TESTING ON THE TIME-ROBUSTNESS OF A LANDSLIDE PREDICTION MODEL

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Abstract. A prediction model for identifying areas likely affected by future landslides are constructed based on the quantitative statistical relationships between the input spatial map data (termed “causal factor”) and the past landslides. The prediction model to be effective tool, the time-robustness of the model is an essential component. We test the time-robustness using the stability analysis of the model. In this contribution, a Fuzzy set theory procedure using algebraic sum operator is used for the construction of the prediction model. Rio Chincina in Colombia is selected as the study area.

The analytical procedures for the stability analysis are as follows:

Step 1. The occurrences of the past landslide were divided into two different time-periods. Group 1 consisted of the landslides occurred prior to or within a given year and Group 2 contained the remaining landslides, which occurred after the year.

Step 2. Using the landslide in Groups 1 and 2 separately, two prediction maps, Map-1 and Map-2, respectively, were obtained.

Step 3. To validate the prediction performance of the prediction map (Map-1) based on the landslides in Group 1, we compared the prediction results in Map-1 and the landslides in Group 2. The comparison produced statistics, termed “prediction rates” indicating the prediction power of Map-1. Similarly, we obtained the prediction rates for Map-2 using the landslides in Group 1.

Step 4. To assess the stability of Map-1 and Map-2, the “difference map (DIF-map)” was made and the corresponding “match rate” was also computed. Higher match rate means increasing similarity of Map-1 and Map-2 and hence increasing stability of the two maps.

Based on the results of this study, we concluded:

- The prediction power of the model is represented by the prediction rates computed in Step 3. A model to be a good prediction tool, the model should have a good prediction power.
- The stability of two prediction maps based on two time-periods assessed in Step 4 is also an essential component of a good prediction tool. In particular, if we were to use the prediction map for the landslide prevention plans or land use-planning study, then the stability study would provide pivotal information on the planning decision.
- The prediction model for Rio Chincina study area using the Fuzzy set theory procedure did have reasonably good prediction power but was not stable enough to be a good model. The model needs a further investigation to improve the performance of the prediction model. A prediction model to be effective, we need both the prediction power and the stability of the model.

1. INTRODUCTION

“When, Where and What scale” of landslides are important aspects in prediction. The research on the spatial map data (termed “causal factor”) integration technology becomes the current trend for the landslide hazard mapping ([1]-[4]). There are a number of researches for the landslide-prediction modeling, however the discussion on the “strategy for the practical utilization of the prediction models” as a pre-assessment tool is needed. Recently, the satellite remote sensing data as a causal factor are also applied to the slope stability evaluation [5]. From those current studies, several difficulties are pointed out as follows:

- Strategy of application of the several prediction models for optimizing the prediction results.
- Interpretation of prediction results for landslide prevention plans.

As a measure for those requirements, we have provided a pair-wise comparative strategy of the prediction models [6] as well as for the landslide-type analysis [7]. So, the subsequent subjects are:

- What is an influence of time-variant factor in the landslide prediction?
- How can we interpret the differences of prediction results affected by the time-variant factor?

Those are the important factors for the practical use of the prediction models.
Based on the above background, the following two purposes were identified in this study:

- To investigate the time-robustness of prediction models by dividing past-landslides into two groups, which had occurred “during two different times”.
- To provide a standardized interpretation for the landslide prevention plans, what is called the “stable hazardous” areas and “non-stable hazardous” areas from geomorphologist’s points of view”, based on the results of prediction models.

2. QUANTITATIVE PREDICTION MODEL

Among many prediction models for landslides([1]-[5]), in this study, a Fuzzy set theory procedure using the algebraic sum operator \( \sum \) was selected based on the previous comparative study. Figure 1 shows the framework of the prediction models based on the favourability function approaches [1]. For each model, computing a prediction value at each pixel produces a prediction map.

3. ANALYTICAL PROCEDURE

Figure 2 shows the analytical procedure provided in this study, which consists of 4 steps as follows:

**Step 1) Preparation of causual factors and the training data sets**

The Rio Chincina area near the Nevado del Ruiz volcano, which is located on the western slope of the central Andean mountain range (Cordillera Central) in Colombia, was selected as the study area. van Westen made an extensive study of the region and constructed the data set of the study area [3]. Through the sensitivity analysis of the causal factors in prediction [9], 7 kinds of thematic maps were selected as shown in Table 1. The elevation, relief, slope and aspect were calculated from the DEM (Digital Elevation Model). Each map consists of 777 x 559 pixels (a total of 434,343 pixels), and each pixel corresponds to a 12.5 x 12.5m area on the ground.

As for the landslide data sets, the past-landslides were divided into two groups, as those that had occurred “prior to 1960” and “after 1960 (during 1961-1988)”. Let’s say those two training groups; “PRE-1960 landslide data” and “POST-1960 landslide data”, respectively. Figure 3 shows these two groups. An attention should be paid that the spatial distribution of “PRE-1960 occurrences” and “POST-1960 occurrences” appears to be fairly different. Those landslide data sets in each study areas are significant for the comparative studies in relation to the time-robustness of prediction models.
Step 2) Making the prediction map

To investigate the influences of the time-variant factor in prediction, two prediction maps were produced by using the "PRE-1960 landslide data sets" and the "POST-1960 landslide data sets", respectively. Let's say these maps as "map-1 and map-2". In those maps, the pixels with the highest 10% estimated values among all pixels in the whole area are classified as the "hazardous area" of which the Digital Number (DN) value is assigned to "1". The other pixels are assigned to "0" as the "non-hazardous area".

Step 3) Making the difference map

To analyze prediction results with respect to an influence of time-variant factor as well as to the landslide types, the differences of "map-1 vs. map-2" are delineated on the difference map termed "DIF-map". The information of "stable hazardous" and "non-stable hazardous" on the DIF map and the effectiveness as the "supporting information" are mentioned in the section 4, as proposed by Chung, et al. [8].

Step 4) Evaluation of the performance of prediction results

To evaluate the performance of prediction models, two indicators of "success rate" and "prediction rate" are calculated. The success rate is used to evaluate the performance of the prediction model itself. While, the prediction rate is used to evaluate the prediction results for whole study area. The definition of these indicators and the calculated results are presented in the section 4.

4. CROSS-VALIDATION ON THE TIME-ROBUSTNESS IN PREDICTION

4.1 Performance of prediction models

As the quantitative indicators of the prediction results, the "success rate" and "prediction rate" are defined as follows:

(a) PRE-1960 landslide occurrences

(b) POST-1960 landslide occurrences (During 1961-1988)

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Table 1 Causal factors used in the Rio Chincina area, Colombia.

<table>
<thead>
<tr>
<th>Causal factors used in the Rio Chincina area, Colombia.</th>
<th>Lithological map</th>
<th>Elevation</th>
<th>Relief</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmapped area</td>
<td>Lake deposits</td>
<td>1200-1250</td>
<td>0 - 2</td>
</tr>
<tr>
<td>Genetically intrusive material</td>
<td>Lahar deposits</td>
<td>1250-1300</td>
<td>10 - 12</td>
</tr>
<tr>
<td>Schists</td>
<td>Gabros and diorite</td>
<td>1300-1350</td>
<td>12 - 14</td>
</tr>
<tr>
<td>Volcanic and metasomatolite</td>
<td>Pyroclastic flow deposits</td>
<td>1350-1400</td>
<td>14 - 16</td>
</tr>
<tr>
<td>Weathered debris flow material</td>
<td>Andesitic intrusive</td>
<td>1400-1450</td>
<td>16 - 18</td>
</tr>
<tr>
<td>Alluvial sediments</td>
<td>Tertiary sediments</td>
<td>1450-1500</td>
<td>18 - 20</td>
</tr>
<tr>
<td>Dispersed pyroclastic deposits</td>
<td>Flavomix deposits</td>
<td>1500-1550</td>
<td>20 - 25</td>
</tr>
<tr>
<td>Distance from valley head in meters</td>
<td>Distance from fault in meters</td>
<td>Slope</td>
<td>Aspect</td>
</tr>
<tr>
<td>0 - 25</td>
<td>0 - 25</td>
<td>North</td>
<td>Flat</td>
</tr>
<tr>
<td>25 - 50</td>
<td>25 - 50</td>
<td>North-East</td>
<td>Flat</td>
</tr>
<tr>
<td>50 - 75</td>
<td>50 - 75</td>
<td>East</td>
<td>Flat</td>
</tr>
<tr>
<td>75 - 100</td>
<td>75 - 100</td>
<td>South-East</td>
<td>Flat</td>
</tr>
<tr>
<td>100 -</td>
<td>100 -</td>
<td>South-West</td>
<td>Flat</td>
</tr>
<tr>
<td>40 - in degrees</td>
<td>in meters</td>
<td>West</td>
<td>Flat</td>
</tr>
<tr>
<td></td>
<td>in meters</td>
<td>North-West</td>
<td>Flat</td>
</tr>
</tbody>
</table>

Note 1) "xx-yy" means "more than or equal to xx and less than yy";
Note 2) "xx-yy" means more than xx.
Note 3) Elevation, relief, slope, and aspect were calculated from DEM (Digital Elevation Model)
pixels, the rate of correctly classifying the landslide pixels used as the training data of PRE-1960 landslide occurrences is indicated on the Y-axis as "success rate-1". For the pixels with highest 20%, 30%,...,90% of estimated value, the success rate-1 is repeatedly calculated. In the same way, the success rate-2 is also calculated as shown in Figure 4(c).

b) Prediction rate

To evaluate how well the prediction performed for whole study area, two prediction rates termed "prediction rate-1" and "prediction rate-2" are defined as:

- **Prediction rate-1**: The proportion of pixels correctly classified for "POST-1960" landslide occurrences in "the map-1".

- **Prediction rate-2**: The proportion of pixels correctly classified for "PRE-1960" landslide occurrences in "the map-2".

Figure 4(b) and Figure 4(d) correspond to the success rate-1 and the success rate-2, respectively.

From Figure 4(a) to Figure 4(d), the following points could be indicated:

- The curve of the prediction rate-2 illustrates fairly different from that of the prediction rate-1, which suggests that the landslide type of the PRE-1960 occurrences may be different from the POST-1960 occurrences. However, from the field investigation by the ITC team (van Wenten [3]), the landslide type of this study area is "almost same as the debris avalanches". Hence, to improve the prediction rates, the only "trigger-parts" of the debris avalanches should be identified for constructing the relationship with the causal factors used in the prediction model.

- The success rate-1 tends to be higher than the prediction rate-1. On the other hand, the success rate-2 is lower than the prediction rate-2. This is one of the difficulties to evaluate the prediction results, because of the bias on the time-variant factor for whole study area. So, let us proceed to further investigation of the differences on the "prediction patterns" and consider the issues on the interpretation of the complex predicted patterns in the next section.

4.2 Difference map(DIF map)

To analyze prediction results between map-1 and map-2, the “Difference maps (DIF-map)” are produced. The DIF map consists of four classes by crossing two maps as shown in Table 2. The descriptions on these cases are as follows:

- **Group-1**: The pixels identified as hazardous in both map-1 and map-2 are assigned the value of “3”. On the DIF map, these pixels are colored “Red”.

- **Group-2**: The pixels identified as hazardous in map-1, but as non-hazardous in map-2, are assigned the value of “2”. On the DIF map, these pixels are colored “Yellow”.

- **Group-3**: The pixels identified as non-hazardous in map-1, but as hazardous in map-2, are assigned the value of “1”. On the DIF map, these pixels are colored “Green”.

- **Group-4**: The pixels identified as non-hazardous in both map-1 and map-2 are assigned the value of “0”. On the DIF map, these pixels are colored “Blue”.

![Figure 4 Success rates and Prediction rates](image)
Figure 5 illustrates those groups on the DIF-map. Note that the group-2 and the group-3 on the DIF-maps affected by the PRE-1960 and the POST-1960 landslides, respectively. Another way to look at those predicted area is that the phenomena of some landslide occurrences at the two periods of time might be different. In practice, the predicted areas marked with circle in Figure 5 consist of the different lithological categories corresponding to the past-landslides as shown in Figure 3. To get such heuristic information, the cross-validation procedure shown in Figure 2 may be significant.

4.3 Matching rate

As a quantitative indicator on a DIF-map, the following "Matching rate" is defined as:

\[
\text{Matching rate} = \frac{\# \text{ of red pixels}}{\text{Total pixels} - \# \text{ of blue pixels}}
\]

(Eq.1)

If two maps match perfectly, then the matching rate = 1. If two maps do not match at all, then the matching rate = 0. Higher matching rate means similar results of the two maps for whole study area. In other words, the landslide types with respect to PRE-1960 and POST-1960 occurrences may be similar. As shown in Figure 5, the prediction patterns on the DIF-maps are fairly different for which the matching rate shows 45.3%. Those results corroborate with the difference of the success rates and prediction rates, as shown in Figure 4.

4.4 Final prediction maps and its interpretation

As for the interpretation on the DIF-map, the supporting information for the investigators is newly provided in Table 3. The pixels with the red color (Group-1) in the DIF-maps can be interpreted as having higher likelihood of future landslide occurrences. Also the geomorphologic setting of the studied rapid debris avalanches (the particular "landslide type" representing the most frequent mass-movement in the study area) might be similar for these pixels. From the viewpoint of a land use planner, those red areas can be termed as the "stable hazardous area", as shown in Table 3. On the other hand, the "non-stable hazardous area", which is covered by the yellow pixels (Group-2) and the green pixels (Group-3) in the DIF-map, means that we don’t have much information on these pixels concerning the studied landslide types.

5. CONCLUDING REMARKS

Based on the results of this study, we concluded:

• The prediction power of the model is represented by the prediction rates computed in Step 3. A model to be a good prediction tool, the model should have a good prediction power.

• The stability of two prediction maps based on “two time-periods” assessed in Step 4 is also an essential component of a good prediction tool. In particular, if we were to use the prediction map for the landslide prevention plans or land use-planning study, then the stability study would provide pivotal information on the planning decision.

• The prediction model for Rio Chincina study area using the Fuzzy set theory procedure did have reasonably good prediction power but was not stable enough to be a good model. To improve the prediction rate, the only “trigger-parts” of the debris avalanches in this study area should be identified for constructing the relationship with the causal factors in the model. A prediction model to be effective, we need both the prediction power and the stability of the model.

As a final product, the "stable hazardous" and “non-stable hazardous” assessment sub-areas are delineate on the DIF-map. The DIF-map and its interpretation are indeed useful as pieces of "heuristic supporting information", not only for evaluating the time-robustness of prediction models but also for analyzing the types of landslides that had occurred at the different period of time. The cross-validation strategy provided in this study supports to get the heuristic information for
evaluating the prediction results.

As for the subsequent subjects, the sensitivity-analysis on the influence of each causal factor for prediction should be investigated. For those experiments, the cross-validation procedure presented in Figure 2 should contribute as one of the strategies for the practical use of many types of quantitative prediction models.

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