# Quantitative Prediction Models for Landslide Hazard Assessment

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From 2D to 2.5D to 3D

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RGB model, perspective view

RGB model, overhead view

### Introduction

Spatial data analysis (SDA )research in the geosciences has concentrated mainly on mineral exploration. Today, application areas such as geological hazard assessment and environmental impact studies are coming to the attention of many scientists and institutions which are assigning greater priority to activities of direct socio-economic importance

Much research work has focused on the mechanics and physical processes of mass movement, but little effort has been made to identify areas likely to be affected by future landslides. Meanwhile, many geological, geomorphological and man-made structures, such as roads and land-use were identified as causal factors of landslides. Spatial databases containing such causal factors have been constructed and managed by geomorphologists using current

At the Spatial Data Analysis Laboratory of the Geological Survey of Canada, mathematical models have been developed for identifying the areas likely to be affected by future landslides and the corresponding computer systems were constructed based on GIS databases and tools.

Jointly, with several international research institutes, the prediction models have been successfully applied to study areas in seven countries: Canada, Japan, Italy, Peru, Colombia,

(iii) mathematical frameworks to make the reasoning transparent and consistent

In those models, special emphasis was placed on: (i) the direct input of experts' knowledge of the causal factors into the prediction models (ii) the validation procedures of the prediction results, and

# Theory

elevation contour

Stereo pair

Quantitative prediction models for landslide hazard are based on a spatial database consisting of several layers of digital maps representing the causal factors of the occurrence of landslides. Three mathematical frameworks used for the models are: ) probability theory:

ii) Zadeh's fuzzy set theory; and (iii) Demoster-Shafer evidential theory.

Corresponding to the three theories, the conditional probability function, the fuzzy membership function, or the belief function are used to represent a quantitative measure of future landslide hazard. In addition to the conditional probability function used within the probability framework, three other functions are introduced into the model; the likelihood ratio, the weights of evidence and the certainty factor function.

These functions representing the landslide hazard were termed "favourability functions" or "FF". The FF can be estimated in many different ways depending upon the availability of the nput data and upon the assumptions made in the processes of modeling and estimation

All models are based on two basic assumptions:

(i) that future landslides will occur under circumstances similar to the ones of past landslides in either the study area or in areas in which the experts have obtained their knowledge on the relationships between the casual factors and the occurrences of the

(ii) that the spatial data representing the causal factors contained in the GIS database can

# **Step 3 - Construction of Prediction Models**

This illustration is based on Bayesian Probabilistic Models

### Step 3.a Creation of unique conditions subareas

The data are combined by UNICON- a procedure that divides the study area into non-overlapping unique-conditions-subareas. It generates an image containing the unique-conditions-subarea identifiers and an ACSII table containing the identifier and the value of each of the input layers for that subarea.

### tep 3.b Computation of probability tables

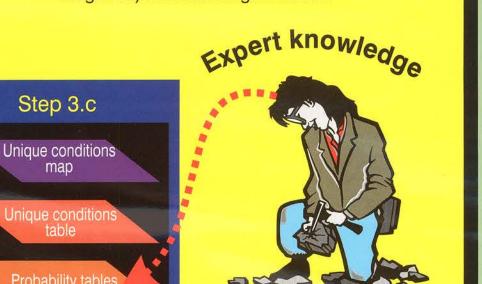
The probabilities obtained provide the bivariate conditional probabilities of the occurrences of the past landslides for each class of each input layer. When the distribution of the occurrences of past landslides is not available, experts' knowledge of the relationships between the landslides and the input layers becomes an essential component of the prediction model and is incorporated into the probability tables.

### Step 3.c Construction of prediction map

For each pixel, the joint conditional probability is estimated using the Bayesian probability rule.

### p 3.d Display of prediction result

Calculating the probabilities for each pixel usually generates a very large number of classes. We reduce the number of classes to 200, each containing 0.5% of the values. We find that it is very effective to produce a false color map with cool colors (blues and greens) for areas of lower hazard and hot colors (reds and magentas) for areas of higher hazard.



The 2D representation of the prediction map from Step 3 can be enhanced by draping it over the shaded relief image. This creates a 2.5-D representation. The correlation between the prediction map and the DEM can be further accentuated by presenting it as a 3-D image or a series of such images in motion picture form.

The 3-D prediction map was created using the trigger points of landslides occurring prior to 1978 and shows the scar of a landslide which occurred after 1978. In this example, the trigger point of the landslide is within an area predicted as "higher"

# Step 1 - Preprocessing

### Step 1.a Remote sensing analysis

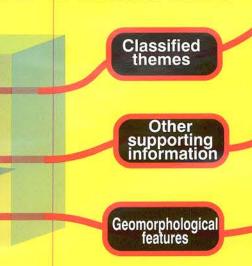
Construction of thematic classes related to landslides

Themes (causal factors) related to landslide hazard, such as forest coverage and/or land-use, which can be extracted from remotely sensed data (eg. LANDSAT TM or SPOT) are

Based on remotely sensed data and field observations, classification techniques are applied and thematic maps related to the occurrences of future landslides are constructed.

### Step 1.b DEM (Digital Elevation Model)

- The DEM is usually extracted from a stereo pair of high resolution remotely sensed data such as RADARSAT or SPOT and/or from digitized elevation contour maps.
- From the DEM, geomorphological features are extracted as causal factors. Commonly used factors are slope, aspect, elevation and geomorphological complexity.
- Drainage patterns can be extracted from the DEM.



### Step 2. GIS database of causal factors including:

Distribution of past landslides normally based on high resolution air-photos and field observations

hematic maps of causal factors: bedrock and surficial (or engineering) geology structural elements such as faults and lineaments man-made features (e.g. roads)

All thematic classes generated by Step 1.

# Conclusions

/isualization

**Pseudo-colour Table (PCT)** 

Intensity Hue Saturation (IHS) model

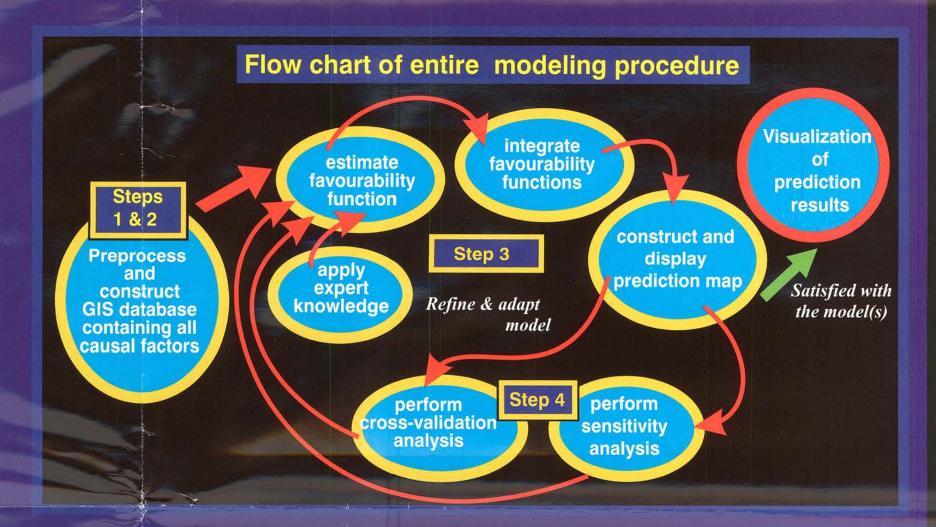
A shaded relief image can be obtained from the DEM.

model of prediction map

replaced by shaded relie

Saturation from RGB

replaced by constant (i.e. 175)



To identify areas with high landslide hazard, a mathematical framework based on favourability functions has been developed using a GIS database. The mathematical framework makes the reasoning transparent and consistent.

The prediction model developed permits the incorporation of experts' knowledge to improve the

To carry out the computation procedures, we have developed a software package based on PCI's EASI/PACE image processing system.

In addition, we present several cross-validation techniques to ensure the verification of our results. This is a fundamental requirement of any predictive model and mathematical modeling.

# Acknowledgments

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We are grateful to **David Garson** who helped us to produce the original version.

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## Step 4 - Cross validation

This illustration is based on Bayesian Probabilistic Models

Step 4. Cross validation of results

To validate the prediction results, we have developed several strategies:

i) Time-Robustness

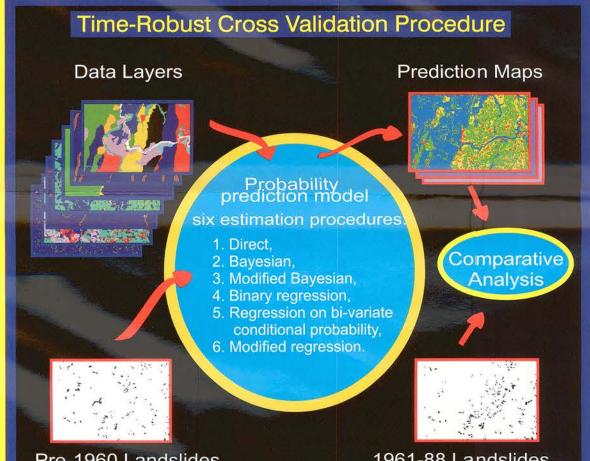
divide the data into two time periods, construct the prediction model based on the period more distant in time and then test the results using the data from the more recent period;

ii) Space-Robustness divide the study area into two separate sub-areas, construct the prediction model based on the data from one sub-

area and then test the results using the data from the other sub-area; (iii) Random Selection

divide the past landslides randomly into two groups, construct the prediction model based on one set of data and then test the results using the other data set;

(iv) Combination variations on the above three methods.



# SDI on CD

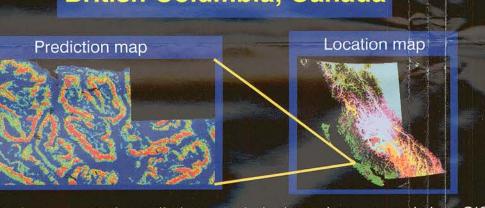
1961-88 Landslides Pre-1960 Landslides

# Rio Chincina, Colombia Selected Data Layers

The catchment basin of the Rio Chincina, on the western slope of the central Andean mountain range in Colombia, was used as a test for various landslide hazard zonation techniques.

This study compares methods in which data-driven approaches and knowledgedriven approaches are considered in isolation and in combination, allowing identification of the most successfu strategies for hazard prediction. We have validated the results by applying both timerobustness and space-robustness techniques.

# British Columbia, Canada



The study generated predictions entirely based on an existing GIS Island, BC, Canada. The year of study was assumed to be 1978. The prediction model was constructed using the database which contained pre-1978 information only. the results were successfully cross-validated using the distribution of debris flows which occurred between 1979 and 996 without any direct input from specialists.

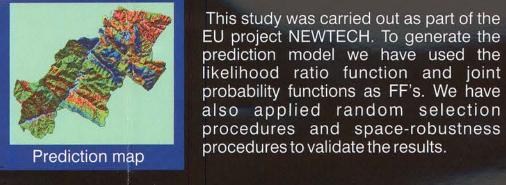
# Puno, Peru A very preliminary study was conducted in conjunction with PCI Inc in the Puno area, to the west of Lake Titicaca.

landslides for this exploratory work, the probability tables were constructed solely by expert knowledge. It would be interesting to compare the results we obtained using this knowledge driven model with those incorporating the locations of past landslides.

15.6Mb Tsitika.pix - 38.6Mb Snowlake.pix - 5.8Mb

Spatial Data Integration

This study combined pre-existing data and new data gathered from field observations to make an inventory of mass movements and to update the pre-existing data.



EU project NEWTECH. To generate the probability functions as FF's. We have also applied random selection procedures and space-robustness procedures to validate the results

Fanhões-Trancão, Portugal

In this study, landslides were divided into three types; shallow translational slides, translational mass movements and rotational slides, as expert knowledge showed that the causal factors differed for these three types. The differences were reflected in the final hazard susceptibility maps. This study represents a successfu integration of field observations and

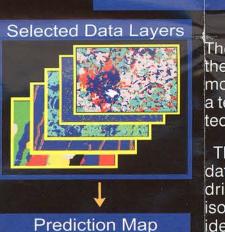
### **Selected References**

Chung, C.F. and Fabbri A.G. 1993 The representation of geoscience information for data integration, Nonrenewable Resources v. 2, n. 2, p. 122-139.

Chung, C.F. and Fabbri A.G. 1999 Prediction models for landslide hazard zonation using a fuzzy set approach in, Marchetti, M (ed.) Geomorphology and Environmental Impact Assessment. Balkema, Rotterdam, The Netherlands, in press

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# **Case Studies**



Prediction map

As we did not have the locations of past

### prediction model we have used the likelihood ratio function and joint

This CD contains programs developed at the GSC to construct prediction models by integrating and

analyzing geoscientific spatial data. The programs are for use with PCI EASI/PACE Image Analysis software. For detailed information about the SDI programs and their use, please consult the accompanying manual. For information on workshops and training, please contact Dr. Chang-Jo Chung at the Geological Survey of Canada.

order to run these programs, the user must have a valid, installed license for PCI's EASI/PACE

oftware, including the Software Toolbox. The program versions on this CD have been compiled under the following operating systems: : Microsoft Windows 3.1, Microsoft Windows 95, Sun Solaris 2.5,

Silicon Graphics Irix 5.3 and Silicon Graphics Irix 6.2. The Windows 3.1 version programs have been tested and verified to run with PCI EASI/PACE version 6.0 only. The Windows 95, Sun and Silicon Graphics versions have been tested and verified to run with PCI EASI/PACE version 6.1 only. Please consult the "readme.txt" file in the root directory of the CD for details about installation.

Disk space required: Programs: 40M Sample databases: Fabriano.pix - 15.6Mb Rio.pix -

spatial data analysis.

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