COMPUTER-AIDED DECISION SUPPORT SYSTEM FOR DISASTER PREVENTION OF HILLSIDE RESIDENTS

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Abstract: This study endeavor focuses on developing a computer-aided decision support system for hillside residents to prevent the occurrence of hillside disaster. Living safety is an essential consideration for the hillside residents. Within this system, the checklist used by personnel or instrument monitoring is adapted for collecting hillside data. Applying fuzzy sets theory, the system analyzes the collected data, diagnoses the safety conditions of the slope, and reasons the type of failure. According to the safety condition of the slope, the possible causes of adverse conditions requiring attention can also be identified. Using this research, safety monitoring programs can not only fill gaps of design insufficiency, but also provide needed safeguards, detailing any adverse effects of hillside development. The primary features of the study are as follows: (1) identify the types of slope failure and items for safety checking, (2) recognize the checking items associated with the possible causes of failure and their relative weights, (3) develop a checking list for the hillside residents to collect the slope data by personnel or instruments, and (4) analyze the collected data and diagnose the failure types and its possible causes of the crisis situations. This system improves the safety of the hillside residents by providing a logic and systematic manner to analyze the collected data in a real time base. Predictions of any adverse conditions and appropriate actions can be taken to prevent the occurrences of hillside disaster. Furthermore, compared with the traditional methods, this system significantly improves computational efficiency and increases currently used data accuracy and consistency.

Key Words: disaster prevention, fuzzy sets theory, safety monitoring, causes diagnosis.

1. INTRODUCTION

Safety is an essential consideration for both hillside residents and engineers, thus unstable slopes should be addressed and repaired. Addressing unstable slopes has continually been a subject of interest to engineers. One obvious reason is that revealing economic losses often result from slope failures and correct remedial methods depend upon correctly estimating triggering causes [1].

As an area's population increases, people start to utilize hillside areas for development. The combination of many adverse factors and wrong approaches have often caused failure in slope development. For safety considerations, slopes should be monitored and unstable slopes should be remedied in proper ways [2,3]. Uncertainties and vagueness are inevitable in the process of safety evaluation and instability origin diagnosis. In addition to geotechnical knowledge, accumulated experience must include knowledge of distribution of instrumental data and environmental conditions. Moreover, the process of safety condition and possible causes that human experts infer always has some logic and empirical rules [4].

In the aspect of construction where experience accumulation is retarded, effective management of knowledge acquisition and problem solving is crucial. Therefore, this paper presents a model that significantly collects field expert's knowledge and experience in a systematic way, analyzes collected data and identifies safety condition and possible origins of hillside instability, preventing possible disasters in development. The sections that follow will briefly introduce the objectives of this paper and describe the system architecture.

2. RESEARCH OBJECTIVES

The primary purpose of this study is to develop a computer-aided decision support system for disaster prevention of hillside residents. The sub-objectives required to achieve the primary goals are the following:

◦ Establish a checklist for hillside residents and engineers who can use instrumentation and visual observation to collect data and clues on site.

◦ Develop a model for slope stability monitoring. Infer stability and failure types of slope through instrumentation measurements, simple observations, or both.

◦ Develop a model for slope instability origin diagnosis. Infer possible causes through instrumentation measurements, simple observations, or both.

◦ Build an automated monitoring system for disaster prevention. Assist users in collecting data, and managing data, inferring slope stability and failure types, diagnosing possible causes to address, thus increasing precision and accuracy in decision making, and preventing possible disasters.

3. SYSTEM ARCHITECTURE

The architecture of the system is developed according to the needs of management of slope safety monitoring process. There are seven elements included in system architecture, separately are user, setter, parameter settings, slope stability inference model, causes diagnosis model, collected data management, and automated data acquisition, which is shown in Figure 1.

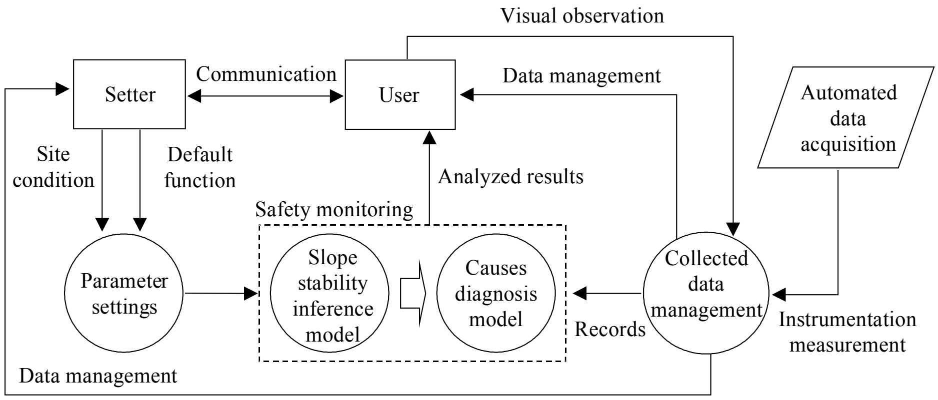

Figure 1. System Architecture

3.1 System User

The users of the system are hillside residents and engineers. This system is provided for assisting the users in collecting data, managing data, inferring slope stability and failure types, and diagnosing possible causes to address.

3.2 System Setter

The setter of the system allows geotechnical engineers who are experienced and knowledgeable in slope engineering to decide parameters that need to be processed in the system.

3.3 Parameter Settings

This system provides flexibility for the setter to add, delete, or modify the check items. The default function, which contains 76 and 38 optional objects, is used to set up the check item of each failure type and its cause respectively. On the other hand, depending on the real conditions determined from site reconnaissance, the setter can add, delete, or modify the check item of each failure type and its cause in the system.

3.4 Slope Stability Inference Model

Slope instability and collapse is induced by many complex and unfavorable conditions. Geologic properties and groundwater conditions will interact with retaining structures or vary with time. For such complicated and uncertain factors that influence hillside stability, slope stability inference requires a systematic manner for analyzing collected data. The process of stability inference model development is shown in Figure 2 and described as following.

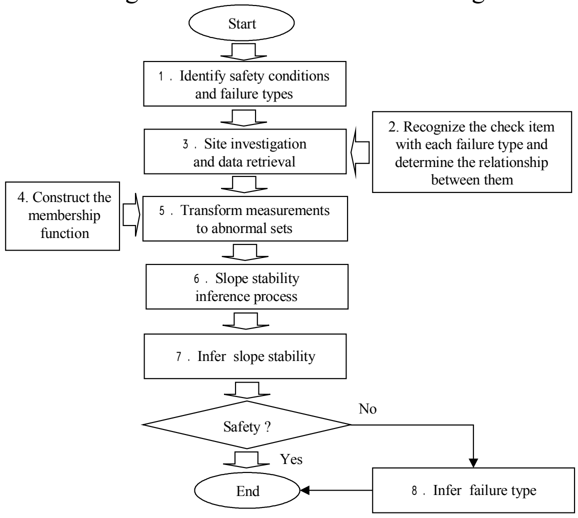

Figure 2. The Slope Stability Inference Model Development Process

3.4.1 Identifying Safety Conditions and Failure Types

Safety conditions and failure types of slopes can be induced through literature and interviews with experts. Safety conditions include stable, potentially unstable, slightly unstable, unstable, and very unstable. Failure types can be divided into nine parts, namely rockfall, toppling, slide, debris flow, creep, subsidence, retaining structure sliding, retaining structure tilt, and retaining structure settlement.

3.4.2 Recognizing the Check Item with Each Failure Type and Determining the Relationship between Them

Different failure types can be induced by dissimilar factors, and the appearance of clues are inconsistent [5]. The procedure of this research recognizes the check item for each failure type and obtains the relationship between them, as shown in Figure 3.

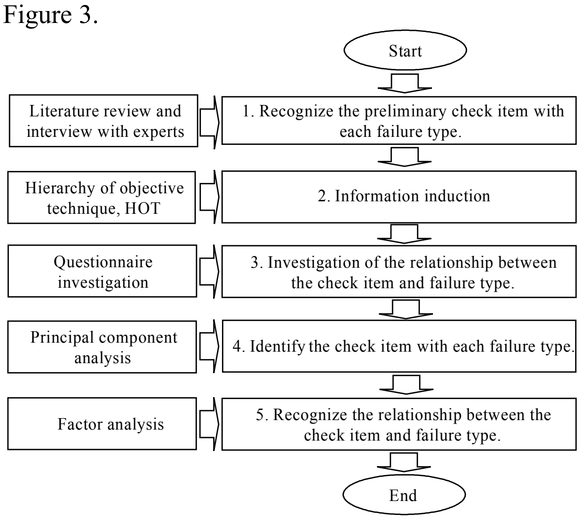

Figure. 3 Procedure for Obtaining the Failure Type Check Item and Its Relationships

3.4.3 Site Investigation and Data Retrieval

Field data collection can be divided into two parts, visual observation and instrumentation [6]. The Work Breakdown Structure (WBS) of data collection is shown in Figure 4. The characteristic comparison of visual observation and instrumentation is shown in Table 1. This study combines the advantages of both methods, making the collection of geologic data more comprehensive and efficient. Moreover, this system provides flexibility for the user to input visual observation data, instrumentation records or both for analysis.

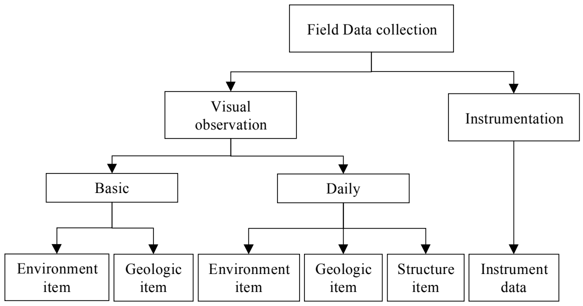

Figure 4. The WBS of Data Collection

Table 1. Comparison of Visual Observation and Instrumentation

	Instrumentation	Visual Observation
Advantages	1. Reliable 2. Ability to detect conditions of surface, subsurface, and structure. 3. Accurate	1. Provides simple information. 2. Observe surficial features. 3. Economic 4. Fast 5. Inspectiion of wild areas. 6. Easy
Disadvantages	1. Expensive 2. Technical ability required. 3. Ability to only inspect specific area.	1. Rough overview. 2. Inability to detect subsurface conditions. 3. Imprecise

3.4.4 Constructing the Membership Function

The fuzzy sets membership function, constructed from the fuzzy statistic method, expresses the concept of abnormal class of each check item. Classical logic is the conventional method used to assess if the check item (Including visual observation and instrument measurement) is normal or not. The statement can be zero or one – and nothing in between [7]. However, geology is a field characterized by varying degrees of vagueness and uncertainties. Classical logic judgment of slope stability and unstable origins is apt to invoke confusion as the check item lies between normal and extraordinary conditions. Thus, this study applies fuzzy set theory to develop the check item of extraordinary membership functions to represent the extraordinary classes of measurements within ambiguous area.

The extraordinary classes of measurement are categorized into five intervals, normal, slightly abnormal, abnormal, very abnormal, and extremely abnormal. The rating of each interval is defined as shown in Table 2. According to the interval ratings, the concept of Fuzzy Statistics Method is used to design a questionnaire to obtain the membership functions of extraordinary classes for each check item. Using pizometer as an example, the membership function is shown in Figure 5.

Table 2. The Abnormal Class of Measurement

Abnormal class	Abnormal level
Normal	1
Slightly abnormal	2
Abnormal	3

Very abnormal	4
Extremely abnormal	5

3.4.5 Transforming Measurements to Abnormal Sets

This section uses the same example and the membership functions developed in Figure 5 to introduce the procedure and equations for converting instrument measurements and visual observations into abnormal sets. In this case, it is assumed the initial value (V_i) of the pizometer is 0.0 m, the very low effect value (V_{vl}) is 3.0 m, the low effect value (V_{lo}) is 5.0 m, the medium effect value (V_{me}) is 7.0 m, the high effect value (V_{hi}) is 9.0 m, the very high effect value (V_{vh}) is 12.0 m, and the measurement (V_m) is 4.0 m. The conversion process is described as follows:

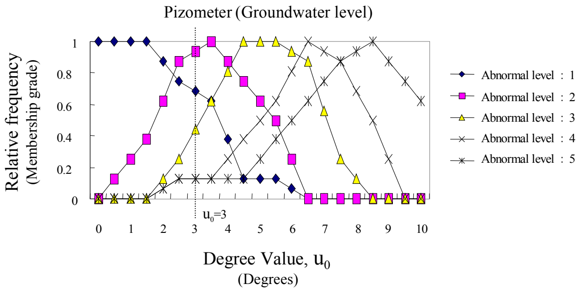

Figure 5. The Membership Function of Pizometer

1. Converting the measurement to the degree value

According to equations (1), (2), (3), (4), and (5), the measurement of 4.0 m is calculated and transformed to degree value (u_0).

a. as $V_i \leqq V_m < V_{vl}$

$u_0 = 0 + [V_m/(V_{vl} - V_i)]*2$ ------------------------ (1)

b. as $V_{vl} \leqq V_m < V_{lo}$

$u_0 = 2 + [(V_m - V_{vl})/(V_{lo} - V_{vl})]*2$ ------------ (2)

c. as $V_{lo} \leqq V_m < V_{me}$

$u_0 = 2 + [(V_m - V_{lo})/(V_{me} - V_{lo})]*2$ ----------- (3)

d. as $V_{me} \leqq V_m < V_{hi}$

$u_0 = 2 + [(V_m - V_{me})/(V_{hi} - V_{me})]*2$ ---------- (4)

e. as $V_{hi} \leqq V_m < V_{vh}$

$u_0 = 2 + [(V_m - V_{hi})/(V_{vh} - V_{hi})]*2$ ----------- (5)

i.e. $u_0 = 2 + [(4.0 - 3.0)/(5.0 - 3.0)]*2 = 3.0$

2. Identifying the corresponding membership grades

The membership function is represented as follows:

$\mu_{\underset{\sim}{A_n}}(u_0)$: membership function of abnormal level n when the degree value equals u_0.

$\underset{\sim}{A_n}$: the fuzzy subset of abnormal level n (n=1~5)

u_0 : measurement degree value

Using the degree value 3.0 calculated in step 1, the intersections of the degree value with the membership functions shown in Figure 5 can be identified. The corresponding relative frequencies are the membership grades.

$\mu_{\underset{\sim}{A_1}} = 0.69, \mu_{\underset{\sim}{A_2}} = 0.94, \mu_{\underset{\sim}{A_3}} = 0.44, \mu_{\underset{\sim}{A_4}} = 0.13, \mu_{\underset{\sim}{A_5}} = 0.13$

3. Representing the abnormal set of check items by the membership grades of abnormal levels calculated in the previous step. The abnormal set of pizometer is described as follows:

The abnormal set of pizometer

$= \left\{ \mu_{\underset{\sim}{A_1}}(u_0), \mu_{\underset{\sim}{A_2}}(u_0), \mu_{\underset{\sim}{A_3}}(u_0), \mu_{\underset{\sim}{A_4}}(u_0), \mu_{\underset{\sim}{A_5}}(u_0) \right\}$

$= \left\{ \mu_{\underset{\sim}{A_1}}(3.0), \mu_{\underset{\sim}{A_2}}(3.0), \mu_{\underset{\sim}{A_3}}(3.0), \mu_{\underset{\sim}{A_4}}(3.0), \mu_{\underset{\sim}{A_5}}(3.0) \right\} = \{0.69, 0.94, 0.44, 0.13, 0.13\}$

3.4.6 Slope Stability Inference Process

The slope stability inference process is developed from a fuzzy set theory based approach, analyzing collected data and determining stability of slope. The fuzzy reasoning engine is

$\underset{\sim}{A} \circ \underset{\sim}{R} = \underset{\sim}{B}$ ---(6)

where

$\underset{\sim}{A} = \{a_1, a_2, \ldots, a_n\}$ is a n-dimensional vector,

a_i : weight of ith factor

$\underset{\sim}{R}$: fuzzy relation among two sets, n-dimensional factor set and m-dimensional assessment set.

$$\underset{\sim}{R} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix} \text{--------------------------------(7)}$$

$\underset{\sim}{B}$: m-dimensional result set

$\circ$: Composition Operator. The fuzzy relation of each check item is approximate. According to the experiments, using M (∧ , ∨) operator decreases the explanation of results. The M (• , +) operator is used, making the results more easily understood.

3.4.7 Slope Stability Inference

Evaluating the result of the fuzzy sets is defined within a universe of possible causes. This fuzzy set is then converted into a crisp value (or a vector of values) which serves as its best representative. This conversion is called defuzzification. This research uses the concept of composite maximum for defuzzification. The composite maximum method is defined as follows [8]:

Universe U with n fuzzy subsets, $\underset{\sim}{A_2}$,…, $\underset{\sim}{A_n}$, and $X_0 \in U$

If

$$\mu_{\underset{\sim}{A_i}}(X_0) = Max\left\{ \mu_{\underset{\sim}{A_1}}(X_0), \mu_{\underset{\sim}{A_2}}(X_0), \mu_{\underset{\sim}{A_3}}(X_0), \ldots, \mu_{\underset{\sim}{A_n}}(X_0) \right\}$$

Then

x^0 is subject to $\underset{\sim}{A_i}$

3.4.8 Failure Type inference

This research inference the possible failure types of unstable slopes according to the analyzed results of stability reasoning using the composite maximum method.

3.5 Causes Diagnosis Model

This section focuses on describing the systematic collection of expert's knowledge and experience, identifying the diagnosable logic in their reasoning. Then, it develops the instability origin diagnosis model to assist engineers in locating possible areas requiring for remedy. The process of origin diagnosis model development is shown in Figure 6 and described as following. However, the process of site investigation and data retrieval, transform measurements to abnormal sets, and concept of infer possible origins, please refer to the section 3.4.

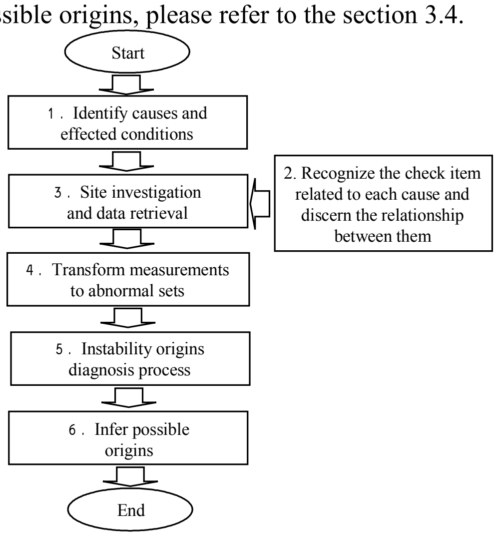

Figure 6. The Origin Diagnosis Model Development Process

3.5.1 Identifying Origins and Resulting Conditions

Through literature and interviews with experts, slope instability origins are derived. These include soil erosion, underground water, pipe abscission, removal of the bottom supports of retaining structures, imperfect geologic structure, poor geologic materials, dearth of drainage systems, earthquakes, rainfall, slope angle, retaining structure drainage, inappropriate retaining structures, mine shafts, and massive soil and rock mixed together. These instability origins are the triggering resources which will be analyzed in the system.

Resulting unstable conditions tied to specific origins should be approached with different remedial treatments. In considering proper treatment and description, unstable slope conditions resulting from different origins are divided into several states through literature review and interviews with experts, effectively "very low effect", "low effect", "medium effect", "high effect", and "very high effect".

3.5.2 Recognizing the Check Item with Each Cause and Determining the Relationship between Them

The procedure of this research recognizes the check item for each cause and obtains the relationship between them, as shown in Figure 7.

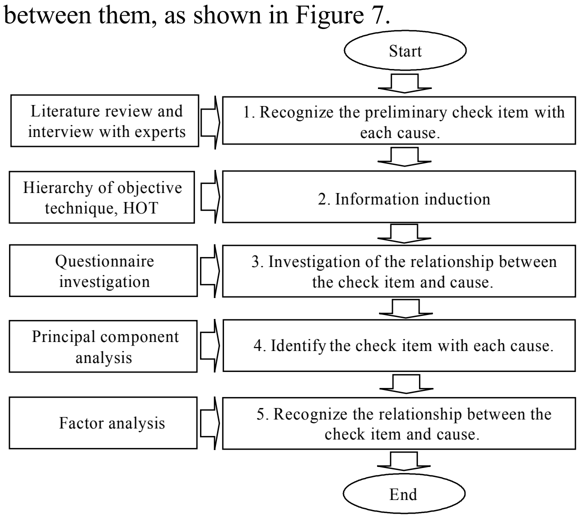

Figure 7. Procedure for Obtaining the Origin Check Item and its Relationships

3.5.3 Slope Instability Origin Diagnosis Process

Describing the diagnosis process in a mathematics manner, it is mapped from the symptomatic set to the diagnostic set based on expert's knowledge and experience [9,10]. This mapping presents a mathematical model of the diagnosis process. For this research, the check item used is "symptomatic set", and the cause is "diagnostic set", represented by fuzzy mathematics as follows:

Symptomatic set: $S=\{s_1, s_2, \ldots, s_n\}$

Diagnostic set: $D=\{d_1, d_2, \ldots, d_m\}$

Through mapping from the symptomatic to the diagnostic set, the fuzzy relationship (8) is derived.

$$\underset{\sim}{P} = (\mu_{ij})_{n\times m} = \{\mu_{ij}(s,d) | (s,d) \in S\times D\}, \mu_{ij}[0,1] \text{------(8)}$$

μ_{ij} is the fuzzy relationship between the two sets $S=\{s_1, s_2, \ldots, s_n\}$ and $D=\{d_1, d_2, \ldots, d_m\}$. Applying principal component analysis and factor analysis, the fuzzy relationship is calculated. Using the fuzzy relation $\underset{\sim}{P}$, the diagnosis process is developed and shown in equation (9).

$$\underset{\sim}{I} \circ \underset{\sim}{P} = \underset{\sim}{O} \text{---(9)}$$

$\underset{\sim}{I} = \{s_k\}, s_k \in S$: the abnormal matrix of check items

$\underset{\sim}{P}$: fuzzy relation

$\underset{\sim}{O}$: matrix result

$\circ$: composition operator

Figure 8 conceptually shows the diagnosis process.

3.6 Collected Data Management

The purpose of collected data management is developed to provide databases query, insert, delete, update, and print data for management of the user and setter. A relational database is also employed in the system.

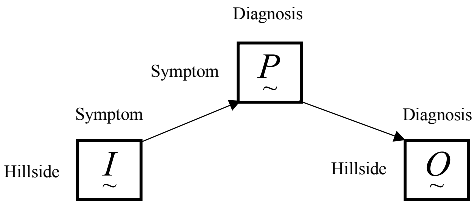

Figure 8. Diagnosis Process Schema

3.7 Automated Data Acquisition

Automated data acquisition of instrument is shown in Figure 9. Through Internet, modem or cable connection, the remote instrument measurements can be sent to the host database.

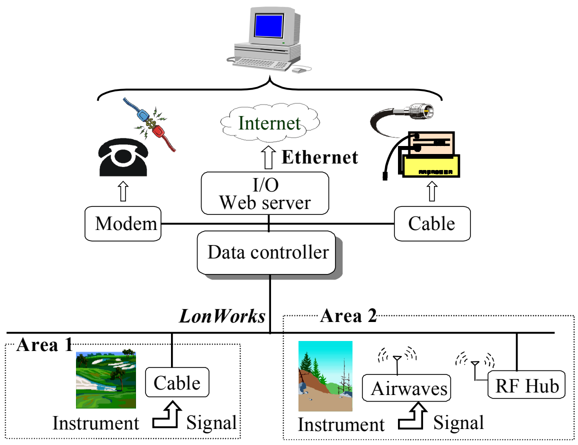

Figure 9. Schematic Diagram of Automated Data Acquisition Configuration

4. CONCLUSION

This research uses the concept of observation method in field reconnaissance, combining the advantages of visual observation with instrumental measurements. As a result, hillside safety monitoring becomes more efficient and powerful. Moreover, this study pioneers application of Fuzzy Statistics Method in the slope safety monitoring program for determining safety conditions and instability causes. Using this method, the knowledge and experience of experts on slope instability is systematically acquired and stored as a knowledge base. Also, the fuzzy process for judging the instability origins conducted by the experts can be defuzzified and obtained. The system's stability inference model and instability origin diagnosis process successfully represent and integrate experts' thinking, knowledge, and experience required for safety and casualty judgement into a computer environment. The application of the real time monitoring system can not only assist hillside residents and engineers in collecting data, managing data, inferring slope stability, and diagnosing possible causes to address, but also increase precision and accuracy in decision making and prevent possible disasters.

Using the present models, the stability inference model and diagnosis process appears to be able to correctly evaluate the safety conditions and possible causes of instability, in comparison with records of slope collapse. Although the stability inference and diagnosis model have currently proven to be valid in the case study, including the membership function of measurement, fuzzy relation, and inference algorithms, it will also gain increasing validity as it is applied to other areas.

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