Novel pseudo-logistic spatial regression for the assessment of local/zonal susceptibility to landslides – case study in Central Vietnam (Bình Định Province)

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Abstract. The exploratory geographic modeling process aims to formalize spatial relationships through the combination of metrics or variables that explain spatial phenomena and integrate spatial dimensions. This study adopts a similarity-based induction process, evaluating multidimensional distances using derived variables or exploratory geographic modeling metrics.

The methodology integrates exploratory geographic modelling, multidimensional distance analysis, and probabilistic classification within a GIS map algebra environment. It incorporates logistic regression principles by embedding similarity-based distance structures into a Gaussian-informed probabilistic framework.

Environmental predictors derived from a 12.5 m digital elevation model—slope, Structural Hydric Erosion (EHE), Potential Structural Deposition (DEP), and Potential Structural Dryness (PSD)—are interpreted as expressions of geomorphological and hydrological dynamics. These variables are treated as interdependent signatures of landscape organization shaped by gravity, water flow, and topographic structure.

To address the absence of true absence data, ISODATA-based isocluster partitioning discretizes the multidimensional environmental space into regions of similarity. Multidimensional scaling (MDS) projects these distances into a two-dimensional Cartesian space, where proximity reflects environmental similarity and separation indicates occurrence versus non-occurrence conditions.

A Maximum Likelihood Classification framework assuming Gaussian distributions is adapted into a para-logistic structure using Mahalanobis distance metrics. The resulting pseudo-logistic model relates occurrence data with structured pseudo-absence locations.

Keywords: Exploratory geographic modelling, Multidimensional distances, Isoclusters and multidimensional scaling, Pseudo-logistic regression, Landslide susceptibility.

1 Introduction

1.1 On the nature of exploratory geographic modelling

The formalization of knowledge within Geographic Information Systems (GIS) can be achieved through statistically robust models that ensure interpretability and reproducibility within a map algebra framework. This process entails integrating empirical observations with domain-specific expertise into structured quantitative relationships (Sergio, J., & Arribas-Bel, D. 2020), enabling the consistent operationalization of spatial processes across heterogeneous datasets and supporting transparent and replicable geospatial modelling (Bivand Roger et al., 2013).

To ensure compatibility with map algebra, models must be decomposable into cell-by-cell matrix operations, whereby coefficients, predictors, and transformations are represented as raster layers and combined through algebraic expressions, in accordance with Tomlin (1990) and (Li & Heap, 2014).

Within this framework, exploratory geographic modelling is understood as a process of constructing and evaluating similarity-based distance structures that describe spatial phenomena. These structures enable the integration of multidimensional environmental information into a coherent analytical space, where spatial relationships are expressed through distance-based metrics. The formalization process therefore relies on the selection of spatially compatible statistical models, their translation into raster-based operations, reproducible workflows and methods, providing insightful and interpretable spatial scenarios (Goodchild et al., 2012).

Susceptibility modelling can be effectively implemented using logistic regression, in which a probabilistic dependent variable is expressed as a function of explanatory variables.

However, several methodological challenges arise, notably sampling bias and the absence of reliable absence data. The latter is commonly addressed through pseudo-absence random generation, which may introduce uncertainty if not properly constrained. Recent studies emphasize the importance of carefully designed pseudo-absence strategies to improve predictive performance and reduce bias (Barbet-Massin et al., 2020).

In this study, these limitations are addressed through a similarity-based framework that replaces conventional pseudo-absence generation with an environmentally structured representation of the multidimensional variable space. This approach leads to a pseudo-logistic formulation grounded in distance-based relationships, here conceptualized as a para-logistic structure, ensuring coherence with the similarity-based modelling strategy. **Fig. 1.** illustrates the overall workflow, highlighting the main structural blocks and their sequence.

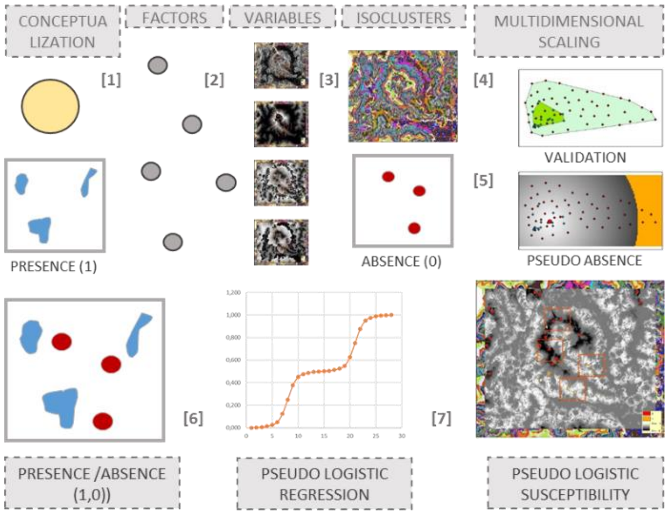

Fig. 1. General workflow structure.

1.2 Isoclusters and multidimensional scaling

Iso-clusters in GIS correspond to statistically derived groupings obtained through unsupervised classification, typically using the ISODATA algorithm. This method iteratively partitions multidimensional data into clusters that minimize within-group variance while maximizing between-group separability, adapting dynamically through cluster splitting and merging (Tou & Gonzalez, 1974).

Within the proposed framework, isoclusters constitute an approximated homogeneous partition of the multidimensional environmental space, forming the basis for constructing similarity-based distance structures. Increasing the number of isoclusters enhances the representation of data complexity, approximating a continuous relational space of environmental configurations and potential occurrences (Jensen, 2015).

The relational structure derived from isoclusters is projected into a two-dimensional space using Multidimensional Scaling (MDS), a multivariate technique that represents similarity or dissimilarity among cases through spatial configuration. By transforming pairwise distances into a geometric representation, MDS ensures that spatial proximity reflects similarity relationships within the multidimensional space.

Formally, MDS aims to find a configuration of points $x1, x2, ,xn$ in a low-dimensional space such that the distances $dij=\|xi-xj\|$ approximate the observed dissimilarities δij. This relationship is typically expressed through a stress function, such as Kruskal's (1964) stress formula:

$$Stress = \sqrt{\frac{\sum_{i<j}(d_{ij}-\delta_{ij})^2}{\sum_{i<j}\delta_{ij}^2}} \quad (1)$$

This optimization preserves the structure of the original distance matrix (Torgerson, 1952). In this context, the MDS space constitutes a reduced-dimensional representation of the similarity-based distance structure, where the separation between occurrence (presence–1) and non-occurrence conditions emerges geometrically.

1.3 Maximum likelihood classification and logistic function.

Maximum Likelihood Classification (MLC) is a supervised classification method based on Gaussian assumptions, assigning observations to classes using class-specific mean vectors and covariance matrices estimated from training data (Richards & Jia, 2006). Within the proposed framework, MLC operates on the MDS-derived space, where distances encode similarity relationships.

A key output of MLC is the confidence layer, which expresses classification certainty based on posterior probabilities, providing a continuous representation of class membership and associated uncertainty (Campbell & Wynne, 2011). Confidence is directly related to the reject fraction, which defines probabilistic thresholds for excluding low-confidence observations. These thresholds can be interpreted as partitions of distance to class centres, approximating a logistic response function.

Consequently, the combination and rescaling of confidence layers of presence (class 1) and environmentally structured pseudo-absence (class 0) defines a continuous susceptibility surface, that can be interpreted an integration two approximated logistic functions based in the confidence reject fraction intervals.

2 Methods, materials and results

2.1 Characterization of the phenomenon under study – Landslides

For the development of this study, and with the objective of establishing an operational experimental framework, landslide susceptibility modelling was selected as the target application. The data used were obtained from fieldwork and mapping in Google Earth, carried out during an Erasmus+ internship at Quy Nhon University in January–February 2020. The study area is located in Bình Định Province (Central Vietnam), comprising four communes within Hoài Ân District (An Hữu, An Nghĩa, Đăk Mang, and Bok Tới), with a total area of approximately 369 km². The analysis was restricted to a representative subregion of about 100 km², located between the Kim Sơn and Đăk Mang rivers.

The classification of slope movements follows the system proposed by Varnes and updated by Hungr et al. (2014), which organizes slope instability types according to movement mechanisms and material characteristics, enabling the identification of conditioning factors and their relative contribution to different processes. Four principal conditioning factors were defined to represent the dominant geomorphological and hydrological controls governing landslide occurrence:

Factor 1 – Slope gradient (stability). Represents terrain inclination and is a primary control on slope stability. Increased slope angles enhance the tangential component of gravitational forces, raising the likelihood of mass movements such as slides and falls;

Factor 2 – Hydrological conditions (water influence). Represents the role of water in reducing material strength through pore pressure increase and reduction of cohesion and friction. It includes infiltration, saturation, and surface runoff processes;

Factor 3 – Morphology and topographic position (overburden effects). Integrates slope position (summit, mid-slope, footslope) and geomorphological form (convex, concave, planar), influencing material accumulation, flow convergence, and stress redistribution;

Factor 4 – Precipitation infiltration and regime. Represents precipitation characteristics and infiltration potential, conditioned by terrain structure, vegetation cover, and hydrological density patterns.

This factors were quantified through expert judgment. A score ranging from 1 (very low relevance) to 20 (very high relevance) was assigned to each factor across 32 landslide types.

Table 1. Extract of Varnes landslide types expert evaluation according selected factors.

CODE	Landslide type	Factor 1	Factor 2	Factor 3	Factor 4
4	Rock flexural topple	15	7	4	1
11	Clay/silt rotational slide	13	15	10	14
14	Clay/silt compound slide	12	13	13	14
23	Mud flow	4	6	14	16
26	Earthflow	10	8	17	16
30	Soil slope deformation	5	17	7	3

This procedure enabled the construction of a factor–movement relationship matrix, used in the generation of multidimensional scaling (MDS) representation in **Fig. 2.** **Fig. 3.** shows **a** spline interpolation of evaluation factors in the multidimensional space.

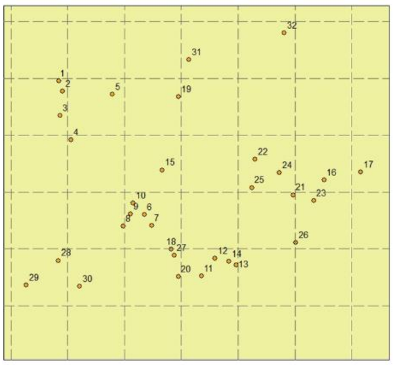

Fig. 2. Landslide types in a multidimensional space.

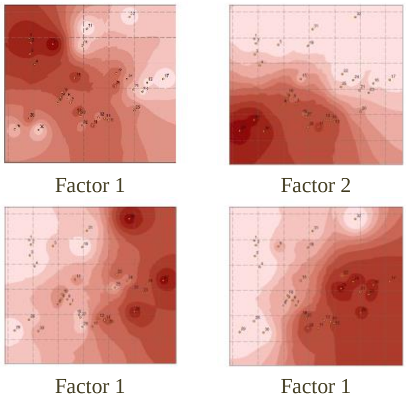

Fig. 3. Spline interpolation of evaluation factors in a multidimensional space (values from 1 to 20, in color intensity).

2.2 Modelling the phenomena – selecting / creating variables

Considering the target phenomenon—landslides, encoded as presence (1), a set of spatial predictor variables were defined to support exploratory geographic modelling and enable the creation of a multidimensional scaling space describing the similarity distances between the types of landslide. The variables are derived with spatial analysis in a GIS environment, including focal and global measures in raster-based operations on a 12.5 m digital elevation model (DEM), exploiting its matricial structure. Given that several variables also correspond to basin-scale metrics, the study area include the full watershed associated with each cell. This approach ensures hydrological consistency in the derived measures. The variables are:

Slope (stability – slope gradient) - Represents terrain inclination and is a primary control on slope stability. Steeper slopes increase the tangential component of gravitational forces, enhancing the probability of mass movements.

Structural hydric erosion (EHE) - An index designed to capture gravitational and frictional controls, computed through map algebra operations. It expresses the cumulative contribution of drainage cell slopes for each location, combining maximum concentrated accumulation based on the D8 model (Jenson and Domingue, 1988) with diffuse accumulation derived from an inverted DEM approach (Neves et al., 2011).

Potential structural deposition (DEP) - A normalized metric estimating material deposition associated with surface runoff, based on the relationship between transport potential and reductions in flow velocity (Neves et al., 2020).

Potential structural dryness (PSD) - An index relating upstream contributing area to relative elevation above drainage channels (HFD – height from drainage) and the natural logarithm of absolute terrain elevation. The formulation was originally developed by Nuno de Sousa Neves (Príncipe et al., 2022).

All variables were standardized through zonal minimum and maximum and are illustrated in **Fig. 3.** and **Fig. 4.**

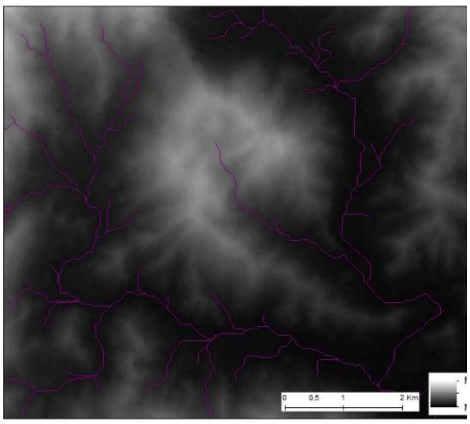

Fig. 4. Digital terrain model (DEM) (values from black – minimum to white (maximum).

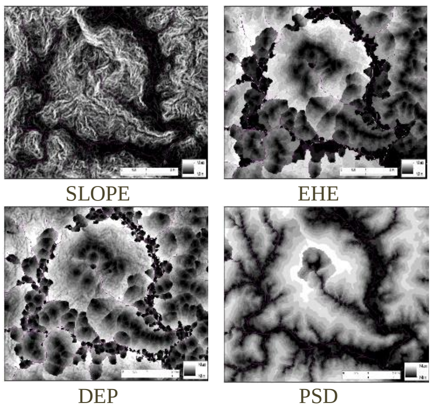

Fig. 5. Exploratory spatial variables (values from black – minimum to white - maximum).

2.3 Isoclusters in the study area

Considering a given phenomenon—here, landslides, the set of spatial exploratory variables created will constitute the multidimensional metaphorical space describing the environmental conditions associated with the process under analysis.

As each set of isoclusters to be created is an approximated homogeneous partition of the multidimensional space of data, increasingly higher number of isoclusters tend to better represent the complexity of the phenomena and approximate the creation of a metaphorical space of relations / proximity is formally equivalent to an expression of similarity or proximity between the possible cases or occurrences and the comprehensive space of homogeneous areas.

Given the combinatorial complexity inherent to such spaces, an approximation of the domain of possible conditions is achieved through the generation of a sufficiently large number of iso-clusters, derived using the ISODATA algorithm.

These clusters represent multidimensional homogeneous areas / features in the predictor space and provide a discretized yet representative sampling of the multidimensional variability, enabling a structured exploration of the relationships between variables and observed occurrences.

For this study were created 50 isoclusters, that constitute the partitions of the multidimensional space in terms of homogeneous areas. **Fig. 6.** Illustrates the standardized variables used in the creation of isoclusters in **Fig. 7.**

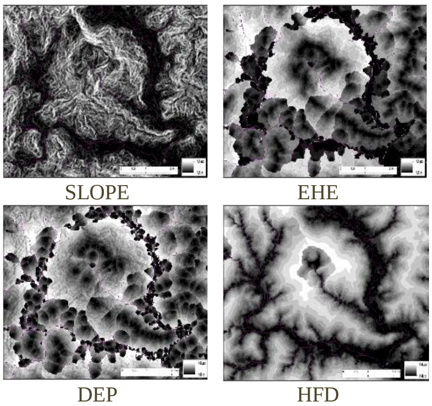

Fig. 6. Exploratory spatial variables (values from black – minimum, to white - maximum).

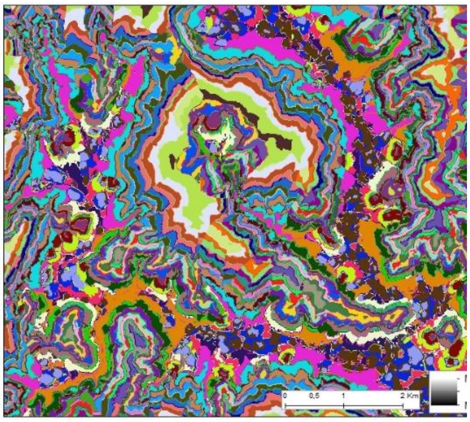

Fig. 7. 50 Isoclusters of the study area (random discrete colors).

2.4 Multidimensional scaling of isoclusters – Evaluation and generation of pseudo-absences

To facilitate interpretation, both the iso-clusters and the observed presence cases are projected into a two-dimensional Cartesian space using Multidimensional Scaling (MDS). This transformation creates a parallel representation of the original multidimensional structure, preserving, as far as possible, the pairwise dissimilarities among observations (Kruskal, 1964). Presence cases are characterized by zonal statistics derived from the predictor variables and are integrated into the same ordination space as the iso-clusters, in **Fig. 8.**, allowing a simultaneous representation of empirical occurrences and the broader universe of potential environmental configurations.

A significant concentration of presence cases in a limited area of the multidimensional scaling space, shown in **Fig. 9.**, indicates reduced variability in the associated predictor values, suggesting that the selected variables effectively capture the defining conditions of the phenomenon.

Under these circumstances, the two-dimensional representation can be interpreted as an approximation of the original multidimensional relationships, where Euclidean distances provide a meaningful proxy for similarity and may be related to the probability or susceptibility of occurrence. Furthermore, concentration of presence cases within the dispersion of iso-clusters, means that variables were well selected and that the general model is robust.

The iso-clusters located at greater distances from this concentration of presences can be interpreted as representing environmental conditions with lower likelihood or susceptibility for the occurrence of the phenomenon.

Based on this assumption, the iso-cluster positioned at the maximum distance from the centroid of presence cases—or alternatively, iso-clusters falling within a defined range of high distances—can be systematically selected to represent absence conditions (0) (Barbet-Massin et al., 2020). **Fig. 10.** shows the euclidean distance to the centroid of landslide areas and **Fig. 11.** shows the definition of a threshold for selecting pseudo-absence cases.

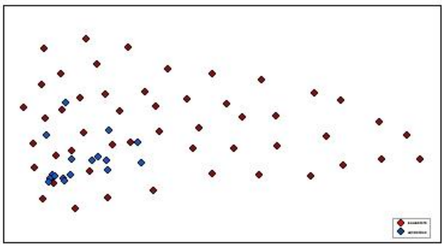

Fig. 8. Landslide areas (centroid) and Iso-clusters in a MDS Cartesian space.

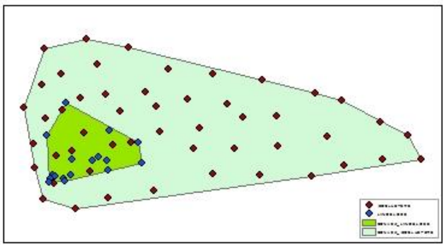

Fig. 9. Convex hull of Landslide areas (centroid) and Isoclusters in a MDS Cartesian space.

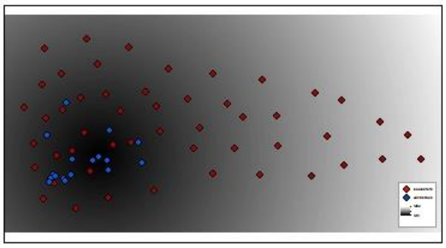

Fig. 10. Distance to landslide areas (centroid) in a MDS Cartesian space.

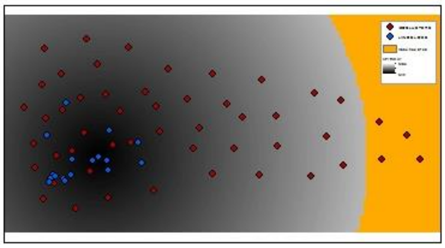

Fig. 11. Absence area as an interval of distance to Landslide areas (centroid) in a MDS Cartesian space.

This approach provides a formally consistent and data-driven criterion for generating absence samples in situations where true absence data are unavailable, supporting more robust modelling frameworks while maintaining coherence with the structure of the multidimensional space.

The use of terms such as “para-logistic” or “pseudo-logistic” implies a distinction from classical logistic regression, particularly regarding the mathematical form of the curve or the classification thresholds employed. From an etymological perspective, the term “para-logistic” suggests a closer approximation to the logistic function, whereas “pseudo-logistic” denotes a more substantial transformation in its mathematical expression, retaining structural similarities that justify their conceptual association with the traditional logistic function. In this context, an equivalence is proposed between confidence parameters from maximum likelihood classification reject fractions (0.000, 0.005, 0.010, 0.025, 0.050, 0.100, 0.250, 0.500, 0.750, 0.900, 0.950, 0.975, 0.990, 0.995, 1.000) and a functional approximation to a logistic-type distribution.

Let $x \in R^p$ be a feature vector. A distance to the class centroid μ_k can be defined using the Mahalanobis distance:

$$D_k(x) = \sqrt{(x + \mu_k)^T \Sigma - 1(x - \mu_k)} \tag{2}$$

where Σ is the covariance matrix. Based on this distance, a likelihood function for class k can be defined as:

$$L_k(x) = e^{(-\frac{1}{2}D_k(x)^2)} \tag{3}$$

Normalizing these likelihoods yields a confidence measure:

$$P(k|x) = \frac{L_k(x)}{\sum_j L_j(x)} \tag{4}$$

This formulation exhibits a structure analogous to the generalized logistic function (*softmax*), thereby establishing a conceptual bridge between distance-based methods and logistic regression (Bishop, 2006).

The classification process assumes the presence of two classes (1 and 0), with explanatory variables acting as discriminative factors. The generation of a binary classification, along with associated confidence values, can be interpreted as a continuous transformation, as shown in **Fig. 12.**, over the interval [0,1]. This transformation may be modeled using a para-logistic function defined as:

$$f_k(x) = \frac{1}{1+e^{\alpha_k(D_k(x)-\tau_k)}} \tag{5}$$

where α_k controls the slope of the curve and τ_k represents a class-specific threshold.

The transition between classes can thus be obtained as the result of map algebra operations applied to confidence values. The combination of two para-logistic curves, one associated with class 1 and the other with class 0, leads to the definition of a pseudo-logistic curve as shown in **Fig. 13.,** with spatial implementation in **Fig. 14.**

. This can be expressed as:

$$P(1|x) = \frac{f_1(x)}{f_1(x)+f_0(x)} \tag{6}$$

or, equivalently, as a logistic-type function based on the difference between distances:

$$P(1|x)\,\frac{1}{1+e^{\beta(D_1(x)-D_0(x))}} \tag{7}$$

where β is a scaling parameter.

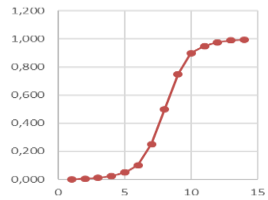

Fig. 12. Representation of Para-logístic regression.

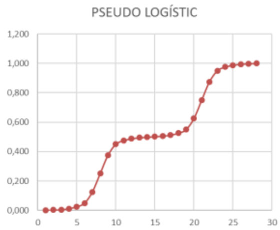

Fig. 13. Representation of Pseudo-logístic regression.

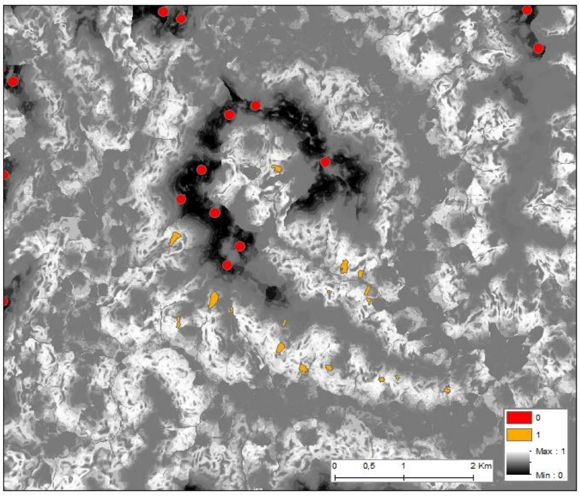

Fig. 14. Pseudo-logistic regression with presence and absence data (values from black – 0, to white - 1).

3 Conclusions

This study presents a conceptual and methodological advancement in landslide susceptibility modelling through the development of a pseudo-logistic spatial regression framework grounded in exploratory geographic modelling and multidimensional similarity structures. The proposed approach reframes susceptibility assessment as a relational process in which environmental conditions, spatial structure, and uncertainty are jointly represented within a continuous analytical space.

A key contribution lies in the treatment of the absence problem. By combining ISODATA-based isocluster segmentation with Multidimensional Scaling (MDS), the study introduces a structured mechanism to approximate absence conditions through distances in feature space. This reduces reliance on arbitrary pseudo-absence selection by exploiting the intrinsic organization of environmental variability.

The reformulation of Maximum Likelihood Classification into a para-logistic and pseudo-logistic structure extends the interpretability of probabilistic outputs into a continuous susceptibility surface. In this formulation, pseudo-logistic regression provides a coherent framework to integrate presence data with environmentally structured pseudo-absence spaces, combining geometric interpretability with probabilistic meaning under conditions of absence uncertainty. At an epistemological level, the framework suggests that environmental modelling benefits from approaches that unify statistical inference with multidimensional spatial representation. Susceptibility, whether ecological or geomorphological, emerges as a gradient of similarity within a structured multidimensional space of environmental relations.

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