Mapping landslide susceptibility in the Three Gorges area, China using GIS, expert knowledge and fuzzy logic

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Abstract This paper presents an approach of integrating knowledge of relationships between landslide and environment conditions with GIS and fuzzy logic to map spatial variation of landslide susceptibility. The GIS techniques were used to derive spatial data characterizing the environmental conditions under which landslides occur. An inference technique constructed under fuzzy logic combines the spatial data on environmental conditions with knowledge of landslide–environment relationships to compute the landslide susceptibility of a location. A case study over a small watershed in the Three Gorges area was conducted to evaluate the validity of this approach. The case study showed that the computed susceptibility values are much higher over areas with landslides than areas without landslides. Thus, we conclude that the approach is capable of capturing landslide susceptibility. However, the accuracy of the computed susceptibility depends on the quality of knowledge on landslide–environment relationships and the ability of GIS in characterizing the environment conditions needed.

Key words expert system; fuzzy logic; GIS; land use planning; landslides; susceptibility

INTRODUCTION

The Three Gorges area of China is of a high landslide risk area. The construction of the Three Gorges dam will dramatically increase the landslide risk in the area. First, the Three Gorges reservoir raised the water level significantly and submerged a large portion of the bottom slopes. This breaches the current slope equilibrium and will cause strong, rapid, potentially violent slope processes to occur over the area. These rapid and strong slope processes will not only increase the frequency, but will also potentially increase the magnitude of landslides in the area. Second, the construction of the Dam displaced over a million people. Much of this displaced population is being resettled onto the upper slopes. This intensifies the land use activities over these areas, and this intensification of land use activities in turn becomes a major landslide triggering factor (Griggs & Gilchrist, 1983; Sidle et al., 1985). Therefore, the resettlement of the displaced population and other land use planning activities must consider the susceptibility of landslides, on one hand in order to reduce potential of the damage and loss of lives caused by landslides and on the other hand to minimize the triggering effect of land use activities on landslides. To consider the potential effects of
landslides in population resettlement and other land use planning activities over the areas, accurate and detailed landslide susceptibility maps are needed.

Conventional (manual) approaches to landslide susceptibility analysis are inadequate for the needs of population resettlement and detailed land use planning. This paper presents an approach for mapping spatial variation of landslide susceptibility by integrating human expertise on landslide–environment relationships with GIS under fuzzy logic. The next section will discuss the theoretical basis on which landslide susceptibility mapping is based. Details of this landslide susceptibility mapping method are presented in the following section. The final section presents a case study using this method in an area in the Three Gorges region. Conclusions are presented.

THEORETICAL BASIS

The theoretical basis for assessing the susceptibility of given locations to landslides can be expressed as: susceptibility to landslides is a function of environmental conditions at the given sites. This concept can be expressed by equation (1):

$$ S = f(E) $$

where $S$ is susceptibility to landslides, $E$ is the environmental conditions (such as geology, topography, vegetation, land use activities), and $f$ is the relationships between landslide susceptibility and the environmental conditions. Under equation (1) one can evaluate the susceptibility of a location to landslides if one knows the relationships and environmental conditions at the site. To map the spatial variation in landslide susceptibility over an area, one needs to defined $f$ and derive a database describing the spatial variation of environmental conditions ($E$).

LANDSLIDE SUSCEPTIBILITY MAPPING USING GIS, EXPERT KNOWLEDGE AND FUZZY LOGIC

We implemented the concept outlined above using GIS, artificial intelligence techniques and fuzzy logic concept. Figure 1 illustrates our approach to landslide susceptibility mapping. In our approach spatial variation of susceptibility to landslides is expressed by a raster fuzzy membership model (Zhu, 1997). Under this model susceptibility is expressed as grades of membership value with a membership value of 0 meaning not susceptible and a membership of unity (or user-defined up limit value) meaning most susceptible to landslide. Any membership value between these two extremes expresses a degree (level) of susceptibility. In this way different levels of susceptibility to landslides can be expressed. On the spatial side, we use a raster data model which is capable of expressing susceptibility at each pixel which can be as small as $30 \times 30$ m or smaller depending on the resolution of the environmental data. Thus this model allows us to express the susceptibility at great details in both the attribute (susceptibility value) and the spatial (spatial extent) domains.
To determine the value of fuzzy membership for susceptibility at each pixel or location, we need to know what environmental variable affects landslide susceptibility and the relationships between landslide susceptibility and this set of environmental variables. We determine the list of environmental variables and obtain the knowledge on the relationships from local landslide researchers using a set of knowledge acquisition techniques (Zhu, 1999). In our implementation, the environmental variables we consider are those intrinsic to landslide potential, such as rock type, strata orientation, and slope gradient, not triggering factors (such as intensity and frequency of storms and earth quakes). The list of variables is decided based on the discussion between the person who conducts the knowledge acquisition (knowledge engineer) and the local landslide researchers. For a given area the local landslide researchers would provide an initial list of environmental variables to be considered. This list is then modified by the knowledge engineer based on the data availability and the importance of the variables impacting the susceptibility in the study area. Due to the data availability and difference in importance to susceptibility over different areas, there is no fixed list of environmental variables to be included. The list varies from region to region. A common list would include geology type, strata orientation and dips, surface slope gradient and aspect, surface profile and planform curvatures, slope shape, and topological relationships of strata along the slope.

The relationships between landslide susceptibility and each individual variable are described by three basic curves (Fig. 2): the bell shaped curve, Z-shaped and S-shaped.
The bell shaped curve describes that there is an optimal environmental value or range over which susceptibility to landslide based on this environmental variable reaches a maximum and as the environmental condition of this variable deviates from this value or range the susceptibility decreases. The Z-shaped curve describes the scenario that there is a threshold value for the environmental variable under concern, smaller than which the susceptibility is maximum and greater than which the susceptibility decreases. The S-shaped curves define the relationships opposite to that characterized by the Z-shaped curves. These curves are defined using a personal construct-based knowledge elicitation approach (Zhu, 1999). This knowledge elicitation approach allows the local landslide researchers to focus on the definition of relationship one variable at a time. The relationship for a given variable is defined by focusing on the determination of critical environmental conditions. For a given environmental variable, the local researchers first determine which type of curve the relationship belongs to and then determines the critical environmental values for this type of curve. For example, if a bell shaped curve is used to capture the relationship between landslide susceptibility and slope gradient, the local landslide researchers will need to provide the environmental value or range of values over which the susceptibility is at a maximum, the environmental values (upper and lower values) at which the susceptibility is at half, and the environmental values (upper and lower values) at which the susceptibility reaches zero.

Data on the spatial distribution of environmental conditions are characterized using a set of geographic information processing techniques (such as digital terrain analysis and GIS database compilation techniques) (Wilson & Gallant, 2000; Zhu et al., 1996). Primitive terrain attributes such as slope gradient, slope aspect and surface curvature (planform and profile) can be easily computed using standard GIS software (such as ArcGIS, 3dMapper). Spatial data layers on rock types can be digitized from

![Figure 2: Three types of curves for capturing the relationships between landslide susceptibility and environmental conditions.](image-url)
geological maps and the spatial distribution of orientation of geological strata can be interpolated from geological map using geostatistical analytical techniques.

The fuzzy membership describing landslide susceptibility for a given location is computed by combining the extracted relationships with the characterized data on environmental conditions through an inference technique constructed under fuzzy logic (Zhu & Band, 1994; Shi et al., 2004; Shi & Zhu, 2004). In general, for pixel \((i,j)\), the inference engine takes the data on environmental conditions for that pixel and combines the GIS data with the relationships to calculate the fuzzy membership representing the susceptibility to landslide at this pixel. The inference engine then moves onto the next pixel in the GIS database and repeats the process of deriving the fuzzy membership for that pixel. When all pixels in the GIS database are exhausted, a fuzzy representation of susceptibility for the entire area is derived.

A CASE STUDY IN THE THREE GORGES AREA

Study area

To test the approach described in section “Landslide Susceptibility Mapping Using GIS, Expert Knowledge and Fuzzy Logic”, we conducted a case study using the approach described to map the spatial variation of landslide susceptibility over an area in Kai Xia of Chong Qing. The study area is centred about the town of Kai Xia and the size of the study area is about 252 km². The average elevation of the area is about 400 m above sea level but with strong local relief. The greatest local relief in the area is about 700 m with an average local relief of 300 m. The majority of slopes are very steep (over 65°), with an average slope of 20°. The geology over the area is of three types: the lower to middle Jurassic system made of sandstone, siltstone, mudstone and shale; the upper Jurassic system consisting of sandstone and siltstone; and the Quaternary system (mostly recently deposits along the river valleys).

Application of the method

Interviews with experts in landslides from the Institute of Mountain Hazards and Environment of Chinese Academy of Sciences were conducted to extract the

<table>
<thead>
<tr>
<th>Rule Set</th>
<th>Descriptions</th>
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<tr>
<td>Geology</td>
<td>The lower to middle Jurassic system is most susceptible; the upper Jurassic system is moderate susceptible; the Quaternary system is not susceptible</td>
</tr>
<tr>
<td>Slope and Strata</td>
<td>Most susceptible when slope orientation matches the orientation of geological strata. Susceptibility decreases as the two orientations part from each other</td>
</tr>
<tr>
<td>Slope Gradient</td>
<td>As the slope gradient increases, susceptibility also increases but at different levels for different geology</td>
</tr>
<tr>
<td>Relative Relief</td>
<td>As the relative relief increases, susceptibility increases but at different levels with different geology</td>
</tr>
<tr>
<td>Slope Shape</td>
<td>Slope shape is an important factor. Upper convex, lower concave slopes are most susceptible to landslides.</td>
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relationships between landslide susceptibility and the environment. The extracted knowledge is expressed a set of rules (Table 1).

The following environmental variables were derived using geographical information processing techniques based on the knowledge from the experts spatial data on: geology types, difference in orientation between slope and geological strata, difference in dip between slope and geological strata, slope gradient, slope height, and slope shape. These environmental data were then linked with the knowledge summarized in Table 1 using a fuzzy inference engine to derive spatial distribution of fuzzy membership values of landslide susceptibility (Fig. 3).

Evaluation of the case study

We validate this case study by examining the usefulness of the fuzzy membership values as a way of measuring landslide susceptibility. For this purpose 21 recently occurred landslides were located and the computed fuzzy membership value for susceptibility at each site was obtained from the derived fuzzy membership map. We assume that if the fuzzy membership is not a good indicator for landslide susceptibility, then the mean of fuzzy membership values at these 21 sites should not be statistically different from the mean fuzzy membership value of the entire study area. In other words, our null hypothesis is that the mean membership value at the 21 sites statistically is the same as that of the whole study area. Our alternative hypothesis is that the mean fuzzy membership value at the 21 landslide sites is significantly higher than the overall
average of membership in the study area. A student $t$-test was conducted to evaluate the null hypothesis (Burt & Barber, 1996). The critical $t$ value greater than which the null hypothesis will not hold is 2.85 (for 20 degree of freedom and 99.5% of confidence) and the computed $t$ value for the 21 landslide sites is 6.91, which is significantly larger than the critical $t$ value. Thus we conclude that the computed fuzzy membership values are good approximates to levels of susceptibility to landslides, and further suggest that the methodology can be used to map landslide susceptibility.

CONCLUSIONS

This paper presented an approach for mapping landslide susceptibility using GIS, expert knowledge and fuzzy logic. The fuzzy logic concept was used to represent landslide susceptibility as fuzzy membership values (different levels of susceptibility). GIS techniques, expert knowledge and fuzzy inference techniques (fuzzy inference engine) were used to compute the fuzzy membership value at every pixel across the landscape. A case study over a watershed in Kai Xian of Chong Qing shows that the computed membership is a good measure for landslide susceptibility. However, it must be pointed out that the sufficiency of the fuzzy membership in representing the susceptibility depends on the quality of knowledge and sufficiency of GIS/remote sensing techniques in characterizing the environmental conditions.

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REFERENCES