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Landslide Spatial Modelling Using Unsupervised Factor Optimisation and Regularised Greedy Forests

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Abstract

This study evaluates the contribution of an unsupervised factor optimisation based on sparse autoencoders (SAEs) to spatial landslide modelling with regularised greedy forests (RGFs). A total of 952 landslides were identified by field surveys, equally divided and used for training and testing of the proposed model. Ten conditioning factors related to landslides, including geo-morphometrical (i.e. altitude, slope, aspect, curvature, slope length, topographic wetness index and sediment transport index) and geo-environmental (i.e. lithology, nearness to roads and nearness to streams), were used to investigate the spatial relationships between the variables and landslides. ¹The steps of the modelling were twofold. First, the factors were

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28 optimised by SAE to reduce information redundancy and correlation in the data. Second, RGF
29 was used to create landslide susceptibility maps with the optimised feature representations. The
30 area under the receiver operating characteristic curve (AUROC) was used to assess the
31 predictive ability of the proposed models. Experimental results show that the proposed SAE–
32 RGF outperforms the RGF and random forest (RF) models in terms of prediction rate and is
33 less sensitive to overfitting and underfitting. The highest prediction rate (AUROC = 0.892) was
34 obtained with only seven features by the SAE–RGF model, which is better than the two other
35 methods (RGF and RF). The unsupervised factor optimisation approach not only reduces
36 computation time but also improves the prediction accuracy of tree-based models, including
37 RGF. The generated landslide susceptibility maps can be implemented to mitigate landslide
38 hazards and to designate land use by stakeholders (e.g. planners and engineers).

39 **Keywords:** landslide susceptibility; regularised greedy forests; unsupervised factor
40 optimisation; GIS; Chukha Dzongkhag; Bhutan

41

42 **1. Introduction**

43 Landslide spatial modelling is a common study that offers helpful information to decision-
44 makers and planners (Kocaman and Gokceoglu, 2019; Comert et al. 2019; Luo et al. 2019;
45 Wang, Fang and Hong 2019; Ozturk et al. 2019). The outcomes of this process (e.g.
46 susceptibility maps, the significance of conditioning factors) are helpful in assessing landslide
47 hazards and in reducing their impact on human lives and infrastructure, such as road networks
48 and agricultural systems. Conventional techniques for assessment of landslide susceptibility
49 are based on field surveys and aerial photograph interpretation. These techniques have been
50 proven to be time consuming and expensive in most cases. Alternative methods are based on
51 automated algorithms that can learn from data on historical landslide events and generalise to
52 other areas where no prior information is accessible. Various algorithms and modelling
53 techniques, which have improved significantly over the last decades, are available. They have
54 been developed to learn from a limited amount of data and to be generalised to areas other than
55 the training area (s). Statistical methods, including bivariate (e.g. frequency ratio, certainty
56 factors, statistical index and entropy index) (Liu and Duan 2018, Shirani et al. 2018) and
57 multivariate (e.g. logistic regression) (Sun et al. 2018, Polykretis and Chalkias 2018), have
58 been widely used by many researchers. Although these algorithms can learn from historical
59 landslide data, they are sensitive to the selection of factors that contribute to landslides.

60 Algorithms that belong to machine learning family, such as artificial neural networks (Pradhan
61 and Lee 2010, Zare et al. 2013, Xiao et al. 2018; Can et al. 2019), support vector machines
62 (Hong et al. 2017), tree-based models (e.g. decision tree, extra trees, random forest) (Chu et al.
63 2019, Dou et al. 2019), fuzzy logic (Peethambaran et al. 2019) and neuro-fuzzy systems
64 (Dehnavi et al. 2015, Aghdam et al. 2016, Polykretis et al. 2017, Chen et al. 2019; Ozer et al.
65 2018, 2019), have been introduced and applied to landslide susceptibility analysis to
66 complement the limitations of statistical methods.

67 In statistical modelling, historical landslide data provide a clue to the selection of a stochastic
68 model that acts as an abstraction for creating landslide predictions. In machine learning,
69 however, data drive the selection of an algorithm to predict future landslides from the input
70 data. That is, statistical models provide distributional assumptions about the nature of the true
71 underlying relationships, whereas machine learning requires less or not a priori belief.
72 Consequently, machine learning algorithms can discover novel relationships in the data,
73 whereas statistical models can only find such relationships when guided by a human. For
74 landslide susceptibility modelling, machine learning will be highly efficient if the input data
75 are incomplete or difficult to understand in their raw form. Nevertheless, machine learning
76 algorithms can overfit or find spurious correlations, which should be carefully designed and
77 analysed to avoid such problems.

78 The recent trend in landslide susceptibility analysis using machine learning is hybrid models
79 that combine the benefits of two or more machine learning models for good reasons. The
80 combination of several algorithms into a single model is crucial because it offers higher
81 generalisation ability than a single algorithm by reducing variance and bias or improving
82 prediction. Significant research has developed and demonstrated the superiority of hybrid
83 models to single models for landslide susceptibility (Huang and Zhao 2018, Pham et al. 2019).
84 Hybrid models can be constructed by ensembles (Kadavi et al. 2018) or by integrating
85 algorithms that do not belong to the same family or that aim at different processing stages (i.e.
86 pre-processing, feature selection/extraction, optimisation, modelling). Examples of hybrid
87 models recently developed for landslide susceptibility mapping include bivariate weights of
88 evidence with multivariate logistic regression and RF (Chen et al. 2019); integrated ensemble
89 fractal dimension with kernel logistic regression (Zhang et al. 2019); entropy and rotation
90 forest-based credal decision tree classifier (He et al. 2019) and meta-optimisation of an
91 adaptive neuro-fuzzy inference system with a grey wolf optimiser and biogeography-based
92 optimisation algorithms (Jaafari et al. 2019).

93 Several other studies also include the development of hybrid susceptibility models using tree-
94 based methods. Kutlug Sahin and Colkesen (2019) examined decision tree-based ensembles
95 models such as canonical correlation forest and rotation forest. The former method outperforms
96 the other on different ensemble techniques, including AdaBoost and bagging. Random forest
97 also found superior to decision trees in (Dou et al. 2019). Kornejady et al. (2019) created a
98 hybrid model which combined random forest and frequency ratio for the evaluation and
99 efficiency of landslide susceptibility and found such models have a good performance (AUC
100 value of 0.831). In another study. Nguyen et al. (2019) found that tree-based models such as
101 best first decision trees-based rotation forest are superior to models created using an adaptive
102 neuro-fuzzy inference system and artificial neural networks optimized by particle swarm
103 optimization.

104 The selection of individual algorithms that form a hybrid model is often subjective. However,
105 certain algorithm characteristics can be used to determine the elements of a hybrid model. For
106 example, category (tree-based, probabilistic, neural networks), predictive ability based on
107 previous work and computational performance are important properties to consider when
108 selecting algorithms for a hybrid model. Tree-based models, such as decision trees, extra trees,
109 RF and boosted trees, have demonstrated good performance, as presented in recent studies (Lee
110 et al. 2018, Song et al. 2019, Meneses et al. 2019). Preparing high-quality spatial data and
111 landslide inventories is also essential to enhance the performance of landslide susceptibility
112 models (Huang and Zhao 2018, Soma et al. 2019).

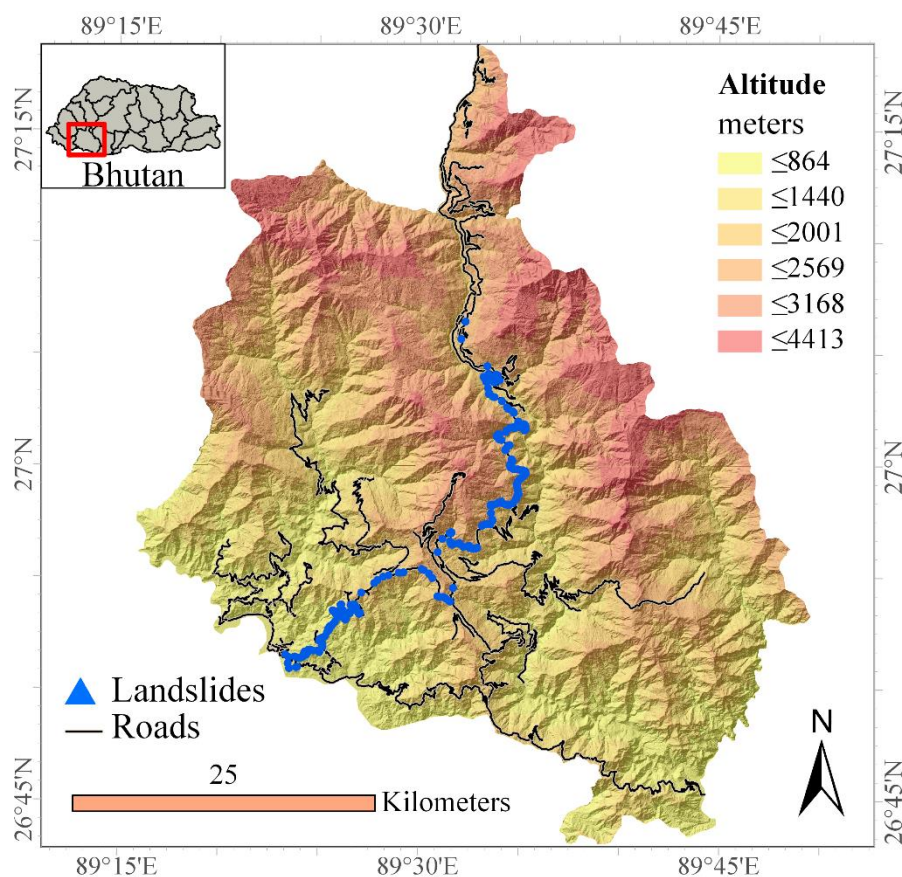
113 This research aims at improving the performance of tree-based models such as regularised
114 greedy forests (RGF) and random forest (RF) for landslide susceptibility modelling. To achieve
115 this aim, an integrated model namely SAE-RGF which combines sparse auto-encoders as an
116 unsupervised factor optimisation and RGF was developed and evaluated in Chukha
117 Dzongkhag, Bhutan. To the best of our knowledge, RGFs have not yet been applied to landslide
118 susceptibility mapping. In this sense, this study contributes to evaluating the effect of feature
119 compression on susceptibility mapping. The proposed model was compared with RGF (without
120 optimization) and other tree models such as RF.

121 **2. Description of the study area**

122 For the case study, Chukha Dzongkhag is chosen to evaluate the models suggested (Figure 1).
123 This area lies between longitudes $89^{\circ} 15'$ – $89^{\circ} 49'$ and latitudes $26^{\circ} 44'$ – $27^{\circ} 18'$ in the
124 southwestern part of Bhutan. It covers approximately $1,879.5 \text{ km}^2$ and has a population of

125 88,342 as of 2015. Its elevation ranges between 0 m to 4,413 m above mean sea level, with a
126 mean elevation of 1,905 m. The slope angles vary from 0° to 89°.

127 Chukha Dzongkhag is in the subtropical and temperate climatic zones. It experiences high
128 annual rainfall (the highest being 4,000–6,000 mm) and nearly regular heavy rains up to 800
129 mm.day⁻¹, mostly during the southwestern monsoon between June and September.
130 Consequently, the area is highly vulnerable to landslides, particularly during the rainy season.
131 Most landslides occur alongside the Phuentsholing–Thimphu dual carriageway, a lifeline
132 infrastructure that links the capital Thimphu with neighbouring nations. The vicinity is also
133 characterised by closely fractured and weathered rocks, such as phyllites, slates and schists,
134 which contain excessive quantities of clay minerals (Kuenza et al. 2010).
135 The area contains steep slope terrain, which makes it highly at risk of slope failures brought by
136 rainfall and associated disasters due to several road cuttings (Kuenza et al. 2010).
137 Landslides frequently block the highway, thereby resulting in huge economic losses.



138
139 **Figure 1:** Location of the study area and landslide inventories provided in this research.

140 3. Methodology

141 3.1 Landslide inventories

142 For efficient mapping of landslide susceptibility, the first step used to train and validate
143 machine learning methods is often regarded as a landslide inventory map. A standard landslide
144 inventory map includes historic landslide records that consist of the location and areal
145 coverage, prevalence facts, mass move type and landslide phenomenon volume in an area.

146 Field investigation and analysis of historical aerial photos and satellite images are two common
147 methods used to prepare landslide inventory maps. In this study, 952 landslides were mapped,
148 verified, and included in a spatial database. Figure 2 shows some photographs taken in the
149 study area. Nearly all the landslides were caused by precipitation and occurred within less than
150 50 m from the Phuentsholing–Thimphu highway. The depths of the landslides in the study
151 region range from several decimetres to a few metres based on visible and on-site intensity
152 measurements. Landslides were mapped as single points (Gariano et al. 2018). The dataset was
153 randomly divided into three subsets for training (70%, 666), validation (10%, 95) and final
154 testing (20%, 191). The training dataset was used to train the proposed models, whereas the
155 validation dataset was used to optimise the parameters of the same models. Finally, using the
156 test datasets, the models were evaluated and compared with each other.

157

158 *3.2 Conditioning factors related to landslides*

159 In relation to a landslide inventory map, the modelling of landslide susceptibility requires
160 conditioning factors that are representative, reliable and readily obtainable. These factors can
161 be determined by field surveys (Oh and Pradhan, 2011) and inventory map analysis, landslide
162 types and characteristics of the study area. In the present study, 10 landslide conditioning
163 factors, including geo-morphometrical and geo-environmental factors, were selected based on
164 the factors that were most commonly used in previous studies and the characteristics of the
165 study area.

166



167

168

Figure 2: Sample of field photographs taken in the study area.

169

170 3.2.1 Geo-morphometrical factors

171 Seven geo-morphometrical factors were obtained with a resolution of 10 m from a digital
172 elevation model generated from topographical maps. Subsequently, a raster resolution of 10 m
173 was used to derive the conditioning factors. The factors were altitude, slope, aspect, curvature,
174 slope length, topographic wetness index (TWI) and sediment transport index (STI). They were
175 extracted using ArcGIS Pro 2.3. The factors with continuous values were reclassified into
176 categorical classes using the Jenks natural breaks optimisation method (Hong et al. 2016)
177 available in ArcGIS Pro 2.3, as recommended and defined by Hung et al. (2016).

178 a) **Altitude:** Elevated areas impact loading on the slope; elevation is therefore an important
179 factor in landslide modelling. High-altitude areas increase the possibility of landslides,
180 particularly if the sliding plain has an orientation close to an open excavation (Walker and
181 Shiels, 2012). In this research, the elevation map was labelled into six classes (Figure 3).

182 b) **Slope:** Slope is a major factor in any analysis of landslide susceptibility and has often been
183 used in past research (Hong et al. 2018, Lee et al. 2018, Sameen et al. 2018). Slope is an
184 important topographical parameter, and landslide frequency is often high on steep slopes. The
185 slope map was labelled into six classes (Figure 3).

186 c) **Aspect:** Slope aspect uses slope path and affects daylight, wind and precipitation exposure.
187 Aspect also impacts vegetation and soil-related factors indirectly, such as vegetation cover, soil
188 thickness and moisture. Slope aspect is therefore regarded as an important parameter in the
189 evaluation of landslide susceptibility (Hong et al. 2017). In this study, aspect was divided into

190 nine classes: flat, north-, northeast-, east-, southeast-, south-, southwest-, west- and northwest-
191 facing classes (Figure 3).

192 d) **Curvature**: Is the curvature of a line formed by the intersection of a random plane with the
193 terrain surface (Youssef et al. 2015). The curvature value can be positive or negative. A positive
194 curvature represents an upwardly convex surface, whereas a negative curvature represents an
195 upwardly concave surface on a point. If its value is near zero, the curvature can also have a flat
196 shape. Curvature plays a key role in landslide modelling and in altering landform
197 characteristics (Mandal and Maiti 2015). A convex surface immediately drains moisture,
198 whereas for a long period a concave surface holds moisture. In this study, a curvature map was
199 used after reclassifying it into six classes (Figure 3).

200 e) **Slope length**: This study considers slope length a landslide conditioning factor because it
201 increases the capability of erosive agents to displace and transport materials downslope
202 (Gomez and Kavzoglu 2005). Slope length was calculated using the digital elevation model
203 and prepared for the modelling process with six classes (Figure 3).

204 f) **TWI**: This parameter is a hydrological factor that contributes to landslide occurrence; it
205 combines local upslope contributing area and slope (Gallant 2000). High TWI values indicate
206 low landslide occurrence probability. In this study, TWI was calculated using the following
207 equation:

$$208 \quad \text{TWI} = \ln \left(\frac{\alpha}{\tan \beta} \right), \quad (1)$$

209 where α is the cumulative upslope area (per unit contour length), and β is the angle of slope at
210 the calculation point. The TWI map for the study region was categorised into six classes (Figure
211 3).

212 g) **STI**: This parameter indicates the amount of sediment transportation through overland flow
213 and is based mainly on the erosion of catchment evolution theories and transportation capacity
214 that restricts sediment flux. In this study, the following equation was used to calculate STI. The
215 generated values were classified into six classes (Figure 3):

$$216 \quad \text{STI} = \left(\frac{A_s}{22.13} \right)^{0.6} \cdot \left(\frac{\sin \beta}{0.0896} \right)^{1.3}, \quad (2)$$

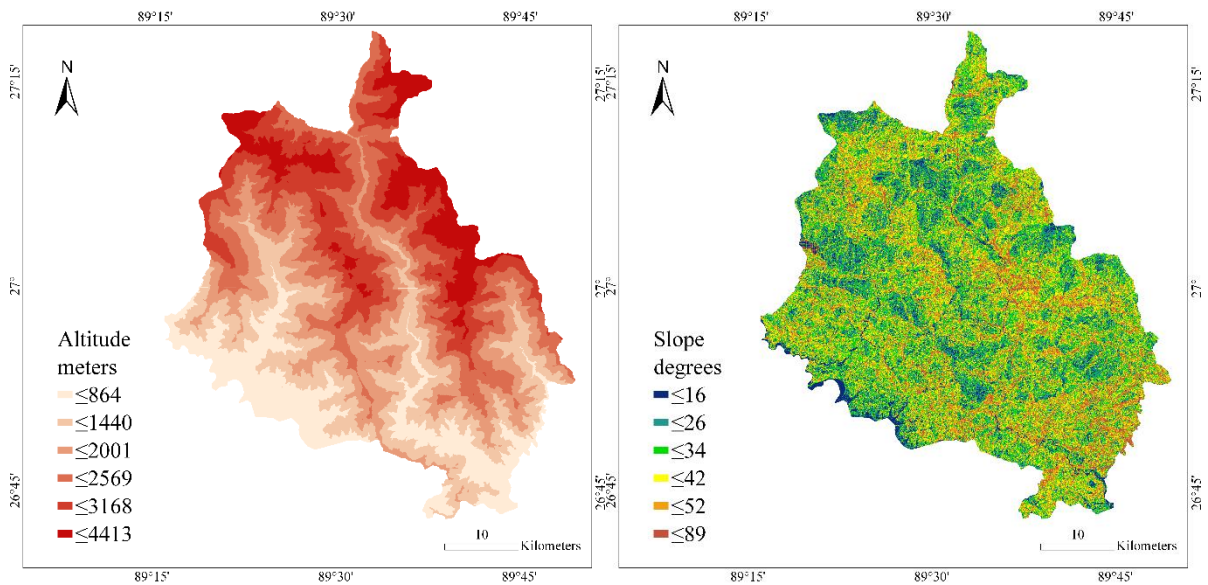
217 where A_s is the specific catchment area (m^2/m), and β is the slope gradient.

218 3.2.2 Geo-environmental factors

219 Three geo-environmental elements, namely, lithology, proximity to roads and proximity to
220 streams, were used in this study, as explained in the following subsection.

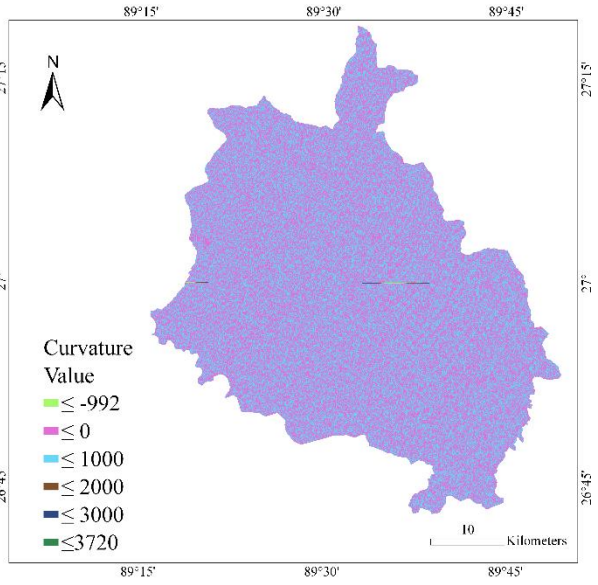
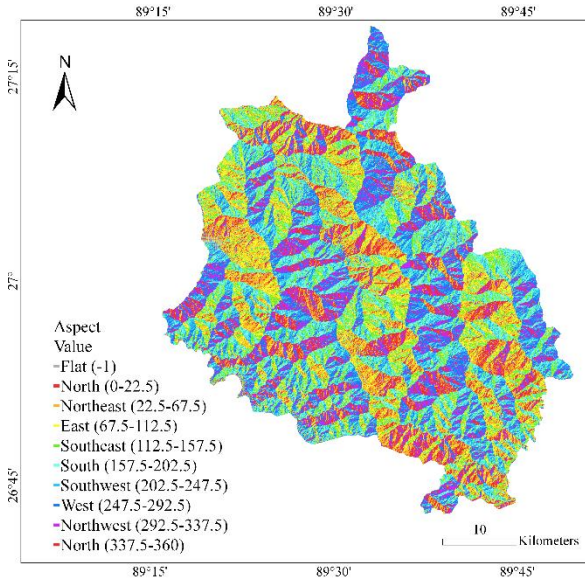
221 a) **Lithology**: The area geologically belongs to the Lesser Himalayan formation. It includes
222 sedimentary and low-grade metamorphic rocks. It consists primary of metasedimentary rocks
223 like phyllite, schist, quartzite, and limestone that are tectonically active. The north part of the
224 area is comprised of the Higher Himalayan crystalline rocks such as garnetiferous mica-shist,
225 quartzite, and gneiss. Lithology is important in the analysis of landslide susceptibility because
226 soft and weathered rocks are more vulnerable to landslides than hard unjointed rocks. The study
227 area, Chukha Dzongkhag, is made up of various types of lithological units (Figure 3).

228 b–c) **Proximity to roads and streams**: Anthropogenic factors, including proximity to roads
229 and streams, are regularly utilised in landslide susceptibility evaluation. Shallow to deep
230 excavations, application of foreign loads and eviction of vegetative cover are common actions
231 during construction along highways and roads. In addition, the intermittent flow regime of a
232 hydrological community and gullies encompasses erosive and saturation processes.
233 Subsequently, pore water pressure can be increased, which may lead to landslides in regions
234 that adjoin drainage channels (Figure 3). Land use and land cover were not considered in this
235 research because all the landslide points fall into one class (forest area) and no variance was in
236 the data.

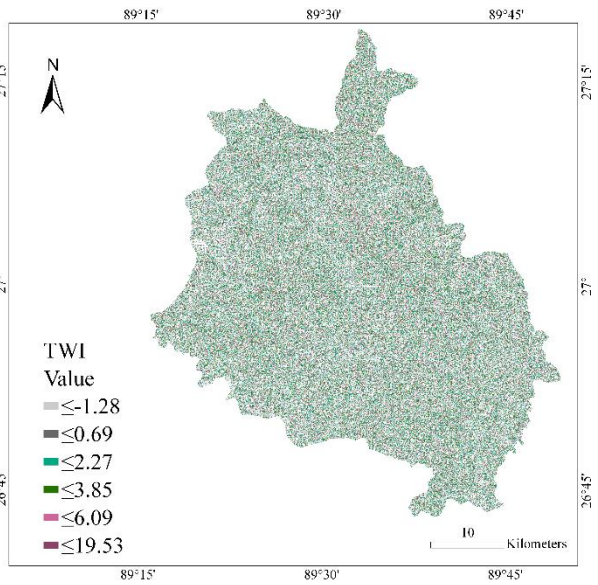
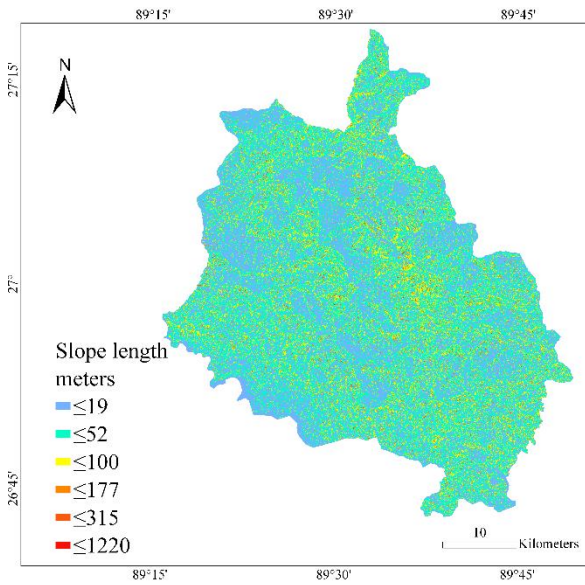


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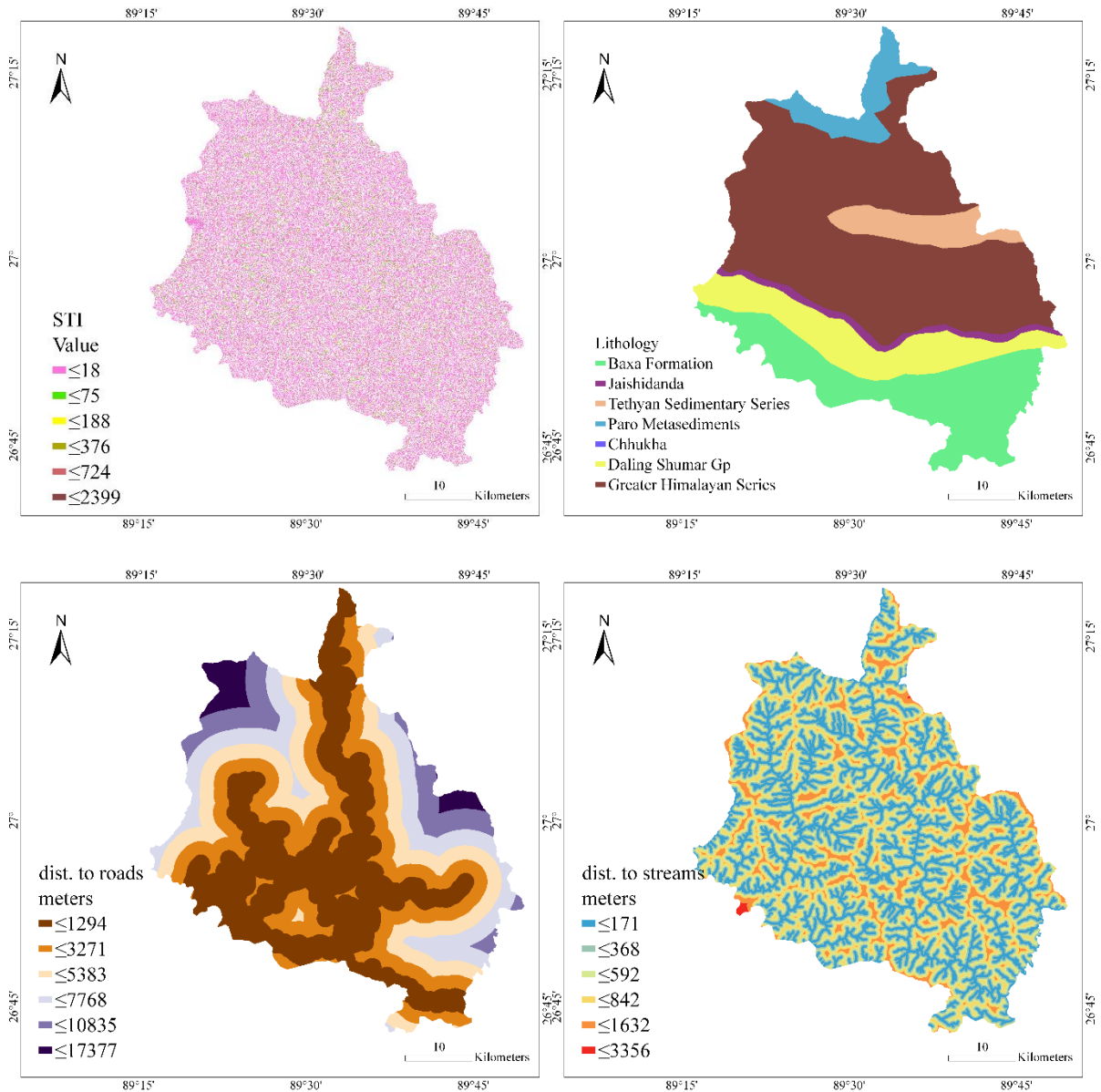
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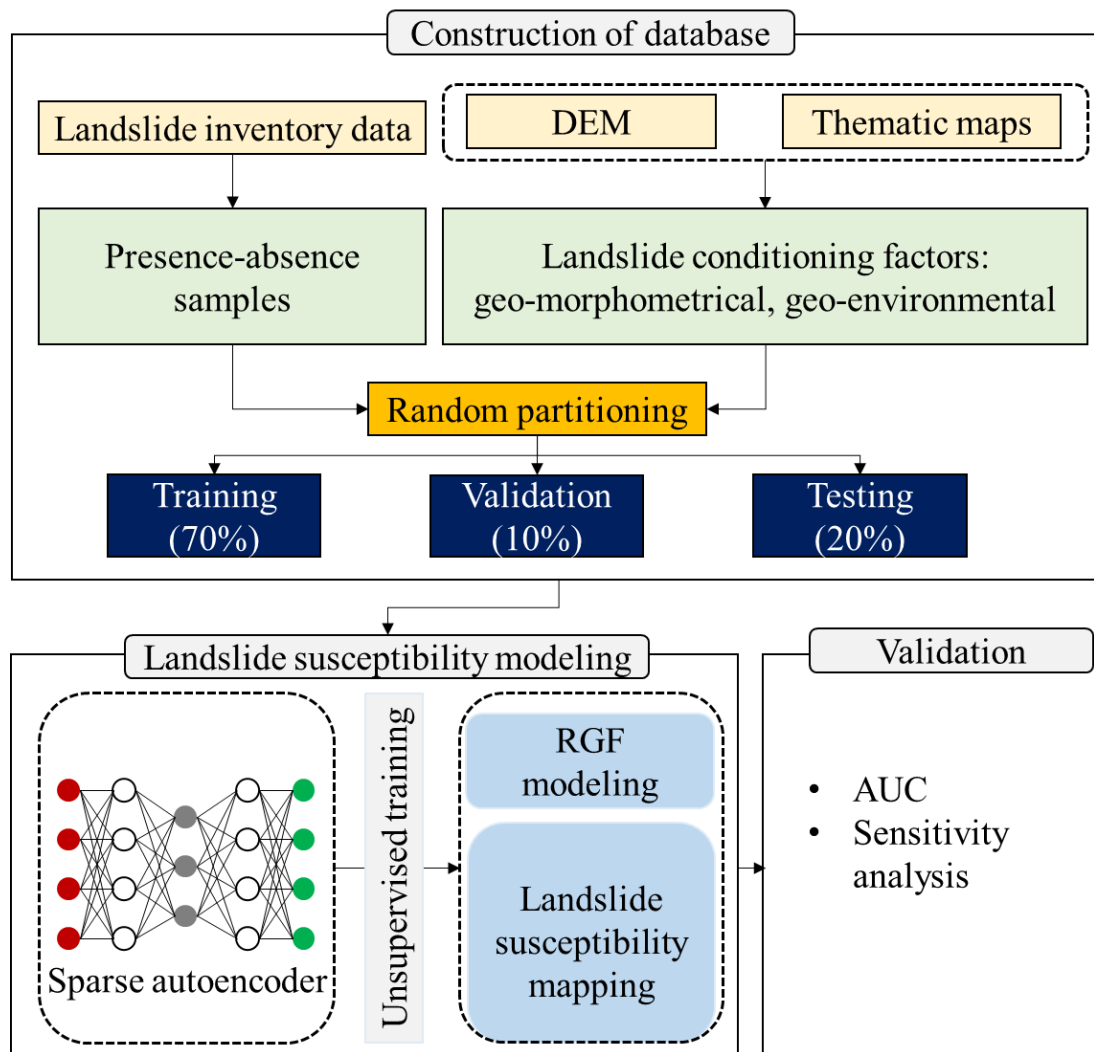
Figure 3: Landslide conditioning factors.

244 3.3 Proposed models

245 A modelling approach based on two machine learning algorithms, namely, SAEs and RGFs,
 246 was developed for landslide susceptibility assessment in Chukha Dzongkhag. The flowchart of
 247 this approach is presented in Figure 4. The landslide presence-absence samples were created
 248 after collecting and preparing the landslide inventory map, the spatial digital elevation model,
 249 and thematic layers. The landslide inventory samples were counted and used to randomly
 250 generate the absence samples. The final data combined the landslide presence and absence
 251 samples with a defined label (1 and 0, respectively) for each sample. Ten landslide conditioning
 252 elements were prepared from a spatial database. The values of the landslide conditioning

253 elements at each sample location were utilised, and the derived information was prepared using
 254 a Microsoft Excel sheet.

255 The independent variables in the data were scaled (zero mean, unit variance) to improve the
 256 training process of SAE (only applied to the factors with continuous values). The dependent
 257 variable was converted with one-hot encoding. The data were then categorised into three
 258 subsets: for training (70%), validation (10%) and testing (20%). The SAE model was trained
 259 in an unsupervised manner, and a set of new features was generated. These new features were
 260 used to train the RGF model. In this study, the validation of the proposed models was based on
 261 a well-known area under the receiver operating characteristic curve (AUROC). Sensitivity
 262 analysis was also considered to assess the consequences of dimensionality reduction on the
 263 RGF model.



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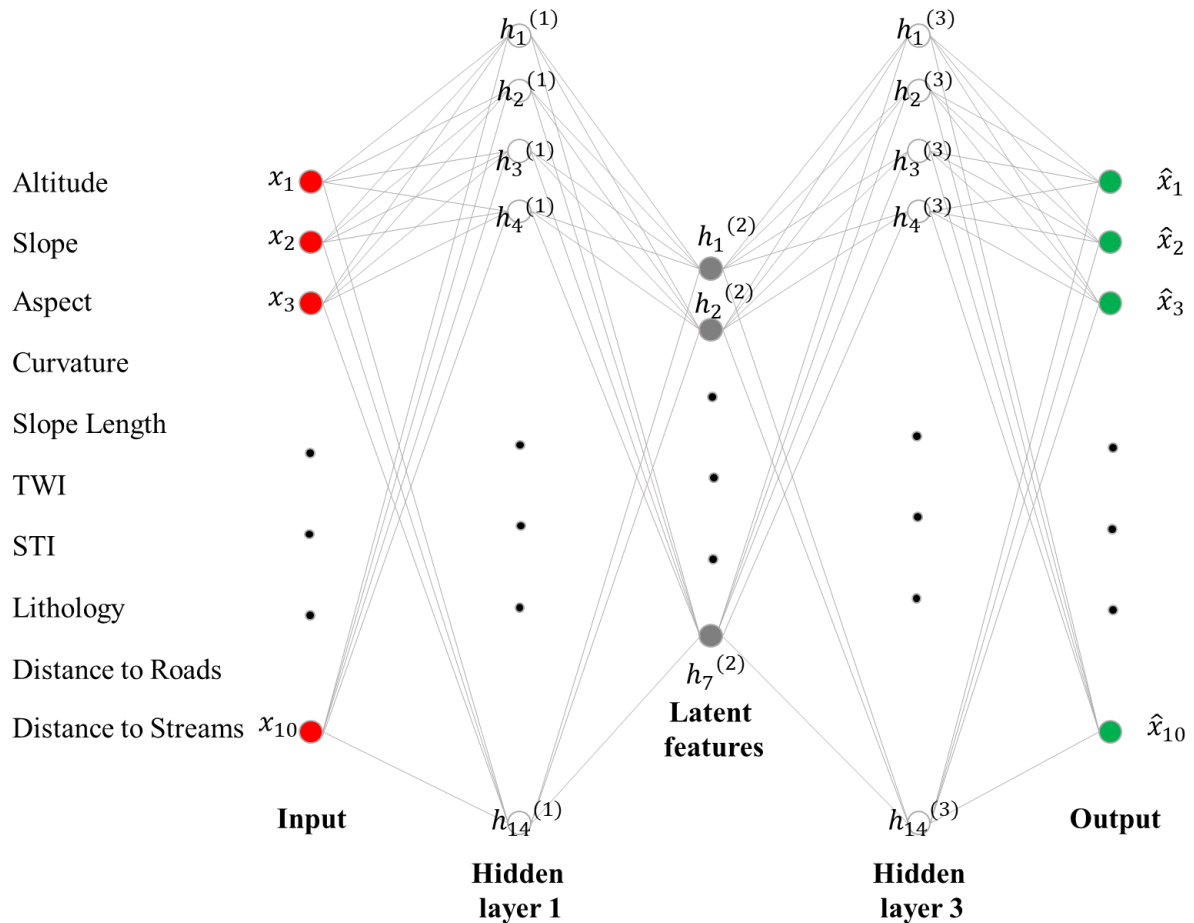
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Figure 4: Flowchart of the proposed methodology.

266 3.3.1 Unsupervised factor optimisation by SAEs

267 Autoencoders are neural networks that can be used to learn features from a dataset in an
268 unsupervised manner (Hinton and Salakhutdinov 2006). They can be shallow (i.e. with one
269 hidden layer) or deep (i.e. with two or more hidden layers). The addition of more hidden layers
270 depends on the complexity and amount of data. The proposed SAE model structure, as
271 presented in Figure 4, has three hidden layers in addition to the input and output layers. The
272 input $x \in \mathfrak{R}^N$ is mapped into a hidden representation $h^{(1)} \in \mathfrak{R}^N$ using $h^{(1)} = f_{\theta_1}(W^1x + b^1)$,
273 which is then used to learn another hidden illustration $h^{(2)} \in \mathfrak{R}^N$ by $h^{(2)} = f_{\theta_2}(h^{(1)} + b^2)$. The
274 output of this illustration is used to learn a third hidden illustration $h^{(3)} \in \mathfrak{R}^N$ by $h^{(3)} =$
275 $f_{\theta_3}(h^{(2)} + b^3)$. The hidden representation $h^{(3)}$ is then utilised to regenerate an approximation
276 \hat{x} of the input. The hidden layer $h^{(2)}$ is considered the new feature representation of the input
277 data. The dimension of the input layer x is 10, and each $h^{(1)}$ and $h^{(3)}$ has 14 hidden nodes,
278 whereas the new feature representation $h^{(2)}$ has only 7 nodes. Therefore, the proposed SAE
279 learns compressed representation, which can reduce the computational time of the RGF model.
280 A sparsity constraint of L1 regularisation (10e-5) was enforced on the three hidden layers of
281 the model to avoid overfitting in the model. The rectified linear unit activation function was
282 used for the hidden layers (encoder), whereas the sigmoid function was used for the output
283 layer (decoder).

284 The optimal parameters of the SAE model were selected by minimising the binary cross-
285 entropy cost function using a backpropagation algorithm and stochastic gradient descent (i.e.
286 Adamax). The model was trained for 1,000 epochs with a batch size of 32 and a learning rate
287 of 0.002. The training was stopped when validation accuracy stopped improving (patience =
288 20 epochs). After the learning process, the SAE model learned a nonlinear function that
289 mapped an input vector $x \in \mathfrak{R}^N$ into a new feature representation $h^{(2)}$.



290

291

Figure 5: Structure of the proposed SAE model.

292 *3.3.2 RGFs*

293 Decision trees are also commonly used models in landslide susceptibility analysis and other
 294 applications. These models have a tree-like structure with terminal and nonterminal nodes. The
 295 former presents the decision outcomes, whereas the latter presents the attribute tests. The major
 296 advantages of these models are easy implementation and graphical presentation of the model
 297 structure. However, these models are susceptible to data noise and can overfit the training data
 298 if inaccurately validated. Researchers have proposed many improved versions of tree-based
 299 models, including boosted trees and their ensembles, such as RF and RGF, to overcome the
 300 limitations of decision trees. RGF combines several boosted trees and additively forms a forest
 301 as a single predictive model (Johnson and Zhang 2014). In boosted decision trees, the trees are
 302 locally optimised; in RGF, the trees are globally optimised. RGF utilises a tree structure
 303 because it uses fully corrective regularised steps. RGF is also faster and frequently more
 304 accurate than boosted trees, particularly for regression problems.

305 *3.4 Model evaluation methods*

306 AUROC was used to assess the predictive capability of the proposed model and compare it
307 with other models. AUROC is widely adopted in landslide susceptibility studies (Pradhan et
308 al. 2010, Shirzadi et al. 2017). The receiver operating characteristic (ROC) curve is constructed
309 based on the sensitivity (the true positive rate) and specificity (the false-negative rate). AUROC
310 is calculated using the following expression:

$$311 \quad \text{AUROC} = \frac{\sum \text{TP} + \sum \text{TN}}{\text{P} + \text{N}}, \quad (3)$$

312 where TP is the true positives, and TN is the true negative. A high AUROC value indicates an
313 accurate model prediction. In general, values of 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9 and 0.9–1
314 indicate insufficient, moderate, good, very good and excellent performance, respectively (Bui
315 et al. 2014).

316 **4. Results and discussion**

317 This section presents the major findings of the research and discusses the factor optimisation
318 analysis, application of RGF and other tree-based landslide susceptibility modelling
319 approaches.

320 *4.1 Factor optimisation analysis*

321 Table 1 lists the results of the unsupervised factor optimisation to RGF-based landslide
322 susceptibility modelling. The feature space of the input data had a dimensionality of 10, which
323 was then reduced to lower dimensions (9–2) by the proposed SAE model. A number of
324 observations can be made from the findings of this experiment. The summary is presented in
325 Table 1. Firstly, a high linear relationship exists between the SAE reconstruction errors on the
326 training and testing datasets ($R^2 = 0.991$), which explains the efficiency of the SAE model in
327 learning low representations of the input data without substantial overfitting and underfitting.
328 The lowest reconstruction errors were 0.522 and 0.517 for the training and testing datasets,
329 respectively, when the number of input features was reduced to eight. The largest
330 reconstruction errors were 0.569 and 0.566 for the training and testing datasets,
331 respectively, when the number of features was reduced to only two. These results suggest that
332 reducing the dimensionality of the input data by using the SAE model requires careful analysis
333 of the number of new representation features. Secondly, the success and prediction rates of the
334 RGF model that was trained on the new representation features learned by the SAE indicate a
335 linear relationship of $R^2 = 0.85$ between the reconstruction errors and the associated success
336 rates. A considerably lower R^2 (0.53) was observed between the reconstruction errors and the

337 associated prediction rates. These results indicate that low reconstruction errors by the SAE do
 338 not necessarily yield high success/prediction rates on the RGF model. The best success
 339 (AUROC = 0.931) and prediction (AUROC = 0.892) rates for the RGF model were observed
 340 when the input features were reduced to seven. Reducing the dimensionality of the input
 341 features into only two degraded the success and prediction rates of the RGF model by 17% and
 342 16%, respectively. Furthermore, transforming the input features into a new set of feature
 343 representations with the same size as the input data (10 features) did not yield the best success
 344 and prediction rates for the RGF model.

345 Table 1: Reconstruction errors estimated for the SAE and the associated success/prediction
 346 rates of the RGF model based on the training and testing datasets.

Number of compressed features	Reconstruction error (training data)	Reconstruction error (testing data)	SAE–RGF success rate	SAE–RGF prediction rate
2	0.569	0.566	0.765	0.736
3	0.553	0.548	0.819	0.715
4	0.545	0.539	0.880	0.829
5	0.532	0.529	0.904	0.826
6	0.541	0.538	0.896	0.763
7	0.540	0.534	0.931	0.892
8	0.522	0.517	0.928	0.848
9	0.533	0.527	0.919	0.889
10	0.534	0.528	0.908	0.830

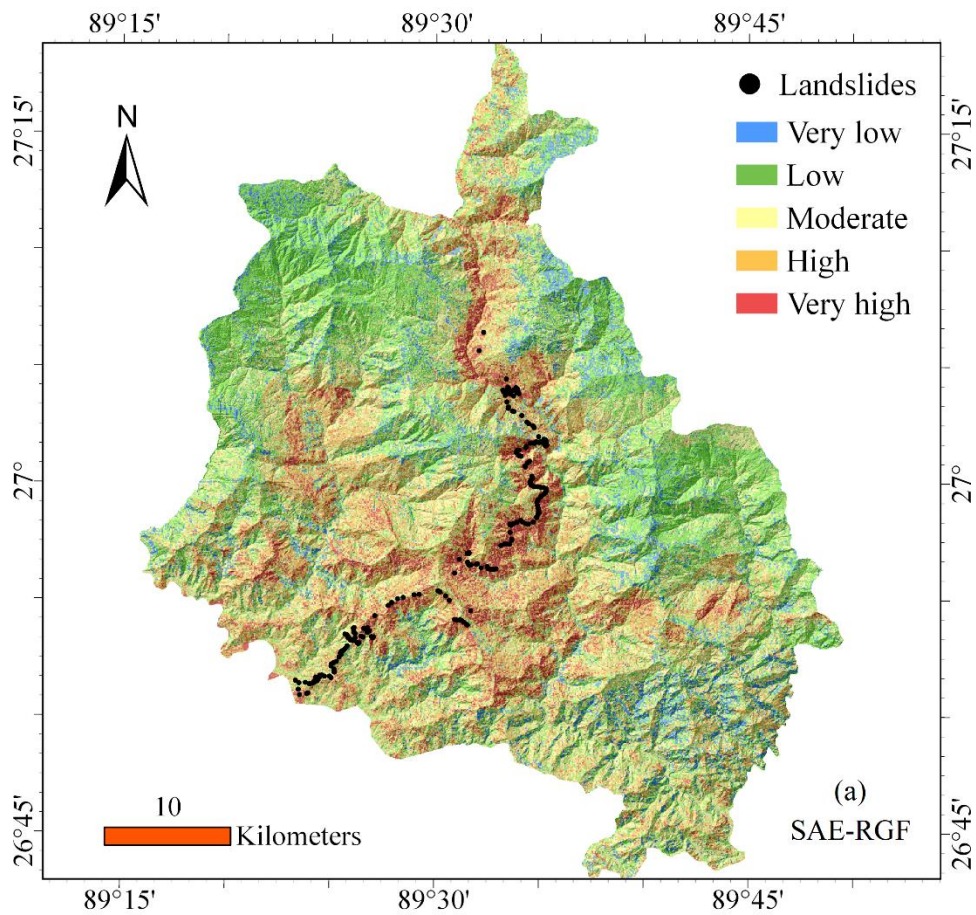
347

348 4.2 Application of SAE–RGF, RGF and RF

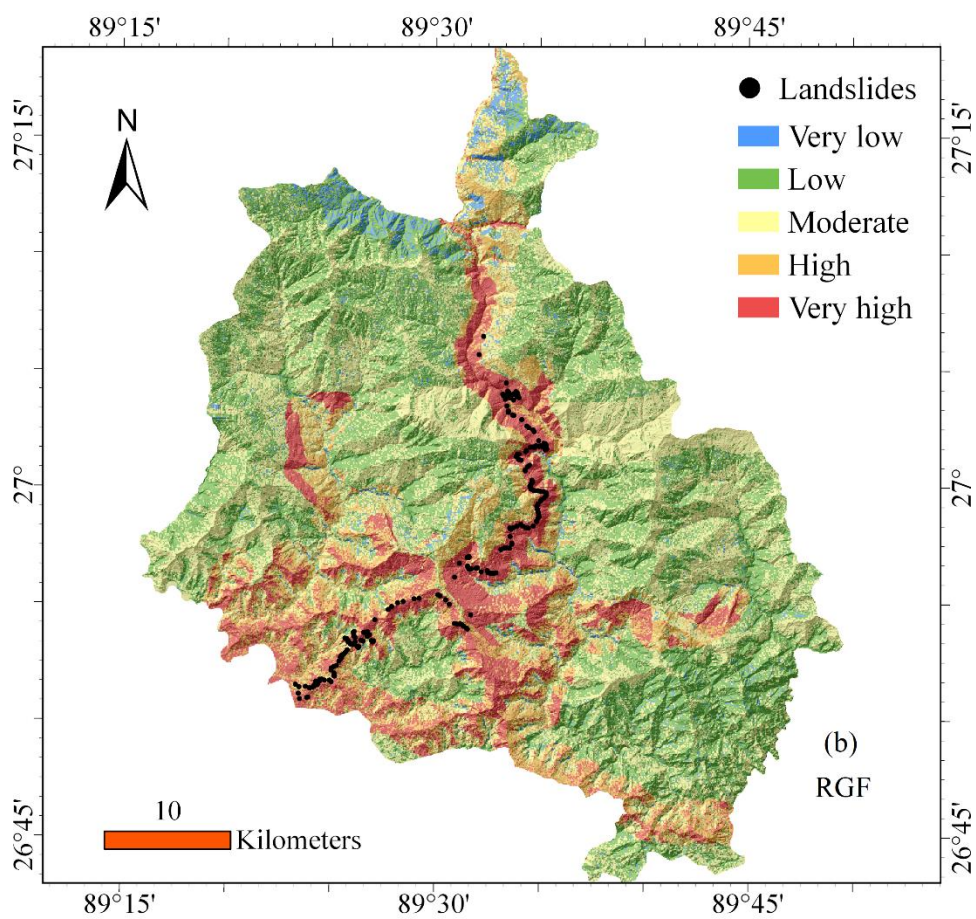
349 Three susceptibility maps were generated for the study area using the proposed SAE–RGF
 350 model and the RGF model without unsupervised factor optimisation, and for comparison, with
 351 another tree-based model (RF) (Figure 6). The susceptibility maps were recategorized into five
 352 classes, namely, *very low*, *low*, *moderate*, *high* and *very high* area. The landslide inventories
 353 were overlaid with the susceptibility maps to support the visual interpretation of the maps. The
 354 SAE–RGF model divided the study area into the five susceptibility classes with percentages of
 355 9%, 32%, 32%, 20% and 7%. The result indicated that 27% of the area, particularly along the
 356 Phuentsholing–Thimphu highway and nearby areas, is under high and very high risks due to

357 landslides. Using the RGF model without applying SAE factor optimisation yielded a reduction
358 in the very low and high susceptible zones by 6% and 7%, respectively. The RGF model
359 predicted that 36% of the area is under low and moderate landslide susceptibility classes. The
360 RGF model also predicted a higher percentage of the area (12%) than what the SAE–RGF
361 model predicted. Significantly different results were observed for the RF model. The study area
362 was divided into 44%, 38%, 10%, 3% and 4% susceptibility classes by the RF model. This
363 model suggested that only 7% of the area is under high and very high susceptible zones.

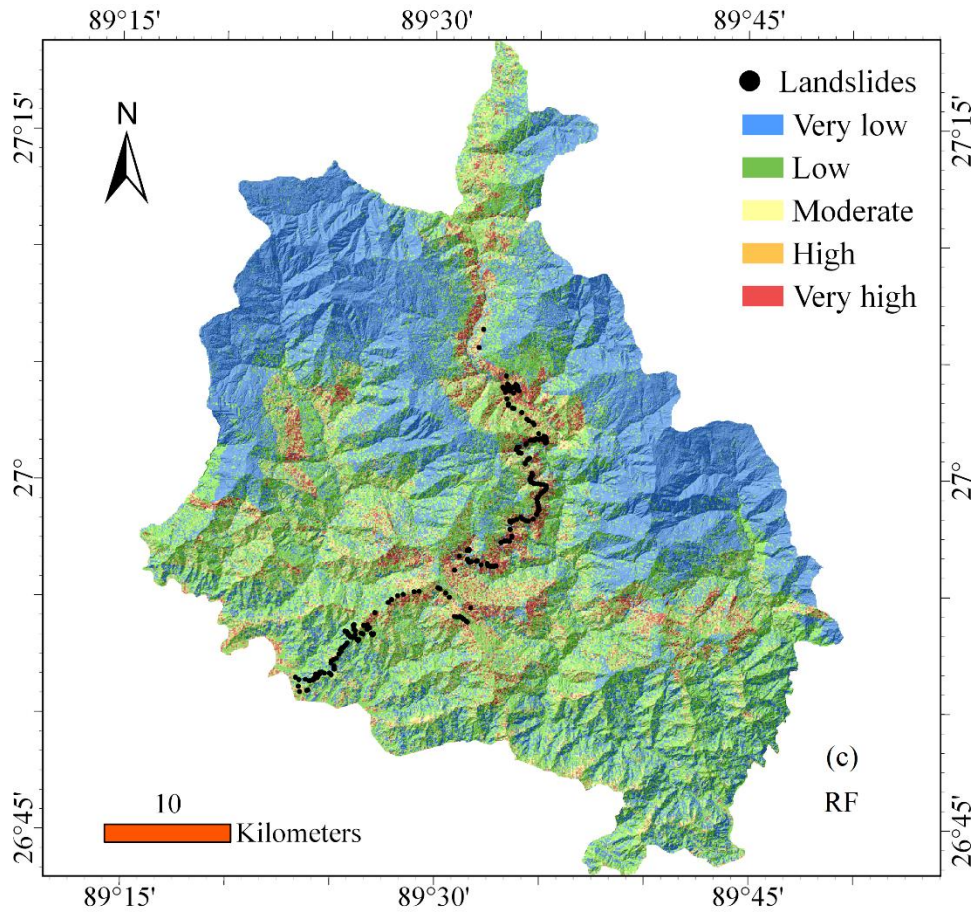
364 Table 2 lists the success and prediction rates of the three models. The best success rate (0.972)
365 was achieved by the RGF model, which outperformed the proposed SAE–RGF (0.931) and RF
366 (0.876) models. However, the results regarding the prediction rates suggested that the proposed
367 SAE–RGF model exhibited the best generalisation capability with a prediction rate of 0.892
368 compared with 0.865 and 0.824 for the RGF and RF models, respectively. Reducing the
369 dimensionality of the input data from 10 to 7 helped improve the prediction capability of the
370 RGF model. The percentage of landslides in the susceptibility classes was utilized by
371 comparing landslide occurrences with the results of the landslide susceptibility maps (Figure
372 7). Approximately 43% and 33% of landslide inventories were identified in the very high and
373 high susceptible zones, respectively, by the SAE–RGF model. The very high susceptible zone
374 for the map produced by the RGF model contained 82% of the landslides. However, the map
375 and AUROC values (success rate = 0.972, prediction rate = 0.865) implied that this
376 phenomenon was due to the overfitting of the training data, and the model failed to predict the
377 absence samples correctly. The very high and high susceptibility classes for the map produced
378 by the RF model contained 27% and 13% of the landslides, respectively. This finding also
379 suggested that the proposed SAE–RGF model helped identify numerous landslides located in
380 the very high susceptible zone without considerable overfitting to the training data and
381 produced reliable landslide susceptibility maps in the study region.



382



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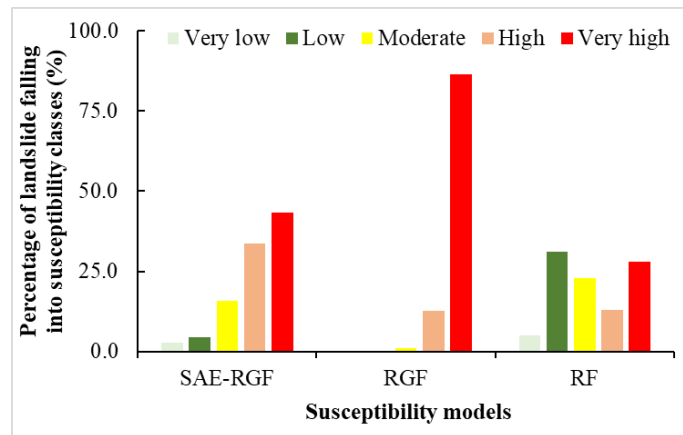
384

385 **Figure 6:** Landslide susceptibility maps produced by (a) SAE–RGF, (b) RGF and (c) RF.

386 **Table 2:** Success and prediction rates of the landslide susceptibility models.

Susceptibility model	Success rate	Prediction rate
SAE–RGF	0.931	0.892
RGF	0.972	0.865
RF	0.876	0.824

387



388

389 **Figure 7:** Graph showing landslides (in %) for different susceptibility classes for the three
 390 models.

391 Tree-based landslide susceptibility modelling methods, including their ensemble, such as RF,
 392 are frequently affected by variations and noise in data. The SAE model proposed in this study
 393 helps reduce information redundancy and noise in the data by learning a new set of nonlinear
 394 feature representations from the input data with a lower dimension than that of the original
 395 feature set. Previous methods on factor optimisation for landslide susceptibility mappings, such
 396 as the methods presented by Jebur et al. (2014) and Dou et al. (2015), are supervised and select
 397 a subset from the original data without any transformation to the input features. Although these
 398 methods help improve the prediction ability of statistical and machine learning methods, such
 399 as statistical index, logistic regression and support vector machines, they require high-quality
 400 training data and do not reduce noise nor improve input features in terms of information
 401 content. By contrast, the proposed SAE–RGF is unsupervised (no training data are required)
 402 and helps tree-based models that are highly sensitive to noise and data variations.
 403 Consequently, using the new representations learned by the SAE–RGF model can help improve
 404 tree-based models, such as RGF and RF, for landslide susceptibility within a study region. The
 405 proposed SAE–RGF model also helps reduce the training and inference prediction times of the
 406 RGF and RF models by reducing the input data dimension from 10 to 7 features.

407 However, the model also has several limitations at the current implementation. First, the
 408 selection of a new dimension, which is often lower than the original dimension of the landslide
 409 factors, can be challenging. It requires several experiments to evaluate different alternatives
 410 until the optimum one can be found. This challenge is getting harder when the original
 411 dimensionality is larger. Search methods can be used such as a grid or random search but that
 412 can be computationally expensive. To address this challenge, future implementations should

413 focus on either automating this process within the workflow or developing a statistical measure
414 that allows a good selection of this parameter. Second, after transforming the factors with a
415 non-linear function learnt by the SAE model, the interpretation of the models is getting much
416 harder than the original models. So, the current strategy is focused on prediction accuracy
417 improvement rather than model interpretation and explainability. Those issues can be explored
418 in future works by using interpretable models to perform factor optimisation.

419 **6. Conclusions**

420 This research demonstrated the use of an unsupervised factor optimisation approach based on
421 sparse autoencoders (SA) to improve the performance of tree-based landslide susceptibility
422 models in Chukha Dzongkhag, Bhutan. The model enables learning a new set of nonlinear
423 feature representations with richer information and lower dimensionality. It is an important
424 pre-processing step for landslide susceptibility modelling that requires neither additional
425 training data nor human supervision. The success and prediction rates estimated based on
426 AUROC indicated the prevalence of the proposed model over RGF and RF models, particularly
427 in terms of generalisation to the test dataset.

428 Originally, the model used 10 landslide conditioning factors, including geo-morphometrical
429 and geo-environmental. The performance of RGF was about 0.972 and 0.865 as for success
430 and prediction rates, respectively. After transforming the factor values with a non-linear
431 function learnt by the SAE, the accuracy of RGF has dropped to 0.908 and 0.830 as for the
432 success and prediction rates, respectively. But interestingly, when the dimensionality of the
433 factors was reduced to only 7 features, the prediction rate of RGF went up to become 0.892.
434 As several landslide conditioning factors are often derived from a single source (DEM), those
435 factors are statistically correlated to each other. Reducing the dimensionality of these factors is
436 therefore useful and boosts the performance of the landslide susceptibility models. However,
437 this comes with a challenge, which is that selecting a good dimension size to transform the
438 factors requires additional experiments and statistical analysis. Further research is thus needed
439 to improve our understanding of how these models should be applied to different geographical
440 regions. Also, automating the selection of an optimised dimension to improve landslide
441 susceptibility can be a good research direction.

442 The proposed model can be useful for disaster managers, urban planners and technicians in
443 landslide-prone regions to improve landslide susceptibility evaluation procedures without
444 raising information and computational resource expenses. Landslide susceptibility maps can

445 be useful in enforcing reconstruction strategies in other geospatial apps and in choosing spatial
446 sites.

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453 **Conflicts of interest**

454 The authors declare no conflict of interest.

455 **Computer Code Availability**

456 The Regularized Greedy Forest algorithm was implemented using the rgf-python library freely
457 available at (<https://github.com/RGF-team/rgf>). The other bench-marked models were
458 implemented using Sklearn (<https://scikit-learn.org>). Moreover, the complete notebook of the
459 experiments presented in the paper is available on GitHub
460 (https://github.com/malzuhairi/rgf_landslides).

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