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An intelligent slope disaster prediction and monitoring system based on WSN and ANP

Che-I Wu [a,*], Hsu-Yang Kung [b], Chi-Hua Chen [c,d], Li-Chia Kuo [b]

[a] Computer Center, National Pingtung University of Science and Technology, Pingtung 912, Taiwan, ROC
[b] Department of Management Information Systems, National Pingtung University of Science and Technology, Pingtung 912, Taiwan, ROC
[c] Institute of Information Management, National Chiao Tung University, Hsinchu 300, Taiwan, ROC
[d] Telecommunication Laboratories, Chunghwa Telecom Co., Ltd, Taoyuan 326, Taiwan, ROC

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ABSTRACT

Taiwan generally has large-scale landslides and torrential rainfall during the typhoon season. As Wireless Sensor Networks (WSN) and mobile communication technologies advance rapidly, state-of-the-art technologies are adopted to build a model to reliably predict and monitor disasters, as well as accumulate environmental variation-related information. By integrating WSN and Analytic Network Process (ANP), this study evaluates the weight of disaster factors that adopt the consistency index of pair comparisons on hillslopes. The weight estimation and classification of disaster factors are based on the K-means model to build the hillslope prediction model. *The Portrait-based Disaster Alerting System* (*PDAS*) is designed and implemented using the proposed disaster prediction model. The PDAS adopts Web-GIS to visualize the environmental information. Evaluation results of the system indicate that the proposed prediction model achieves more accurate disaster determination than the conventional method.

1. Introduction

Increasing numbers of natural calamities have occurred in Taiwan in recent years. These disasters often cause serious natural destruction after torrential rainfall or earthquakes, causing heavy losses to people's lives and property. The KALMAEGI typhoon damaged many parts of Taiwan in July 2008, due to the heavy torrential rainfall. Moreover, the survivors did not know how to report the disaster promptly to the authorities, so rescue teams could not locate the survivors. Therefore, wireless hand-held devices are required to transmit the multimedia information of disasters, such as images, sounds and characters.

Taiwan generally has large-scale slope failure and torrential rainfall to cause sediment disaster during the typhoon season. Those disasters often result in the serious nature destruction and create the heavy losses of people's lives and properties. The kind of hillslopes disaster is numerous, and this mainly discussing topic of thesis choose often appear slope failure for sediment disaster to study in Taiwan. It expects to make discussion with the topic this thesis that can help people and prevention and rescuing units to prevent and alarm creating disaster. It was usually the gold period to prevent and rescue disaster with taking place before and creating at that time. It had taken place relevant disasters that all the materials were afterwards to collect and study, and judge causing disaster factors in the past, the time has already had no enough to save a critical situation. Therefore, this research study and analyze the past slope failure as basis of consulting, and combining new information technology to propose two major system themes, which are prediction supporting model and awareness monitoring system, to assist and solve problems of disaster. At first the mainly causing disaster factors of slope failure must be discussed and selected, so survey and examine the trial zone environment in thesis research. Numerous environment causing disaster factors will be chosen, assessed, analyzed, then select seven causing factors which include gradient, soil characteristics, 24-h accumulated rainfall, vegetation index, soil displacement, soil hydrous and temperature, to cause slope failure. Then according to values of selecting disaster factors into designed prediction supporting model, the model system will assess and analyze the taking place disaster grade and possibility. In order to reach and develop early alarming effect, the prediction supporting model can make sure disaster preventing and alarming functions really, and the study also plans complemented monitoring and transmitting tools. The system will utilize these monitoring and transmitting functions to complete effect of pre-warning and informing immediately.

This study also mainly proposes and designs a real-time disaster information system, which is important for people to develop PDAS to assist the prevention disaster works, to obtain, inform, and display the disaster situation. In order to achieve forecasting

* Corresponding author. Tel.: +886 87703202.
E-mail address: joey@mail.npust.edu.tw (C.-I. Wu).

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and monitoring disaster functions, PDAS is also implemented using the proposed disaster prediction supporting model, which prediction efficiency model includes Analytic Network Process (ANP), Back-Propagation Neural Network Analysis (BPN), and Multivariate Statistical Analysis (MSA), to compare the adaptable model.

As Wireless Sensor Networks (WSN) and mobile communication technologies advance rapidly, state-of-the-art technologies are adopted to build a model to reliably predict and monitor disasters, as well as accumulate environmental variation-related information. The PDAS also combines multimedia transmission technology and quality of service (QoS) mechanism to reveal the real disaster situations, for example, the accurate position and the real-time image/video of accident events. Heterogeneous Network Users use the handheld devices to transmit and receive multimedia information about slope failure via the wireless/mobile and internet communications.

Accordingly, this study adopts Embedded Multimedia Communication technology to design the Portrait-based Disaster Alerting System (PDAS) in order to solve the space and time limitations. Users can use the hand-held devices with high mobility via wireless network (3G/GPRS/GSM) to obtain disaster multimedia stream service (Castillo-Effer, Quintela, Moreno, Jordan, & Westhoff, 2004). Additionally, this investigation also combines customized services, Location-Aware Service, Wireless Sensor Network, Multicast, Web GIS, Intelligent Agents and Analytic Network Process (ANP) (Neaupane & Piantanakulchai, 2006). The PDAS transmits the sensing and prediction information of the monitored area to the database system to analyze the data. Additionally, geographical information system (GIS) technology combines the analysis system and alarming mechanisms to operate the model. The detected materials then accede to ANP model to appraise, analyze and process sensing hillslopes disaster factor data. Finally, a warning message based on the analytical results is released to mark where the victim stays immediately on the Web-GIS layer. This information would inform the prevention and relief personnel about the disaster area clearly and quickly.

2. Research background and theory discussion

The Portrait-based Disaster Alerting System, (PDAS) is designed to provide (i) mobile user (MU), (ii) Hillslope Monitoring Sensor (HMS), (iii) Integrated Service Server (ISS), and (iv) Intelligent Hillslope Decision System (IHDS). The PDAS offers sensing and predicting information of the disaster area. Required research background and relevant technology for this study are (1) Geographic Information System (GIS) and (2) Wireless Sensor Networks (WSN).

2.1. Geographic Information System (GIS)

GIS develops geographical coordinate information that assesses space distribution and database management technology, as well as combines systems such as geographical mathematics and map surveying. GIS has two parts, namely subject and operation. Geographical information systems are adopted to store several different geographical information, there are two types including raster and vector. Digital geographical materials stored in geographical information databases are classified as Spatial Data, Geography Data, and Attribute Data (ESRI, 1996, 2000). Fig. 1 shows the operation of a GIS.

2.2. Wireless Sensor Networks (WSN)

Recently developed sensors can not only detect the goal and change of the environment, but also handle the collected data. However, some problems need to be considered. If a base station is far from sensors, then the sensors need to adopt the routing network method so that a lot of sensors group a path to transfer materials to the base station (Evans-Pughe, 2003). Additionally, the battery of sensors may not be replaceable, energy that is considered indispensable needs to be controlled when configuring sensor design and network management (Akyildiz, Weilian, Sankarasubramaniam, & Cayirci, 2002). The hardware structure of the sensor comprises four major parts, (i) sensing unit, (ii) processing unit, (iii) transceiver unit, and (iv) power unit. Sensors can be adopted in location systems, mobilizers and power generators. The system adopts an MTS420 sensor to accumulate temperature, and an MDA300 sensor to measure the soil water content (ECHO 10) and temperature (108-L) (Ruiz & Loureiro, 2003). A TMOTE SKY displacement sensor is adopted to obtain slope materials instantly, to combine and analyze ANP model to obtain the disaster weight, and to judge the probability of disaster at any time, as shown in Fig. 2.

3. System design

The PDAS is a four-tier system as shown in Fig. 3. Users can utilize various terminal devices that include PC, notebook, Tablet PC, 3G/4G mobile phone and *personal digital assistant* (PDA) to access PDAS. The Portrait-based Disaster Alerting System, (PDAS) is designed to provide (i) *mobile user (MU)*, (ii) *Hillslope Monitoring Sensor (HMS)*, (iii) *Integrated Service Server (ISS), and* (iv) *Intelligent Hillslope Decision System (IHDS).*

3.1. Mobile user site

Mobile user' sites provide functions such as location-based service, customized service, heterogeneous networks, web-based GIS. mobile users can adopt the terminal servers of hand-held devices to link mobile communication network or internet network, to login and use PDAS systems, and to perform GPS to locate

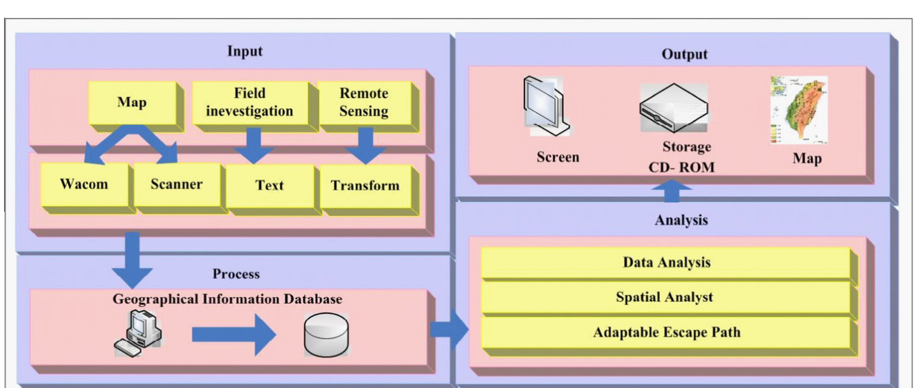
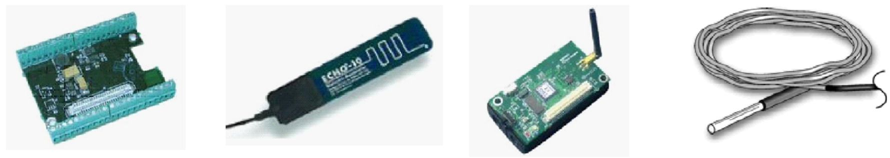


Fig. 1. The architecture of Geographic Information System.



(a) MDA300 (b) ECHO-10 (c) MRP4200 (d) 108-L

Fig. 2. Sensor devices.

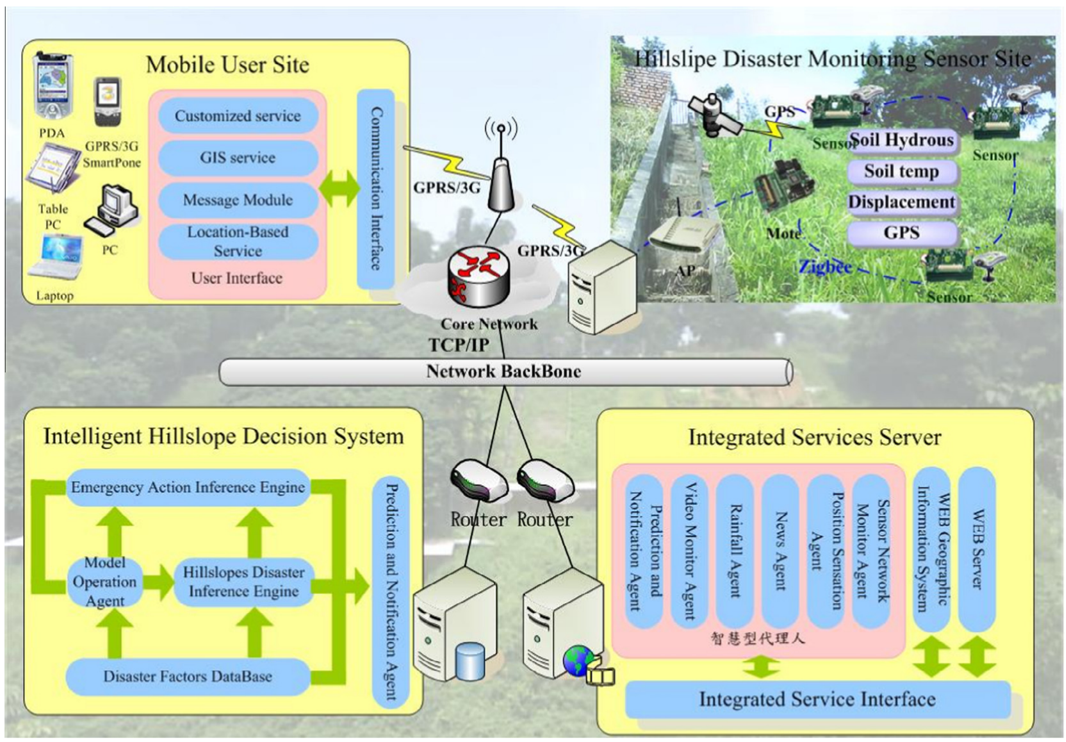


Fig. 3. Architecture of PDAS system.

Location-Aware Services automatically. PDAS has a user position system to provide customized services at time, including different devices to offer different pictures, and information about the debris-flow and rainfall in the disaster area. Since users adopt different network protocols, the system lets mobile equipment integrate different environments (Fujiwara, Makie, & Watanabe, 2004), such as GSM, GPRS, internet and IEEE802.11x. Web GIS is similar to web mapping, with an emphasis on analysis, processing of project specific geo-data and exploratory aspects.

3.2. Hillslopes monitoring sensor site

The research has a sensing area located on the hillslopes ablation test zone at National Pingtung University of Science and Technology. The area has 4 level slopes, and it can be divided into vegetation indexes 10%, 60%, and 80%. We choose vegetation index 10% to observe area A and vegetation index 60% for area B, shown as Fig. 4.

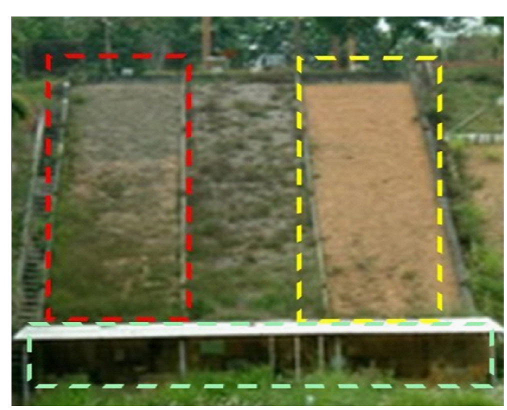


Fig. 4. Sensing area.

Fig. 5 shows the deployment diagram of the sensing area. Communication platforms were assigned by Tmote Sky (MoteIV corporation) and NPR2400 (Crossbow Technology Micaz). Tmote Sky with KXM52-1050 (Kionix) Displacement was obtained by Tri-Axis Accelerometers; soil temperature was measured by 108-L Temperature Probe (Campbell Scientific, Inc); soil hydrous values were collected by ECH2O (Decagon Devices, Inc) with MDA300CA Sensor Board, and position was judged by GPS with MTS420 (Crossbow Technology), as shown in Fig. 6. The common limitation of most monitoring systems is that sensors that are destroyed by the large-scale disaster cannot send data back to the database server. Therefore, the proposed system sends data back to the base station every second. Moreover, to ensure that the WSN continues

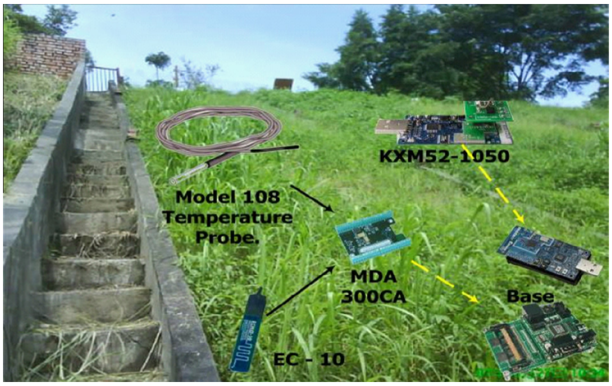


Fig. 5. WSN deploying diagram.

working successfully, the WSN power system is designed to conjoin power and battery (Lindsey & Raghavendra, 2002).

3.3. Integrated service server

The Integrated service server comprises two parts: (i) the web server providing web-based information service based over heterogeneous network environments, such as GPRS, GSM, IEEE 802.11b and internet, and (ii) the Intelligent Agents providing mobile clients with customized information. Multimedia server provides functions such as Intelligent Agents, Real-time Disasters Alters, Virtual Reality of Multimedia, Real-time Disaster Monitoring, Disasters Multimedia Management, Multicast Chat Room, Web Service and Web GIS.

3.3.1. Intelligent Agents

The intelligent agent performs functions such as collecting, searching, classifying and processing data, enabling users can obtain real-time information (Wooldridge, 1995). The intelligent agent system has the following six parts:

(i) Sensor network monitor agent (SNMA), which accumulates the sensor information for experts to analyze and research;
(ii) Position sensation agent (PSA), which selects user coordinates to store on the database server;
(iii) Prediction and notification agent (PNA), which predicts disasters, and relays them to users;
(iv) News agent (NA), which catches and filters news about debris flow news to mobile clients;
(v) Rainfall information agent (RIA), which monitors information about the precipitation station to users at any time, and
(vi) Video monitor agent (VMA), which monitors the IP-CAM in sensing zones, and sends this information to users at any time.

3.3.2. Real-time Disaster Monitor

PDAS integrates IP Cameras of road monitoring system of disaster areas in Pingtung County to expand the controlling range of the disaster. The system adopts an encoder to compress huge multimedia materials into appropriate sizes, and provides a steady stream service and effective real-time control service (Chang & Guo, 2006).

3.3.3. Disaster Multimedia Management

Mobile users can take pictures and videos of a disaster situation by 3G handheld devices. The users then store these files, and transmit then to the server through the mobile and wireless communication network. Moreover, PDAS establishes the image management agent to safeguard the information management of historical images in the Internet.

3.4. Intelligent hillslopes decision system

The IHDS monitors hillslopes conditions; predicts hillslopes degree of hazard; accurately identifies the present condition, and provides suitable emergency measures. IHDS comprises two parts, the (1) Hillslopes Disaster Inference Engine; and the (2) Emergency Action Inference Engine.

3.4.1. Hillslopes Disaster Inference Engine

This engine defines seven disaster factors, namely including gradient, soil characteristics, 24-h accumulated rainfall, vegetation index, soil displacement, soil hydrous and soil temperature, to evaluate and analyze the probability of hillslopes disaster. Table 1 shows the classification of disaster factors.

The hillslope prediction model was built according to the ANP model. The research samples are the monitoring results in Nantou County from 2006 to 2008. To increase the model accuracy, all 20 samples were chosen from three degrees for testing to avoid bias towards a particular degree.

The ANP model compares in pairs with relative weight estimation and formation of supermatrix, and adopts supermatrix weight of which is two factors in seven disaster factors to choose the best way (Chen, Lin, Chang, Ho, & Lo, 2013; Saaty, 1980, 1996). Therefore, this rule that is the ANP comparing two relative weights is followed to build the most adaptive model, as shown in Fig. 7.

The model process is divided into four steps as follows:

- Step I: Pair comparison with relative weight estimation

Table 2 shows a sample of a questionnaire with cluster comparison, which is scored using a sample calculation with relative weight and consistency index. The geography expert fills in the table to define the weight of each disaster factor. The pair comparison formula is shown below:

Fig. 6. Soil hydrous sensor, Tri-Axis Accelerometers, and GPS receiver.

Table 1
Disaster factors classification.

Factors	Gradient	Soil characteristic	Rainfall (mm)	Vegetation index	Soil displacement (cm)	Soil hydrous (%)	Soil temperature (°C)
Class	Level 7	Gravel	>450	Loose	>100	>80	>50
	Level 6	Sand	350–450	Medium	70–100	60–80	30–50
	Level 5	Silt	250–350	Dense	40–70	20–60	15–30
	Level 4	Clay	<250	Extremely dense	0–40	0–20	<15
	Level 3						

$$\ddot{A} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \vdots & 1 \end{bmatrix} = \begin{bmatrix} w_1/w_2 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \cdots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \vdots & w_n/w_n \end{bmatrix} \quad (1)$$

W_i: weight of the main element i; $i = 1,2,3,\ldots,n$; a_{ij}: ratio between two main elements; $i, j = 1,2,3,\ldots,n$

$$a_{ij} = 1/a_{ji} \quad \text{and} \quad a_{ik} = a_{ij} * a_{jk} \quad (2)$$

$$W = [w_k], \quad \text{where} \quad w_k = \sum_{j=1}^{n} a'_{ij}/n \quad (3)$$

While a pair comparative matrix is a positively reciprocal matrix, a policymaker that compares the values in the pair matrix cannot easily reach an identical situation of main elements. Therefore, the system must adopt examination of consistency to obtain the consistency index (CI); to filter the information, and to guarantee that the calculation results reflects actual conditions.

The a_{ij} value in the positive reciprocal matrix changes with even a very small change in the λ_{max} value. Hence, between two difference intensity of λ_{max} and n consistency level of commenting criterion can be determined. The definition formula is given below:

$$C.I. = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

n : number of assessing element

The systems policymaker judges consistency as C.I. = 0, but shows inconsistency if C.I. > 0.1. Saaty (1980) suggested that the deviation value is acceptable if C.I. ⩽ 0.1.

- Step II: Formation of initial supermatrix

Table 3 shows the weight of each disaster factor and eigenvector, which are calculated from the data in Table 2. The consistency index indicates that the true result of calculation is guaranteed to respond to actual conditions. The weight that can be inserted into the order supermatrix forms the first supermatrix. Fig. 8 shows the first supermatrix obtained in calculating the weight values and filling them in order, as in Step 1.

- Step III: Formation of weight supermatrix

The Step II initial supermatrix is transformed to a matrix in which each of its columns sums to unity.

- Step IV: Limiting supermatrix

The final supermatrix is obtained when a high stable value of disaster factors to multiply matrix repeatedly (2 (n − 1) multiplications each), then we get the terminal supermatrix. Fig. 9 shows the process of deriving the weight of the supermatrix from the element-by-element multiplication of the initial supermatrix and the limiting supermatrix with global priority weights. The weight of the supermatrix is raised to the power weight until its convergence using MATLAB.

Through limiting supermatrix table substitutes our training disaster factor samples, all of the samples are convert to weights in the range 0.1255–0.4836. For instance, consider a sample belonging to Gradient level 6, implying sandy soilsand, rainfall above 450 mm, loose vegetation, soil displacement below 40 cm, soil hydrosity above 80%, and soil temperature above 50. The weight of this sample is 0.0596 + 0.0464 + 0.126 + 0.0652 + 0.0093 + 0.0664 + 0.0138 = 0.3867. Various classifications are

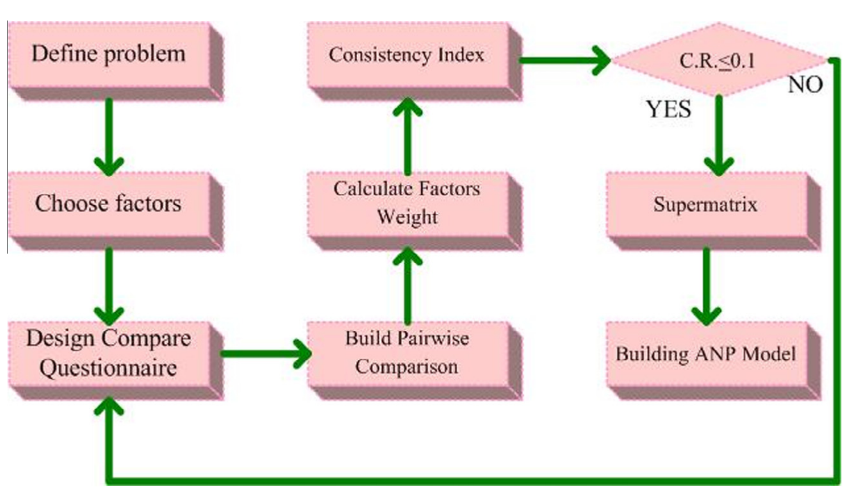


Fig. 7. ANP model flowchart.

Table 2
ANP factor weight questionnaire.

Scale of relative importance (Saaty, 1980)									
Factor-soil slope	Evaluation								
	1	2	3	4	5	6	7	8	9
Soil slope is much more important than soil category	□	□	□	□	□	■	□	□	□
Soil slope is much more important than rain	□	□	□	□	■	□	□	□	□
Soil slope is much more important than natural discovery	□	□	■	□	□	□	□	□	□
Soil displacement is much more important than soil slope	□	□	□	□	□	■	□	□	□
Soil slope is much more important than soil hydrous	□	□	■	□	□	□	□	□	□
Soil slope is much more important than soil temperature	□	□	■	□	□	□	□	□	□

1: Equal importance; 3: moderate importance; 5: strong importance, 7: very strong or demonstrated importance; 9: extreme importance 2, 4, 6, 8: reciprocals of above.

Table 3
Vector of each factor.

Factor	G	SC	RN	NC	SD	SH	ST	Eigenvector
G	1	6	5	3	1/6	3	3	0.213523
SC	1/6	1	1/3	1/3	1/9	1/3	1	0.034842
RN	1/5	3	1	3	1/4	1	2	0.103668
NC	1/3	3	1/3	1	1/6	1/3	2	0.065188
SD	6	9	4	6	1	3	9	0.427613
SH	1/3	3	1	3	1/3	1	2	0.11151
ST	1/3	1	1/2	1/2	1/9	1/2	1	0.043656
λ_{max} = 7.773956					C.R. = 0.097722			

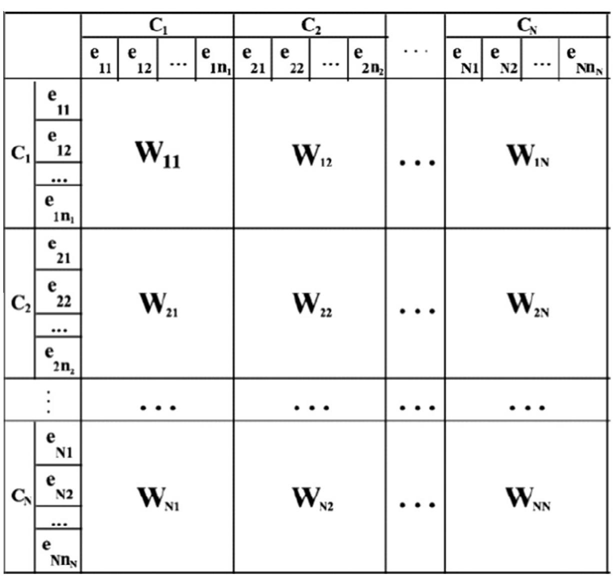


Fig. 8. Formation of initial supermatrix.

available, including natural breaks, quartile, equal intervals and K-means.

3.4.2. Emergency Action Inference Engine (EAIE)

The EAIE receives the requests of emergency action measures from the Hillslopes Disaster Inference Engine, and checks whether current environmental conditions and hillslopes level correspond to the hillslopes emergency action measures in the knowledge base. Table 4 shows the actions of the EAIE (Sharpe, 1938).

4. System evaluation

Most previous researches have adopted Back-Propagation Neural Network (BPN) and Multivariate Statistical Analysis (MSA) to estimate and predict hillslopes disasters. Therefore, this study compares prediction efficiency of the proposed hillslopes prediction model derived from Analytic Network Process with a model built by BPN and MSA.

4.1. Back-Propagation Neural Network

The following inference factors significantly influence the learning efficiency and convergence of the BPN algorithm: (a) the number of learning cycles, (b) the learning rate, (c) the number of network layers and (d) the number of neurons in each hidden layer (Kung, Chen, & Ku, 2012; Lin & Chen, 2013; Lo et al., 2011; Skapura, 1995). In general, too many learning cycles, network layers and neurons of hidden layers lead over-learning and high error rates.

4.2. Multivariate Statistical Analysis

Multivariate Statistical Analysis evaluates variable value and variable characteristics of influence factors (Varnes, 1978). The analysis model first calculates each greater variable value (V) for each higher hillslopes disaster, as shown in formula (5). The weight of each variable is calculated as in formula (6). The respective degree index (DI), which the instability index (Dt), is calculated from the variable weights. The analysis considers the main factors, and then in order to build the MSA, shown as formula (7) and (8).

$$V = \frac{\sigma}{\overline{X}} \times 100\% \quad \begin{array}{l} \sigma : \text{Standard deviation} \\ \overline{X} : \text{Destruction percentage average of each factor} \end{array} \tag{5}$$

$$W_i = \frac{V_i}{V_1 + V_2 + V_3 + \cdots V_n} \quad , i = 1 \ldots n \tag{6}$$

$$d_i = \frac{9(\overline{X}_i - \overline{X}_{\min})}{(\overline{X}_{\max} - \overline{X}_{\min})} + 1 \tag{7}$$

$$Dt = Ss^{0.18} \times Rn^{0.13} \times Nd^{0.15} \times Ge^{0.15} \times Gm^{0.09} \times Sw^{0.15} \times St^{0.15} \tag{8}$$

		Gradient					Soils Characteristic				Rainfall				Vegetable index				Soil Displacement				soil Hydrous				soil Temperature			
		Level 7	Level 6	Level 5	Level 4	Level 3	Gravel	Sand	Silt	Clay	>450mm	350-450	250-350	<250mm	loosely	medium	densely	extremely	>100	70-100	40-70	0-40	>80	60-80	20-60	0-20%	>50	30-50	15-30	<15
Gradient	Level 7	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099
	Level 6	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
	Level 5	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030
	Level 4	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
	Level 3	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
Soils Characteristic	Gravel	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107
	Sand	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
	Silt	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
	Clay	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018
Rainfall	>450mm	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
	350-450	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063
	250-350	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030
	<250mm	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
Vegetable index	loosely	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
	medium	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026
	densely	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012
	extremely dense	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
Soil Displacement	>100	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
	70-100	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
	40-70	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
	0-40	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
soil Hydrous	>80	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066
	60-80	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031
	20-60	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
	0-20%	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
soil Temperature	>50	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
	30-50	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
	15-30	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
	<15	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014

Fig. 9. The limiting supermatrix with global priority weights.

Table 4
Emergency Action Inference.

Slope degree	Emergency Action Inference
Safe area	Conserve natural environment
Dangerous area	Continuing to observe this area, and strengthen the draining water facilities and plants to protect slopes
Very dangerous area	As well as the above actions, coordinate other approaches, such as building the retaining wall, and setting up the ground anchor

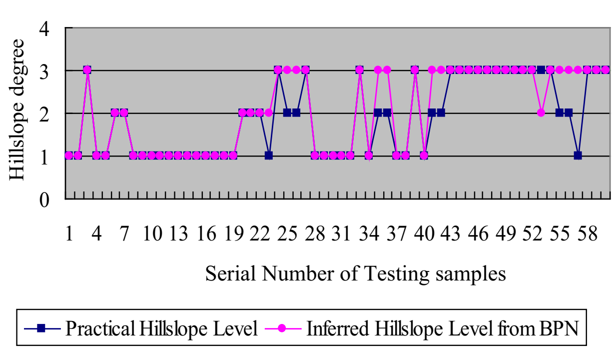


Fig. 10. The corresponding trend diagram of practical hillslopes level and inferred hillslopes level from the BNP model.

4.3. Prediction efficiency

To achieve the same conditions for building each modes, the contrastive model was built by adopting the same 60 data that were adopted to train the hillslope prediction model. The prediction model presents the complete interaction of input variables, and has a high accuracy.

Figs. 10–12 show the corresponding trend diagrams of the actual hillslope levels and those inferred from the BPN, MSA and proposed ANP hillslope prediction models, respectively. As indicated in Figs. 10 and 11, the actual changes in hillslope levels did not overlap with the inferred levels from the traditional model. Analytical results indicate that the traditional model had a low accuracy. In contrast, the actual hillslopes levels overlapped well with those inferred by the proposed drought forecast model, as indicated in Fig. 12.

Tables 5–7 show the confusion matrices of the inferred hillslope levels from the MSA, BPN and ANP models, respectively. The total correct rate for predicting the hillslopes level of the coming day by the traditional BPN and MSA models were 61.67% and 81.67%, respectively, while that of the proposed model was over 88.33% after training. Thus, these results indicate that the ANP model higher hillslope prediction efficiency than the traditional BPN and MSA models.

5. Conclusions and future work

This study designs and develops a "Portrait-based Disaster Alerting System (PDAS) with Wireless Sensors" that can be adopted at any time and any place. The PDAS can be adopted in mobile devices, such as PDAs, laptop computers and 3G smart phones. Users of the system can not only adopt the customized services and interface to inquire and view those disaster data easily, but also obtain rich real-time multimedia by these devices. In summary, the PDAS has at least the following four advantages: (1) PDAS can transfer real-time multimedia and urgent messages to users

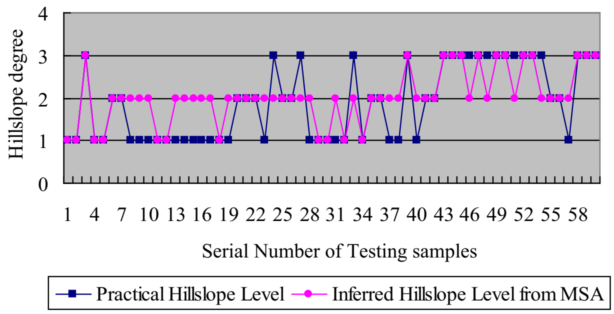


Fig. 11. The corresponding trend diagram of practical hillslopes level and inferred hillslopes level from the MSA model.

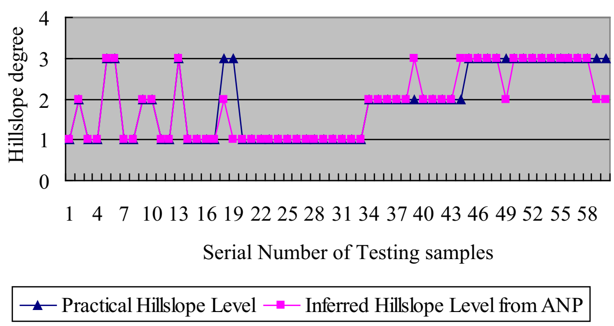


Fig. 12. The corresponding trend diagram of practical hillslopes level and inferred hillslopes level from the ANP model.

through mobile communication. (2) PDAS provides real-time multimedia for users by adopting "Multimedia Streaming for Embedded Applications Technique", "Adaptive Multimedia QoS Technique" and "Image Compression Technique for MPEG-J". (3) PDAS provides the information about disasters, and sends the GPS coordinates of the disaster area to Disaster Prevention and Response Center to reduce the effect of disasters. (4) Historical disaster data is analyzed using the ANP model, enabling users to predict and prevent disasters. (5) An integrated application of new technology is to be used for disaster prevention. (6) A combination of disasters statistical clustering classification collects disaster data are divided into several different grades of disaster.

But future research of the study will add (1) planning escape paths, (2) wireless network provisioning technology solutions, and (3) solving power problem for sensors to achieve a more complete prediction system.

This study also mainly proposes and designs a real-time disaster information system, which is important for people to develop PDAS to assist the prevention disaster works, to obtain, inform, and display the disaster situation. In order to achieve forecasting and monitoring disaster functions, PDAS is also implemented using the proposed disaster prediction supporting model, which prediction efficiency model includes Analytic Network Process (ANP), Back-Propagation Neural Network Analysis (BPN), and Multivariate Statistical Analysis (MSA), to compare the adaptable model. The PDAS integrates technology and management parts to analyze the factors of slope failure, scheme forecasting model, and establish monitoring and informing multimedia system.

Hopefully, the PDAS will become an integrated disaster information system for prevention and relief of mudslide disasters. By adopting the Multimedia Recognition technique", PDAS can intelligently monitoring disasters automatically, reducing the casualty rate in combination with the Medical Information System. Sensors can thus accumulate accurate disaster data for the ANP model. The PDAS has also integration services of prediction supporting model, awareness monitoring system, and establishing real-time disaster informing system, this thesis can reach the comprehension effects of prevention and rescuing information function.

Table 5
The confusion matrix of inferred hillslope level from the MSA model.

Desire	Target				
	Safe area	Dangerous area	Very dangerous area	Total	Total error rate
Safe area	11	16	0	27	0.38333
Dangerous area	0	14	0	14	Total correct rate
Very dangerous area	0	7	13	20	
Total	11	37	13		0.61667

Table 6
The confusion matrix of inferred hillslopes level from the BPN model.

Desire	Target				
	Safe area	Dangerous area	Very dangerous area	Total	Total error rate
Safe area	25	1	1	27	0.18333
Dangerous area	0	5	8	13	Total correct rate
Very dangerous area	0	1	19	20	
Total	25	7	28		0.81667

Table 7
The confusion matrix of inferred hillslope levels from the ANP model.

Desire	Target				
	Safe area	Dangerous area	Very dangerous area	Total	Total error rate
Safe area	25	0	0	25	0.11667
Dangerous area	0	12	2	14	Total correct rate
Very dangerous area	0	5	16	21	
Total	25	17	18		0.88333

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