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Mapping Susceptibility With Open-Source Tools: A New Plugin for QGIS

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In this study, a new tool for quantitative, data-driven susceptibility zoning (SZ) is presented. The SZ plugin has been implemented as a QGIS plugin to maximize its operational use within the geoscientific community. QGIS is in fact a commonly used open-source geographic information system. We have scripted the plugin in Python, and developed it as a collection of functions that allow one to pre-process the input data, calculate the susceptibility, and then estimate the quality of the classification results. The susceptibility zoning can be carried out *via* a number of classifiers including weight of evidence, frequency ratio, logistic regression, random forest, support vector machine, and decision tree. The plugin allows one to use any kind of mapping units, to fit the model, to test it *via* a k-fold cross-validation, and to visualize the relative receiving operating characteristic (ROC) curves. Moreover, a new classification method of the susceptibility index (SI) has been implemented in the SZ plugin. A typical workflow of the SZ plugin is described, and its application for landslide susceptibility zoning in Northeast India is reported. The data of the predisposing factors used are open, and the analysis has been carried out using a logistic regression and weight of evidence models. The corresponding area under the curve of the relative ROC curves reflects an optimal model prediction capacity. The user-friendly graphical interface of the plugin has allowed us to perform the analysis efficiently in few steps.

Keywords: SZ plugin, susceptibility, Northeast India, QGIS, landslide

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1 INTRODUCTION

The measure of how much a specific area is prone to natural hazards is called susceptibility. It does not evaluate when or how often the given hazard may occur (Guzzetti et al., 2006), but it provides the expected locations where such processes may take place in the future. Mathematically, the susceptibility is the estimation of the likelihood of spatial occurrence of natural hazard evaluated on the basis of terrain and environmental conditions (Brabb, 1985). In most cases, this likelihood can be obtained *via* rigorous probabilistic models, although other tools are also able to convey similar information without relying on complex multivariate statistics (e.g., Ciurleo et al., 2017; Lombardo et al., 2020a). All these methods fall under the definition of data-driven models, and they empirically classify a landscape, labeling it as prone or not prone to slope failures. The way a classifier specifically works is to weigh the contribution of each predisposing factor to the occurrence of natural hazards, taking into account the presence/absence proportion of past records, given other predisposing factors in the model. The basic idea behind data-driven models is that "the past is the key to the future" (Carrara et al., 1995). Thus, an area that has been affected by natural hazards in the past under certain circumstances may undergo similar environmental stresses and suffer from analogous hazards in the future. Therefore, the statistical analysis of susceptibility is based on a spatial dataset of past events, which acts as the dependent variable of any given model, together with a set of geo-environmental factors acting as explanatory variables.

This study presents the susceptibility zoning (SZ) plugin, a new tool for susceptibility analysis integrated within one of the most common open-source GIS platforms, QGIS (QGIS Development Team, 2022). Specifically, the SZ plugin is a collection of functions implemented as a QGIS plugin, supporting a number of preprocessing requirements, as well as the susceptibility mapping and validation itself. Moreover, the plugin is equipped with a series of plotting routines aimed at exploring and interpreting each model components as well as estimating the predictive ability of the model when dealing with unknown data.

A number of tools for susceptibility zoning are already available in the literature, including LSAT (ArcGIS toolbox) (Torizin, 2012; Polat, 2021), BSA tool (ArcMap tool) (Jebur et al., 2015), LAND-SE (R script) (Rossi and Reichenbach, 2016), frmod (Python script) (Dávid, 2021), and GeoFIS (standalone) (Osna et al., 2014). The SZ plugin, to our knowledge, is the first tool that enables susceptibility routines within QGIS.

This study describes in detail the SZ plugin graphical user interface together with all its functions and provides a sample application to landslide susceptibility in Northeast India. A previous version of this plugin (v0.1) was already published in 2020 by Titti and Sarretta (2020), but here we have extended the available options encompassing other modeling approaches within the same plugin, and we have equipped the SZ plugin with a suite of plotting and performance evaluation tools. The current version (v1.0) is available in the following GitHub repository CNR-IRPI-Padova/SZ.

2 PLUGIN DESCRIPTION

The SZ plugin has been developed specifically for landslide susceptibility zoning; however, it can be used to map any kind of susceptibility. The code has been written in Python and developed as a QGIS plugin. QGIS is a software for geographic information system (GIS) that is completely open-source and supported by a large community of users and developers. A positive consequence of this open approach is that anyone can develop their own plugin to address specific needs. Hundreds of plugins are freely available from official and non-official repositories, but none has focused on susceptibility modeling.

In order to better integrate the plugin with the graphical user interface (GUI) of QGIS and simplify its usability, the SZ plugin can be accessed from the QGIS processing toolbox, the main element of the processing GUI. In detail, the SZ plugin is a collector of QGIS processing scripts. Some functions can pre-process data according to the asset required by the core model functions, which can estimate and validate the susceptibility using a suite of possible models. These include the following: weight of evidence (WoE, Hussin et al., 2016), frequency ratio (FR, Arabameri et al., 2019), logistic regression (LR, Lombardo et al., 2020b), random forest (RF, Catani et al., 2013), support vector machine (SVM, Lin et al., 2017), and decision trees (DT, Yeon et al., 2010). The evaluation of the results and the classification of the final map proposed are based on the receiving operating characteristic (ROC) curves (**Section 3.2**).

Working mainly with vector layers, the SZ plugin allows one to use any shapes or form of the mapping unit. In landslide susceptibility, the most common ones consist in grid cells (Reichenbach et al., 2018), terrain units (Van Westen et al., 1997), unique condition units (UCU, Ermini et al., 2005), slope units (Alvioli et al., 2016), geo-hydrological units (Zêzere et al., 2017), topographic units (Eeckhaut et al., 2009), and administrative units (Lombardo et al., 2019).

Figure 1 shows the GUI of the plugin inside QGIS, listing the implemented functions, which are separated into four groups: Data preparation, SI, SI k-fold, and Classify SI.

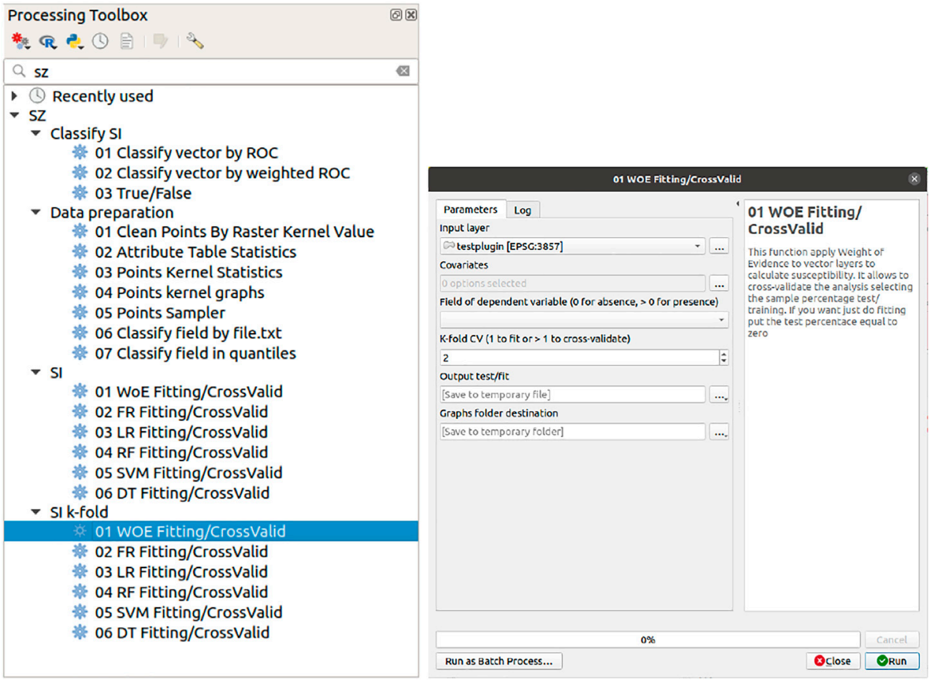
"Data preparation" includes pre-processing functions for vector data. "SI" and "SI k-fold" are the core groups, which allow users to choose among a number of possible statistical models. "SI" and "SI k-fold" allow one to fit or cross-validate (CV) the selected model. If a cross-validation is selected, the "SI" function uses a binomial sampler splitting the dataset randomly into train and test samples, while, the "SI k-fold" function uses the k-fold cross-validation (**Section 3.1**) method where the user can choose the number of subsamples. "Classify SI," instead, provides performance metrics to evaluate the goodness-of-fit or predictive skills in case of cross-validation. The former case returns a single performance value, whereas the latter provides summary statistics for the number of cross-validations opted by the user.

It must be stresses that to maximize the model performance, its assessment offers a new ROC-based classification method which selects the cutoffs required to build the ROC curves to maximizes the relative area under the curve (AUC). Details are reported in **Section 3.2**.

2.1 Functions' Description

The sub-section of the SZ plugin called "Data preparation" is useful to pre-process and set the data to be used by the "SI" and "SI k-fold" functions. These functions are as follows:

- Clean points by raster kernel value: it is a filter function that removes all the points of a layer that do not satisfy the minimum value selected in a fixed neighborhood. The values of the neighborhood are collected from an overlapping raster layer.
- Attribute table statistics: this function detects, field by field, the unique values and lists the ID of the feature which reports the same value. Moreover, it produces histograms of the unique values frequency using the Plotly library.



Input layer: testplugin [EPSG:3857]

Covariates: 0 options selected

Field of dependent variable (0 for absence, > 0 for presence)

K-fold CV (1 to fit or > 1 to cross-validate): 2

Output test/fit: [Save to temporary file]

Graphs folder destination: [Save to temporary folder]

01 WOE Fitting/CrossValid

This function apply Weight of Evidence to vector layers to calculate susceptibility. It allows to cross-validate the analysis selecting the sample percentage test/training. If you want just do fitting put the test percentace equal to zero

FIGURE 1 | SZ plugin GUI.

- Points kernel statistics: it calculates the effective, maximum, minimum, standard deviation, sum, average, and maximum range value of the point neighborhood.
- Points kernel graphs: the results of the previous function are plotted by this function as frequency graphs.
- Points sampler: this function randomly samples the vector points according to the train/test scheme selected by the user.
- Classify field by file.txt: to apply the WoE or FR method, the covariates should be cut in a number of classes. This function classifies the vector fields according to the bin limiting values that the operator may choose. These need to be reported in a text file.
- Classify field in quantiles: if the operator does not wish to provide the bin limiting values, the vector fields can be classified according to any quantile representation (i.e., deciles, quartiles).

"SI" and "SI k-fold" functions applies WoE, LR, DT, RF, or FR to calculate susceptibility. They require a polygonal layer which includes one field per each covariate and one field with the dependent variable (number of landslides, tornado, and floods) per mapping unit. The "SI" function allows to cross-validate the results selecting the sample percentage of training and test or allowing one to fit the model to the whole dataset, whereas the "SI k-fold" function allows to cross-validate the results with a k-fold method (**Section 3.1**) or also fit the model to the whole dataset.

The functions produce vectors of training/testing or fitting results and report in a text file the relative weights or regression coefficients (depending on the model the user has chosen). Also, it produces a graph of the ROC curves with the associated AUCs. The close the AUC is to 1, the higher the capacity of the given model is to suitably classify the study area into stable or unstable conditions. The ROC analysis as well as all the probabilistic models available within the SZ plugin (LR, DT, RF, and SVM) is based on the library Scikit-learn (Pedregosa et al., 2011). As for bivariate statistical models (WoE and FR), they have been implemented manually and added to the collection because they are largely used in the literature from many years (van Westen et al., 2000).

The last group of functions is "Classify SI" which includes "01 Classify vector by ROC," "02 Classify vector by weighted ROC," and "03 True/False". Using genetic algorithms (GA) the 01 and 02 "Classify SI" functions classify the susceptibility index (SI) into the indicated number of classes through the reconstruction of the segmented ROC curve in order to maximize the AUC (for more details **Section 3.2**).

The only difference between the "01 Classify vector by ROC" and the "02 Classify vector by weighted ROC" is the use of weighted ROC curve. The weights can be established among the input vector fields.

"03 True/False" produces a map of mapping units labeled as follows: True Positive, True Negative, False Positive, and False Negative according to a selected cutoff of the susceptibility index.

2.2 Software Availability

The SZ plugin has been implemented in Python 3. It requires many dependencies such as: Numpy, Scipy, GDAL, Scikit-learn (Pedregosa et al., 2011), Pandas (The pandas development team, 2019), Matplotlib (Hunter, 2007), and Plotly (Inc., 2015). The

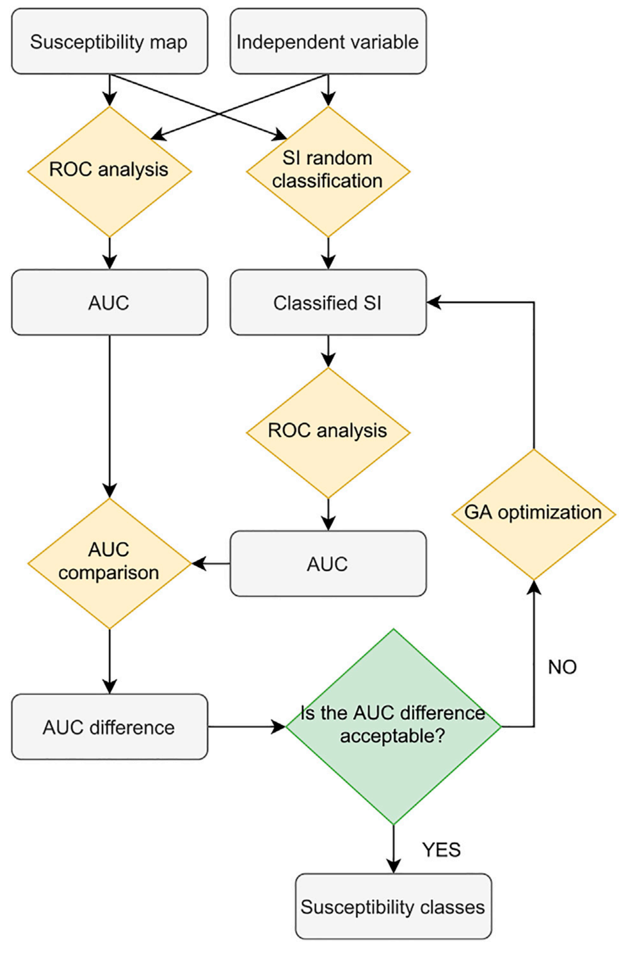


FIGURE 2 | Workflow of GA-based classifier functions.

version of SZ plugin used in this study is the v1.0 (Titti et al., 2021b). The latest version of the SZ plugin is always available on the GitHub repository CNR-IRPI-Padova/SZ.

The plugin has been tested with QGIS 3.16 on Ubuntu 20.04 and Windows 11. To support and increase the usability of the plugin a video tutorial has been published at: https://www.youtube.com/watch?v=XpsiCkVF11s (last access 2022/02/03).

3 BACKGROUND

To understand the functionalities of the plugin, the explanation on how the plugin handles the cross-validation, performance assessment, and susceptibility index is reported hereafter. Moreover, the **Section 4** shows the application of the tool to landslide susceptibility zoning using the WoE and LR.

3.1 Cross-Validation

Validation routines involve the test of the performance of a data-driven model with respect to unknown data. Ideally, the unknown data should belong to a temporal replicate of the modeled process. However, geomorphological studies often lack of multitemporal inventories. Thus, testing the model performance most of the times requires the implementation of cross-validation routines. These are commonly performed by splitting the entire input dataset into two subsets, one used for training the given data-driven model and the other one to test. This structure revolves around considering a subsample of the whole dataset in the same way as one would consider future landslide occurrences, thus offering the chance to compare locations labeled to be stable/unstable with respect to a set of actual stable/unstable instances.

The literature reports few ways to extract the testing subset. The most common in the geomorphological literature is to extract a random sample from the full dataset. Most of the times this is done just once (Arabameri et al., 2020); in this case, most of the variability of a study area is disregarded. In other cases, the random samples are extracted, without any constraint, a large number of times with the purpose of depicting the potential variability of a test site (Amato et al., 2019). In fewer cases, the variability of a given study area is accounted for by extracting samples that are constrained to be selected just once across replicates, leading to two-fold (Yeon et al., 2010), five-fold (Dang et al., 2019), or ten-fold (Lombardo and Tanyas, 2021) cross-validations. All the examples mentioned before adopt a cross-validation scheme where the extraction, constrained or unconstrained, is randomized in space. However, this operation is statistically appropriate only if one assumes that the presence/absence label assigned to a given mapping unit of choice is independent from the labels of the surrounding mapping units. In other words, these procedures assume that there is no spatial structure in the data other than the one captured by the selected explanatory variables. This is an acceptable assumption for medium (e.g., slope units) to large (e.g., catchments) mapping units, but it is not valid for fine mapping units such as grid-cells. In such cases, the most appropriate way to implement cross-validation routines is to constrain the testing subsets in space, each one being representative of a specific sector of the study area. In turn, this operation ensures that any residual spatial structure in the data, not captured by the explanatory variables, would not affect the validation estimates. In other words, the testing is free or as free as possible from any spatial effect that may bias the performance toward results that are forcefully better than what they should be. This operation is commonly referred to as spatial-cross validation (e.g., Petschko et al., 2014).

Out of the cross-validation schemes described above, the current version of the SZ plugin offers two options. The first is a cross-validation where the train/test split is performed just once as per the majority of cases in the geoscientific literature ("SI" functions). This is achieved by using the *train_test_split* function in Scikit-learn. The second is a *k*-fold cross-validation where from the whole dataset, the test data is randomly extracted according to number (k) of mutually exclusive subsets ("SI k-fold" functions). The training data is represented by the complementary subsets. In other words, if k is equal to 10, then ten non-overlapping test sub-samples (each one made of 10% of the total mapping units) are created to test the prediction skill of the model and the ten complementary 90% subsets are used to calibrate the model instead. Thus, the union of the ten

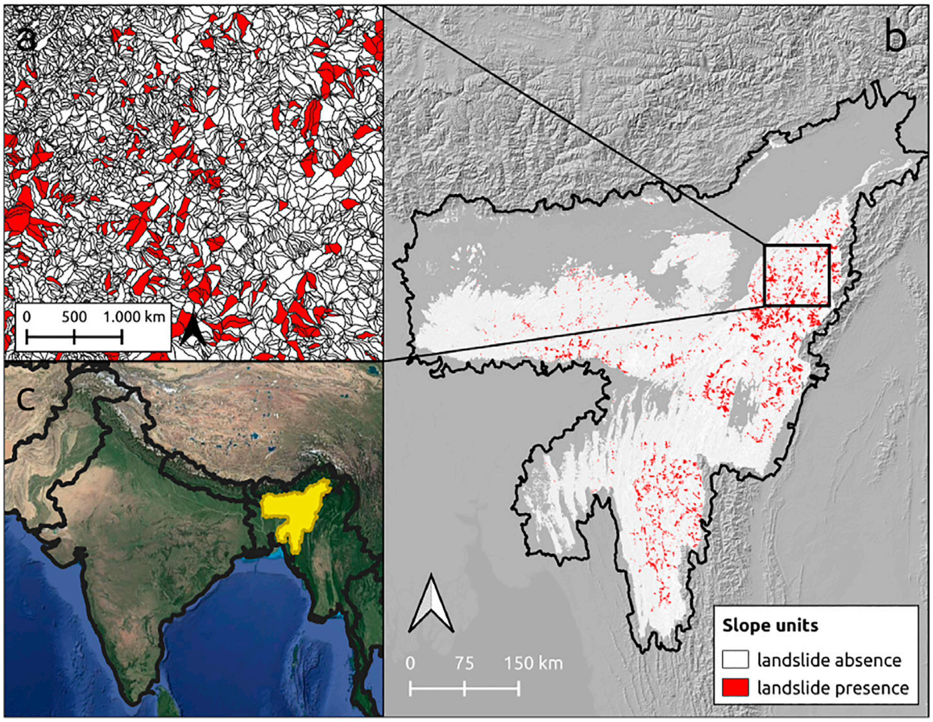


FIGURE 3 | Study area and relative slope units of the SZ plugin application to landslide susceptibility (Map data panel c ©Google). Panel b shows in white and red the slope units investigated after the exclusion of the alluvial plains. The red zones represent the unstable slope units, whereas the white zones represent the stable ones.

TABLE 1 | Predisposing factors and their acronyms (see more details at the end of Section 4).

	Data type	Layer	Pixel size	Data source
1	Morphology	Raster	30 × 30 m	SRTM (Farr et al., 2007)
2	Geology	Vector	—	USGS
3	Land cover	Raster	300 × 300 m	ESA 2010 and UCLouvain
4	PGA	Raster	90 × 90 m	CHIRPS (Funk et al., 2015)
5	Precipitation	Raster	5 × 5 km	IMRG (Huffman et al., 2019)
6	NDVI	Raster	30 × 30 m	Landsat 7 C1 Tier 1

10% subsets returns the whole study area, in such case the resulting susceptibility map would have been generated by fully predicted instances. Any test sample is balanced in terms of presence/absence. The presence/absence proportion of the test sample is equal to the proportion of presence/absence of the complete dataset. The spatial-cross validation is not implemented in the current version of the SZ plugin, but it is part of the development plan for the subsequent versions.

3.2 Performance Assessment

The model performance is evaluated *via* the receiving operating characteristic (ROC) curves and their relative AUC (Chung and Fabbri, 2003; Fawcett, 2006).

Each mapping unit of a susceptibility map can be labeled as True Positive (*TP*), True Negative (*TN*), False Positive (*FP*), and False Negative (*FN*) unit (Rahmati et al., 2019) according to the presence/absence of the dependent variable (landslides in our application) and to positive/negative (stable/unstable) label assigned. After sorting the susceptibility index by descending order, the spectrum of susceptibility values can be split into two categories, prone or not, to the occurrence of the hazard. The susceptibility cutoffs, which assign the binary label (stable/unstable), are assigned continuously until the lowest value of susceptibility. The ROC curve then plots the relation between TP_{rate} and FP_{rate} as follows:

$$TP_{rate} = \frac{TP}{TP + FN} FP_{rate} = \frac{FP}{FP + TN}. \tag{1}$$

3.3 Susceptibility Index Classifier

In the literature, several methods have been used to segment the susceptibility index into discrete classes. The continuous spectrum of susceptibility values has been sliced into quantiles; other cases report their classification on the number of landslides per class or on the ratio between the landslide area and the surface area of each class in comparison to the entire study area (Lombardo et al., 2020a). The SZ plugin proposes a new genetic algorithm-based classifier.

The genetic algorithm (GA) is an iterative meta-heuristic algorithm based on the numerical reproduction of Charles Darwin's natural selection theory (Chatterjee et al., 1996). The meta-heuristic algorithms are designed to explore the search

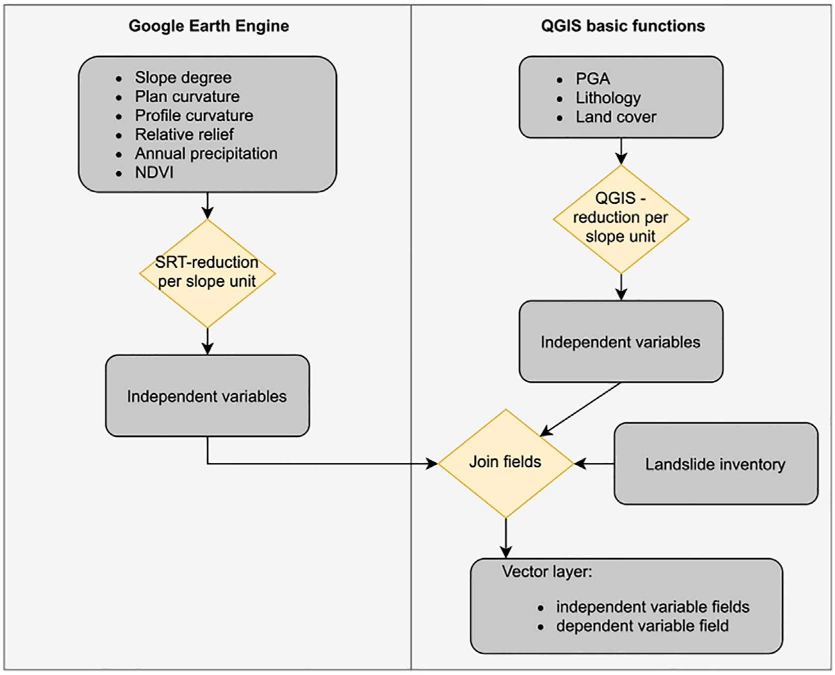


FIGURE 4 | Flowchart of the data collection and preprocessing using the SRT (GEE) and QGIS.

space from several points of view and to get the solution as near as possible to the optimal (Said et al., 2014).

A GA near-optimal solution is reached through the iterative delineation of the best object selected from a group of admissible solutions which are evolved by operators such as crossover, mutation, inversion, and others (Chatterjee et al., 1996). The quality evaluation of the solutions is indicated by the fitness function that assigns a score or fitness determining the minimum requirement for potential solutions (Mitchell, 1995). During the iterations, the best subsequent population is selected and the worst excluded to avoid future reproduction (Razali, 2015). The result may be an exception of the population (as unexpected genetic mutation) or the effect of continuous and slow improvements.

The idea behind the new GA tool featured in the SZ plugin is to classify the SI into a number of classes, by optimizing their respective boundaries. These represent cutoffs necessary to build the ROC curve and to maximize the relative AUC. Maximization of the AUC of the segmented ROC is the fitness function of the iterative meta-heuristic algorithm. **Figure 2** shows the classifier workflow. The ROC curve maybe weighted or none.

4 APPLICATION TO LANDSLIDE SUSCEPTIBILITY

The SZ plugin was born from the necessity of specific functions not available in QGIS with the goal of producing a landslide susceptibility map of South Asia using the WoE method (Titti et al., 2021a) in the context of the Belt and Road Initiative (Lei et al., 2018). After that, several other applications have supported the SZ plugin development. Among these, in Titti et al. (2021c), the classifier ("Si classify" functions) of the plugin was built to reclassify the landslide susceptibility in Tajikistan. Subsequent experiments have then stimulated the development of additional functions, leading to the current version of the SZ plugin.

Here, we present the current set of functionalities offered through the SZ plugin in the context of landslide susceptibility, although we recall that these can be used even outside the geomorphological context. The selected study area corresponds to the north-eastern sector of India, including Assam, Manipur, Meghalaya, Mizoram, Nagaland, and Tripura (**Figure 3**). This area has been selected because it appears to be one of the areas most susceptible to landslides in South Asia, according to the analysis conducted by Titti et al. (2021a). In their study, the authors' goal was to highlight regions mostly prone to landslides across countries involved into the Belt and Road Initiative. The application presented here and the analysis conducted in Tajikistan (Titti et al., 2021c) follow an analogous criterion.

All the data used in the application presented here are open-data. The landslide inventory used for the analysis was provided by the Geological Survey of India and is available at the Bhukosh website (https://bhukosh.gsi.gov.in, accessed 15 November 2021). It is an open database developed to evaluate the spatial distribution of natural hazards in India. In the selected study area, it includes 5,759 Landslide Identification Points (LIP). The catalog includes landslides triggered by rainfall, anthropogenic activity, road/slope cut, quarrying, toe erosion, and ground motion.

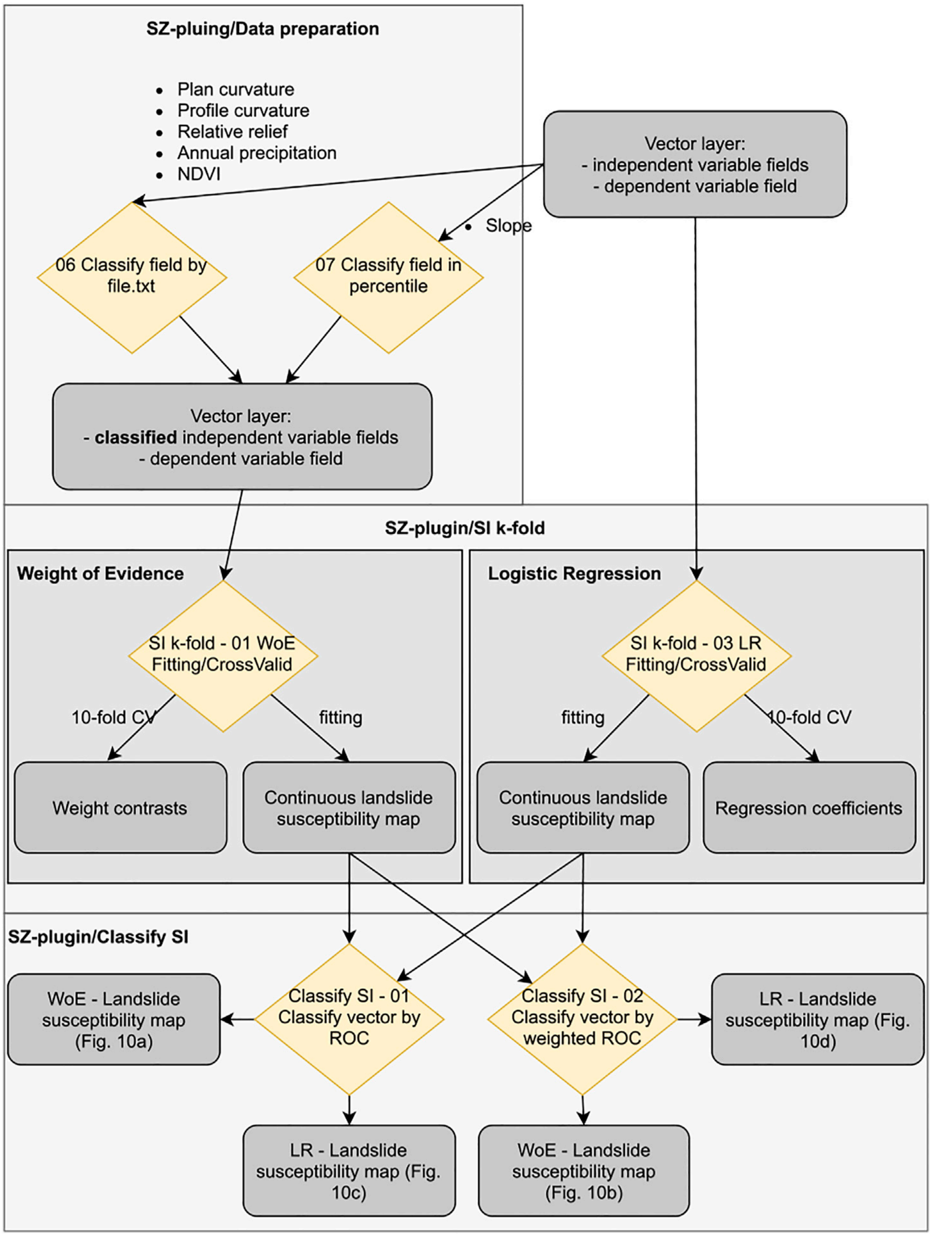

SZ-pluing/Data preparation
Plan curvature
Profile curvature
Relative relief
Annual precipitation
NDVI
Vector layer:
- independent variable fields
- dependent variable field
Slope
06 Classify field by file.txt
07 Classify field in percentile
Vector layer:
- classified independent variable fields
- dependent variable field
SZ-plugin/SI k-fold
Weight of Evidence
SI k-fold - 01 WoE Fitting/CrossValid
10-fold CV
fitting
Weight contrasts
Continuous landslide susceptibility map
Logistic Regression
SI k-fold - 03 LR Fitting/CrossValid
fitting
10-fold CV
Continuous landslide susceptibility map
Regression coefficients
SZ-plugin/Classify SI
WoE - Landslide susceptibility map (Fig. 10a)
Classify SI - 01 Classify vector by ROC
Classify SI - 02 Classify vector by weighted ROC
LR - Landslide susceptibility map (Fig. 10d)
LR - Landslide susceptibility map (Fig. 10c)
WoE - Landslide susceptibility map (Fig. 10b)

FIGURE 5 | Step by step flowchart of the functions used form the SZ plugin.

Slope units have been used as the reference mapping unit. A slope unit is a terrain unit derivable from a DEM, under the constraint of internal aspect homogeneity in areas defined between ridges and streamlines (Alvioli et al., 2020). The shapes have been calculated using *r.slopeunits*, a tool developed in GRASS GIS by Alvioli et al. (2016). In this case, we parameterized *r.slopeunits* with a flow accumulation threshold of 5,000,000 m^2, a minimum unit area of 500,000 m^2, and a circular variance of 0.3. The alluvial plains have been excluded from the analysis because considered not susceptible *a priori*. As a result, 124,553 slope units were generated with a maximum surface extension of 27 km^2, a mean of 1 km^2, and a standard deviation of 1.1 km^2.

All the data used as a predisposing factor are also open data. They consist of lithology, land cover, slope, plan curvature (tangent to the contour line), profile curvature (tangent to the slope line), relative relief (maximum elevation range in a circular neighborhood of 1 km of radius), peak ground acceleration (PGA), annual rainfall, Normalized Difference Vegetation Index (NDVI), and area of each mapping unit (**Table 1** for the respective data sources).

The landslide susceptibility zoning of the study area is carried out using Weight of Evidence (WoE) and Logistic Regression

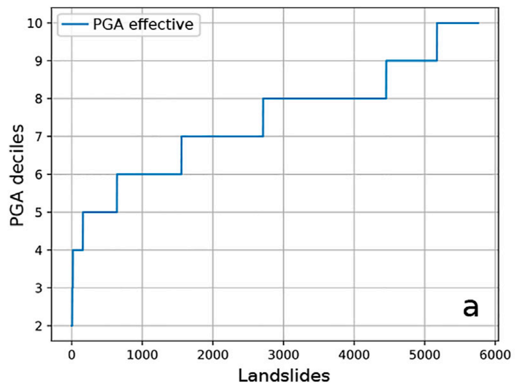


FIGURE 6 | Results of the functions “03 Points kernel statistics” and “04 Points kernel graphs.” **(A)** Cumulative effective LIP PGA value; **(B)** cumulative average PGA value in a LIP around of 5 km × 5 km.

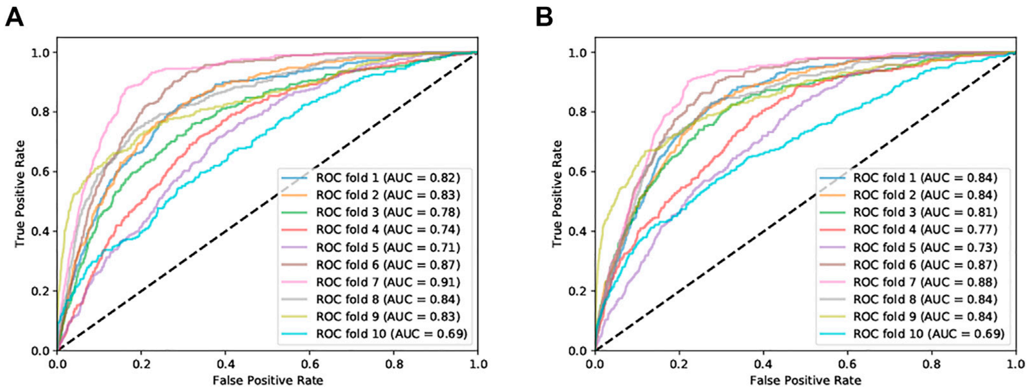


FIGURE 7 | ROC curves of the 10-fold cross-validation. **(A)** ROC of the WoE cross-validation and **(B)** ROC of the LR cross-validation.

(LR) methods. The Weights of Evidence technique is a bivariate statistical approach (Bonham-Carter et al., 1988; Bonham-Carter, 1990). It quantifies how prone an event occurrence is according to the proportion of presence/absence for each predisposing factor class. The WoE assigns two weights per class: W$^+$ and W$^-$. The weights represent, respectively, the positive and negative influence of the predisposing factors on a potential natural hazard. They are calculated by the following:

$$W^{+} = \ln \frac{\frac{M_1}{M_1+M_2}}{\frac{M_3}{M_3+M_4}}, \tag{2}$$

$$W^{-} = \ln \frac{\frac{M_2}{M_1+M_2}}{\frac{M_4}{M_3+M_4}}, \tag{3}$$

$$W_f = W^{+} - W^{-} \tag{4}$$

where M_1 is the number of mapping units where both the factor class and the event are present; M_2 is the number of mapping units where the factor class is absent, while the event is present; M_3 is the number of mapping units where the factor class is present, while the event is absent; M_4 is the number of mapping units where both the factor class and the event are absent. The weight contrast (W_f) is the final weight assigned to each class factor. It evaluates the relation between the spatial distribution of the causes and the spatial distribution of the events (Dahal et al., 2008).

The local sum of the factor weight contrasts produces the Susceptibility Index (SI), as follows:

$$SI = \sum_{i=1}^{n} W_{fi} \tag{5}$$

The second model tested is the logistic regression. It is an extension of the classical linear regression analysis. The latter commonly requires a continuous target variable (y), whose estimation is achieved as a linear combination of n input covariates (x), as follows:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i, \tag{6}$$

where β_0 is the intercept and β_i are the covariate coefficients.

However, the above scheme is not suitable to model a discrete target variable. In such cases, and specifically for a target variable

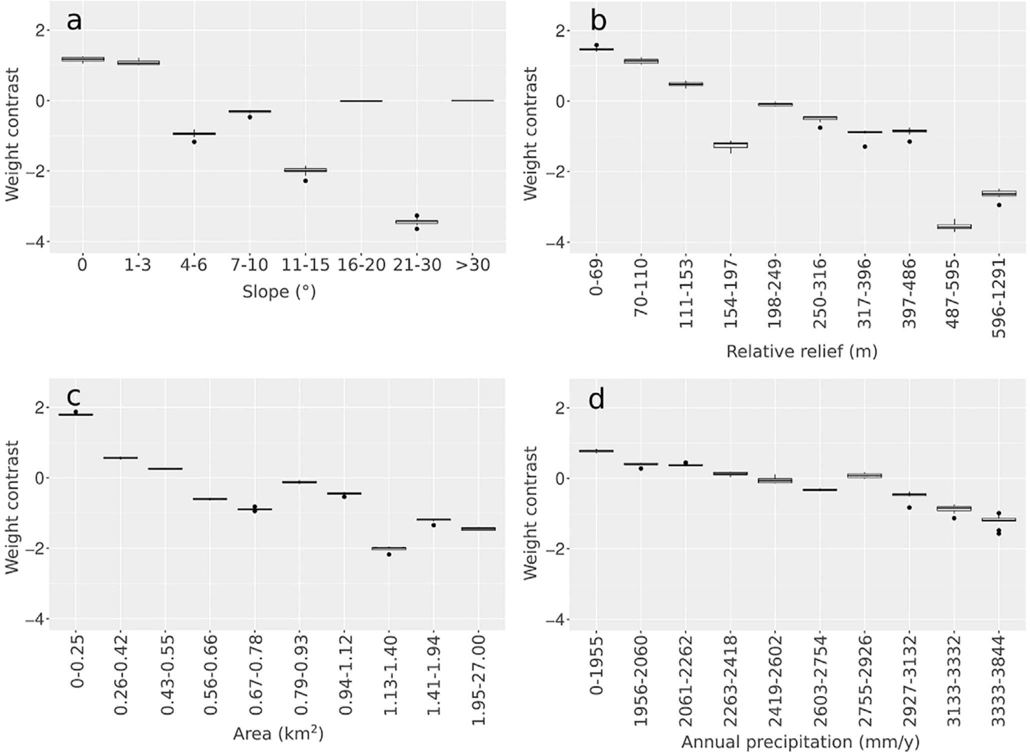


FIGURE 8 | Boxplots from the WoE 10-fold cross-validation weight contrast of **(A)** slope, **(B)** relative relief, **(C)** area, and **(D)** annual precipitation.

that can take only two discrete values, a logistic regression represents the most common solution. Its structure takes a vector (y) reporting a series of zero and one. The zero conventionally conveys the absence of a given process in space, time or both, whereas one conveys the opposite case where the process is present. The model still linearly regresses, this time the odd ratio (Szumilas, 2010), with respect to n input covariates x. The use of the logit link function, which then transforms this quantity into a probability (Menard, 2002), commonly referred to the actual occurrence of the process of interest, as follows:

$$P(y = 1) = \frac{1}{1 + \exp\left(-\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)\right)} \tag{7}$$

As a result, one can interpret an increase in the estimated regression coefficients as a linear increase or decrease of the probability $P(y = 1)$, determined by the sign of β_i.

The application and validation of the WoE and LR results are described in detail by the schema in **Figure 5**. The data preprocess, instead, is described in **Figure 4**. Flowcharts outline step by step how the SZ plugin functions have been used to carry out the landslide susceptibility map of the Northeast India.

As described in **Figure 4**, the average per mapping unit of slope, plan curvature, profile curvature, relative relief, annual precipitation, and NDVI have been calculated using a script implemented by us in Google Earth Engine (GEE) (Gorelick et al., 2017) called the spatial reduction tool (SRT). Using the TAGEE package for terrain analysis developed by Safanelli et al. (2020), the SRT allows to calculate terrain variables that are DEM derived such as slope, elevation, aspect, northness, eastness, mean curvature, Gaussian curvature, minimal curvature, maximal curvature, shape index, horizontal curvature, and vertical curvature. Moreover, the SRT allows one to calculate the relative relief and collect data from various databases such as precipitation, temperature, and NDVI. Finally, the SRT spatially reduces the pixel based variables into their mean and standard deviation per selected mapping unit. Notably, any shape can be used as a reference mapping unit (Titti and Lombardo, 2022).

As regards other predictors, the majority of the continuous variable (PGA) and the majority of the categorical variables (lithology and land cover), per mapping units, have been calculated using QGIS basic functions and aggregated in one vector layer.

The next steps are described in **Figure 5**. To verify the quality of the landslide inventory and to avoid mistakes related to the landslides survey, the landslide catalog has been filtered using the function "01 Clean points by raster kernel value" assuming a minimum slope degree of 8°in a neighborhood of 500 m of radius. One landslide only has been deleted. Then the resulting inventory attributes has been investigated using the following functions: "02 Attribute table statistics," that is, to know the landslide triggers; then "03 Points kernel statistics" and "04 Points kernel graphs" to plot the frequency distribution of the effective, maximum, minimum, standard deviation, sum, average, and maximum range value for a specific thematic map of the LIP neighborhood. To provide an example of the functions "03

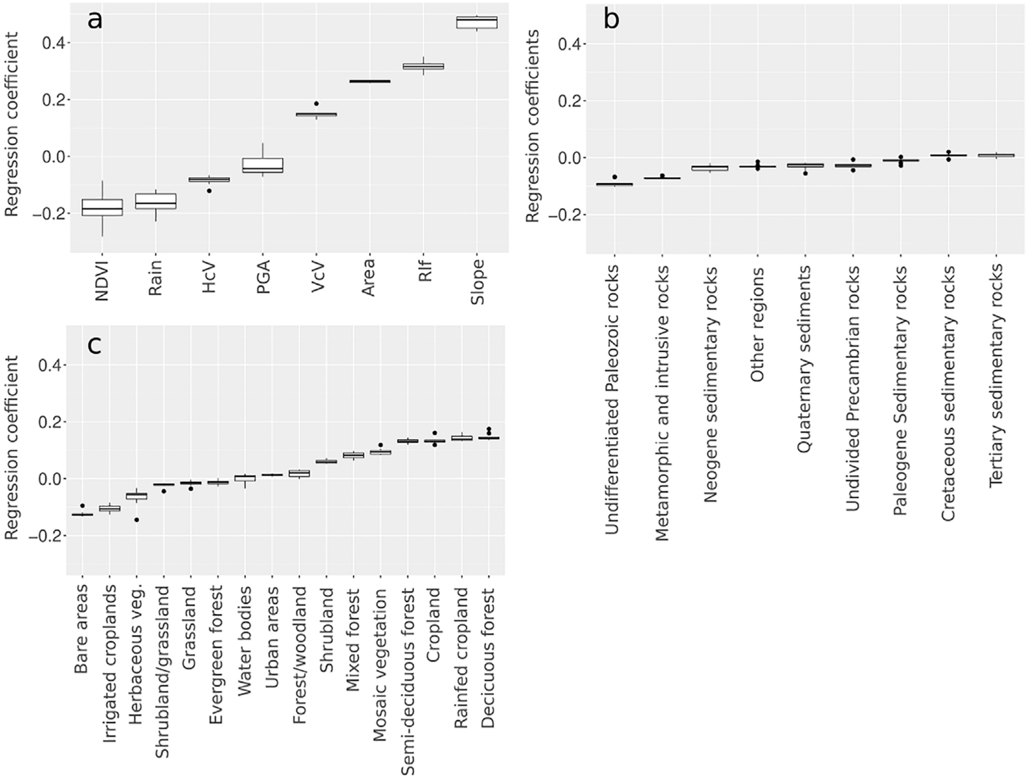


FIGURE 9 | Boxplots from the LR 10-fold cross-validation regression coefficients of **(A)** continuous covariates, **(B)** lithology, and **(C)** land cover.

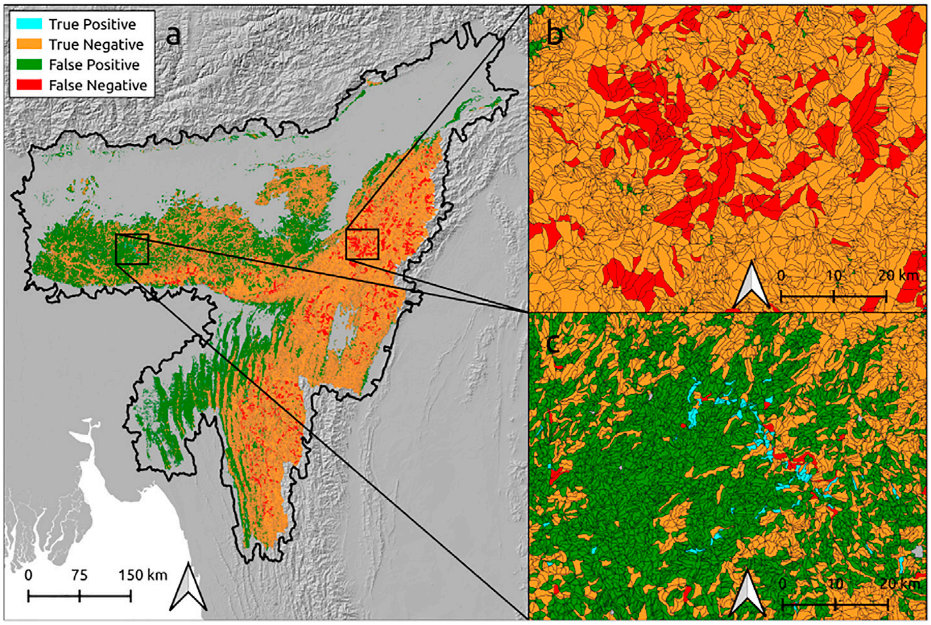


FIGURE 10 | True-positive, true-negative, false-positive, and false-negative mapping units with respect to a cutoff value equal to the median of the LR susceptibility index.

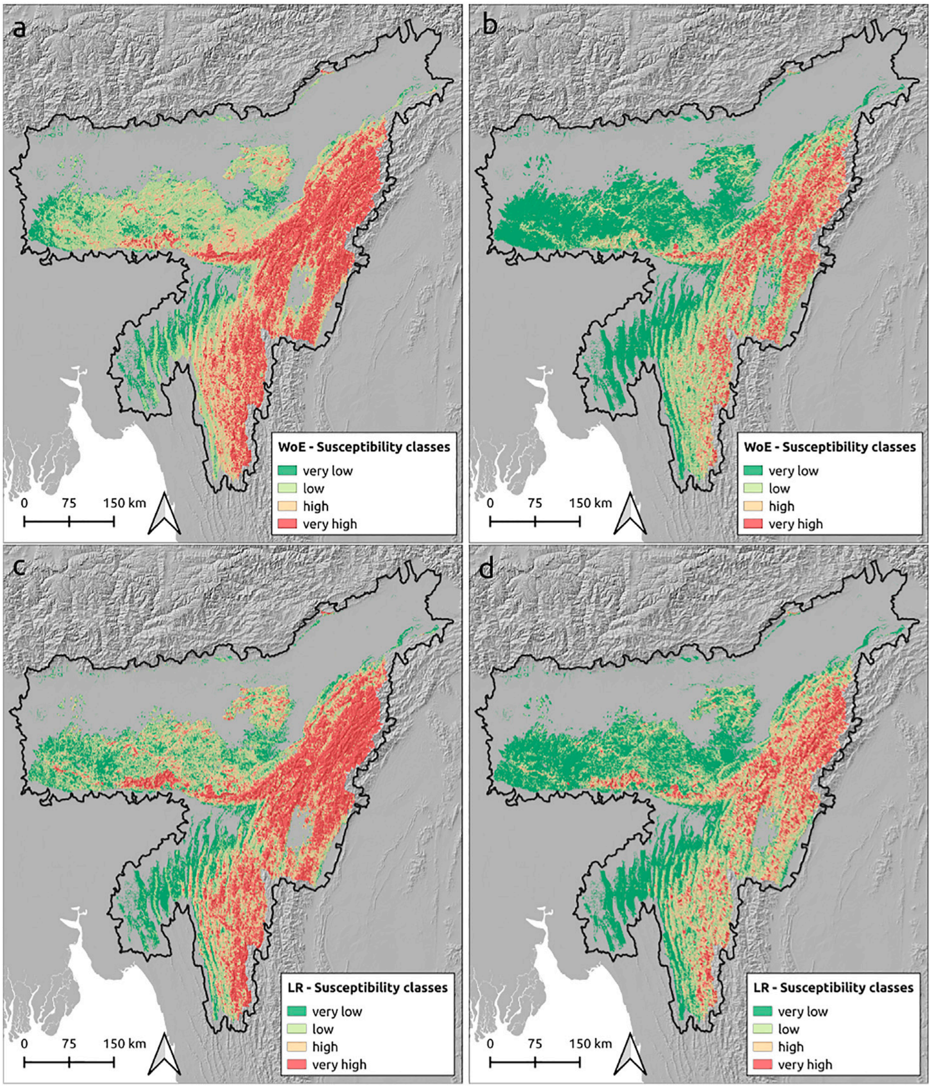


FIGURE 11 | Landslide susceptibility maps classified using the WoE and the LR model. **(A)** Classifier has maximized the AUC of the ROC curve derived from the WoE map; **(B)** classifier has maximized the AUC of the area-weighted ROC curve derived from the WoE map; **(C)** classifier has maximized the AUC of the ROC curve derived from the LR map; **(D)** classifier has maximized the AUC of the area-weighted ROC curve derived from the LR map.

Points kernel statistics" and "04 Points kernel graphs," **Figure 6A** shows the cumulative effective PGA value across LIPs, whereas **Figure 6B** depicts the cumulative average PGA value in a LIP around of 5 km × 5 km.

The landslide susceptibility zoning of the study area is carried out using the methods WoE and LR. To apply the WoE, the variables need to be classified. This step is done by using the functions "06 Classify field by file.txt" and "07 Classify field in percentile". The slope has been classified in eight classes: 0°, 1 + 3°, 4 + 6°, 7 + 10°, 11 + 15°, 16 + 20°, 21 + 30°, and > 30°, whereas the other continuous factors, in deciles.

After that, the susceptibility can be modeled with WoE. At the beginning the reference map has been built fitting the entire dataset with an AUC equal to 0.79, then the model has been 10-fold cross-validated. The relative ROC curves are visible in **Figure 7A** with an AUC mean equal to 0.8 and variability measured with a standard deviation equal to 0.07. Both the runs were tested by using "SI k-fold: 01 WoE Fitting/CrossValid," selecting different input parameters. The weight contrasts of the slope, relative relief, area and annual precipitation resulting from the cross-validation are reported in **Figure 8**.

To apply the LR method, the categorical covariates have been processed to generate one variable per category, measuring the percentage of surface covered by each category with respect to the extent of each slope units. Then to avoid multi-collinearity issues (the sum of all percentage classes always returns 100%, thus being a linear combination by definition), the most representative class across all slope units has been removed. This operation should sufficiently perturb the dependence structure among the remaining classes, ensuring that a linear combination of their respective values would not yield the same result.

Finally, the susceptibility can be modeled, first by fitting the complete dataset (AUC = 0.81) and then through a 10-fold cross-validation (AUC mean equal to 0.81 and standard deviation equal to 0.06). Both analyses have been carried out *via* the "SI k-fold: 03 LR Fitting/CrossValid". The ROC curves of the cross-validation are shown in **Figure 7B**, whereas the regression coefficients are reported in **Figure 9**.

To make the maps suitable for stakeholders and end users involved in land planning, the final maps have been classified into four classes by using the "01 Classify vector by ROC" (**Figures 11A,C**) and "02 Classify vector by weighted ROC" functions (**Figures 11B,D**). The latter classification has been weighted according to the slope units' area.

Figure 10 shows the result of the function "Classify SI/03 True/False" which maps the distribution of the true-positive, true-negative, false-positive, and false-negative mapping units respect to a cutoff value equal to the median of the LR susceptibility index.

In **Figure 11**, it is evident that the susceptibility patterns produced by WoE and LR are quite similar. Differences become more visible when using the weighted and non-weighted classifiers. In both models (WoE and LR), the "very high" class covers a larger area in the non-weighted-classified map than in the weighted ones. The "very high" class in the WoE non weighted-classified map covers the 31% of the total surface mapped (130,736 km^2) and the 14% in the weighted ones. The LR classified maps have given a similar response to the classification: 31 and 12% of the total surface mapped for the non-weighted-classified map and weighted-classified map, respectively.

We reported additional references about the predisposing factors and landslide inventory as follows: lithology (https://catalog.data.gov accessed 2021-08-23), land cover (http://due.esrin.esa.int, accessed 2021-04-15), PGA (https://sedac.ciesin.columbia.edu, accessed 2021-04-15), annual precipitation from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), and NDVI from Landsat Seven Collection 1 Tier 1 composites for 32-day period provided by U.S. Geological Survey, landslide inventory (https://bhukosh.gsi.gov.in, accessed 2021-11-15).

The effective reduced data and the outputs of the application described above are downloadable from the GitHub repository CNR-IRPI-Padova/SZ.

5 CONCLUSION

A new plugin for landslide susceptibility zoning is introduced here. The SZ plugin is a collection of processing scripts in Python which runs as part of the QGIS platform. This framework has been chosen to maximize the accessibility to our plugin. QGIS is the most widely used open-source GIS environment.

The implemented functions have been organized into four groups: "Data preparation," "SI" (susceptibility index), "SI k-fold," and "Classify SI," which allow one to carry out a complete susceptibility analysis from the data preprocessing and the prediction analysis to the reclassification of the susceptibility index. The susceptibility can be generated using six different classifiers: weight of evidence, frequency ratio, support vector machine, decision tree, random forest, and logistic regression. The statistical models may be applied to fit the input dataset or cross-validate the final map. In particular, the latter can be done by a simple random split in test/train samples or by a k-fold method. Both are completed by a receiving operating characteristic (ROC) analysis for performance assessment. Finally, a GA-based (genetic algorithms) classifier has been implemented to classify the susceptibility index.

Many libraries in R and other libraries such as Scikit-learn in Python are probably the best solutions to perform susceptibility with statistical models, but they require a good knowledge in coding. Overall, the tool proposed can simplify the access to statistical assessments of susceptibility for users who are not familiar in coding or for those who wish to achieve results rapidly.

In this study, the version 1.0 of the SZ plugin has been presented to the geoscientific community. Several improvements and new functionalities are under development which will be uploaded with the further versions of the plugin.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary Material.

AUTHOR CONTRIBUTIONS

Software conceptualization: GT; software development: GT; software fine-tuning: GT, AS, SC, and LL; application and data curation: GT and LL; figures: GT; writing—original manuscript draft: GT; and writing—review and editing: GT, LL, AS, SC, AP, and LB. All authors have read and agreed to the published version of the manuscript.

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