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Landslide hotspot identification by instance-based learning: A comparison of k-nearest neighbour and the entropy-based distance algorithm (Kstar)

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ABSTRACT

Instance-based learning remains comparatively under-examined in landslide susceptibility mapping, including applications in which upper susceptibility classes are interpreted as landslide hotspots for spatial prioritisation. This paper compares two algorithms from that family, k-nearest neighbour (kNN) and KStar, in the Huoi Reng catchment of central Vietnam under a controlled design. The susceptibility database combined a landslide inventory interpreted from Google Earth historical imagery with sixteen conditioning factors derived from SRTM topography, 1:50,000 geological and structural mapping, Sentinel-2 imagery, JAXA land-cover data, and CMORPH rainfall. All layers were aligned to a common 10 m grid, and a balanced cell-based modelling table was constructed from 8,130 mapped landslide cells and an equal number of non-landslide cells. Both algorithms were trained and tested using the same 66%/34% partition. Continuous 0-1 susceptibility surfaces were treated as the principal outputs, whereas a shared four-class scheme was used only to compare the derived hotspot footprint of the upper susceptibility classes. kNN shows stronger threshold-dependent performance on the testing subset, with higher accuracy (90.21%), Kappa (0.805), weighted recall (0.902), weighted F1-score (0.902), and positive-class precision (0.861). KStar, by contrast, achieves markedly higher ROC AUC (0.983 versus 0.903) and higher positive-class recall (0.979 versus 0.955), indicating lower omission of mapped landslide cells but at the cost of lower positive-class precision (0.835 versus 0.861). Under common class thresholds, kNN assigns 52.44% of the catchment to the High and Very high classes and contains 86.98% of mapped landslide cells, whereas KStar restricts those classes to 34.43% of the catchment while still containing 80.38% of mapped landslide cells. Supplementary factor-concentration analysis indicates that the mapped inventory is enriched in the 100-500 m elevation belt, slopes above 30°, east to south-east aspects, high terrain ruggedness and wetness, negative mass-balance conditions, shale and quartz-sericite schist, GeoEngineering 1, impermeable hydrogeological settings, Weathering 1, short fault-buffer distances, the 5,000-5,300 mm rainfall belt, high BSI, and dense-forest terrain occupancy. Overall, the comparison shows that similarity formulation materially affects susceptibility ranking, omission-commission trade-offs, and the mapped footprint of upper susceptibility classes that may subsequently be interpreted as hotspot zones.

Keywords: *landslide hotspot identification; landslide susceptibility mapping; instance-based learning; k-nearest neighbour; KStar; model comparison*

1. Introduction

Landslide susceptibility mapping expresses the relative spatial propensity for slope failure under a given combination of terrain, lithological, hydrological, and land-surface conditions. In the present paper, hotspot identification is used only in the applied cartographic sense of delineating the upper susceptibility classes from continuous model outputs. It does not

denote a separate probabilistic construct. Hazard would additionally require temporal probability, and risk would further require exposure and vulnerability. The modelling target therefore remains landslide susceptibility, while hotspot mapping is treated as a downstream interpretation of the upper classes (Reichenbach et al., 2018).

Comparative studies in landslide modelling are now dominated by random forests, boosting frameworks, support vector machines, and neural networks (Merghadi et al., 2020; Reichenbach et al., 2018). Comparisons within the instance-based learning family remain much less common, even though lazy classifiers are theoretically attractive where environmental controls operate through locally structured combinations of slope, lithology, weathering, drainage, and land cover rather than through a single smooth global rule (Aha et al., 1991). For steep tropical catchments, that premise is plausible because topography, materials, and rainfall forcing vary substantially over short distances.

k-nearest neighbour is the canonical example of this family. Its appeal lies in its transparency and low modelling overhead, but its behaviour depends strongly on neighbourhood definition and distance metric (Cover & Hart, 1967). KStar belongs to the same family yet replaces direct geometric proximity with an entropy-based distance that expresses similarity through transformation probability rather than simple Euclidean closeness (Cleary & Trigg, 1995). In susceptibility mapping, that distinction can alter both continuous ranking and, where upper classes are extracted for applied interpretation, the mapped hotspot footprint under a common class scheme.

The present paper is a model-assessment study rather than a proposal of a new susceptibility framework. Its contribution lies in isolating how two instance-based formulations of similarity behave when data preparation, cell-based sampling design, train-test partition, and cartographic thresholds are held constant. The specific objectives are to: (i) compile a multi-source susceptibility database for the Huoi Reng catchment; (ii) compare kNN and KStar under the same validation design; (iii) evaluate both continuous and classified outputs; and (iv) interpret the observed model differences in the context of the sixteen conditioning factors used to represent terrain, materials, hydro-climate, and land-surface conditions. In that sense, hotspot identification is treated as an application of the upper susceptibility classes rather than as the primary modelling target.

2. Study area and data

2.1 Study area and landslide inventory

The Huoi Reng catchment, located in Lam Thuy commune, Quang Tri Province, central Vietnam, encompasses a mapped area of approximately 143.78 km² based on a 10 m resolution analysis grid. Geographically, the watershed extends between 17°40'-17°55' N latitude and 105°50'-106°05' E longitude, corresponding to an overall area of about 150 km².

Topographically, elevation ranges from 45.78 m to 1,252.44 m above sea level, reflecting a highly heterogeneous relief. The landscape is characterized by rugged mountainous terrain, strong dissection, steep hillslopes, and narrow valley floors. These geomorphological conditions promote rapid hydrological response, facilitating both surface runoff concentration and localized soil saturation during high-intensity rainfall events, thereby increasing susceptibility to slope instability.

The landslide inventory was interpreted from Google Earth historical imagery covering 2007-2024 and then rasterised to the common analysis grid. The mapped distribution is spatially structured rather than even across the catchment. Landslides cluster most strongly in the western

and north-western sectors and along several central-western slope corridors, whereas the eastern side is comparatively less affected. This pattern is consistent with a compound control by terrain dissection, adverse material conditions, and the main rainfall gradient represented in the predictor set.

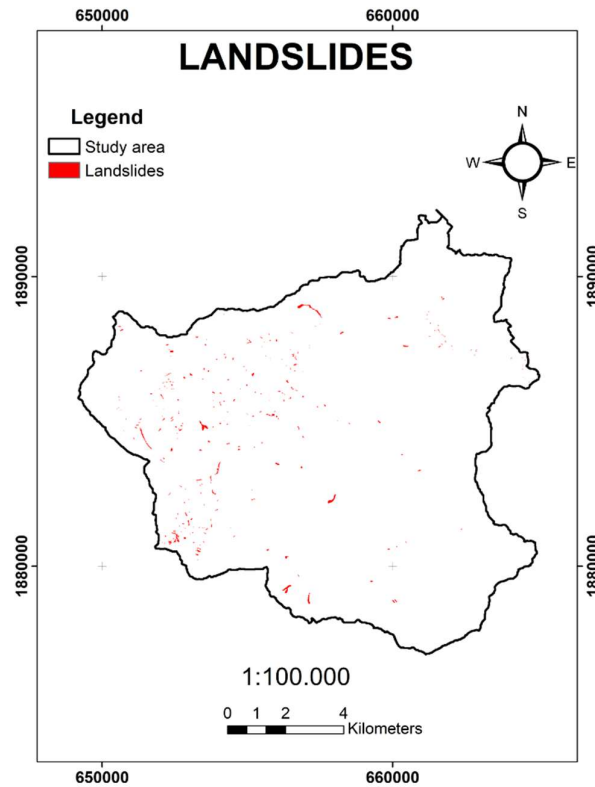


Figure 1. Mapped landslide inventory used for susceptibility modelling in the Huoi Reng catchment.

2.2 Source data and preprocessing

The susceptibility database was assembled from multiple geospatial sources. Topographic derivatives were extracted from the SRTM digital elevation model; geological and structural information came from 1:50,000 mapping and associated fault and lineament layers; spectral variables were derived from Sentinel-2 imagery; land-cover information was obtained from the JAXA product for Vietnam; and rainfall was represented using CMORPH data from NOAA. Before cell-wise extraction, all layers were projected to a common coordinate reference system, resampled where necessary, and aligned to the same 10 m grid so that each observation contained a consistent predictor vector.

Table 1 summarises the source datasets used to assemble the susceptibility database.

Table 1. Source data used to assemble the landslide susceptibility database.

Group	Input data	Source	Format
Inventory	Landslide inventory	Google Earth historical imagery (2007-2024)	KML
Topography	Digital elevation model	SRTM DEM	TIF
Geology	Lithology	1:50,000 geological map	TAB

Group	Input data	Source	Format
Geology	Faults and lineaments	Structural layers	TAB
Environment	Sentinel-2 imagery	European Space Agency	TIF
Environment	Land use/land cover	Japan Aerospace Exploration Agency	TIF
Hydrometeorology	Rainfall	CMORPH, NOAA	NC

2.3 Sixteen conditioning factors

Sixteen conditioning factors were retained: Elevation, Slope, Aspect, TRI, TWI, MBI, Lithology, GeoEngineering, GeoHydro, Weathering, Fault Buffer, NDVI, BSI, NDMI, Rainfall, and LULC. Together, these variables describe terrain configuration, slope position, material properties, hydrogeological behaviour, structural context, vegetation, surface condition, moisture status, rainfall forcing, and land-cover occupancy. NDMI was normalised to a 0-1 range for the class-wise factor statistics so that it could be compared directly with other binned variables. Appendix A groups representative factor maps by theme so that the main text can remain focused on model assessment rather than map inventory alone.

Table 2 lists the sixteen factors together with their geomorphological rationale.

Table 2. The sixteen conditioning factors used in the susceptibility models and their geomorphological rationale.

Factor	Type	Theme	Geomorphological rationale
Elevation	Continuous	Topography	Represents altitudinal organisation of relief, geomorphic belt, and associated process setting.
Slope	Continuous	Topography	Represents the gradient component of slope instability and controls the balance between driving and resisting forces.
Aspect	Categorical	Topography	Captures directional differences in insolation, slope microclimate, and potential moisture exposure.
TRI	Continuous	Topography	Represents terrain dissection and local topographic roughness.
TWI	Continuous	Hydro-topography	Represents potential hydrological convergence and local saturation tendency.
MBI	Continuous	Slope position	Distinguishes erosional from depositional slope positions.
Lithology	Categorical	Geology	Represents lithological strength, anisotropy, and weathering susceptibility.
GeoEngineering	Categorical	Engineering geology	Represents substrate competence from an engineering-ground perspective.

Factor	Type	Theme	Geomorphological rationale
GeoHydro	Categorical	Hydrogeology	Represents transmissivity class and the potential for perched saturation.
Weathering	Categorical	Weathering state	Represents the depth and mechanical weakening of weathered materials.
Fault Buffer	Categorical	Structure	Represents proximity to mapped structural corridors; interpreted cautiously because the current class coding is non-monotonic.
NDVI	Continuous	Vegetation	Represents vegetation density and land-surface occupancy.
BSI	Continuous	Surface condition	Represents exposed or disturbed surface conditions associated with sparse cover or bare ground.
NDMI	Continuous	Moisture-related spectral response	Represents vegetation and surface moisture conditions derived from multispectral imagery; normalised to 0-1 for class-wise statistics.
Rainfall	Continuous	Hydroclimate	Represents spatial forcing by the principal rainfall belts in the catchment.
LULC	Categorical	Land cover	Represents land-cover occupancy, including dense forest, planted land, shrubland, and water.

2.4 Descriptive relations between mapped landslides and conditioning factors

Factor-concentration statistics were reviewed before model comparison in order to identify which environmental classes are most enriched in mapped landslide cells. These summaries are not substitutes for algorithm-specific importance measures. They are used instead as a descriptive plausibility check: if the susceptibility maps are credible, their upper classes should coincide with the terrain, material, and hydro-climatic settings in which the inventory is demonstrably concentrated. When those upper classes are later viewed as hotspot zones in an applied sense, the same benchmark remains useful.

Across the sixteen-factor set, the clearest enrichment occurs in the 100-500 m elevation belt, on slopes steeper than 30°, on east to south-east aspects, in highly dissected terrain with strong hydrological convergence, and on erosional slope positions. Material controls are equally pronounced in shale, quartz-sericite schist, GeoEngineering 1, impermeable hydrogeological settings, and Weathering 1. Surface and climatic signals are strongest in the upper BSI class, the principal 5,000-5,300 mm rainfall belt, and dense-forest terrain occupancy. Fault Buffer is now represented by a near-to-far decay pattern, with the 100 m and 250 m classes mildly overrepresented and the more distant classes progressively underrepresented. That relation is consistent with a local structural influence, although the variable still expresses proximity rather than fault mechanics per se. Vegetation and moisture-index responses are retained in the summary because they may capture environmental context as much as direct causation.

Table 3 condenses the most enriched classes for each of the sixteen conditioning factors.

Table 3. Enrichment summary for the sixteen conditioning factors used in the susceptibility models. NDMI classes refer to the 0-1 normalised bins used in the statistical workflow.

Factor	Most enriched class(es)	StatIndex	Interpretation
Elevation	100-200 m; 200-500 m	1.40; 1.26	Failures concentrate in the low-to-mid mountain belt rather than at the highest elevations.
Slope	30-45°; >45°	1.17; 1.37	Gradient is a strong preparatory control on instability.
Aspect	East; South-east	1.66; 1.32	The inventory is enriched on aspects that may receive greater moisture under the regional monsoon setting, although that relation is interpretive rather than independently demonstrated here.
TRI	>3.5	1.16	Strong terrain dissection is associated with failure concentration.
TWI	>9	1.70	Hydrological convergence favours saturation and failure initiation.
MBI	<-0.5	1.46	Erosional slope positions are more failure-prone than depositional settings.
Lithology	Shale; quartz-sericite schist	1.17; 1.25	Weak or anisotropic materials are consistently overrepresented.
GeoEngineering	GeoEngineering 1	1.51	Engineering-ground conditions indicate weak or unstable substrate.
GeoHydro	Impermeable water group	1.22	Limited transmissivity is consistent with local saturation of the weathered mantle.
Weathering	Weathering 1	1.55	Weathered material coincides strongly with the mapped inventory.
Fault Buffer	100 m; 250 m	1.36; 1.08	Short fault-buffer distances are mildly enriched, suggesting a local structural influence, although proximity should not be read as a direct measure of fault activity.
NDVI	>0.4	2.52	Dense vegetation chiefly reflects steep-slope occupancy rather than direct causation.
BSI	>-0.1	5.24	Exposed or disturbed surfaces are strongly enriched in mapped failures.
NDMI	<0.2; >0.6	2.80; 2.04	The NDMI signal is non-monotonic after normalisation; the class tails are more informative than the central range and should

Factor	Most enriched class(es)	StatIndex	Interpretation
			be read as contextual moisture indicators.
Rainfall	5,000-5,300 mm	1.82	The principal rainfall belt coincides with susceptible terrain.
LULC	Dense forest	1.49	The signal reflects terrain occupancy of steep natural slopes rather than a destabilising effect of forest cover.

3. Methods

3.1 Cell-based sampling design and baseline model configuration

Raster cells constituted the unit of analysis. The mapped landslide inventory occupied 8,130 cells on the common 10 m grid. To avoid overwhelming the positive class with the much larger number of cells outside the inventory, an equal number of non-landslide cells was sampled from areas beyond the mapped landslides. The resulting modelling table therefore contained 16,260 observations and 17 attributes, including the binary response variable.

A 66%/34% train-test partition was applied once and then held fixed across both classifiers, yielding 5,528 testing instances. Keeping the partition fixed ensured that any difference in performance was attributable to the algorithms rather than to sample composition. kNN was implemented in Weka as IBk with $k = 1$ and Euclidean distance. KStar was implemented with $B = 20$ and the standard entropy-based distance formulation. These settings were treated as baseline implementations for controlled comparison rather than as the product of extensive model-specific hyperparameter optimisation. This choice keeps the focus on similarity formulation, but it also limits any claim that either algorithm has been tuned to its absolute optimum in this catchment.

3.2 Continuous susceptibility and class-based representation

The continuous 0-1 susceptibility surfaces were retained as the principal outputs because they preserve the ranking behaviour of the classifiers. Classified maps were produced only as a secondary representation for cartographic consistency and class-concentration analysis. A common four-class scheme was then applied to both surfaces: 0-0.14 (Low), 0.14-0.40 (Medium), 0.40-0.66 (High), and 0.66-1.00 (Very high). Holding the same thresholds across both models reduces the risk that differences in class extent will reflect cartographic choices rather than model behaviour (Jenks, 1967).

Class concentration was summarised by the share of mapped landslide cells within each class and by a StatIndex defined as $(L_i/L_{\text{total}})/(A_i/A_{\text{total}})$, where L_i is the number of mapped landslide cells in class i and A_i is the area share of class i . Values above 1 indicate overrepresentation of mapped landslide cells relative to class area.

3.3 Evaluation metrics and scope of inference

Model performance was assessed using accuracy, Cohen's Kappa, weighted precision, weighted recall, weighted F1-score, and ROC AUC (Cohen, 1960; Fawcett, 2006). Because omission of mapped landslide cells can be more consequential than false alarms in susceptibility work, class-specific precision, recall, and F1-score for the positive landslide class were also examined. This is good practice where weighted summaries can conceal materially different behaviour for the positive class (Saito & Rehmsmeier, 2015).

No spatially independent cross-validation or external validation dataset was available for the present comparison. The reported scores should therefore be interpreted as results from a controlled hold-out comparison at cell level, not as fully independent estimates of model transferability. Given the likely spatial autocorrelation among neighbouring cells, some inflation of performance cannot be excluded.

4. Results

4.1 Comparative predictive performance

Table 4 summarises the predictive performance of both models on the shared testing subset. kNN shows stronger threshold-dependent performance overall, whereas KStar yields stronger ranking behaviour and higher positive-class recall.

Table 4. Predictive performance of kNN and KStar on the testing subset. Positive-class measures refer to mapped landslide cells.

Model	Accuracy	Kappa	Weighted precision	Weighted recall	Weighted F1	ROC AUC	Positive-class precision	Positive-class recall	Positive-class F1
kNN	90.21	0.805	0.907	0.902	0.902	0.903	0.861	0.955	0.906
KStar	89.45	0.790	0.906	0.895	0.894	0.983	0.835	0.979	0.901

The overall accuracy difference is modest, but the error structure differs more clearly. kNN correctly classifies 4,987 of 5,528 testing cases, compared with 4,945 for KStar. KStar reduces false negatives for the landslide class from 122 to 58, but increases false positives from 419 to 525. In practical terms, KStar lowers omission at the expense of lower positive-class precision, whereas kNN delivers a cleaner binary split under the chosen operating threshold.

The much higher ROC AUC of KStar indicates that its susceptibility ranking is stronger even though its threshold-dependent summaries are slightly weaker. Such divergence is plausible rather than contradictory: a model may order observations well across the full score range while still performing less efficiently after a single decision threshold is imposed (Fawcett, 2006). Comparative susceptibility studies therefore benefit from both threshold-dependent and threshold-independent measures rather than accuracy alone (Merghadi et al., 2020; Saito & Rehmsmeier, 2015).

4.2 Continuous susceptibility patterns

The continuous maps show broad agreement on the principal susceptible domain. Both models assign higher susceptibility to the western half of the catchment, the north-western slopes, and several central-western ridge-valley corridors. These sectors coincide with the mapped landslide inventory and with the combined influence of steep terrain, strong dissection, unfavourable material properties, and the principal rainfall belt.

The spatial texture of the two surfaces is nevertheless different. kNN forms wider and more connected belts of elevated susceptibility along dissected slopes. KStar yields a more conservative spatial footprint, confining high scores to narrower tracts and leaving a larger low-susceptibility background in the eastern catchment. This contrast is consistent with the test results, although it should still be treated as catchment-specific until examined under more spatially independent validation.

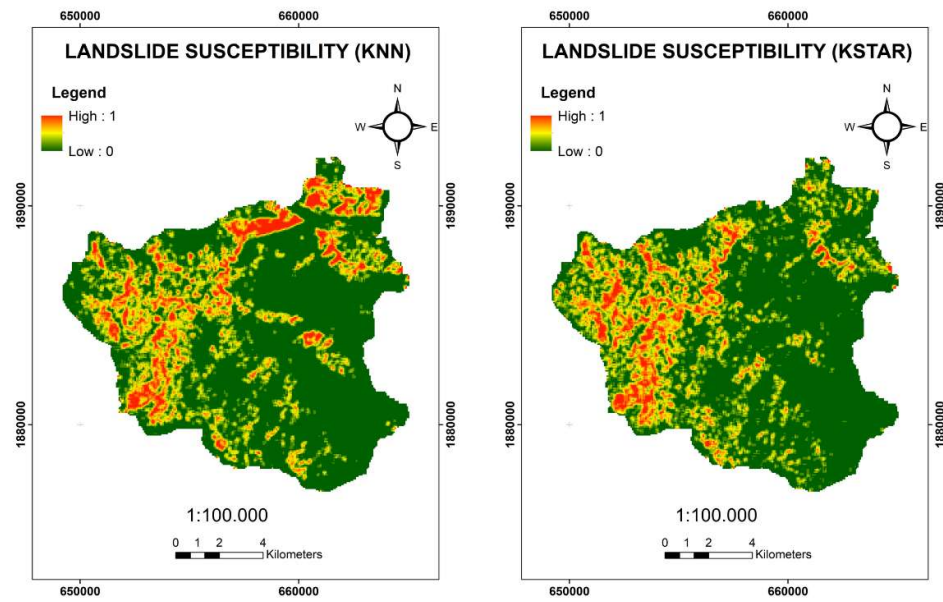


Figure 2. Continuous landslide susceptibility maps derived from the *k*-nearest neighbour and KStar models.

4.3 Common-threshold class comparison

The class-based comparison translates the continuous differences into a common four-class representation. Because the same thresholds were applied to both models, differences in class extent and class concentration can be interpreted primarily as model differences rather than as threshold artefacts.

Table 5. Class extent, mapped landslide concentration, and StatIndex under the common four-class thresholds.

Model	Class	Area share (%)	Mapped landslide share (%)	StatIndex
KStar	Low	25.86	1.07	0.04
KStar	Medium	39.72	18.55	0.47
KStar	High	26.34	63.06	2.39
KStar	Very high	8.09	17.32	2.14
kNN	Low	9.77	1.65	0.17
kNN	Medium	37.80	11.37	0.30
kNN	High	28.90	41.08	1.42
kNN	Very high	23.54	45.90	1.95

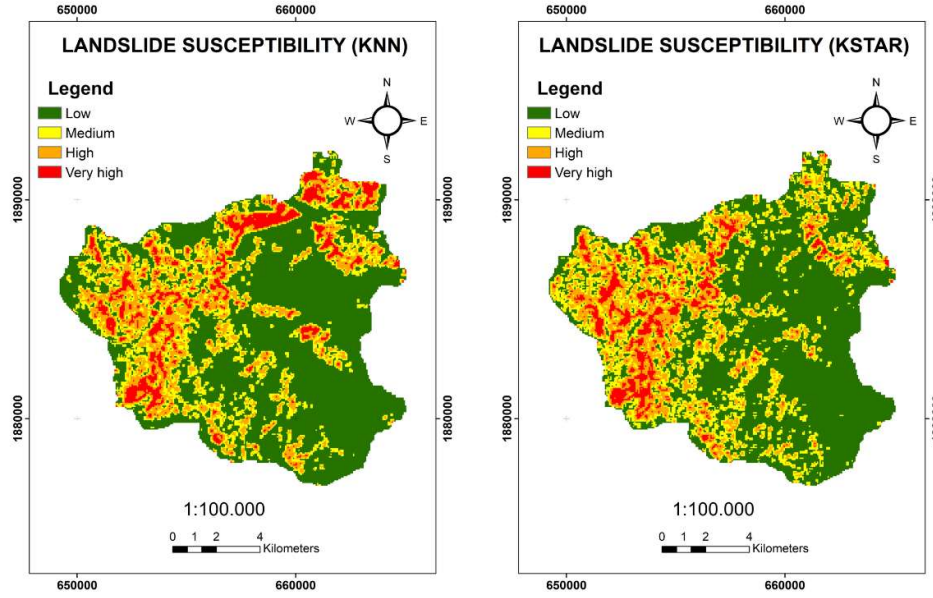


Figure 3. Classified landslide susceptibility maps using the common four-class thresholds (Low, Medium, High, and Very high).

Within this common representation, kNN allocates 52.44% of the catchment to the High and Very high classes, and those classes contain 86.98% of mapped landslide cells. KStar assigns only 34.43% of the catchment to the same upper classes, yet still contains 80.38% of mapped landslide cells there. The contrast indicates that KStar is more parsimonious spatially, whereas kNN is more expansive and captures a larger share of the mapped inventory.

StatIndex sharpens that reading. In KStar, the High and Very high classes have StatIndex values of 2.39 and 2.14, indicating strong enrichment of mapped landslide cells relative to class area. In kNN, the corresponding values are 1.42 and 1.95. KStar therefore concentrates susceptibility more efficiently in its upper classes, but does so by reducing their areal footprint. kNN is less concentrated in relative terms, yet contains more mapped landslide cells overall because its upper classes are broader.

5. Discussion

5.1 Environmental coherence of the susceptibility patterns

The sixteen-factor summary suggests that the mapped susceptibility patterns are environmentally coherent rather than merely numerically plausible. Topographic preparation is expressed through the joint enrichment of the 100-500 m elevation belt, slopes above 30°, east to south-east aspects, TRI values above 3.5, TWI values above 9, and negative MBI. Taken together, these signals describe steep, dissected hillslopes with strong hydrological convergence and erosional slope positions. The aspect pattern is plausibly consistent with moisture-receiving slopes under the regional monsoonal setting, although that climatic interpretation is inferential rather than independently tested here. Overall, the topographic signal is in line with the established roles of slope gradient, flow concentration, and terrain organisation in landslide susceptibility (Beven & Kirkby, 1979; Riley et al., 1999; Reichenbach et al., 2018).

Material controls point in the same direction. Shale and quartz-sericite schist are enriched relative to their areal extent, as are GeoEngineering 1, impermeable hydrogeological settings, Weathering 1, and the shortest fault-buffer classes. These relations are physically

credible because weak or anisotropic materials, advanced weathering, restricted transmissivity, and local structural proximity may all favour perched saturation and reduced effective shear strength. The Fault Buffer variable is nevertheless treated cautiously: it is interpreted here as a proximity indicator rather than as a direct measure of fault-related weakening.

Surface and hydro-climatic variables refine, rather than overturn, that interpretation. The highest BSI class is strongly enriched, indicating that exposed or disturbed surfaces are associated with mapped failures. The principal rainfall belt of 5,000-5,300 mm is likewise overrepresented, which is consistent with sustained moisture loading under the prevailing climatic regime. NDVI, NDMI, and dense forest should be read more cautiously. In this catchment they are more plausibly interpreted as contextual variables linked to steep natural-slope occupancy and moisture status than as direct destabilising agents in their own right (Gao, 1996; Rouse et al., 1974).

5.2 What the model comparison adds

The comparison indicates that two lazy learners trained on the same susceptibility database can respond differently to the same environmental structure because they formalise similarity differently. kNN with $k = 1$ inherits the local behaviour of the nearest mapped examples. In a catchment where adverse conditions vary gradually along connected hillslopes, that logic can spread high susceptibility across broader belts of environmentally similar cells. KStar evaluates similarity through an entropy-based distance. In the present dataset, that appears to confine the highest scores to cells where several unfavourable conditions co-occur more distinctly rather than merely nearby in Euclidean space. When upper classes are extracted for applied hotspot identification, the same difference reappears as a broader kNN hotspot footprint and a tighter KStar one.

This distinction helps explain why ROC AUC and threshold-dependent summaries diverge. KStar orders observations more effectively across the full score range, which is reflected in the higher AUC and higher positive-class recall. Once a single decision threshold is imposed, however, the same score distribution admits more stable cells to the positive class, thereby reducing positive-class precision and slightly weakening threshold-dependent performance. kNN behaves in the opposite direction: it yields the stronger binary split under the chosen threshold, but its continuous ranking is less discriminating. Similar divergences are recognised in classifier evaluation and are not unusual in susceptibility studies that compare models with different score distributions (Fawcett, 2006; Saito & Rehmsmeier, 2015).

The broader landslide-susceptibility literature already shows that classifier choice can alter both predictive metrics and the mapped extent of upper susceptibility classes (Merghadi et al., 2020; Reichenbach et al., 2018). Direct evidence for KStar in landslide mapping remains limited, which is precisely why the present comparison is useful but also why its scope should be kept in proportion. The results support the view that similarity formulation matters for susceptibility mapping, but they do not justify a general claim that one of the two algorithms will dominate across catchments with different inventories, scales, or predictor definitions.

5.3 Implications for model selection and limits of inference

For this catchment and this sampling design, kNN is the more defensible choice when balanced threshold-dependent performance and broader precautionary capture are the principal priorities. KStar is more attractive when lower omission of mapped landslide cells and tighter spatial concentration are preferred. These are not interchangeable outcomes; they correspond to different downstream applications of the same susceptibility surface and, where required, to

different ways of delineating upper-class hotspot zones from that surface.

Several limitations qualify that reading. First, the landslide inventory was interpreted from remotely sensed imagery, so some small or older failures may have been missed and some boundaries are necessarily approximate. Secondly, the modelling exercise is spatial rather than temporal; the results therefore describe susceptibility, not hazard. Thirdly, the class thresholds were fixed for comparison rather than optimised separately for each model. That was the correct choice for controlled comparison, but it means the classified maps should be read as one standardised representation of the continuous surfaces rather than as the only defensible zoning scheme. Fourthly, the train-test split was not spatially independent, so the reported metrics may be optimistic to some degree. Finally, the baseline parameter settings were chosen for controlled comparison rather than exhaustive optimisation. The findings are therefore best read as evidence for the practical sensitivity of susceptibility mapping to similarity formulation, not as proof that one algorithm has been globally optimised.

6. Conclusions

This study presented a controlled comparison of k-nearest neighbour and KStar for landslide susceptibility mapping in the Huoi Reng catchment. By holding constant the 16 conditioning factors, the cell-based sampling design, the train-test partition, and the common class thresholds, the analysis was able to isolate the effect of similarity formulation on both the continuous susceptibility ranking and the spatial configuration of the upper susceptibility classes.

Within this framework, kNN provided the stronger threshold-dependent performance, whereas KStar showed stronger threshold-independent discrimination and lower omission of mapped landslide cells. In practical terms, kNN is more suitable where balanced classification performance and broader precautionary capture are preferred, while KStar is more suitable where reduced omission and a more spatially compact delineation of upper susceptibility zones are required.

These findings should be interpreted as catchment-specific and conditional on the present inventory, sampling design, and baseline parameter settings. The main methodological implication is that, even within the same instance-based learning family, alternative definitions of similarity can lead to materially different susceptibility rankings and materially different mapped patterns in the upper susceptibility classes. This difference is relevant for downstream applications such as field prioritisation, screening, and spatial planning based on susceptibility outputs.

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Appendix A. Representative conditioning-factor maps

The grouped plates below document the predictor space used in the modelling exercise. They are placed in the appendix so that the main text can remain focused on model assessment and comparative interpretation.

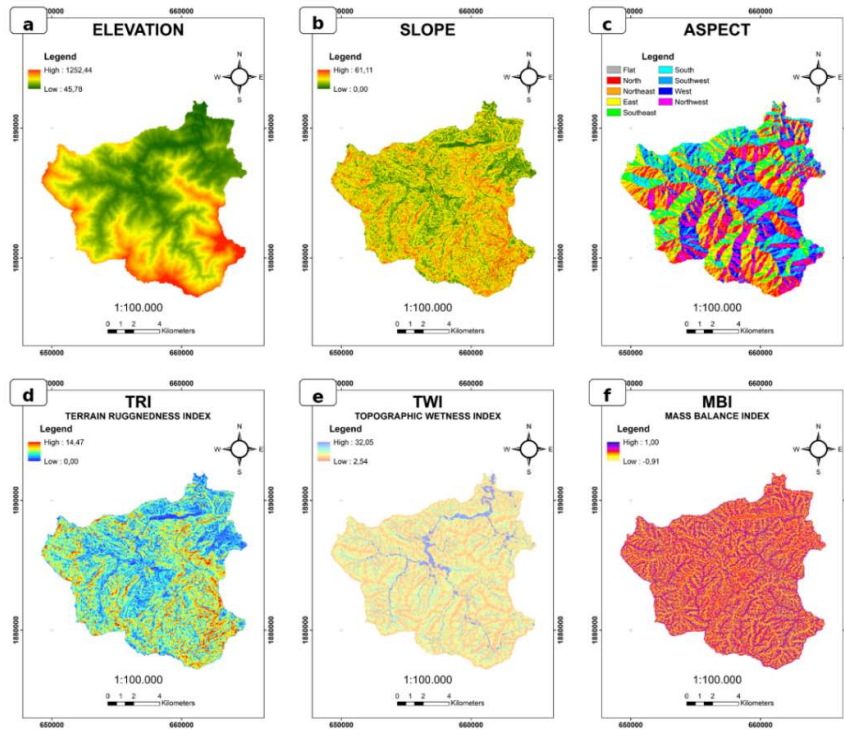


Plate A1. Terrain conditioning factors used in the susceptibility models: Elevation, Slope, Aspect, TRI, TWI, and MBI.

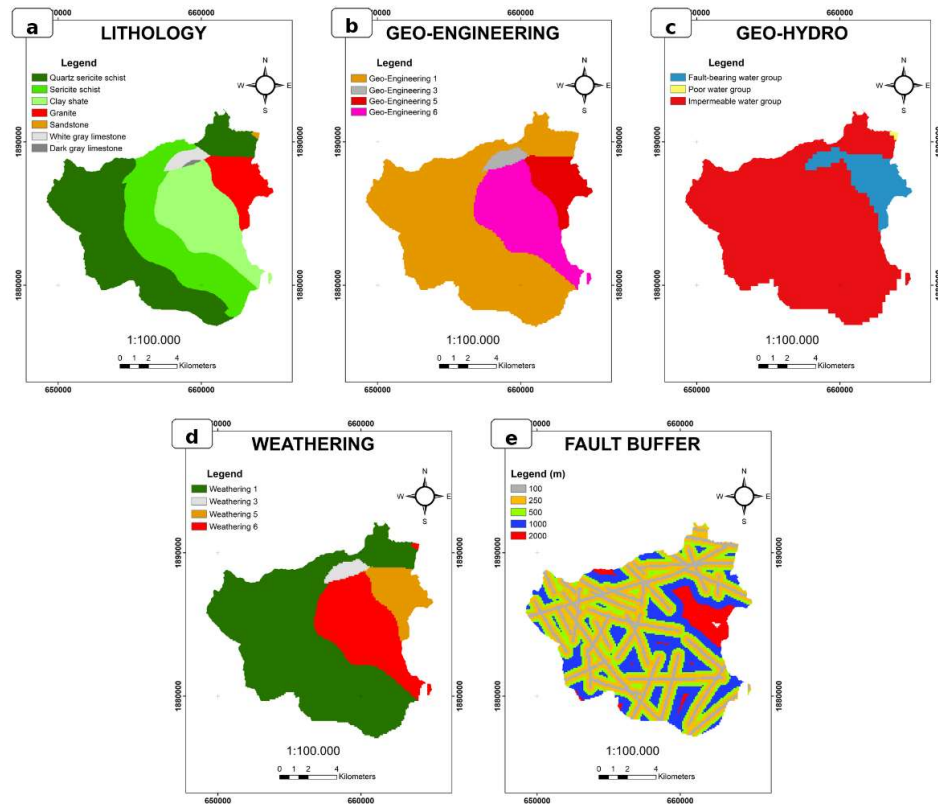


Plate A2. Geological, geotechnical, hydrogeological, weathering, and structural conditioning factors: Lithology, GeoEngineering, GeoHydro, Weathering, and Fault Buffer.

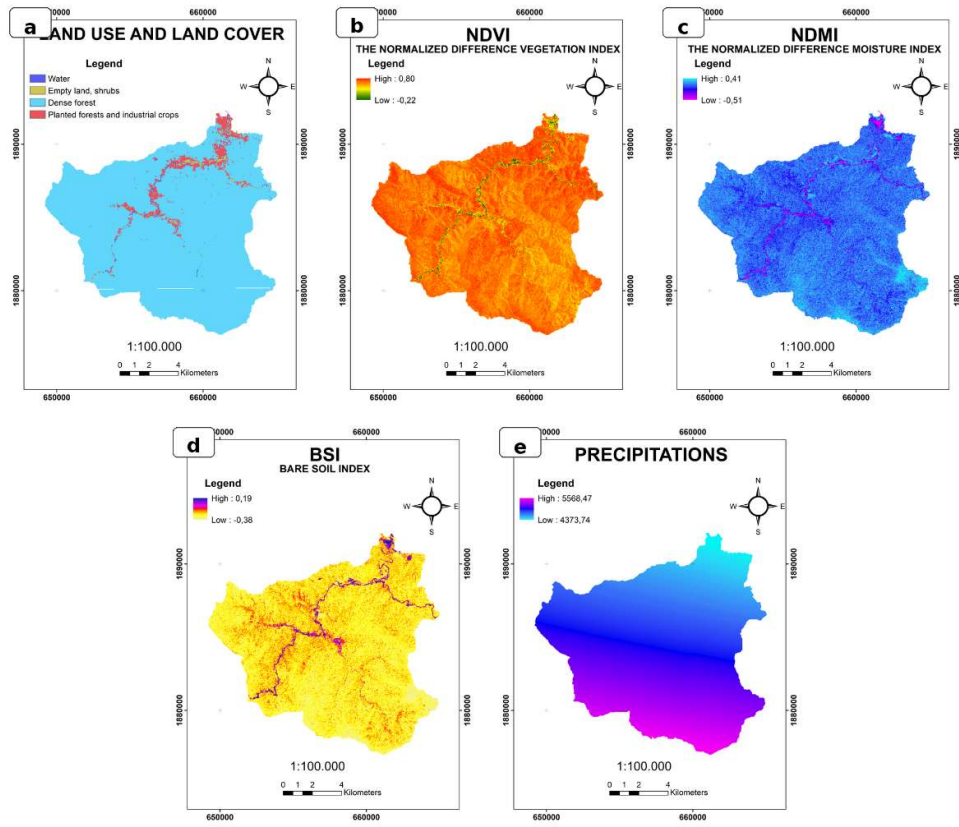


Plate A3. Surface and hydro-climatic conditioning factors: LULC, NDVI, the NDMI raster used in the model set, BSI, and Rainfall.