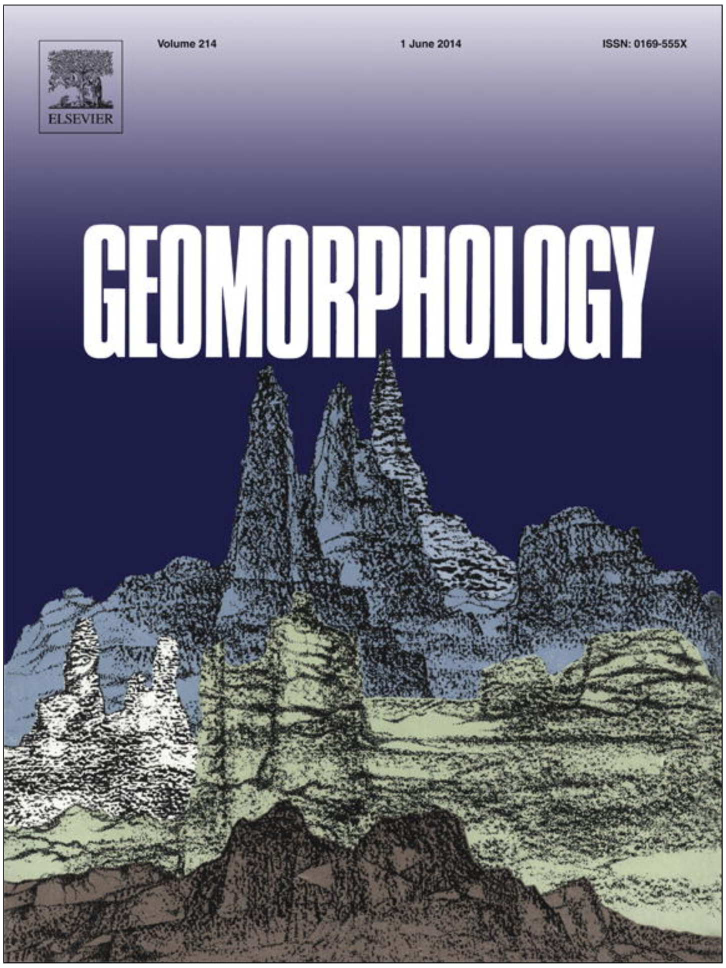
Volume 214
1 June 2014
ISSN: 0169-555X
ELSEVIER
GEOMORPHOLOGY

Geomorphology 214 (2014) 128–138

Contents lists available at ScienceDirect

Geomorphology

journal homepage: www.elsevier.com/locate/geomorph

An expert knowledge-based approach to landslide susceptibility mapping using GIS and fuzzy logic

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A R T I C L E I N F O

Article history:
Received 27 September 2013
Received in revised form 1 February 2014
Accepted 4 February 2014
Available online 11 February 2014

Keywords:
Landslide susceptibility mapping
Expert knowledge-based approach
Fuzzy logic
Geographic information system

A B S T R A C T

This paper presents an expert knowledge-based approach to landslide susceptibility mapping in an effort to overcome the deficiencies of data-driven approaches. The proposed approach consists of three generic steps: (1) extraction of knowledge on the relationship between landslide susceptibility and predisposing factors from domain experts, (2) characterization of predisposing factors using GIS techniques, and (3) prediction of landslide susceptibility under fuzzy logic. The approach was tested in two study areas in China — the Kaixian study area (about 250 km^2) and the Three Gorges study area (about 4600 km^2). The Kaixian study area was used to develop the approach and to evaluate its validity. The Three Gorges study area was used to test both the portability and the applicability of the developed approach for mapping landslide susceptibility over large study areas. Performance was evaluated by examining if the mean of the computed susceptibility values at landslide sites was statistically different from that of the entire study area. A z-score test was used to examine the statistical significance of the difference. The computed z for the Kaixian area was 3.70 and the corresponding p-value was less than 0.001. This suggests that the computed landslide susceptibility values are good indicators of landslide occurrences. In the Three Gorges study area, the computed z was 10.75 and the corresponding p-value was less than 0.001. In addition, we divided the susceptibility value into four levels: low (0.0–0.25), moderate (0.25–0.5), high (0.5–0.75) and very high (0.75–1.0). No landslides were found for areas of low susceptibility. Landslide density was about three times higher in areas of very high susceptibility than that in the moderate susceptibility areas, and more than twice as high as that in the high susceptibility areas. The results from the Three Gorge study area suggest that the extracted expert knowledge can be extrapolated to another study area and the developed approach can be used in large-scale projects. Results from these case studies suggest that the expert knowledge-based approach is effective in mapping landslide susceptibility and that its performance is maintained when it is moved to a new area from the model development area without changes to the knowledge base.

1. Introduction

As major geological hazards, landslides account for a great number of human casualties and an enormous amount of property loss, and cause significant damage to natural ecosystems and human-built infrastructures (Chung et al., 1995; Dai and Lee, 2002; Lee and Choi, 2004; Guzzetti et al., 2005). In order to mitigate losses and damages, many landslide susceptibility studies have been conducted to map the locations that are prone to landslides (e.g., Carrara, 1988; Carrara et al., 1991; van Westen et al., 1993; Aleotti and Chowdhury, 1999; Guzzetti et al., 1999; Dai et al., 2002; Zhou et al., 2002; Brenning, 2005; Alexander, 2008; Carrara and Pike, 2008; Xu et al., 2012).

Despite the development of various methods, most landslide susceptibility mapping studies are founded upon a single conceptual model, which assumes that landslide susceptibility is related to predisposing factors and that susceptibility can be evaluated as long as the predisposing factors and the relationships between the predisposing factors and the landslide susceptibility are known. The predisposing factors are considered to be the intrinsic nature and condition of the land, which make the area susceptible to failure but do not actually trigger a

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http://dx.doi.org/10.1016/j.geomorph.2014.02.003

landslide, and thereby tend to leave the area in a marginally stable state (Carrara et al., 1995; Dai et al., 2002). The common predisposing factors are geological formation (rock types, orientation and dip of strata, and faults), slope gradient, relative relief, land cover, soil physical properties and drainage patterns. Other terms that have been used for predisposing factors include "causative factors" (Varnes, 1984; Donati and Turrini, 2002; Zhou et al., 2002), "causal factors" (Carrara et al, 1995), "intrinsic factors" (Atkinson and Massari, 1998; Dai and Lee, 2001), "conditioning factors" (Sanchez et al., 1999; Zêzere et al., 1999), "quasi-static factors" (Dai and Lee, 2001; Xu et al., 2012), and "preparatory factors" (Dai et al., 2002; Ermini et al., 2005). The function depicts the relationship between landslide susceptibility and the predisposing factors (Varnes, 1984; Carrara, 1988; Carrara et al., 1995; Zhu et al., 2004). Most of the existing studies use multivariate statistical analysis to model the relationships based on past landslide events and predisposing factors at those sites (e.g., Dai et al., 2002; Fabbri et al., 2003; Ermini et al., 2005; Saito et al., 2009).

The multivariate statistical models for capturing and representing the relationships between landslide susceptibility and predisposing factors suffer from two critical shortcomings. The first is that the multivariate statistical models are data driven, and the quality of training data is critical. In the training process, landslide presence is used as positive evidence and landslide absence is used as negative evidence. The quality of landslide-presence data is controlled by the quality of field observations. Typically, the quality of the presence data is acceptable even though studies have reported drastic variation in the quality of field observations (van Westen et al., 1993; Carrara et al., 1995). The quality of landslide absence data is of great concern because the data are made up of locations that have been free of landslides up to the time of the analysis. Having no history of landslide events does not necessarily imply that a location is not susceptible to landslides, or that landslides will not occur in the future. The set of locations currently free of landslides could contain sites that in fact are very susceptible to them but that have not yet failed, simply because there are no triggering factors. Studies have shown that data-driven models are very sensitive to training data and that a slight change of input data can lead to significant changes in the coefficients of the derived regression/discriminant/logistic models (Kirkby et al., 1987; Carrara, 1988; Atkinson and Massari, 1998; Dai and Lee, 2001, 2002). As a result, these models often have very limited transportability, meaning that a model developed in one area often does not work well when applied in other areas.

Furthermore, data-driven approaches are extremely data hungry (Mitchell, 1997), which requires a large amount of fieldwork, even with the assistance of remotely sensed data. In landslide susceptibility mapping studies, one often needs both remote sensing data and an intensive field survey to build an accurate landslide inventory and to construct statistical models for a given study area. Intensive fieldwork is time consuming and expensive, and might even be impossible in areas with limited accessibility or for projects over large areas, due to budgetary concerns.

The second shortcoming is that these statistical approaches are often based on linear or generalized linear models, which can only represent the relationships in a monotonic way (inherent generalization; Van Westen et al., 2003). However, the actual relationships are complex and inherently nonlinear. For example, the relationship between strata (strike and dip) and landslide susceptibility is highly nonlinear because this relationship is also related to the slope information including gradient and aspect (Atkinson and Massari, 1998; Donati and Turrini, 2002; Lee et al., 2002; Liu et al., 2004; Zhu et al, 2004; Ayalew and Yamagishi, 2005). These linear or generalized linear models are thus insufficient to represent complicated nonlinear relationships.

This paper presents an expert knowledge-based approach to landslide-susceptibility mapping, which circumvents or at least partly reduces the influence of the shortcomings inherent to data-driven approaches. The study is exclusively concerned with deep seated landslides.

Expert knowledge is developed through a combination of the theoretical understanding of a physical process and years of field experience in a wide range of areas (Luger, 2005). Compared to the statistical functions used in data-driven models for geographical modeling, experts' knowledge has been purported to be more reliable, consistent, and generally applicable when the knowledge is formalized under fuzzy logic or as Bayesian probability, especially for large-scale projects (Fisher, 1989; Hudson, 1990, 1992; Zhu et al., 2004). In the landslide domain, local landslide experts develop their empirical knowledge through the accumulation of information on the complicated nonlinear relationship between landslide susceptibility and predisposing factors.

The basic idea of an expert knowledge-based approach to landslide susceptibility mapping is to obtain the relationships between landslide susceptibility and predisposing factors for a certain study area directly from local landslide experts and then apply these relationships to an evaluation of the landslide susceptibility at each location in the study area (Fig. 1; Zhu et al., 2004). This distinguishes the expert knowledge-based approach from existing statistical approaches to landside susceptibility mapping. With the former, the relationships *f* are approximated by the knowledge of domain experts, while for the latter, the relationships *f* are approximated statistically, based on past landslide occurrences.

In the expert knowledge-based approach, the expert knowledge of the complicated nonlinear relationships between landslide susceptibility and predisposing factors is extracted under fuzzy logic and represented as a set of fuzzy membership functions. Each fuzzy membership function describes the relationship between landslide susceptibility and an individual predisposing factor. Conditions on the predisposing factors of a study area can be characterized using geographic information system (GIS)/remote sensing techniques and can then be compiled in a raster GIS database (Lan et al., 2004; Fourniadis et al., 2007; Remondo and Oguchi, 2009). The knowledge, in the form of fuzzy membership functions, can then be combined with the GIS database to predict the landslide susceptibility at every location across the study area (Zhu and Band, 1994; Zhu et al., 2001).

2. Methodology

The expert knowledge-based approach to landslide susceptibility mapping consists of three general steps (Fig. 2): (1) extraction of knowledge from local domain expert(s), (2) characterization of predisposing factors using GIS/remote sensing techniques, and (3) prediction of landslide susceptibility (fuzzy inference).

2.1. Extraction of knowledge from local domain experts

The quality and sufficiency of knowledge, in terms of the relationships between landslide susceptibility and predisposing factors, are essential to the success of an expert knowledge-based approach to landslide susceptibility mapping. However, the knowledge often exists in the form of human expertise and has to be extracted and stored in a knowledge base to be used in a knowledge-based system. The extraction of knowledge from local domain experts is thus a crucial step and

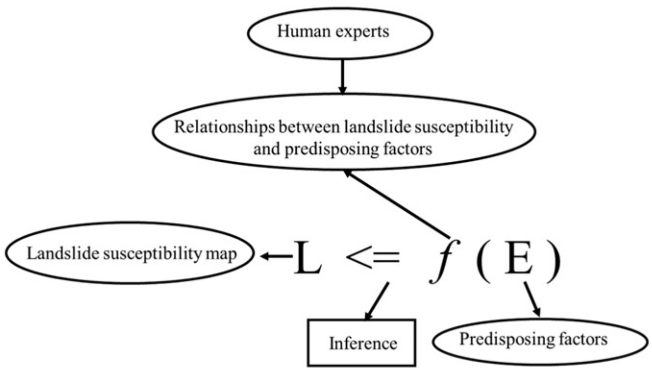

Fig. 1. Basic idea of expert knowledge-based landslide susceptibility mapping.

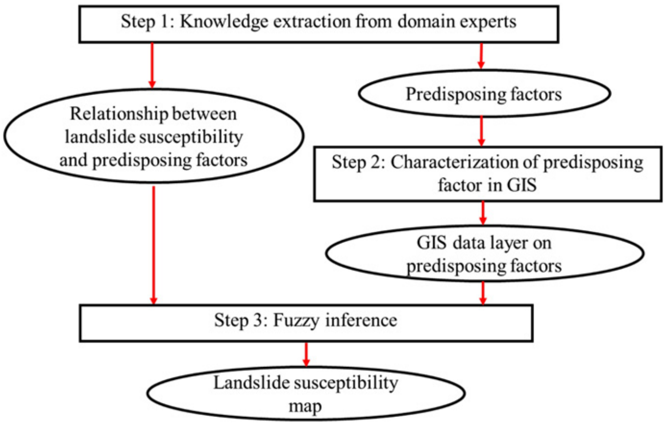

Fig. 2. Framework of expert knowledge-based landslide susceptibility mapping.

should be conducted by a proficient knowledge engineer, the person who queries the landslide experts, following a well-defined knowledge acquisition process (Russell and Norvig, 1995; Zhu, 1999).

A landslide expert should be someone who has been trained as a geologist/geomorphologist and who has an extensive theoretical understanding as well as field experience in landslide studies. In this study, a single local expert was used to demonstrate the expert knowledge-based approach. The use of multiple experts deserves a separate study due to the complication of resolving conflicts in knowledge among experts. The quality and the extrapolation of the extracted knowledge depend heavily on the quality of the expert (Zhu, 1999).

Two types of knowledge were needed from local landslide experts: (1) What are the predisposing factors that affect landslide susceptibility (in the specified study area)? (2) How does this set of predisposing factors affect landslide susceptibility, and what are the relationships between this set of predisposing factors and landslide susceptibility (in the specified study area)?

2.1.1. List of the predisposing factors

The list of predisposing factors is first given by the local landslide experts based on their knowledge regarding predisposing factors and is important in mapping landslide susceptibility in the given study area. The specific list of variables and its extrapolation are heavily dependent on the quality of the local expert, which is discussed in detail later in this paper. In landslide susceptibility mapping, a commonly used list of predisposing factors includes geological variables such as rock type, strata strike, and strata dip, topographic variables such as slope gradient, slope aspect, slope shape, relative relief, planform curvature, and profile curvature (Oguchi, 1997), and land use/cover types (Brabb, 1984; Atkinson and Massari, 1998; Aleotti and Chowdhury, 1999; Dai and Lee, 2001; Donati and Turrini, 2002; Zhu et al., 2004; Ermini et al., 2005).

2.1.2. Construction of the fuzzy membership functions to formulate the expert knowledge

The relationship between landslide susceptibility and an individual predisposing factor is described as a function (f) and then adjusted by the knowledge engineer based on the availability and importance of the predisposing factors. Here we adopt a set of personal construct-based knowledge acquisition processes developed by Zhu (1999). This knowledge acquisition process was designed to extract expert knowledge for mapping natural resources as spatial continua under a GIS environment and has been successfully used in soil mapping (Zhu and Band, 1994; Zhu, 1999; Zhu et al., 2001).

Based on the data type of the predisposing factor, there can be different choices for the function f, as expressed in the following formula:

$$f_v\left(e_{ij,v}\right) = \begin{cases} w_{1,v} & if\ e_{ij,v} = c_{1,v} \\ w_{2,v} & f\ e_{ij,v} = c_{2,v} \\ \cdots & \\ w_{m,v} & f\ e_{ij,v} = c_{m,v} \end{cases} \tag{1}$$

where f_v is the function describing the relationship between landslide susceptibility and the predisposing factor v (of categorical type); $e_{ij,v}$ is the value of predisposing factor v at location i,j; and $w_{1,v}$, $w_{2,v}$, …, and $w_{m,v}$ are the corresponding landslide susceptibilities when factor v takes the value of $c_{1,v}$, $c_{2,v}$, …, and $c_{m,v}$. An example of this variable type is that geology and local landslide experts can often provide relative ranking, ranging from 0 to 1, for each geological type or group of geological types in terms of their impact on landslides.

For continuous data types, the function is often represented as a fuzzy membership function in the fuzzy logic realm (Zadeh, 1965a,b; Robinson, 1988; Burrough, 1989; Fisher and Pathirana, 1990; Zhu, 1997; Burrough et al., 2001; Zhu et al., 2001; Schmidt and Hewitt, 2004). A specific function describes how landslide susceptibility varies with regard to changes in a predisposing factor. Three basic curves commonly used to describe fuzzy membership functions are the bell-shaped curve, Z-shaped curve, and S-shaped curve (Burrough, 1989; MacMillan et al., 2000; Shi, 2002; Zhu et al., 2004 — see Fig. 3 for examples). The bell-shaped curve is generic (Fig. 3a). It is used in a scenario in which

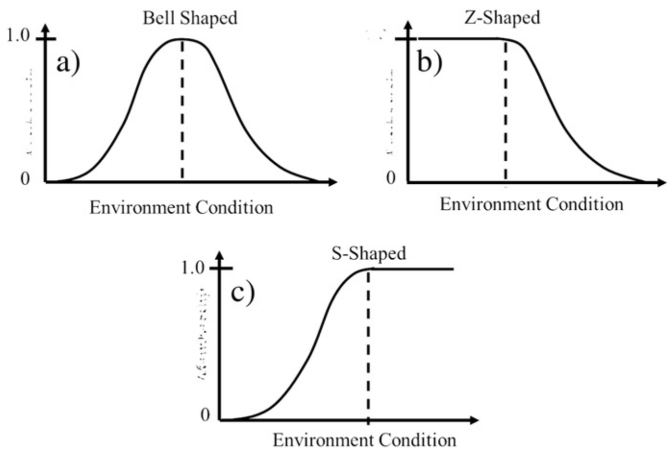

Fig. 3. Three basic curves for capturing the relationships for continuous factors: a) bell-shaped curve; b) Z-shaped curve; c) S-shaped curve.

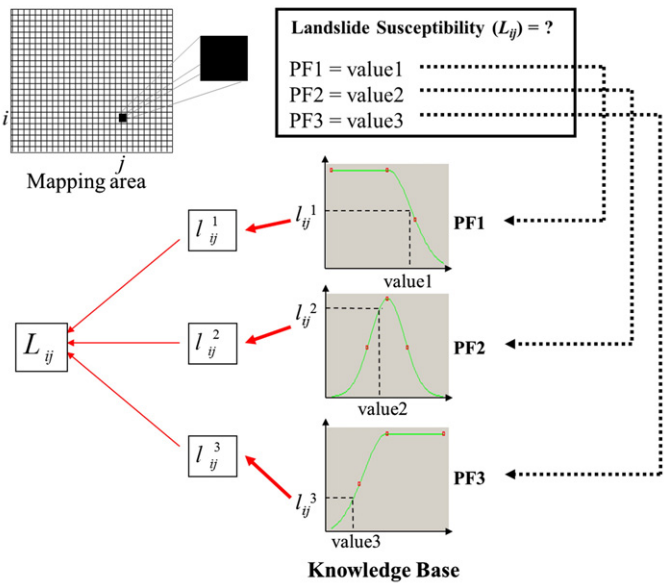

Fig. 4. Illustration of performing fuzzy landslide susceptibility inference.

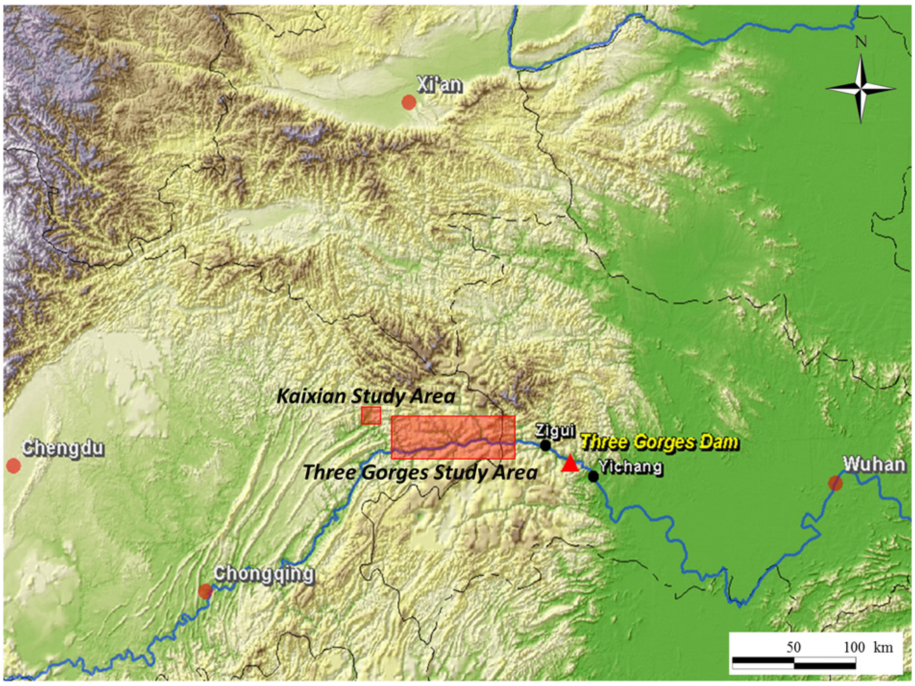

Fig. 5. Locations of the two study areas.

a predisposing factor has an optimal value or has a range of optimal values. At this optimal value, or within this range of optimal values, landslide susceptibility based on the predisposing factor reaches a maximum (1.0 is often used). While the value of the predisposing factor deviates from this optimal value or this range of optimal values, landslide susceptibility based on the predisposing factor decreases. The Z-shaped curve and S-shape curve are used in scenarios in which a predisposing factor has a threshold at which the susceptibility reaches maximum. For a Z-shaped curve (Fig. 3b), when the value of the predisposing factor is lower than this threshold, landslide susceptibility based on the predisposing factor stays at the maximum value; when the value of the predisposing factor is greater than this threshold and increases gradually, landslide susceptibility decreases gradually. The S-shaped curve (Fig. 3c) is the reverse of the Z-shaped curve. In this study, a general Gaussian-style function, which allows users to control the shape of the curve more easily, is adopted to approximate the basic shape of the curves (Zhu, 2008):

$$f_v\left(e_{ij,v}\right) = \exp\left[-\left(\frac{\left|e_{ij,v} - e_v\right| \times 0.8326}{w}\right)^2\right] \tag{2}$$

where f_v and e_v have the same meanings as above; $e_{ij,v}$ is the value of the v-th predisposing factor at location (i,j); w is a parameter controlling the shape of the curve and is defined as the difference between the value of the predisposing factor when the membership is at unity (1) and when it is 0.5 (cross-over).

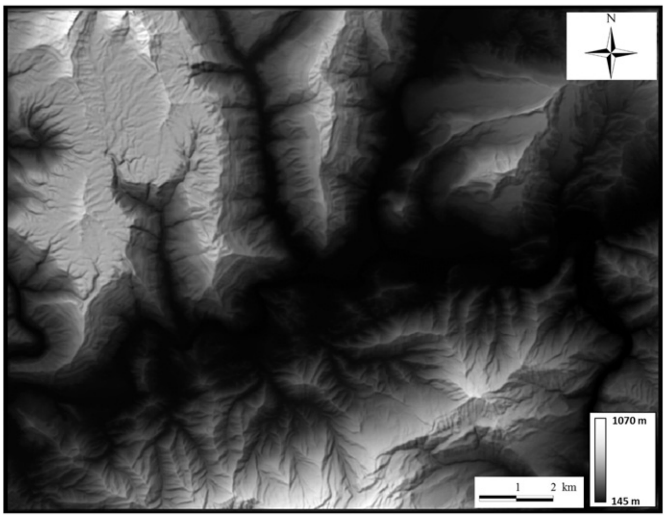

Fig. 6. Shaded relief map of the Kaixian study area.

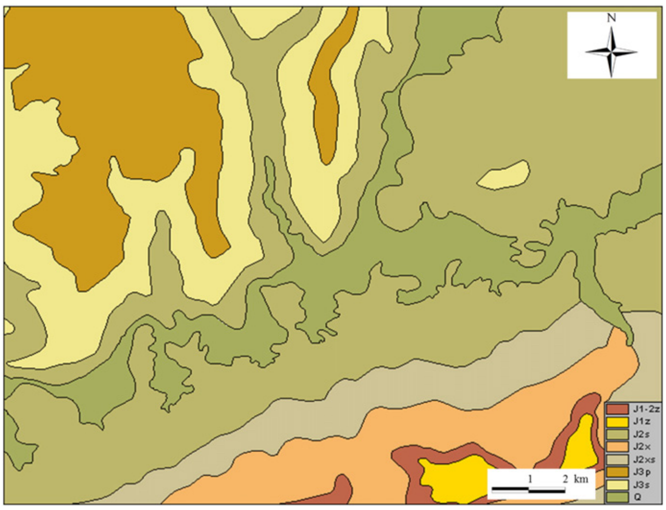

Fig. 7. Lithology map of the Kaixian study area. J_{1-2z}: Middle to Lower Jurassic Zi Liu Jing shale and sandstone. J_{1z}: Lower Jurassic Zi Liu Jing sandstone, siltstone and shale. J_{2s}: Upper Jurassic Shang Sha Qu Miao mudstone, sandstone and siltstone. J_{2x}: Middle Jurassic Xin Tian Gou mudstone, sandstone and siltstone. J_{2xs}: Middle Jurassic Xia Sha Qu Miao mudstone and shale. J_{3p}: Upper Jurassic Feng Lai mudstones and sandstone. J_{3s}: Upper Jurassic Zhu Ning sandstone, siltstone, and mudstone. Q: Quaternary deposits.

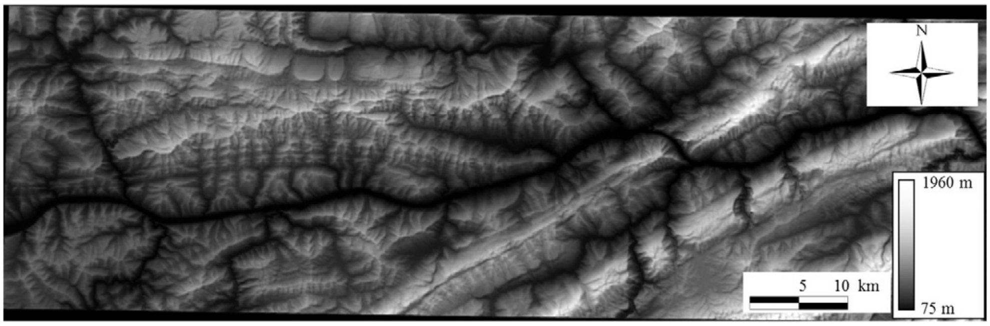

Fig. 8. Shaded relief map of the Three Gorges study area.

The curve type and parameters are determined based on the knowledge of local experts. For example, if the expert stated that landslide susceptibility increases as the slope gradient increases, an S-shaped curve is employed. If an expert suggested that susceptibility is very high for areas with a slope gradient over 40° ($e_{\text{gradient}} = 40$) and susceptibility is reduced by roughly half at 15° ($w = |40 - 15| = 25$), this knowledge provides us with the following membership function:

$$f_v\left(e_{ij,v}\right) = \begin{cases} 1 & \text{if } e_{ij,v} > 40^\circ \\ \exp\left[-\left(\dfrac{\left|e_{ij,v} - 40\right| \times 0.8326}{25}\right)^2\right] & \text{otherwise} \end{cases}. \quad (3)$$

2.2. Characterization of predisposing environmental layers

Some of the predisposing factors can be characterized using standard GIS data processing techniques. For instance, primary topographic attributes (such as slope gradient, slope aspect, planform curvature, and profile curvature) can be derived from DEM data using standard terrain analytical methods in GIS. Lithology type and strata information can be digitized from geological maps. However, some predisposing factors are easy for human experts to recognize but hard for the computer to characterize. Slope shape, an important predisposing factor in landslide-susceptibility mapping for some study areas, is an example. Landslide experts/researchers can easily identify different shapes of slope such as straight slope and upper convex–lower concave slope. However, characterizing these features using computer programs in an automated way is not straightforward. Customized techniques are needed (see Section 3.2.2).

2.3. Calculation of landslide susceptibility (fuzzy inference)

For a given study area, the fuzzy membership describing landslide susceptibility is evaluated on a cell-by-cell basis, by combining the extracted relationships with the characterized data on predisposing factors through an inference technique developed under fuzzy logic. Fig. 4 illustrates the fuzzy inference process for evaluating the landslide susceptibility of a given cell (i,j). First, the inference engine obtains all the predisposing factor values for this cell from the raster GIS database containing the data layers of the predisposing factors. In the illustration, we have three predisposing factors, PF1, PF2, and PF3, and the values at the cell are value1, value2, and value3, respectively (Fig. 4). Second, the inference engine loads in the knowledge base, which stores the relationships between landslide susceptibility and predisposing factors. For each predisposing factor, the inference engine evaluates landslide susceptibility based on this predisposing factor for the cell by applying the corresponding fuzzy membership curve to the value of the corresponding predisposing factor at this cell. In the illustration, landslide susceptibility based on predisposing factors PF1, PF2, and PF3 are represented as $l_{ij,1}$, $l_{ij,2}$, and $l_{ij,3}$ correspondingly. Third, the overall landslide susceptibility (L_{ij}) for the cell is computed by aggregating the landslide susceptibilities based on these individual predisposing factors.

This inference process for a given cell can be represented using a general formula:

$$L_{ij} = \mathop{T}_{v=1}^{n}\left(f_v\left(e_{ij,v}\right)\right) \quad (4)$$

where L_{ij} is the landslide susceptibility at the cell (i,j); n is the number of predisposing factors; and T is the aggregating function for calculating the overall landslide susceptibility for the cell (i,j). There can be different choices for the aggregating function T. The arithmetic mean is one of the aggregating functions that have been used in landslide-susceptibility studies (Liu et al., 2004; Zhu et al., 2004). We adapt the arithmetic mean aggregating function in this landslide-susceptibility mapping scenario as a simple illustration.

This fuzzy inference process is repeated for every cell in the study area. A landslide-susceptibility map in the form of fuzzy membership for the entire area is thus calculated. Once we have the fuzzy

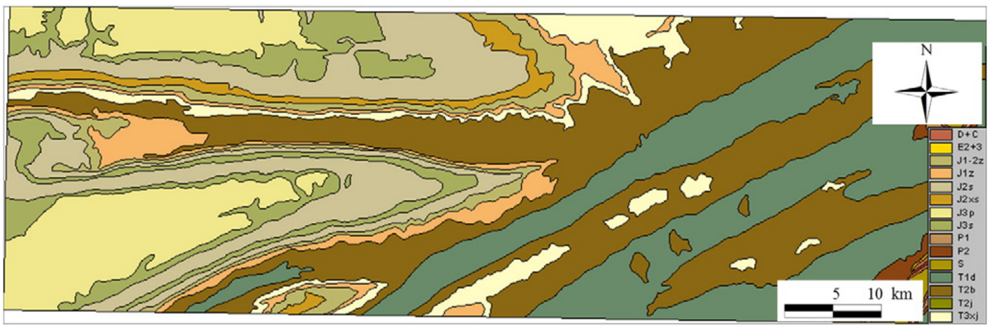

Fig. 9. Lithology map of the Three Gorges study area. D + C: Devonian to Carboniferous deposits. E_{2+3}: Lower Tertiary coal deposits and sandstone. P_1: Lower Permian coal deposits. P_2: Upper Permian limestone, shale and coal deposits. S: Silurian sandstone and shale. T_{1d}: Lower Tertiary Da Zhi limestone. T_{2b}: Middle Tertiary Ba Dong limestone, shale and mudstone. T_{2j}: Middle Tertiary Jia Ling Jiang limestone. T_{3xj}: Upper Tertiary Xu Jia He sandstone, siltstone, and shale.

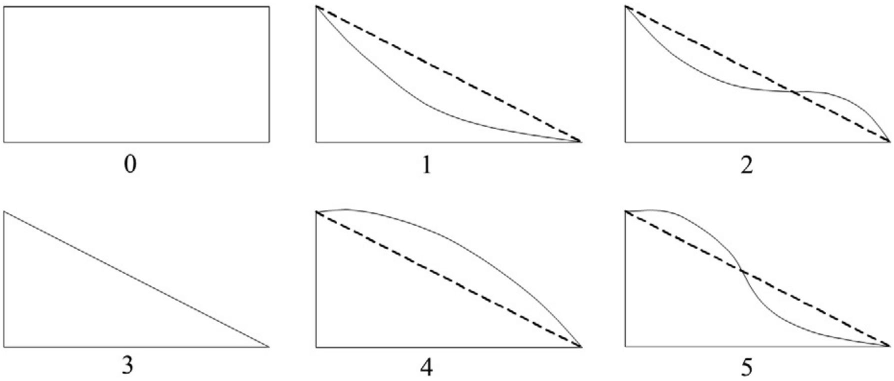

Fig. 10. Classification of slope shapes in the study area. 0: Flat area. 1: Concave hillslope. 2: Upper concave, lower convex hillslope. 3: Straight hillslope. 4: Convex hillslope. 5: Upper convex, lower concave hillslope.

landslide-susceptibility map, a landslide-susceptibility classification map can be derived (i.e., a map of landslide-susceptibility levels, such as very low, low, high, and very high).

3. Case study

3.1. Study areas

The middle-upper reach of the Yangtze River in China is by nature a high landslide risk area (Wu et al., 2001; Liu et al., 2004; Zhu et al., 2004). In this study, two areas in this region were used to test the proposed expert knowledge-based approach: the Kaixian and Three Gorges study areas (Fig. 5). The Kaixian study area was used to develop and test the methodology for landslide-susceptibility mapping. The Three Gorges study area is about 50 km to the east of the Kaixian study area and was used to test the portability of the developed expert knowledge-based approach and the applicability of the developed approach for large-scale study.

3.1.1. The Kaixian study area

The Kaixian study area is located in Kaixian County, in the Chongqing Municipality. It has an area of about 250 km^2 and elevations from 145 to 1070 m above sea level, with an average of 390 m (Fig. 6). The area has a high local relief, with an average elevation of about 300 m and a maximum about 700 m. Most of the slopes in this area are very steep with an average gradient of about 20°. The lithology over the area is of three major types: the lower to middle Jurassic system (including J_{2s}, J_{2xs}, J2x, J_{1-2z}, and J_{1z}), which is mainly made of sandstone, siltstone, mudstone, and shale; the upper Jurassic system (including J_{3s} and J_{3p}), which primarily consists of sandstone and siltstone; and the Quaternary system (Q) which is mainly composed of relatively recent deposits along the river valleys (Fig. 7).

3.1.2. The Three Gorges study area

The Three Gorges study area is a rectangular area between Yunyang County and Wushan County along the Yangtze River in the Chongqing Municipality. The area is about 120 km long and about 40 km wide (Fig. 8). The Three Gorges have been formed by severe incision into the massive limestone mountains of lower Paleozoic and Mesozoic age, along narrow fault zones, in response to Quaternary uplift (Liu et al., 2004). In the study area, there are two major types of lithology: the Jurassic system (including J_{2s}, J_{3p}, J_{3s}, J_{1z}, J_{2xs}, and J_{2x}), which primarily consists of mudstone, sandstone, siltstone, shale, and coal; and the Triassic system (including T_{2b}, T_{1j}, T_{3xj}, and T_{1d}), which is primarily composed of limestone, shale, claystone, dolomite, gypsum, sandstone, siltstone, and coal (Fig. 9). It has geomorphological and geological settings similar to the Kaixian study area. According to the local landslide researchers, this study area also has a landslide mechanism similar to the Kaixian study area, and hence the knowledge of the relationships between landslide susceptibility and preparatory factors is similar except that these two areas have different lithology types.

3.2. Model development and evaluation in the Kaixian study area

The implementation of the proposed approach in the Kaixian study area consists of three general steps, described earlier: knowledge extraction from domain experts, predisposing factor layer characterization, and fuzzy inference.

3.2.1. Knowledge extraction

The expert in this study is Jianping Qiao, one of the coauthors of this paper. Qiao has been trained as a mountain geomorphologist and has worked on landslide research for 20 years (as of this study). His major research specialty is landslide mechanisms and landslide susceptibility and he has completed many research projects on these topics in western China.

Table 1
Summary of expert knowledge as rule sets.

Rule sets	Descriptions	Parameters for fuzzy membership functions
Geology	The lower to middle Jurassic system is most susceptible; the upper Jurassic system is moderate susceptible; the Quaternary system is not susceptible	Susceptibility = 1 for the lower to middle Jurassic systems; Susceptibility = 0.5 for the upper Jurassic system; Susceptibility = 0.2 for the Quaternary system
Slope gradient	As the slope gradient increases, susceptibility also increases but at different levels for different geology	Susceptibility = 1 when slope gradient is great than or equal to 30°; Susceptibility = 0.5 when slope gradient is 15°
Slope and strata	Most susceptible when slope orientation matches the orientation of geological strata and the dip of the strata match the slope gradient. Susceptibility decreases as the two orientations part from each other.	As expressed in Eq. (7)
Relative relief	As the relative relief increases, susceptibility increases but at different levels with different geology	Susceptibility = 1 when relative relief is 300 m or more. Susceptibility = 0.5 when relative relief is at 150 m.
Slope shape	Slope shape is an important factor. Upper convex, lower concave slopes are most susceptible to landslides.	As expressed in Eq. (9)

Table 2
Landslide predisposing factors and their data sources.

Predisposing factors		Data sources
Geology	Lithology	Digitized and rasterized from the geology map of Kaixian County (1:200,000), which was created in 1978.
	Strata dip	Strata dip was generated using the Inverse Distance Weighting (IDW) interpolation.
	Strata strike	Strata strike was generated using the Nearest Neighborhood interpolation.
Topography	Slope gradient and aspect	Slope gradient and slope aspect were calculated from DEM data. The DEM for Kaixian has a 5 m resolution and was generated from the 1:10,000 topographic map created in 1978. The DEM for the Three Gorges Area has a 25 m resolution and was generated from 50,000 topographic map created in the 1970s.
	Slope relative relief and slope shape	Slope relative height and slope shape were characterized as described in Section 3.2.2.

Through an interview with the local domain expert, we identified seven essential predisposing factors: lithology, strata dip, strata strike, slope gradient, slope aspect, slope relative relief, and slope shape. Relative relief of a hillslope is defined as the difference between the elevations at the highest ridge and the lowest valley areas of a hillslope. The reason for using slope shape instead of slope curvature is that the former characterizes the shape of the whole slope while the latter measures the curvature at a given pixel that is local to that pixel. Thus the former is preferred. The slope shapes in the study area were classified into six general types by Qiao (Fig. 10): flat (0); concave (1); upper concave, lower convex (2); straight (3); convex (4); and upper convex, lower concave (5).

The relationships between landslide susceptibility and the predisposing factors in the study area were also obtained from the local expert, Qiao, using the method described in Zhu (1999) and formulated as the fuzzy membership functions. Table 1 provides a summary of the domain knowledge and the key parameters used to define the fuzzy membership functions on the relationship between landslide susceptibility and the predisposing factors.

The membership functions quantitatively describing the relationships were constructed with the knowledge and the specific parameters provided by the local experts. The landslide susceptibility due to lithology is expressed as Eq. (5) where $l_{i,j}$ is the lithology at location (i,j).

$$f_{\text{Lithology}}\left(l_{ij}\right)=\begin{cases}1.0 & \text{if } l_{ij}=J_{2s}, J_{2xs}, J_{2x}, J_{1\text{-}2z}, \text{ or } J_{1z} \text{ (most susceptible)}\\ 0.5 & \text{if } l_{ij}=J_{3s} \text{ or } J_{3p} \text{ (moderately susceptible)}\\ 0.2 & \text{if } l_{ij}=Q \text{ (least susceptible)}\end{cases}. \tag{5}$$

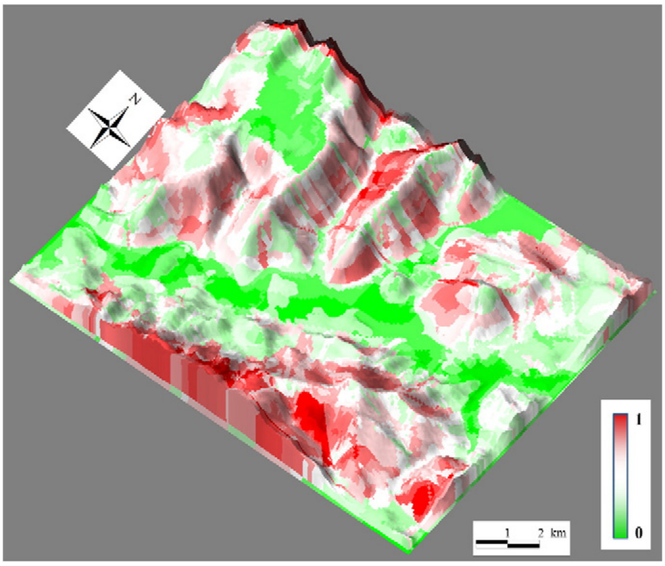

Fig. 11. Aggregated landslide susceptibility map (perspective view) using the Arithmetic Mean method for the Kaixian study area. Color: 0 — not susceptible at all to landslide occurrence. 1 — extremely susceptible to landslide occurrence.

The landslide susceptibility due to slope gradient is computed by Eq. (6) where s_{ij} is the slope gradient at location (i,j).

$$f_{\text{Slope Gradient}}\left(g_{ij}\right)=\begin{cases}1.0 & \text{if } g_{ij}\geq 30\\ \exp\left[-\left(\dfrac{\left|g_{ij}-30\right|\times 0.8326}{15}\right)^2\right] & \text{if } g_{ij}<30\end{cases}. \tag{6}$$

Susceptibility due to the combination strata information and slope information is defined in Eq. (7).

$$f_{\text{Strata Slope}}\left(d_{ij},s_{ij},g_{ij},a_{ij}\right)=\begin{cases}0.0 & \text{if}\left|s_{ij}-a_{ij}\right|>90\\ 0.0 & \text{if } d_{ij}>g_{ij}\\ \exp\left[-\left(\dfrac{\left|d_{ij}-g_{ij}\right|\times 0.8326}{45}\right)^2\right]\times\cos\left(s_{ij}-a_{ij}\right) & \text{otherwise}\end{cases} \tag{7}$$

where d_{ij} is the strata dip at cell (i,j); s_{ij} is the strata strike at cell (i,j); g_{ij} is the slope gradient at cell (i,j); and a_{ij} is the slope aspect at cell (i,j).

The landslide susceptibility due to slope relative relief over a given lithology type (l_{ij}) is defined in Eq. (8) where r_{ij} is the relative relief for location (i,j).

$$f_{\text{Slope Relative Relief}}\left(r_{ij}\right)=f_{\text{lithology}}\left(l_{ij}\right)\times\begin{cases}1.0 & \text{if } r_{ij}\geq 300\\ \exp\left[-\left(\dfrac{\left|r_{ij}-300\right|\times 0.8326}{150}\right)^2\right] & \text{if } r_{ij}<300\end{cases}. \tag{8}$$

Landslide susceptibility due to slope shape is defined in Eq. (9) where ss_{ij} is the slope shape for location (i,j):

$$f_{\text{Slope Shape}}\left(ss_{ij}\right)=\begin{cases}0.0 & \text{if } ss_{ij}=0 \text{ (flat area)}\\ 0.1 & \text{if } ss_{ij}=1 \text{ (concave slope)}\\ 0.3 & \text{if } ss_{ij}=2 \text{ (upper concave, lower convex slope)}\\ 0.5 & \text{if } ss_{ij}=3 \text{ (straight slope)}\\ 0.8 & \text{if } ss_{ij}=4 \text{ (convex slope)}\\ 1.0 & \text{if } ss_{ij}=5 \text{ (upper convex, lower concave slope)}\end{cases}. \tag{9}$$

3.2.2. Characterization of predisposing factor layers

Landslide predisposing factors and their data sources are listed in Table 2, and the characterization methods of the two topographic factors (relative relief and slope shape) using GIS techniques are described below.

The relative relief information was computed in three sub-steps:

(i) Extract areas of ridges and areas of valleys for the study area. This can be done in either an automated way or a manually digitizing way. We extracted the ridge areas and valley areas using a network extraction technique (Band, 1993).
(ii) Calculate relative relief. From each cell in the ridge area (suppose the elevation value is *E_Ridge*), the algorithm traces down along the flow direction until a cell in the valley area (suppose the elevation value is *E_Valley*) is reached. The elevation difference

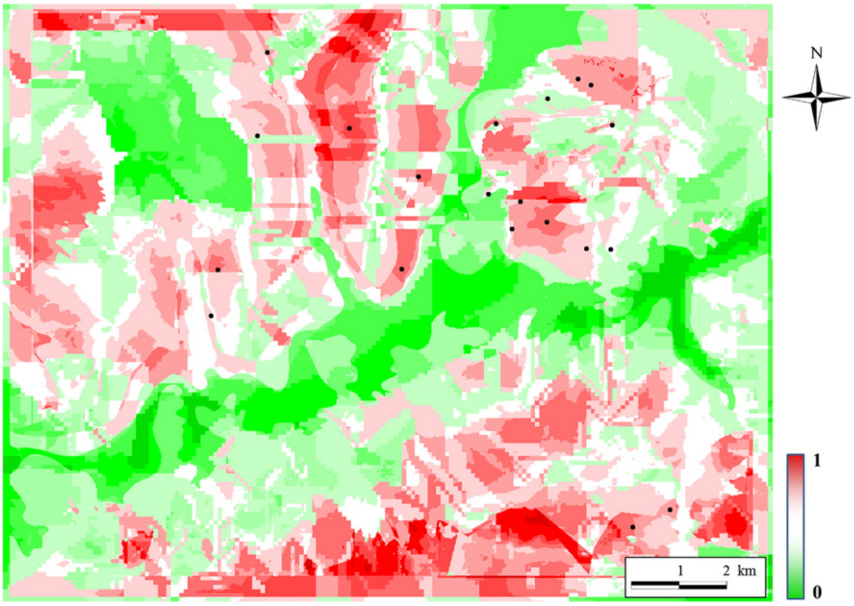

Fig. 12. Aggregated landside susceptibility map with landslide points for the Kaixian study area. Black dots represent the locations of observed landslides.

(i.e., *E_Ridge* − *E_Valley*) was set as the relative relief for all the cells along this path (from ridge to valley).

(iii) Interpolate the relative relief to the whole study area. It is not guaranteed that every cell in the study area is assigned a relative relief after step (ii), so the Nearest Neighborhood interpolation method was used to make sure every cell was assigned a slope relative relief for the whole study area.

Slope shape was characterized in the following three sub-steps:

(i) Extract areas of ridges and areas of valleys for the study area. This is the same as the first sub-step for the relative relief.
(ii) Determine slope shape. From each cell in the ridge area, the algorithm traces down along the flow direction until a cell in the valley area is reached. All elevation values along this path (from the cell in the ridge area to the cell in the valley area) were recorded. Using this series of elevation data, slope shape along this path was determined based on the slope shape classification, as shown in Fig. 10.
(iii) Interpolate the slope shape information to the whole study area. The Nearest Neighborhood interpolation method was used to assign slope shapes to those cells that did not receive a slope shape assignment after step (ii).

3.2.3. Fuzzy inference of landslide susceptibility

Fuzzy inference of landslide susceptibility in the Kaixian study area was performed by linking the knowledge from the local landslide expert and the characterized predisposing environmental factors. This was discussed in Section 3.3; the details are not repeated here. The inferred landslide-susceptibility map is shown in Fig. 11, where the following general pattern can be observed: high landslide susceptibility values are located over the back slope areas (red areas in Fig. 11), moderate landslide susceptibility values are located around the ridge areas and foot slope areas (white areas), and low landslide susceptibility values are located in the valley areas and areas with very low relief such as plateau areas (green areas). This general pattern is largely due to the spatial pattern of the predisposing factors, particularly slope gradient and relative relief. Slope gradient and lithology are widely recognized as the two most important landslide intrinsic causal factors. This general pattern is clearer for areas with easily identifiable ridge lines and stream lines, but fuzzier for areas where the terrain skeleton is not easily discernible. For example, in Fig. 11, the pattern can easily be observed in the northwest quarter of the study area, while it is not as detectable in the southeast quarter. This is partly due to the algorithms used to characterize relative relief and slope shape. In this study, ridge lines and stream lines were two of the input data layers used to characterize relative relief and slope shape. For areas with clearly identifiable ridge lines and stream lines, the characterized predisposing factors also exhibit clear patterns and vice versa.

3.2.4. Evaluations of the inferred landslide susceptibility

To evaluate the effectiveness of the model, we compared the distribution of observed landslides with the inferred landslide susceptibility, and a *z*-score test was performed by determining if the mean of the

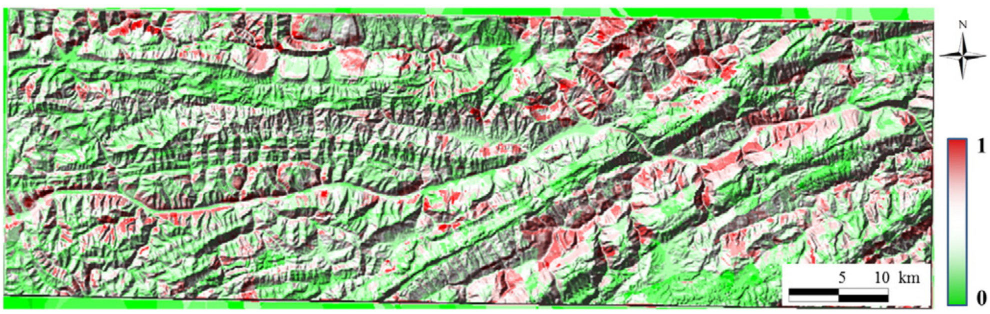

Fig. 13. Aggregated landslide susceptibility map using the Arithmetic Mean method for the Three Gorges study area.

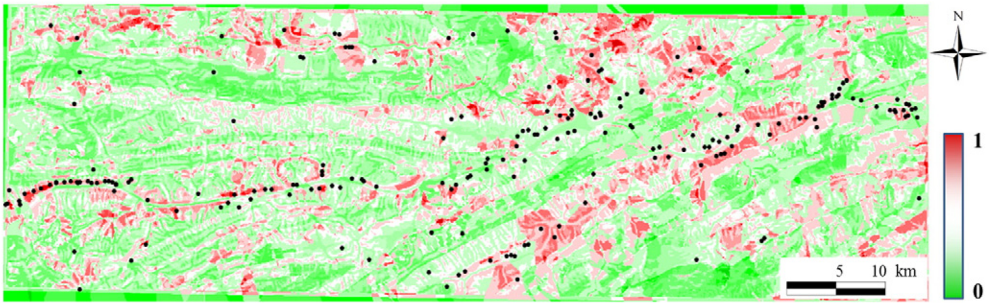

Fig. 14. Aggregated detailed landside susceptibility map with landslide points for the Three Gorges study area. Black dots represent the locations of observed landslides.

computed susceptibility values at landslide sites was statistically different from the mean for the entire study area.

Twenty-one landslides that occurred after 1978 were compiled and located (Fig. 12). The landslide occurrences were restricted to those that occurred after 1978 because the digital terrain for this area was created from a topographic map that was produced in 1978. The landslide susceptibility values at the landslide sites were then extracted from the landslide-susceptibility map (Fig. 12). The computed z based on the 21 sites was 3.70, and the corresponding p-value was far less than 0.001. This suggests that the computed landslide-susceptibility values are good indictors of landslide occurrences and further suggests that the developed expert knowledge-based approach can be used to map landslide susceptibility.

3.3. Model application in the Three Gorges study area

The Three Gorges study area was used to test the portability of the developed approach and its applicability to large areas. The knowledge of the relationships between landslide susceptibility and predisposing environmental factors developed in the Kaixian study area was transferred to this study area with just one change: the addition of knowledge associated with the new lithology in the Three Gorges study area. These new lithology types were grouped into "most susceptible," "moderately susceptible," and "least susceptible," as was done for the Kaixian area. The predisposing-factor characterization step and the landslide-susceptibility inference were conducted exactly as for the Kaixian study area.

The landslide susceptibility for the Three Gorges area is shown in Fig. 13. We evaluated the usefulness of the mapped landslide susceptibility for the Three Gorges study area in the same way as we did for the Kaixian area. In the Three Gorges study area, there were 205 observed landslides (Fig. 14; note the high concentration of landslides that occurred along the Yangtze River). The computed z is 10.75 and the corresponding p-value is far less than 0.001. Thus, we conclude that the computed landslide susceptibility values are good indictors of landslide occurrences. This further suggests that expert knowledge can be extrapolated to another study area and the developed approach can be used in large-scale projects.

We further evaluated the usefulness of the mapped landslide susceptibility for the Three Gorges study area by associating landslides with the classified landslide susceptibility map. For this purpose, landslide susceptibility was divided into four levels using an equal interval approach: low (0–0.25), moderate (0.25–0.50), high (0.50–0.75), and very high (0.75–1). The intent was to examine the difference in landslide density among the different levels based on susceptibility.

Table 3 lists the density of landslides over the four susceptibility-level areas. There is a clear trend that an increase in mapped landslide-susceptibility level is associated with a high density of field-observed landslide events. There were no landslide events that took place over the areas mapped as low susceptibility, and the density of landslide events over the areas mapped as moderate susceptibility was very low (about one-fourth of the density over the areas mapped as high susceptibility and one-tenth of the density over the areas mapped as very high susceptibility). As a result, we conclude that the computed landslide-susceptibility values are useful in indicating the probability of future landslides over an area.

4. Discussion

Clearly, the quality of knowledge on relationships between landslide susceptibility and predisposing factors from local experts is the key to the success of this knowledge-based approach. As described above, two types of knowledge were needed: (1) the list of predisposing factors that are important to assess landslide susceptibility, and (2) the relationships between the susceptibility and these predisposing factors. The latter, in turn, consists of (2a) the form of the individual relationships, and (2b) the critical values of the predisposing factors at which susceptibility is at its highest, and the critical values at which susceptibility is minimal. The provision of information (knowledge) on (1) is not a challenging task for most competent hillslope geomorphologists or geotechnical engineers, let alone for researchers who specialize in landslides, because this is basic knowledge in landslide research. Sub-type (2a) should not pose much of a challenge for an experienced landslide researcher because the approach described in this paper does not require the local expert to specify the mathematical forms of the relationships. Rather, the forms (in terms of three basic membership functions) are derived from the basic understanding of how these factors are related to landslide susceptibility as shown in Table 1. We expect that this level of understanding is not a challenge for someone with a few years of field-research experience in landslides.

Sub-type (2b) could be considered a challenge if the local expert was asked to provide the susceptibility value for every environmental value of a given variable. In this study, we adopted an approach based on personal construct theory (Zhu, 1999). This approach uses the concept of bipolar distinction, which is believed to be the key element in human learning (Kelly, 1955, 1970). The approach allows the expert to focus on the values for environmental conditions when the susceptibility is at its highest and the values for the environmental conditions when

Table 3
Landslide susceptibility levels and density of landslide events in the Three Gorges study area.

Landslide susceptibility level	Area (km^2)	Number of landslide occurrences	Landslide density (number of landslide occurrences per square kilometer)
Low	71	0	0.000
Moderate	2079	35	0.017
High	2321	143	0.062
Very high	179	27	0.151
Total	4650	205	–

the susceptibility reaches 0. This makes knowledge acquisition from the local expert manageable.

We tested only this approach, using the knowledge from a single expert as an illustration of the idea for using expert knowledge in landslide-susceptibility mapping. It is possible to use the knowledge from multiple experts with this approach, but the issue of how to integrate knowledge from different experts under the fuzzy logic framework, particularly how to resolve the difference in knowledge among different experts, needs to be resolved. Knowledge integration has long been of interest in the Artificial Intelligence (AI) community, and many different frameworks to integrate knowledge have been proposed. Examination of these frameworks for landslide susceptibility using this expert-knowledge approach should be the subject of a separate study.

The portability of a model or an approach is important not only in terms of its usefulness over a wider area, but also in terms of how well we understand the processes the model or approach captured. The results of our case studies suggest that this knowledge-based approach holds up well when it is transferred without changes to an area that is about 19 times larger and much more complicated than the area in which the knowledge base was developed. How this method compares to data-driven approaches, which are widely applied in landslide-susceptibility mapping, in terms of portability is of great interest, but such a comparison is beyond the scope of this paper and merits a detailed study in its own right.

The expert knowledge approach in this study does not use past landslides to develop the knowledge base. It is essentially different from the statistical methods in that the expert knowledge approach does not use data of landslide occurrence and absence to extract the relationships between landslide susceptibility and predisposing factors. It does not have the false negatives during its model development as the statistical methods and some of the data mining methods do.

5. Conclusions

This research was primarily motivated by several major deficiencies in data-driven approaches for mapping landslide susceptibility, including strong sensitivity to training data, which leads to a lack of expandability and portability, and their unsuitability for large area applications. In this paper we presented an alternative approach: an expert knowledge-based approach to address the issues related to the data-driven approaches.

The proposed expert knowledge-based approach includes three general steps: (1) extraction of knowledge on relationships between landslide susceptibility and predisposing factors from local domain experts by using knowledge acquisition techniques, (2) characterization of the needed predisposing factors by using GIS techniques, and (3) fuzzy landslide susceptibility inference to predict landslide susceptibility.

The proposed approach was conducted and evaluated in two case study areas: Kaixian and Three Gorges. The Kaixian study area was used to develop and test the methodology. The Three Gorges study area was used to test the portability of the expert knowledge and the applicability of the developed methodology for large-scale study areas. From the results of the case study we conclude that the expert knowledge-based methodology is effective for mapping landslide susceptibility, and its performance was maintained when it was moved to a new and significantly larger area without changes to the knowledge base. This suggests that the knowledge-based approach is portable and is suitable for application over large areas.

Acknowledgments

Funding for this research was provided by the Natural Science Foundation of China (Project Nos. 41023010 and 40971236), Ministry of Science and Technology of China (Project Nos.: 2010DFB24140 and 2011BAK12B01), and National High Technology Research and Development Program of China (863 Program, Project No. 2011AA120305). The support received by A-Xing Zhu through the Vilas Associate Award, the Hammel Faculty Fellow, and the Manasse Chair Professorship from the University of Wisconsin-Madison is greatly appreciated.

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