Transcript: Implementation of the landslide susceptibility model in GIS

Slide 2:

The following slides will focus on the implementation of the LS and LHA in a GIS environment and will cover:

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A short introduction of the modelling tool; a reminder of the model input data workflow; two examples of deriving and implementing fuzzy functions for continuous-based and categorical variables; and finally, the model diagrams of the resulting susceptibility and hazard maps.

I should mention these slides focus on rainfall-induced landslides only, however, the modelling process is similar for earthquake-triggered ones.

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To implement the LS & LHA[1] methodologies in a GIS environment we used the Model Builder tool in ArcMap application within ArcGIS.

Model Builder is an application used to create, edit, and manage models. Models are workflows that string together sequences of geoprocessing tools, feeding the output of one tool into another tool as input.

A simple application is illustrated in the right-hand side figure, where the model executes a clipping operation using a given reference area, adds a field, and then calculates a value for the new field. This operation is executed in a single workflow of one iteration. While Model Builder is very useful for constructing and executing simple workflows, it also provides advanced methods for extending ArcGIS functionality by allowing us to create and share our models as tools. Model Builder has the benefit of being easy to use for creating workflows containing a series of tools and it is compatible with other applications through scripting. For more information on how to use Model Builder, please check the ArcMap documentation available online or directly through the installed application.

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The data workflow used in Model Builder to create the LS&H maps uses a number of interdependent elements: first, the LS predisposing factor (or predictor) classes are assigned weights through the frequency ratio analysis and expert elicitation; these weights are used to define a rule set for each predictor, which is in effect a description of the relationship between landslide spatial likelihood and each predictor class. This qualitative description is then translated in quantitative terms through function parameters, which are finally used to define a fuzzy membership function. There are two basic model functions depending on the type of variable or data associated with each predictor: the upper one, A, for continuous data, is a general Gaussian-style function, where the denominator **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 cross-over (0.5). The

[1] LS(A) – Landslide Susceptibility (Assessment); LHA – Landslide Hazard Assessment

lower function, B, is used for categorical data, where $\boldsymbol{e_{ij,v}}$ is the value of predisposing factor **v** at location (**ij**), as in function A, and $\boldsymbol{w_{1,v}}$, $\boldsymbol{w_{2,v}}$, **…,** and $\boldsymbol{w_{m,v}}$ are the corresponding landslide susceptibilities when factor ***v*** takes the value of $\boldsymbol{c_{1,v}}$, $\boldsymbol{c_{2,v}}$, **…,** and $\boldsymbol{c_{m,v}}$. For more details on the fuzzy inference methodology, please consult the papers of Zhu et al., 2008, 2014 referenced at the end of this presentation.

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Taking an example for each type of variable, we start with the fuzzy function definition for continuous-based variables, such as slope gradient. The frequency ratio analysis allowed us to assign weights to each slope class and identify the type of function applicable for this predictor, which in this case, is a bell-shaped function. Therefore, the rule set definition for this predictor states that: susceptibility is at maximum for slopes btw 15° and 35°; as the slope decreases below 15° and increases above 35°, susceptibility decreases at different rates.

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Knowing the shape of the function and its rule set description, the parameters used for defining the fuzzy function can then be selected. In this case, the bell-shaped curve was split in two part, one for the left (akin to an s-shape) and one for the right (similar to a z-shaped curve), with different parameters for each side, as indicated here; for example, susceptibility is assumed to be at cross-over (S = 0.5) when slope gradient ≥ 45° (for the right side of curve) and ≤ 15° (for the left side of the curve). These numbers are then transferred in their corresponding fuzzy function and implemented in the Model Builder.

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Model Builder uses a model diagram to stream and visualise the entire process; the diagram in this slide is composed of the following elements: in blue, the **input parameter** (In this case, the slope map with values in degrees); in yellow, the **tools** (here, the raster calculator in which the fuzzy function is implemented sequentially); and finally, in green, intermediary or final **outputs**. This particular model diagram contains 14 processes embedded in a single iteration.

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The model tool and raster calculator dialog boxes on the left-hand side of the screen are used to create and execute the fuzzy function as an algebraic expression that will output a raster.

The results of this processing are illustrated by the fuzzy slope map here, where, after the application of the fuzzy membership function, each pixel takes a value from 0 to 1 reflecting the certainty degree of membership to landslide susceptibility, with 0 meaning not susceptible and 1 susceptible.

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In a second example, we used lithology to illustrate the implementation of the model for categorical variables. After the analysis of the frequency ratio results, the rule set definition states that the most susceptible geological groups are those with fractured/tectonised rocks and mixed lithologies, typically foliated, bedded and prone to weathering; the least susceptible is the Himal Group – Gneiss…

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…as indicated by the weights attributed to each class in the following function…

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…and instructed in the Model Builder diagram shown here. The resulting fuzzy lithology map shows each pixel associated with a lithology class taking the value indicated in the fuzzy membership function, which is the weight resulting from the frequency ratio and expert elicitation analyses.

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Lastly, Model Builder is also used to derive the LS and H maps. For LS, the Raster Calculator dialog box shows the aggregation function described in Step 5 of susceptibility assessment methodology, while the model diagram illustrates the use of 7 fuzzy predictor maps as input parameters. The modeling output is illustrated in the right-hand side figure.

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The model for LHA takes into account two input parameters: the extreme rainfall data and the formerly presented susceptibility map. These are multiplied as indicated in the raster calculator box on the left-hand side. The resulting hazard map for rainfall-induced landslides is depicted in the adjacent figure. For more information on the LS and HA methodologies, please revise the provided training material and references.