

Modeling Slope Stability Uncertainty: A Case Study at the H.J. Andrews Long-Term Ecological Research Site, Oregon

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Abstract.—A slope stability model employing Digital Elevation Model (DEM) data was used in a Geographic Information System (GIS) to predict landslide susceptibility in a large region of the H.J. Andrews Long-Term Ecological Research (LTER) site, located in the Western Cascades of Oregon. To assess the uncertainty of the final output, several different, but equally probable, versions of the input DEM were created through the addition of random, spatially autocorrelated noise (error) files. The DEMs were then processed to produce a family of slope stability maps from which the uncertainty effects of DEM elevation error upon the final susceptibility index could be assessed. The slope stability model itself involved the overlay of rock strengths with slope classes to establish landslide susceptibility indices. The inherent nature of error in DEMs used for modeling slope stability, coupled with much of the Pacific Northwest's commercial timber being located in mountainous terrain, makes this an intriguing problem to solve. The ability to understand the resultant uncertainty due to elevation error when applied to the model has the potential to facilitate improved natural resource management decisions in relation to harvesting and subsequent slope stability.

INTRODUCTION

The US Pacific Northwest contains some of the most productive temperate forests in the world and timber harvesting has been a primary land use in the area for over 100 years. Because most of the commercial timber is in mountainous terrain, such land use activities tend to decrease slope stability and therefore increase the rate of mass movements. One of the major concerns associated with an increase in such movement is the cumulative effects it has on the entire watershed—such as decreased water quality, loss of spawning habitat and organic matter, and debris jams that may break during peak flows, thereby scouring channels and destroying riparian vegetation. Thus, the ability to predict slope failure is a valuable resource in determining the impacts of forestry practices (Swanson *et al.* 1981).

While methods such as ground and aerial surveys can aid in locating existing and potential landslide areas, they also suffer several disadvantages. For example, in the Western Cascade range, ground surveys are difficult to carry out since accessibility is a major problem in a region characterized by steep slopes and very few roads (Swanson *et al.* 1981). This effectively reduces the amount of terrain that can be covered, which in turn may lead to an underestimation of landslide occurrences.

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Similarly, there can be difficulties in obtaining suitable aerial photography as a result of highly variable weather and climate conditions, seasonal considerations, and problems with photographic interpretation. Unfortunately, landslide inventories in the Western Cascades are best conducted during the winter rainy season and/or immediately after major storms when cloud cover is most prevalent. Also, landslides may be too small to be detected by aerial photography (Swanson and Lienkaemper 1985); or difficult to identify because they are either hidden under the forest canopy (McKean *et al.* 1991), masked in shadow by steep, narrow ridges and tall, dense forest vegetation (Skaugset 1992); or located on streamsides.

Alternatively, we can use Geographic Information Systems (GIS) to help model landslide susceptibility by applying the critical factors used in determining slope stability. While this approach permits large-scale evaluation of the landscape, it suffers from a lack of knowledge about the uncertainty of the final output resulting from errors occurring in the parameters used to model potential slope failure. The purpose of this paper is to describe how the application of a slope stability model based on DEM-derived values was enhanced to assess the uncertainty in predicting slope failure in the H.J. Andrews Long-Term Ecological Research (LTER) site. The model overlays slope gradient values with a generalized geology map to yield landslide susceptibility classes.

In order to apply the procedure to the slope stability model, the uncertainty assessment technique described in Hunter and Goodchild (1995) was employed in which different, but equally probable, versions of the source DEM were created through the addition of random, spatially autocorrelated elevation error files. The DEMs were then processed to produce a family of slope stability maps from which the effects of error in DEM elevations upon the final landslide susceptibility indices could be assessed. This paper is structured such that a description of the uncertainty model is presented next, followed by discussion of the application of the method to the slope stability model, and finishing with some closing remarks.

DISCUSSION OF THE UNCERTAINTY MODEL

Before discussing the uncertainty model used in this research, some explanatory remarks are required regarding the term 'uncertainty' itself. In general terms, it denotes a lack of sureness or definite knowledge about an outcome or result and, in the context of GIS, we suggest there is a clear distinction between 'error' and 'uncertainty', since the former implies that some degree of knowledge has been attained about differences between actual results or observations and the truth to which they pertain. On the other hand, 'uncertainty' conveys the fact that it is the lack of such knowledge which is responsible for our hesitancy in accepting those same results or observations without caution, and the term 'error' is often used when it would be more appropriate to use 'uncertainty'.

The uncertainty model that has been used here is a version of the one originally developed by Goodchild *et al.* (1992). In general terms it may be defined as a stochastic process capable of generating a population of distorted versions of the same reality, with each version being a sample from the same population. The traditional Gaussian model (where the mean of the population is an estimate of the true value and the standard deviation is a measure of the variation in observations) is one attempt at describing error, but it says nothing about local variation or the

processes by which it has accumulated. The model applied here is viewed as an advance on the simple Gaussian approach since it has the ability to show spatial variation in uncertainty, as well as the capacity to include in its realizations the probable effects of error propagation resulting from the various algorithms and processes that have been progressively applied to the data sets employed. By studying different versions of the final output, it is possible to see how differences in input affect the outcome, and in essence the purpose of the model could be described as an attempt to "find a Gaussian distribution for maps".

Elsewhere, in a paper by Hunter and Goodchild (in review), it has been argued that while it is possible to distort or perturb a data set according to an error description (such as the Root Mean Square Error (RMSE) value for a DEM) without any consideration of the likely spatial autocorrelation between point sample elevations, the process may be stochastic but inevitably lacks a certain 'truthfulness'—since adjacent elevations in a DEM which are otherwise similar in value can be severely distorted, thereby creating large pits and peaks which often do not intuitively occur in nature. This approach produces what are known as 'random maps'.

On the other hand, the assumption of complete spatial dependence between neighbouring points produces realizations of a DEM which appear 'truthful' but not stochastic, since elevations are unnaturally constrained to maintain their relative differences to each other and the introduction of a noise (or error) component has the effect of moving all DEM elevations up or down by a constant amount. Hence, there is a need to find the value in the domain $0 < \rho < 0.25$ (where ρ is a measure of spatial autocorrelation) which meets the requirements of being both stochastic and 'truthful'. The limit of 0.25 ensures stationarity (as discussed in Cliff and Ord, 1981, p. 147) when the Rook's case is used to test a cell's elevation against its four neighbours sharing a common edge.

Application of the uncertainty model consists of four stages (as described more fully in Hunter and Goodchild, 1995), with the first stage requiring the user to combine whatever data, processes and models are needed to generate the desired output—in other words, applying the GIS as would normally occur without any consideration of uncertainty. Secondly, the parameters necessary for the realization process are determined by reading system variables associated with the source DEM, such as the number of rows and columns in the data file, the cell size, and geo-referencing details. These will be required later when the elevation noise files are transformed to agree with the original DEM. An error estimate for the DEM will also need to be identified and this is usually a global value of the elevation error present, such as the RMSE as supplied by the DEM producer.

Whilst not a direct step in the realization procedure, the noise files to be employed are usually pre-computed and permanently stored in the system for future use. To date, it has been considered sufficient in the applications tested for about ten files to be held against each ρ value, with the default values being $\rho = 0.0, 0.05, 0.10, 0.15, 0.20, 0.21, 0.22, 0.23, 0.24, 0.245$, and 0.249 . As for the maximum value of ρ employed (0.249), experience has shown there is little to be gained from using values higher than this since the realization process becomes so constrained that there is no discernible difference between the realized maps and the original product.

In stage 3 of the methodology, it is expected that users will want to see a small number of trial realizations and the default values of ρ listed above are applied. A single realization for each value is obtained by first applying the parameters derived from stage 2 to geo-reference and transform the coordinates of the noise grid. Next, the error estimate is applied to map the noise values from a normal distribution of $N(0,1)$ to $N(0, RMSE)$. This adjusted noise file is added to the source data to produce a realization to which the commands employed to create the original GIS product are applied. The realized maps and the differences between the realizations and the original output can be displayed in map or graph form. Finally, in stage 4 of the process the user focuses on a specific ρ value in the range $0 < \rho < 0.25$, and applies a series of noise realizations to produce a set of distorted DEMs for which a family of outputs are created. These enable assessment of the uncertainty in the final product due to elevation error in the original DEM.

THE CASE STUDY AND DISCUSSION OF RESULTS

The H.J. Andrews Experimental Forest is located approximately 80 km east of Eugene, Oregon. Lookout Creek Basin (the test area) lies within the forest and drains nearly 6400 hectares in the Western Cascade Range. The overall site was established as an Experimental Forest in 1948 after which trial harvests took place and concomitant road construction occurred throughout the 1960s. Since 1970, site emphasis has shifted to ecosystem research and the levels of timber harvesting and road building have been reduced. The upper areas of Lookout Creek Basin are formed from lava flows ranging in age from 3 to 13 million years, while lower areas are underlain by older (14 to 25 million years BP), more weathered and hydrothermally altered clastic volcanic rocks (Swanson *et al.* unpublished).

Two types of landslides occur in the basin. The most common are relatively small (averaging approx. 2000 m³), shallow, rapid debris slides that take place on hillslopes during intense rainfall and rain-on-snow events. The second type are relatively large, deep-seated, slow-moving landslides (earthflows) that move seasonally at rates varying from centimeters to meters per year. An extensive inventory was conducted which documented over 140 debris slides since 1950 in the basin (Dyrness 1967, Swanson and Dyrness 1975, Swanson *et al.* 1981). Landslide susceptibility in the basin has been interpreted to be a function of both slope steepness and soil strength, as represented by the type of underlying bedrock (Dyrness 1967, Swanson and Dyrness 1975).

Table 1.—Derivation of landslide susceptibility classes.

Slope	Rock Strength	Susceptibility
0° < 10°	Weak	Moderate
	Moderate	Low
	Strong	Low
10° – 20°	Weak	High
	Moderate	Moderate
	Strong	Low
> 20°	Weak	High
	Moderate	High
	Strong	Low

In applying GIS to produce a landslide susceptibility index map, a DEM produced by the U.S. Geological Survey (USGS) was used which has a 30-m resolution and an elevation RMSE of 7 meters. The basin is located within a portion of the DEM measuring 309 x 426 cells and occupies some 69,952 cells or 53% of it (Figure 1). Elevation values in the basin vary from 411 meters above sea level in the south-west to 1615 meters in the south-east.

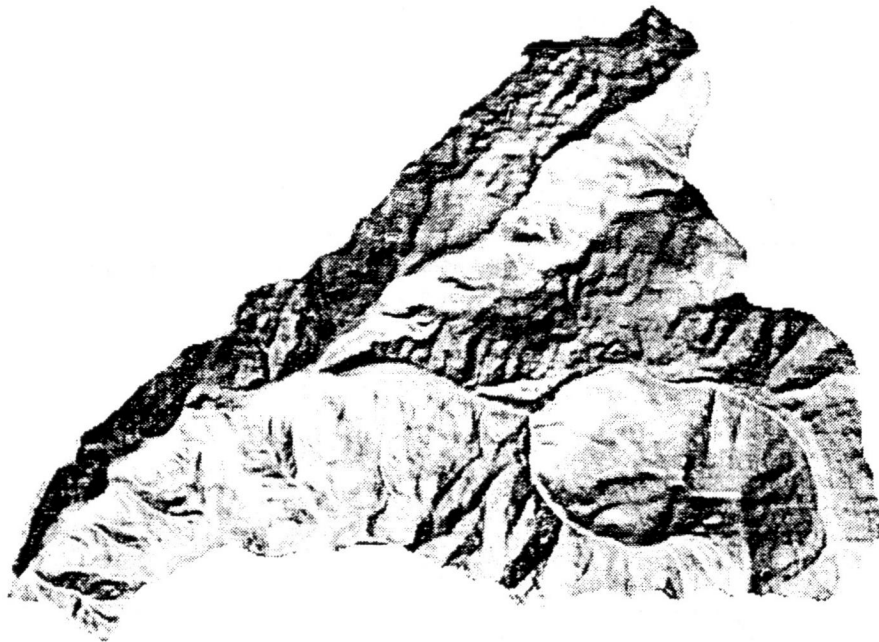
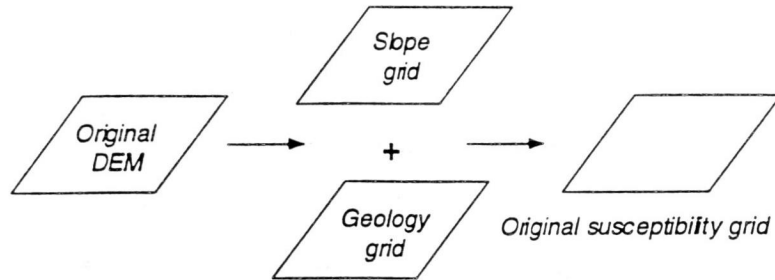


Figure 1.—Hill-shaded view of the DEM covering the Lower Creek Basin test area.

In deriving a landslide susceptibility index map, the slope gradient was first calculated from the DEM for each cell and then reclassified into 3 categories—greater than 20° representing 'high' slopes, 10° – 20° for 'moderate', and $< 10^\circ$ for 'low'. A geological map was also created with the same grid cell size and georeferencing as the DEM. Bedrock was classified by strength, with young lava flows and intrusive bodies being graded as 'strong'; intermediate age clastic rocks including well-welded ashflow units as 'moderate'; and old hydrothermally altered clastic rocks (18-25 million years BP) as 'weak'. Using the Arc GRID software throughout the research, the slope gradient and rock strength grids were combined to yield a matrix of nine values, which were then reclassified into three levels of landslide susceptibility—'high', 'moderate', and 'low' (see Table 1). This is the traditional manner in which GIS is used to solve the problem, as shown in Figure 2, and the combination of the DEM with the derived slope grid and geology grid produces a single susceptibility index grid.

Clearly, there is considerable potential here for applying the uncertainty model to assess the cumulative effect upon the final susceptibility index derived for each cell—given that it is a function of the DEM resolution and its estimated elevation error; the slope gradient calculation for each cell; and the method of reclassifying the slope values and rock types to derive the index. In the alternative approach which permits uncertainty to be assessed (Figure 2), elevation noise files with varying levels of spatial autocorrelation were applied to the original DEM to establish corresponding sets of slope files for the test site. The range of ten default values of ρ as described in the previous section was used. The realized slope files were then taken in turn with the geology file and used to derive ten susceptibility index grids.

Traditional Method



Proposed Method

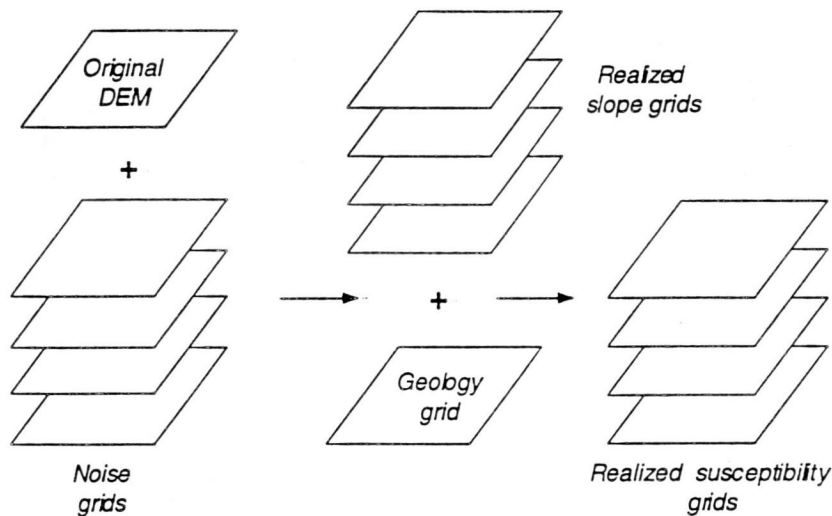


Figure 2.—Comparison of the traditional and proposed methods of calculating landslide susceptibility.

Each realized grid was subtracted from the original susceptibility grid to give a set of ten difference grids (one for each value of ρ), and two graphs were produced showing the mean and standard deviation of the differences respectively for each grid as plotted against ρ . Both graphs indicated that mean and standard deviation values increased slightly from $\rho = 0$ to $\rho = 0.21$, then dropped suddenly as ρ approached 0.25. The value of $\rho = 0.21$ was estimated as the point at which distortion of the DEM produced an output that was both stochastic and 'truthful', however this aspect of the uncertainty model remains subjective and is the subject of continuing research.

It should be noted here that the actual mean and standard deviation values for each realized grid have little significance since they apply to nominal data, even though the susceptibility indices of 'low', 'moderate' and 'high' were assigned numeric values to enable differencing. Nevertheless, the graphs still serve a useful purpose in identifying a ρ value which can be used for more detailed processing.

The procedure was then repeated by taking nine elevation error grids at the single value of $\rho = 0.21$ and creating nine realized susceptibility index grids. Since cells exhibiting high instability are of greatest interest, both the original

susceptibility index grid and the realized grids were reclassified so that cells with 'low' and 'moderate' indices were assigned a value of zero, while cells with a 'high' index were allocated a value of unity. The nine realized grids were added together to produce a single grid containing cumulative values denoting the number of times each cell scored a 'high' index on a scale of 0–9. While only nine realizations of the landslide susceptibility index grid were created due to time constraints in preparing this paper, it is considered that a much greater number (such as 100 realizations) would be used in practice to ensure the absence of any bias in the elevation error files used to perturb the DEM. However, the results obtained still enable useful comments to be made about the process.

To visualize the results, we took the original susceptibility map and overlaid all grid cells with a 'high' index (shaded black) on a set of site contours produced at 100 m interval (Figure 3, top). For comparison, we then took the cumulative index grid described previously and selected all cells that scored a 'high' index at least once (Figure 3, middle), together with those that achieved the maximum score of nine (Figure 3, bottom). These cells were also shaded black and overlaid on the same set of contours. Alternatively, we could choose cells on the basis of some probabilistic measure, for example, by selecting all cells which score a 'high' value at least seven out of nine times.

Table 2.—Relationship between 'high' cell scores and area of the site affected.

'High Score'	No. Cells	Area of Site
≥1	20,280	29%
≥2	16,843	24%
≥3	14,428	21%
≥4	12,549	18%
≥5	11,034	16%
≥6	9,651	14%
≥7	8,349	12%
≥8	6,872	10%
9	4,982	7%
Original Map	10,168	14%

In the original susceptibility map, the Boolean nature of the slope reclassification into categories with thresholds at 10° and 20° meant that a cell could receive only one index value. However, with the proposed method even though we maintain the same thresholds (and their values are not in question here), we can see how the susceptibility index for a cell behaves under variation of the input DEM. Obviously, cells lying on 'weak' or 'moderate' rock and having slope gradients close to either of the

thresholds are most likely to exhibit variation in their susceptibility index.

Table 2 compares the number of 'high' cells in the original susceptibility grid and the area of test site affected, with the number of cells achieving a 'high' score between 1–9 in the cumulative realized grid. From a user's perspective, selecting cells that achieve a 'high' score at least once is clearly the least conservative choice, given that the elevations of many of these cells will have been perturbed several standard deviations from the mean during the process. We believe this would lead to overestimation of the area affected. On the other hand, selecting only those cells that attain a 'high' score the maximum nine times is the most conservative approach and most likely underestimates the true area of the site susceptible to landslides. There is, however, no right or wrong answer to the selection problem, and the level of risk a user is prepared to accept in the end product becomes a matter of personal choice. In other words, users must learn to live with some degree of uncertainty in their outputs and make value judgements appropriate to individual project requirements.



Figure 3.—(Top) All cells in the original susceptibility index map scoring a 'high' value are shown in black overlaid on 100m contours. (Middle) All cells shown scoring at least one 'high' value in the realization process. (Bottom) All cells shown scoring the maximum nine 'high' value.

Finally, there is another error source which will affect the susceptibility index that has not been considered here—positional uncertainty in the geological boundaries used to derive rock strengths. At this stage, the uncertainty model described here is not capable of handling this issue since a solution requires perturbation of the original geological polygons in the horizontal plane. However, research is currently being conducted in this area and another paper elsewhere in this proceedings describes the experimental work that has been done to date to overcome the problem (see Hunter *et al.* 1996).

CONCLUSIONS

In this paper, the authors have described a process whereby a simple slope stability model used in identifying landslides with the aid of GIS, has been modified to assess the uncertainty in the final susceptibility map as a result of elevation error in the original DEM and its propagation effects upon the intermediate processes involved. Several different, but equally probable, versions of the input DEM were created through the addition of random, spatially autocorrelated noise (error) files, and then processed to produce a family of slope stability maps. Users may then choose the level of risk they are prepared to accept in the final output and identify cells susceptible to landslides that meet their criteria.

There are two benefits to the research. Firstly, the inclusion of uncertainty assessment in the process has the potential to facilitate improved natural resource management decisions in relation to harvesting and subsequent slope stability. And secondly, from a user's perspective the application of the uncertainty model to applications such as the one described here provides a new dimension to their ability to understand the meaning of their GIS products.

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BIOGRAPHICAL SKETCHES

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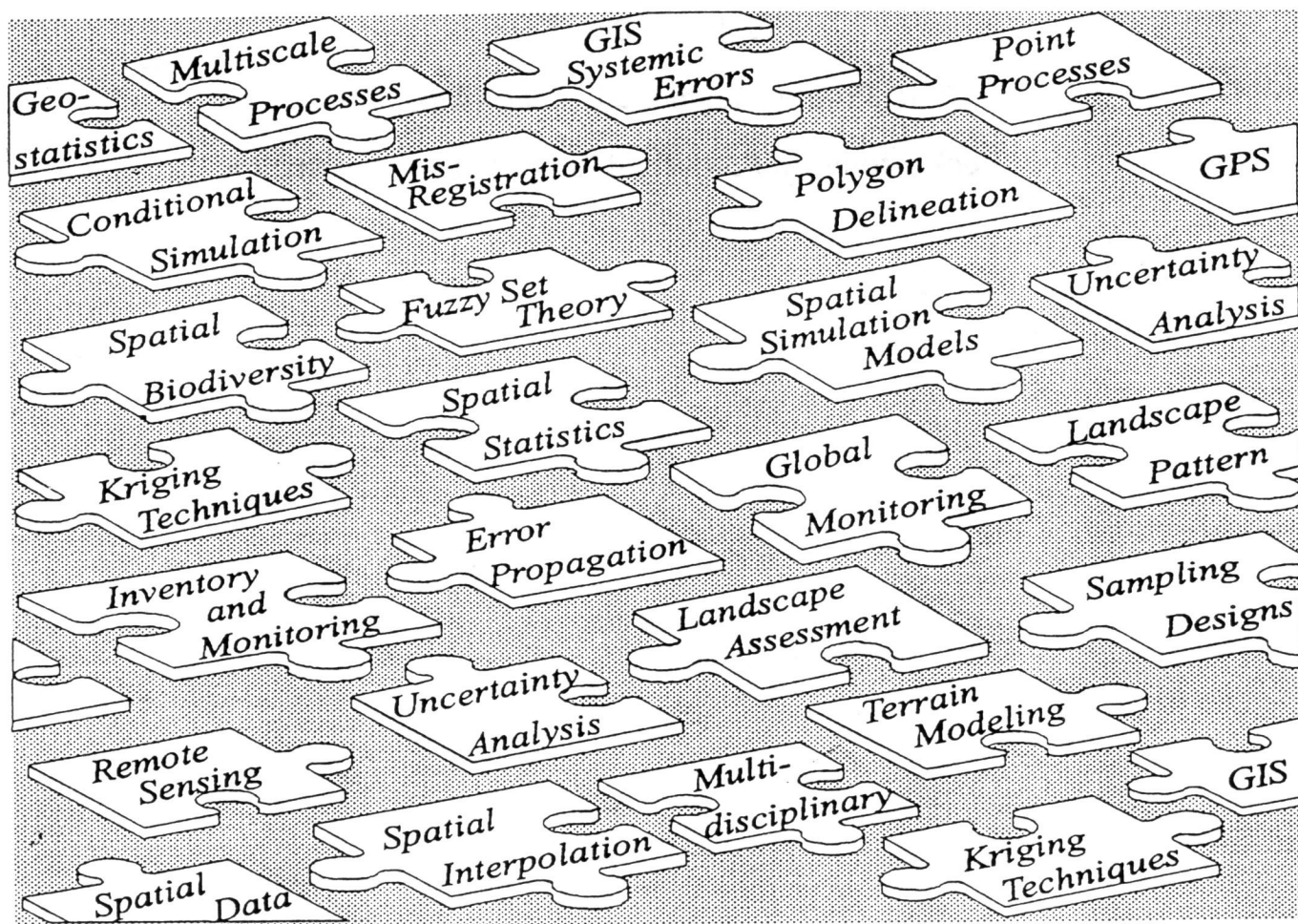
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