0.053	0.063	0.048
	0.183	0.176	0.151	0.155	0.161
	0.138	0.136	0.106	0.120	0.113
	0.107	0.087	0.072	0.090	0.103

Step 7: Finally, the overall priorities for the candidate indicators W_{anp} are calculated by multiplying W_2 by W_c .

$$We have w_{ANP} = W_2 \times w_c = \begin{bmatrix} 0.033 & 0.033 & 0.024 & 0.022 & 0.022 \\ 0.036 & 0.042 & 0.031 & 0.028 & 0.030 \\ 0.027 & 0.050 & 0.048 & 0.043 & 0.038 \\ 0.027 & 0.041 & 0.037 & 0.033 & 0.037 \\ 0.031 & 0.031 & 0.092 & 0.078 & 0.083 \\ 0.176 & 0.168 & 0.195 & 0.147 & 0.169 \\ 0.056 & 0.054 & 0.076 & 0.083 & 0.087 \\ 0.069 & 0.068 & 0.062 & 0.069 & 0.060 \\ 0.051 & 0.054 & 0.056 & 0.088 & 0.053 \\ 0.059 & 0.060 & 0.053 & 0.063 & 0.048 \\ 0.183 & 0.176 & 0.151 & 0.155 & 0.161 \\ 0.138 & 0.136 & 0.106 & 0.120 & 0.113 \\ 0.107 & 0.087 & 0.072 & 0.090 & 0.103 \end{bmatrix} \times \begin{bmatrix} 0.027 \\ 0.033 \\ 0.030 \\ 0.031 \\ 0.027 \\ 0.031 \\ 0.027 \\ 0.031 \\ 0.031 \\ 0.005 \\ 0.051 \\ 0.059 \\ 0.059 \\ 0.060 \\ 0.051 \\ 0.059 \\ 0.060 \\ 0.051 \\ 0.059 \\ 0.063 \\ 0.059 \\ 0.063 \\ 0.053 \\ 0.053 \\ 0.053 \\ 0.053 \\ 0.055 \\ 0.165 \\ 0.122 \\ 0.093 \end{bmatrix}$$

Our final results in the ANP Phase are (*C1*, *C2*, *C3*, *C4*, *C5*, *C6*, *C7*, *C8*, *C9*, *C10*, *C11*, *C12*, *C13*) = (0.027, 0.033, 0.040, 0.035, 0.064, 0.172, 0.072, 0.065, 0.058, 0.055, 0.165, 0.122, 0.093). These ANP results are interpreted as follows. The highest weight of indicators in this disaster resilience indicators prioritization example is *C6* (0.172). Next is indicator 11, *C11*. These weights are used as priorities in judging its importance while allocating the limited resources of public sectors. That is (*C1*, *C2*, *C3*, *C4*, *C5*, *C6*, *C7*, *C8*, *C9*, *C10*, *C11*, *C12*, *C13*) = (*W*₁, *W*₂, *W*₃, *W*₄, *W*₅, *W*₆, *W*₇, *W*₈, *W*₉, *W*₁₀, *W*₁₁, *W*₁₂, *W*₁₃) = (0.027, 0.033, 0.040, 0.035, 0.064, 0.172, 0.072, 0.065, 0.058, 0.055, 0.165, 0.122, 0.093), *W_i* are the values of the thirteen disaster resilience indicators.

After all the priorities are calculated, the initial supermatrix is formed and obtained using Eq. (5) and the integrated priorities and ranking of the disaster resilience indicators are shown in Table 4. River basin management organizations (*C6*) has the highest priority of 0.172, followed by Environmentally sensitive area (*C11*), water resource conservation (*C12*) and slope area conservation (*C13*) with priorities of 0.165, 0.122 and 0.093, respectively.

The ranking of the indicators shows that in actual disaster situation, Management institute of basin will play the most important role. Under the prerequisite of concerns of environmentally sensitive area, the disaster prevention system shall provide conservation of water resource and conservation for the slope area to support the disaster situation.

5 Discussion and Conclusion

The set of all indicators determined using the combined fuzzy Delphi and ANP approach is different from the solutions that are obtained by applying either AHP or ANP by itself. In this research, FDM and ANP are integrated to construct a model for evaluating the disaster resilience indicators. With the consensus of experts, the implementation of the model lead to the some significant contributions. One should note that consideration of interdependencies in the resilience dimensions and analysis of the disaster resilience indicators selection problem from a multi-objective perspective result in different evaluation and selection attributes to be focused on. The combined fuzzy Delphi and ANP approach, which aims to quantify the interdependencies and multiple objectives inherent in the disaster resilience problem in a systematic way, appears as an effective solution aid.

The application of the ANP model to the empirical example demonstrates the procedure of finding weight by considering interdependence of indicators. The proposed model provides a methodology for indicator selection based on interdependent relationships. Scoring and ranking techniques are intuitively simple but they do not ensure resource feasibility and are insufficient for dealing with indicator interdependence. Previous research mainly focused on problems assuming independence. Although there are lots of difficulties for solving problems considering interdependent properties, most real-world problems, especially disaster resilience indicator evaluation problems, have interdependent properties. However, it is very difficult to judge whether they are interdependent or not. Therefore, group decision making is more helpful to determine such interdependence than decisions made by only one or two persons. Group discussion is necessary to determine the degree of impact of the considered indicators because the degree of impact does vary according to each decision maker. Group discussion is very effective to determine important problems and is not likely to be biased as in the case of a single decision maker.

This paper shows an example solving indicator interdependence based on fuzzy Delphi and ANP by group expert interview. Using this method we conclude that we can solve problems having multiple indicators, interdependence and resource feasibility. The empirical example uses the fuzzy Delphi and ANP methodology for analysis. When all of the non-dominated solutions are found by our proposed algorithm, a decision-maker can evaluate the objective values of these solutions and identify a satisfactory indicator. In this paper, we show an indicator method to quantify the combined effects of factors on organizational performance measures using the supermatrix approach. The selection of an appropriate set of disaster resilience indicators is very helpful to all land use and engineering organizations. In addition, we develop upon the work conducted on disaster resilience indicators prioritization considering the impact relationship among indicators. The ANP is presented in this paper as a valuable method to support the selection of disaster resilience indicators that is efficient for a public sector to perform the disaster resilience improvements study. At last, this study moves one step closer to the developing of a new methodology for solving the interdependent disaster resilience indicator prioritization problem. The determination of a good selection of disaster resilience indicators may not only include these 13 disaster resilience indicators (PIFs), the sensitivity analysis applicable to the indicator problem issues may also need to be taken into consideration in the future study.

To sum up, the network evaluation model constructed in this research not only can convert the abstract disaster resilience concept into concrete ideology, it can also convert subjective qualitative characteristics, local demands and implied mutual influences into integrated quantitative values for guidance of actual situation. The research results can be used as the evaluation foundation for important guidance for future disaster resilience indicators development and planning. The results also can be used as a reference for relevant government policy making. In addition, the integrated research model not only can be directly used as a systematic and practical objective evaluation tool in the disaster resilience research field, but also can be extended to solve relevant multiple criteria decision making problems in management, evaluation and decision making in other urban science fields.

Appendix 1: Interdependences Among Each Resilience Dimension

The following Table 5 Table A6 show the data among interdependent resilience dimension's degree of relative impact for each resilience dimension individually.

W ₃₁	ST	OI	SE
ST	1	3	9
OI	1/3	1	5
SE	1	1	3

 Table 5
 Relative impacts of interdependent resilience dimensions on the dimension 1 (ST)

We defined the interdependence weight of the resilience dimension as $W_{31} = (0.540, 0.300, 0.163)$.

W ₃₂	ST	BE	OI	SE	NE
ST	1	1/3	1/5	1	1
BE	3	1	3	3	1
OI	5	1/3	1	3	1
SE	1	1/3	1/3	1	1
NE	1	1	1	1	1

Table 6 Relative impacts of interdependent resilience dimensions on the dimension 2 (BE)

We defined the interdependence weight of the resilience dimension as $W_{32} = (0.105, 0.349, 0.249, 0.116, 0.181)$.

Table 7 Relative impacts of interdependent resilience dimensions on the dimension 3 (OI)

W ₃₃	ST	BE	OI	SE	NE
ST	1	3	3	1	1/3
BE	1/3	1	1/5	1/3	1
OI	1/3	5	1	3	1
SE	1	3	1/3	1	3
NE	3	1	1	1/3	1

We defined the interdependence weight of the resilience dimension as $W_{33} = (0.088, 0.480, 0.261, 0.083, 0.088)$.

Table 8 Relative impacts of interdependent resilience dimensions on the dimension 4 (SE)

W ₃₄	ST	OI	SE	NE
ST	1	3	1/3	1
OI	1/3	1	3	1/5
SE	3	1/3	1	3
NE	1	5	1/3	1

We defined the interdependence weight of the resilience dimension as $W_{34} = (0.243, 0.162, 0.319, 0.276)$.

	-	-			
W ₃₅	ST	BE	OI	SE	NE
ST	1	3	3	3	1/5
BE	1/3	1	1/3	3	1/3
OI	1/3	3	1	3	1/7
SE	1/3	1/3	1/3	1	1
NE	5	3	7	1	1

Table 9 Relative impacts of interdependent resilience dimensions on the dimension 5 (NE)

We defined the interdependence weight of the resilience dimension as $W_{35} = (0.236, 0.108, 0.142, 0.087, 0.427)$

Appendix 2: Interdependences Among Indicators Respect to Each Dimension

In Table 10, the second row (the degree of interdependence among the indicators with respect to each indicator) was obtained from decision-makers according to the Saaty's nine scale. The third row was normalized and summed to one. We defined the indicator interdependence weight matrix for resilience dimension ST as W_{41}

W ₄₁	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
ST1	1	1	3	1	3	1/3	1/5	1/5	1/3	1/5	1/5	1/5	1/3
ST2	1	1	3	3	3	1/3	1/3	1/3	1/3	1	1/7	1/5	1/3
BE1	1/3	1/3	1	3	1/3	1	1/3	1/3	1/3	1/5	1/7	1/5	1/5
BE2	1	1/3	1/3	1	1	1	1/3	1/3	1/3	1/3	1/7	1/5	1/5
011	1/3	1/3	3	1	1	1/5	1	1/3	1	1/3	1/3	1/7	1/3
<i>OI2</i>	3	3	1	1	5	1	5	7	5	5	1	3	3
OI3	5	3	3	3	1	1/5	1	1	1	1	1/5	1/5	1/5
SE1	5	3	3	3	3	1/7	1	1	3	1	1/5	1/3	1/3
SE2	3	3	3	3	1	1/5	1	1/3	1	1	1/5	1/3	1/3
SE3	5	1	5	3	3	1/5	1	1	1	1	1/5	1/3	1/3
NE1	5	7	7	7	3	1	5	5	5	5	1	1	3
NE2	5	5	5	5	7	1/3	5	3	3	3	1	1	1
NE3	3	3	5	5	3	1/3	5	3	3	3	1/3	1	1
ST1	0.027	0.030	0.071	0.026	0.087	0.053	0.008	0.009	0.014	0.009	0.039	0.025	0.031
ST2	0.027	0.030	0.071	0.077	0.087	0.053	0.013	0.015	0.014	0.045	0.028	0.025	0.031
BE1	0.009	0.010	0.024	0.077	0.010	0.159	0.013	0.015	0.014	0.009	0.028	0.025	0.019
BE2	0.027	0.010	0.008	0.026	0.029	0.159	0.013	0.015	0.014	0.015	0.028	0.025	0.019
011	0.009	0.010	0.071	0.026	0.029	0.032	0.038	0.015	0.041	0.015	0.065	0.018	0.031
012	0.080	0.091	0.024	0.026	0.146	0.159	0.191	0.306	0.205	0.227	0.196	0.368	0.283
OI3	0.133	0.091	0.071	0.077	0.029	0.032	0.038	0.044	0.041	0.045	0.039	0.025	0.019
SE1	0.133	0.091	0.071	0.077	0.087	0.023	0.038	0.044	0.123	0.045	0.039	0.041	0.031
SE2	0.080	0.091	0.071	0.077	0.029	0.032	0.038	0.015	0.041	0.045	0.039	0.041	0.031
SE3	0.133	0.030	0.118	0.077	0.087	0.032	0.038	0.044	0.041	0.045	0.039	0.041	0.031
NE1	0.133	0.212	0.165	0.179	0.087	0.159	0.191	0.219	0.205	0.227	0.196	0.123	0.283
NE2	0.133	0.152	0.118	0.128	0.204	0.053	0.191	0.131	0.123	0.136	0.196	0.123	0.094
NE3	0.080	0.091	0.118	0.128	0.087	0.053	0.191	0.131	0.123	0.136	0.065	0.123	0.094

Table 10 Inner dependence matrix of indicators with respect to the dimension 1 (ST)

Table 11	Inner	dependence	matrix	of indicato	rs with	respect	to	the	dimension	2	(BE))
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W ₄₂	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
ST1	1	1	1	1	3	1/3	1/5	1/5	1/3	1/5	1/5	1/5	1/3
ST2	1	1	1	3	3	1/3	1/3	1/3	1/3	1	1/7	1/5	1/3
BE1	1	1	1	3	1	1	1/3	1/3	1/3	1/3	1/5	1/5	1
BE2	1	1/3	1/3	1	1	1	1/3	1/3	1/3	1/3	1/5	1/3	1
<i>OI1</i>	1/3	1/3	1	1	1	1/5	1	1/3	1	1/3	1/3	1/7	1/3
<i>OI</i> 2	3	3	1	1	5	1	5	7	5	5	1	3	3
<i>OI3</i>	5	3	3	3	1	1/5	1	1	1	1	1/5	1/5	1/5
SE1	5	3	3	3	3	1/7	1	1	3	1	1/5	1/3	1/3
SE2	3	3	3	3	1	1/5	1	1/3	1	1	1/5	1/3	1/3

W ₄₂	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
SE3	5	1	3	3	3	1/5	1	1	1	1	1/5	1/3	1/3
NE1	5	7	5	5	3	1	5	5	5	5	1	1	3
NE2	5	5	5	3	7	1/3	5	3	3	3	1	1	1
NE3	3	3	1	1	3	1/3	5	3	3	3	1/3	1	1
ST1	0.026	0.030	0.035	0.032	0.086	0.053	0.008	0.009	0.014	0.009	0.038	0.024	0.027
ST2	0.026	0.030	0.035	0.097	0.086	0.053	0.013	0.015	0.014	0.045	0.027	0.024	0.027
BE1	0.026	0.030	0.035	0.097	0.029	0.159	0.013	0.015	0.014	0.015	0.038	0.024	0.082
BE2	0.026	0.010	0.012	0.032	0.029	0.159	0.013	0.015	0.014	0.015	0.038	0.040	0.082
011	0.009	0.010	0.035	0.032	0.029	0.032	0.038	0.015	0.041	0.015	0.064	0.017	0.027
<i>OI2</i>	0.078	0.091	0.035	0.032	0.143	0.159	0.191	0.306	0.205	0.225	0.192	0.362	0.246
0I3	0.130	0.091	0.106	0.097	0.029	0.032	0.038	0.044	0.041	0.045	0.038	0.024	0.016
SE1	0.130	0.091	0.106	0.097	0.086	0.023	0.038	0.044	0.123	0.045	0.038	0.040	0.027
SE2	0.078	0.091	0.106	0.097	0.029	0.032	0.038	0.015	0.041	0.045	0.038	0.040	0.027
SE3	0.130	0.030	0.106	0.097	0.086	0.032	0.038	0.044	0.041	0.045	0.038	0.040	0.027
NE1	0.130	0.212	0.176	0.161	0.086	0.159	0.191	0.219	0.205	0.225	0.192	0.121	0.246
NE2	0.130	0.152	0.176	0.097	0.200	0.053	0.191	0.131	0.123	0.135	0.192	0.121	0.082
NE3	0.078	0.091	0.035	0.032	0.086	0.053	0.191	0.131	0.123	0.135	0.064	0.121	0.082

Table 12 Inner dependence matrix of indicators with respect to the dimension 3 (OI)

W ₄₃	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
ST1	1	1	1	1	1/3	1/3	1/5	1/5	1/3	1/5	1/5	1/5	1/3
ST2	1	1	1	3	1/3	1/3	1/3	1/3	1/3	1	1/7	1/5	1/3
BE1	1	1	1	3	1	1	1/3	1/3	1/3	1/3	1/5	1/5	1
BE2	1	1/3	1/3	1	1/3	1	1/3	1/3	1/3	1/3	1/5	1/3	1
011	3	3	1	3	1	1/5	3	3	1	1	1	1	3
012	3	3	1	1	5	1	5	7	5	5	1	3	3
013	5	3	3	3	1/3	1/5	1	1	1	3	1	1	1
SE1	5	3	3	3	1/3	1/7	1	1	3	1	1/5	1/3	1/3
SE2	3	3	3	3	1	1/5	1	1/3	1	1	1/5	1/3	1/3
SE3	5	1	3	3	1	1/5	1/3	1	1	1	1/5	1/3	1/3
NE1	5	7	5	5	1	1	1	5	5	5	1	1	3
NE2	5	5	5	3	1	1/3	1	3	3	3	1	1	1
NE3	3	3	1	1	1/3	1/3	1	3	3	3	1/3	1	1
ST1	0.024	0.030	0.035	0.030	0.026	0.053	0.013	0.008	0.014	0.008	0.030	0.020	0.021
ST2	0.024	0.030	0.035	0.091	0.026	0.053	0.021	0.013	0.014	0.040	0.021	0.020	0.021
BE1	0.024	0.030	0.035	0.091	0.077	0.159	0.021	0.013	0.014	0.013	0.030	0.020	0.064
BE2	0.024	0.010	0.012	0.030	0.026	0.159	0.021	0.013	0.014	0.013	0.030	0.034	0.064
<i>OI1</i>	0.073	0.091	0.035	0.091	0.077	0.032	0.193	0.117	0.041	0.040	0.150	0.101	0.191
<i>OI</i> 2	0.073	0.091	0.035	0.030	0.385	0.159	0.322	0.274	0.205	0.201	0.150	0.302	0.191
OI3	0.122	0.091	0.106	0.091	0.026	0.032	0.064	0.039	0.041	0.121	0.150	0.101	0.064
SE1	0.122	0.091	0.106	0.091	0.026	0.023	0.064	0.039	0.123	0.040	0.030	0.034	0.021
SE2	0.073	0.091	0.106	0.091	0.077	0.032	0.064	0.013	0.041	0.040	0.030	0.034	0.021
SE3	0.122	0.030	0.106	0.091	0.077	0.032	0.021	0.039	0.041	0.040	0.030	0.034	0.021
NE1	0.122	0.212	0.176	0.152	0.077	0.159	0.064	0.196	0.205	0.201	0.150	0.101	0.191
NE2	0.122	0.152	0.176	0.091	0.077	0.053	0.064	0.117	0.123	0.121	0.150	0.101	0.064

W ₄₃	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
NE3	0.073	0.091	0.035	0.030	0.026	0.053	0.064	0.117	0.123	0.121	0.050	0.101	0.064

Table 12 continued

Table 13 Inner dependence matrix of indicators with respect to the dimension 4 (SE)

W ₄₄	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
ST1	1	1	1	1	1/3	1/3	1/5	1/5	1/5	1/5	1/5	1/5	1/3
ST2	1	1	1	3	1/3	1/3	1/3	1/5	1/5	1/3	1/7	1/5	1/3
BE1	1	1	1	3	1	1	1/3	1/3	1/3	1/3	1/5	1/5	1
BE2	1	1/3	1/3	1	1/3	1	1/3	1/3	1/3	1/3	1/5	1/3	1
<i>OI1</i>	3	3	1	3	1	1/5	3	1	1/3	1	1	1	3
<i>OI2</i>	3	3	1	1	5	1	5	3	1	3	1	3	3
<i>OI3</i>	5	3	3	3	1/3	1/5	1	1	1	3	1	1	1
SE1	5	5	3	3	1	1/3	1	1	1	1	1/5	1/3	1/3
SE2	5	5	3	3	3	1	1	1	1	1	1/3	1/3	1/3
SE3	5	3	3	3	1	1/3	1/3	1	1	1	1/3	1/3	1/3
NE1	5	7	5	5	1	1	1	5	3	3	1	1	3
NE2	5	5	5	3	1	1/3	1	3	3	3	1	1	1
NE3	3	3	1	1	1/3	1/3	1	3	3	3	1/3	1	1
ST1	0.023	0.030	0.035	0.030	0.021	0.045	0.013	0.010	0.013	0.010	0.029	0.020	0.021
ST2	0.023	0.030	0.035	0.091	0.021	0.045	0.021	0.010	0.013	0.017	0.021	0.020	0.021
BE1	0.023	0.030	0.035	0.091	0.064	0.135	0.021	0.017	0.022	0.017	0.029	0.020	0.064
BE2	0.023	0.010	0.012	0.030	0.021	0.135	0.021	0.017	0.022	0.017	0.029	0.034	0.064
<i>OI1</i>	0.070	0.091	0.035	0.091	0.064	0.027	0.193	0.050	0.022	0.050	0.144	0.101	0.191
<i>OI2</i>	0.070	0.091	0.035	0.030	0.319	0.135	0.322	0.150	0.065	0.149	0.144	0.302	0.191
OI3	0.116	0.091	0.106	0.091	0.021	0.027	0.064	0.050	0.065	0.149	0.144	0.101	0.064
SE1	0.116	0.152	0.106	0.091	0.064	0.045	0.064	0.050	0.065	0.050	0.029	0.034	0.021
SE2	0.116	0.152	0.106	0.091	0.191	0.135	0.064	0.050	0.065	0.050	0.048	0.034	0.021
SE3	0.116	0.091	0.106	0.091	0.064	0.045	0.021	0.050	0.065	0.050	0.048	0.034	0.021
NE1	0.116	0.212	0.176	0.152	0.064	0.135	0.064	0.249	0.195	0.149	0.144	0.101	0.191
NE2	0.116	0.152	0.176	0.091	0.064	0.045	0.064	0.150	0.195	0.149	0.144	0.101	0.064
NE3	0.070	0.091	0.035	0.030	0.021	0.045	0.064	0.150	0.195	0.149	0.048	0.101	0.064

Table 14 Inner dependence matr	x of indicators with respe-	ct to the dimension 5 (NE)
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W_{45}	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
ST1	1	1	1	1	1/3	1/3	1/5	1/5	1/3	1/5	1/7	1/5	1/5
ST2	1	1	1	3	1/3	1/3	1/3	1/3	1/3	1	1/7	1/5	1/3
BE1	1	1	1	3	1	1	1/3	1/3	1/3	1/3	1/5	1/5	1/3
BE2	1	1/3	1/3	1	1/3	1	1/3	1/3	1/3	1/3	1/5	1/3	1
011	3	3	1	3	1	1/5	3	3	1	1	1/3	1	1
012	3	3	1	1	5	1	5	7	5	5	1/3	3	1
0I3	5	3	3	3	1/3	1/5	1	1	1	3	1	1	1
SE1	5	3	3	3	1/3	1/7	1	1	3	1	1/3	1/3	1/3
SE2	3	3	3	3	1	1/5	1	1/3	1	1	1/5	1/3	1/3
SE3	5	1	3	3	1	1/5	1/3	1	1	1	1/5	1/3	1/3

Table 14 continued

W_{45}	ST1	ST2	BE1	BE2	011	012	013	SE1	SE2	SE3	NE1	NE2	NE3
NE1	7	7	5	5	3	3	1	3	5	5	1	1	1
NE2	5	5	5	3	1	1/3	1	3	3	3	1	1	1
NE3	5	3	3	1	1	1	1	3	3	3	1	1	1
ST1	0.022	0.030	0.033	0.030	0.021	0.037	0.013	0.008	0.014	0.008	0.023	0.020	0.023
ST2	0.022	0.030	0.033	0.091	0.021	0.037	0.021	0.014	0.014	0.040	0.023	0.020	0.038
BE1	0.022	0.030	0.033	0.091	0.064	0.112	0.021	0.014	0.014	0.013	0.033	0.020	0.038
BE2	0.022	0.010	0.011	0.030	0.021	0.112	0.021	0.014	0.014	0.013	0.033	0.034	0.113
<i>OI1</i>	0.067	0.091	0.033	0.091	0.064	0.022	0.193	0.127	0.041	0.040	0.055	0.101	0.113
<i>OI2</i>	0.067	0.091	0.033	0.030	0.319	0.112	0.322	0.297	0.205	0.201	0.055	0.302	0.113
OI3	0.111	0.091	0.099	0.091	0.021	0.022	0.064	0.042	0.041	0.121	0.164	0.101	0.113
SE1	0.111	0.091	0.099	0.091	0.021	0.016	0.064	0.042	0.123	0.040	0.055	0.034	0.038
SE2	0.067	0.091	0.099	0.091	0.064	0.022	0.064	0.014	0.041	0.040	0.033	0.034	0.038
SE3	0.111	0.030	0.099	0.091	0.064	0.022	0.021	0.042	0.041	0.040	0.033	0.034	0.038
NE1	0.156	0.212	0.165	0.152	0.191	0.335	0.064	0.127	0.205	0.201	0.164	0.101	0.113
NE2	0.111	0.152	0.165	0.091	0.064	0.037	0.064	0.127	0.123	0.121	0.164	0.101	0.113
NE3	0.111	0.091	0.099	0.030	0.064	0.112	0.064	0.127	0.123	0.121	0.164	0.101	0.113

References

- Adger, W. N. (2000). Social and ecological resilience: Are they related? Progress in Human Geography, 24(3), 347–364.
- Anadalingam, G., & Olsson, C. E. (1989). A multi-stage multi-attribute decision model for project selection. *European Journal of Operational Research*, 43, 271–283.
- Anderson, M. B. (1995). Vulnerability to disaster and sustainable development: A general framework for assessing vulnerability. In C. Munasinghe (Ed.), *Disaster prevention for sustainable development* (pp. 17–27). Washington, DC: World Bank.
- Andrews, S. S., & Carroll, C. R. (2001). Designing a soil quality assessment tool for sustainable agroecosystem management. *Ecological Applications*, 11, 1573–1585.
- Bell, S., & Morse, S. (2004). Experiences with sustainability indicators and stakeholder participation: A case study relating to a 'Blue Plan' project in Malta. *Sustainable Development*, 12, 1–14.
- Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., et al. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752.
- Buckle, P., Graham, M., & Smale, S. (2001). Assessing resilience and vulnerability: Principles, strategies and actions, emergency management Australia. Australia: Department of Defense Project.
- Budescu, D., Zwick, R., & Rapoport, A. (1986). A comparison of the eigenvalue method and the geometric mean procedure for ratio scaling. *Applied Psychological Measurement*, 10(1), 69–78.
- Buss, M. D. J. (1983). How to rank computer projects. Harvard Business Review, 61(1), 118–125.
- Buttoud, G. (2000). How can policy take into consideration the "full value" of forests? Land Use Policy, 17, 169–175.
- Carpenter, S., Walker, B., & Anderies, J. M. (2001). From metaphor to measurement: Resilience of what to what? *Ecosystems*, 4(8), 765–781.
- Chan, S. L., & Huang, S. L. (2004). A system approach for the development of a sustainable community-the application of the sensitivity model (SM). *Journal of Environmental Management*, 72, 133–147.
- Chang, P. T., Huang, L. C., & Lin, H. J. (2000). The fuzzy Delphi method via fuzzy statistics and membership function fitting and an application to the human resources. *Fuzzy Sets and Systems*, 112, 511–520.
- Chang, I. S., Tsujimura, Y., Gen, M., & Tozawa, T. (1995). An efficient approach for large scale project planning based on fuzzy Delphi method. *Fuzzy Sets and Systems*, 76, 277–288.

- Chang, P. C., & Wang, Y. W. (2006). Fuzzy Delphi and back-propagation model for sales forecasting in PCB industry. *Expert Systems with Applications*, 30, 715–726.
- Chen, Z., Li, H., & Wong, C. T. C. (2005). Environmental planning: Analytic network process model for environmentally conscious construction planning. *Journal of Construction Engineering and Man*agement, 131(1), 92–101.
- Chen, C. S., & Liu, Y. C. (2007). A methodology for evaluation and classification of rock mass quality on tunnel engineering. *Tunnelling and Underground Space Technology*, 22, 377–387.
- Cheng, J. H. (2001). Indexes of competitive power and core competence in selecting Asia-Pacific ports. Journal of Chinese Institute of Transportation, 13(1), 1–25. (in Chinese).
- Cheng, E. W. L., & Li, H. (2007). Application of ANP in process models: An example of strategic partnering. *Building and Environment*, 42, 278–287.
- Cheng, C. H., & Lin, Y. (2002). Evaluating the best main battle tank using fuzzy decision theory with linguistic criteria evaluation. *European Journal of Operational Research*, 142, 174–186.
- Chu, H. C., & Hwang, G. J. (2008). A Delphi-based approach to developing expert systems with the cooperation of multiple experts. *Expert Systems with Applications*, 34, 2826–2840.
- Chung, S. H., Lee, A. H. I., & Pearn, W. L. (2005). Analytic network process (ANP) approach for product mix planning in semiconductor fabricator. *International Journal of Production Economics*, 96, 15–36.
- Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., et al. (2008). Community and regional resilience: perspectives from hazards, disasters, and emergency management. CARRI research report 1. Oak Ridge National Lab: Community and Regional Resilience Initiative.
- Czajkowski, A., & Jones, S. (1986). Selecting interrelated R&D projects in space technology planning. IEEE Transactions on Engineering Management, 33(1), 17–24.
- Dalkey, N., & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. Management Science, 9(3), 458.
- Dantzig, G. B. (1958) On integer and partial linear programming problems. The RAND Corporation, Paper P-1410.
- Dong, Y. C., Xu, Y. F., Li, H. Y., & Dai, M. (2008). A comparative study of the numerical scales and the prioritization methods in AHP. *European Journal of Operational Research*, 186, 229–242.
- Dzeng, R. J., & Wen, K. S. (2005). Evaluating project teaming strategies for construction of Taipei 101 using resource-based theory. *International Journal of Project Management*, 23, 483–491.
- Fiksel, J. (2003). Designing resilient, sustainable systems. Environmental Science and Technology, 37(23), 5330–5339.
- Graham, B., Regehr, G., & Wright, J. G. (2003). Delphi as a method to establish consensus for diagnostic criteria. *Journal of Clinical Epidemiology*, 56, 1150–1156.
- Handmer, J. W., & Dovers, S. R. (1996). A typology of resilience: Rethinking institutions for sustainable development. *Industrial and Environmental Crisis Quarterly*, 9(4), 482–511.
- Helmer, O. H. (1966). The Delphi method for systematizing judgments about the future. California: Institute of Government and Public Affairs, University of California.
- Herman, M. W., & Koczkodaj, W. W. (1996). A Monte Carlo study of pairwise comparison. *Information Processing Letters*, 57, 25–29.
- Holling, C. S., Schindler, D. W., Walker, B. H., & Roughgarden, J. (1995). Biodiversity in the functioning of ecosystems: An ecological primer and synthesis. In C. A. Perrings, K. G. Maler, C. Folke, C. S. Holling, & B. O. Jansson (Eds.), *Biodiversity loss: Ecological and economic issues* (pp. 44–83). Cambridge: Cambridge University Press.
- Horwitch, M., & Thietart, R. A. (1987). The effect of business interdependencies on product R&D-intensive business performance. *Management Science*, 33(2), 178–197.
- Hsiao, T. Y. (2006). Establish standards of standard costing with the application of convergent gray zone test. European Journal of Operational Research, 168, 593–611.
- Hsu, T. H., & Yang, T. H. (2000). Application of fuzzy analytic hierarchy process in the selection of advertising media. *Journal of Management and Systems*, 7(1), 19–39.
- Huang, J. J., Tzeng, G. H., & Ong, C. S. (2005). Multidimensional data in multidimensional scaling using the analytic network process. *Pattern Recognition Letters*, 26, 755–767.
- Ishikawa, A., Amagasa, T., Tamizawa, G., Totsuta, R., & Mieno, H. (1993). The max-min Delphi method and Fuzzy Delphi method via fuzzy integration. *Fuzzy Sets and Systems*, 55, 241–253.
- Jing, L. (2008). Regional flood resilience assessment in Dong-ting lake region of China. A presentation prepared for the CASiFiCA workshop, Beijing, Academy of Disaster Reduction and Emergency Management. Beijing: Beijing Normal University.
- Keeney, S., Hasson, F., & McKenna, H. P. (2001). A critical review of the Delphi technique as a research methodology for nursing. *International Journal of Nursing Studies*, 38, 195–200.

- Keeney, R. L., & Raiffa, H. (1976). Decisions with multiple objectives: Preferences and value trade-offs. New York: Wiley.
- Kim, G., Park, C. S., & Yoon, K. P. (1997). Identifying investment opportunities for advanced manufacturing systems with comparative-integrated performance measurement. *International Journal of Production Economics*, 50, 23–33.
- King, D. (2001). Uses and limitations of socioeconomic indicators of community vulnerability to natural hazards: Data and disasters in northern Australia. *Natural Hazards*, 24, 147–156.
- King, J. L., & Scherem, E. L. (1978). Cost-benefit analysis in information system development and operation. Comput Survey, 10(1), 20–34.
- Klein, R. J. T., Smit, M. J., & Goosen, H. (1998). Resilience and vulnerability: Coastal dynamics or Dutch dikes? *The Geographical Journal*, 164(3), 259–268.
- Kuo, Y. F. & Chen, P. C. (in press). Constructing performance appraisal indicators for mobility of the service industries using Fuzzy Delphi Method. *Expert Systems with Applications*.
- Lee, S. M. (1972). Linear programming for decision analysis. Philadelphia, PA: Auerbach Publishers.
- Lee, J. W., & Kim, S. H. (2000). Using analytic network process and goal programming for interdependent information system project selection. *Computers and Operations Research*, 27, 367–382.
- Lee, J. W., & Kim, S. H. (2001). An integrated approach for interdependent information system project selection. *International Journal of Project Management*, 19(2), 111–118.
- Lee, T. R., & Li, J. M. (2006). Key factors in forming an e-marketplace: An empirical analysis. *Electronic Commerce Research and Applications*, 5, 105–116.
- Maclaren, V. W. (1996). Urban sustainability reporting. Journal of the American Planning Association, 62(2), 184–202.
- Martin, D. (1998). Automatic neighbourhood identification from population surfaces. Computer, Environment and Urban Systems, 22(2), 107–120.
- Mayunga, J. S. (2007). Understanding and applying the concept of community disaster resilience: A capitalbased approach. A draft working paper prepared for the summer academy for social vulnerability and resilience building, 22–28, Munich, Germany.
- McManus, S., Seville, E., Brunsdon, D., & Vargo, J. (2007). Resilience management: A framework for assessing and improving the resilience of organizations. New Zealand: Resilient Organizations.
- Meade, L. M., & Presley, A. (2002). R&D project selection using the analytic network process. *IEEE Transactions on Engineering Management*, 49(1), 59–66.
- Meade, L., & Sarkis, J. (1998). Strategic analysis of logistics and supply chain management systems using the analytic network process. *Transportation Research Part E: Logistics and Transportation Review*, 34(3), 201–215.
- Momoh, J. A., & Zhu, J. Z. (1998). Application of AHP/ANP to unit commitment in the deregulated power industry. *IEEE International Conference on Systems, Man, and Cybernetics*, 1, 817–822.
- Murray, T. J., Pipino, L. L., & Gigch, J. P. (1985). A pilot study of fuzzy set modification of Delphi. Human Systems Management, 5, 76–80.
- Niemiraa, M. P., & Saaty, T. L. (2004). An analytic network process model for financial-crisis forecasting. International Journal of Forecasting, 20, 573–587.
- Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal* of Community Psychology, 41(1–2), 127–150.
- Reza, K., Hossein, A., & Yvon, G. (1988). An integrated approach to project evaluation and selection. *IEEE Transactions on Engineering Management*, 35(4), 265–270.
- Ringuest, J. L., & Graves, S. B. (1989). The linear multi-objective R&D project selection problem. *IEEE Transactions on Engineering Management*, 36(1), 54–57.
- Roper-Low, G. C., & Sharp, J. A. (1990). The analytic hierarchy process and its application to an information technology decision. *Journal of Optical Research Society*, 41(1), 49–59.
- Rose, A. (2004). Defining and measuring economic resilience to earthquakes. A paper prepared for the Multidisciplinary Center for Earthquake Engineering Research. Buffalo: MCEER Publications.
- Saaty, T. L. (1980). The analytic hierarchy process. New York: McGraw-Hill.
- Saaty, T. L. (1996). The analytic network process. New York: RWS Publications.
- Saaty, T. L. (2005). Theory and applications of the analytic network process: Decision making with benefits, opportunities, cost, and risk. Pittsburgh: RWS Publications.
- Saaty, T. L., & Takizawa, M. (1986). Dependence and independence: From linear hierarchies to nonlinear networks. *European Journal of Operational Research*, 26, 229–237.
- Saaty, T. L., & Vargas, L. G. (1998). Diagnosis with dependent symptoms: Bayes theorem and the analytic hierarchy process. *Operations Research*, 46(4), 491–502.

- Sanathanam, R., & Kyparisis, G. J. (1996). A decision model for interdependent information system project selection. *European Journal of Operational Research*, 89, 380–399.
- Sarkis, J. (2002). Quantitative models for performance measurement systems-alternate considerations. International Journal of Production Economics, 86, 81–90.
- Sarkis, J. (2003). A strategic decision framework for green supply chain management. Journal of Cleaner Production, 11(4), 397–409.
- Schniederjans, M. J., & Kim, G. Y. (1987). A goal programming model to optimize departmental preferences in course assignment. *Computers and Operational Research*, 14(2), 87–96.
- Spangenberg, J. H. (2002). Institutional sustainability indicators: An analysis of agenda 21 and a draft set of indicators for monitoring their effectiveness. *Sustainable Development*, 10(2), 103–115.
- Spencer, C., Robertson, A. I., & Curtis, A. (1998). Development and testing of a rapid appraisal wetland condition index in south-eastern Australia. *Journal of Environmental Management*, 54, 143–159.
- Weber, R., Werners, B., & Zimmerman, H. J. (1990). Planning models for research and development. European Journal of Operational Research, 48, 175–188.
- Weingarther, H. M. (1966). Capital budgeting of interrelated projects: Survey and synthesis. Management Science, 12(7), 485–516.
- Wey, W. M., & Wu, K. Y. (2007). Using ANP priorities with goal programming in resource allocation in transportation. *Mathematical and Computer Modeling*, 46, 985–1000.
- Wu, W. W., & Lee, Y. T. (2007). Selecting knowledge management strategies by using the analytic network process. *Expert Systems with Applications*, 32, 841–847.
- Yu, R., & Tzeng, G. H. (2006). A soft computing method for multi-criteria decision making with dependence and feedback. *Applied Mathematics and Computation*, 180, 63–75.
- Zheng, C. B. (2001). Fuzzy assessment model for maturity of software organization in improving its staff's capability. Master Thesis. Taipei: Taiwan University of Science and Technology (In Chinese).