Space-time landslide size modelling in Taiwan

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Abstract

Landslide susceptibility assessment using data-driven models has predominantly focused on predicting where landslides may occur and not on how large they might be. The spatio-temporal evaluation of landslide susceptibility has only recently been addressed, as a basis for predicting where and when landslides might occur. The present study combines these new developments by proposing a data-driven model capable of estimating how large landslides may be, for the Taiwan territory in a fourteen year time window. To solve this task, our model assumes that landslide sizes follow a Log-Gaussian probability distribution in space and time. Spatially the area is subdivided into 46074 slope units, with 14 annual timesteps from 2004 to 2018. Based on this subdivision, the model we implemented regressed landslide sizes against a covariate set that includes temporally static and dynamic properties. In the validation of our model, we nested a wide range of cross-validation (CV) procedures, such as a randomized 10fold-CV, a spatially constrained CV, a temporal leave-one-year-out CV, and a spatio-temporal CV. The final performance was described both numerically as well as in map forms.

Overall, our space-time model achieves interpretable and satisfying results. With the

availability of more complete landslide inventories, both temporally and spatially, we envision that spatio-temporal landslide size prediction will become the next challenge for geomorphologists to finally address a fundamental component of the landslide hazard definition. And, because of its spatio-temporal nature, we also envision that it may lead to simulation studies for varying climate scenarios.

Keywords: dynamic landslide area prediction; space-time modelling; slope unit; spatio-temporal cross-validation

1. Introduction

Landslides are a common natural hazard in many mountainous landscapes worldwide, and a serious threat to human lives and properties (Rossi et al., 2019; Merghadi et al., 2020). Therefore, accurate prediction of landslide location and size is a crucial requirement for reliable hazard and subsequent risk assessment. The most generally accepted definition of landslide hazard requires the estimation of three aspects: i) the probability of occurrence at a given location, ii) within a specified period, and iii) with a given magnitude (Varnes, 1984; Guzzetti et al., 1999; Guzzetti et al., 2005). This definition essentially addresses three main questions that a decision maker requires to implement any risk mitigation strategy: “where”, “how frequent”, and “how large” landslides might be in a certain area. This definition was later improved by Corominas et al. (2014) as they introduced the landslide intensity concept to measure the spatial variation in the level of threat that landslides may carry across a landscape. However, the intensity that Corominas and co-authors mainly considered consisted of dynamic spatially distributed characteristics such as velocity, impact pressure or kinematic energy, which are derived using physically-based models. The parameters for these models are virtually impossible to collect over larger areas, due to the heterogeneity of the landscape, which is the reason why recent efforts have been made towards expressing landslide intensity over larger areas in terms of counts (Lombardo et al., 2018) or sizes (Lombardo et al., 2021) as a basis for data-driven modelling. These publication represent two examples of a long list of data-driven studies in the context of landslide prediction, which were largely dedicated to purely predicting occurrence locations (or susceptibility), and only recently they have branched out towards other landslide characteristics. Specifically, data driven susceptibility models were initially framed in a bivariate statistical structure (e.g., Van Westen et al., 2003; Nandi and Shakoor, 2010), and this essentially remained the case until they were superseded by their multivariate statistics counterpart (e.g., Chung et al., 1995; Atkinson and Massari, 1998). Only recent years have witnessed the spread of machine learning (e.g., Merghadi et al., 2020) and deep learning (e.g., Fang et al., 2021; Aguilera et al., 2022) architectures with improved predicting performance they ensure. These models have mostly been used purely in space, with very few applications to the space-time context (Lombardo et al., 2020), aside from empirical rainfall thresholds (Jaiswal et al., 2010; Nefeslioglu and Gorum, 2020) or coseismic near-real time prediction (Nowicki Jessee et al., 2018).

Specifically for statistical studies a common assumption is the choice of a suitable distribution reflecting the data on landslides. For this reason, susceptibility models assume a Bernoulli probability distribution (Steger et al., 2016; Steger et al., 2017), whereas intensity models based on counts assume the Poisson probability distribution (Lombardo et al., 2019; Opitz et al., 2022) instead. When it comes to model landslide area, the choice is not straightforward. In fact, it is common that a landslide area distribution is quite heavily tailed. In other words, the vast majority of inventories includes a predominant number of small landslides and only few extremely large ones, which is common in response to major triggering events, such as rainfall (Jones et al., 2021; Emberson et al., 2022) or earthquakes (Zhang et al., 2019; Tanyaş et al., 2022). This is the reason that has led Malamud et al. (2004) to propose the Inverse Gamma distribution as a universal empirical size model, which lead to a series of studies on landslide Frequency Area Distribution (FAD; Tanyaş et al., 2018). However, one weakness of the FAD approach is that it neglects the spatial distribution of the landslides it considers, something that has been recently accounted for in a few articles on the subject. Specifically, Lombardo et al. (2021) and Moreno et al. (2022) were the first to propose a Log-Gaussian model able to estimate the expected planimetric extent of landslides over a given landscape. However, their model lacked the ability to inform whether any given slope will be unstable. For this reason, Aguilera et al. (2022) and Bryce et al. (2022) extended this framework by building a joint landslide susceptibility and area prediction model. But even in these cases, one main issue still persisted, for they produced temporally stationary estimates of landslide extents. By leaving the temporal dimension unexplored, most studies neglected a crucial requirement of both hazard definitions proposed by Guzzetti et al. (1999) and Corominas et al. (2014), and even reported in the international guidelines for landslide risk (Fell et al., 2008). Also, such stationary models may not be valid over large areas and in the context of rapid climate change, because global warming can influence landslide activity, abundance, and frequency (Gariano and Guzzetti, 2016). Therefore, an important research gap to be addressed relates to how these purely spatial size models can be reliably extended over time.

One way to do so based on physically-based modelling (Park et al., 2019; Van den Bout et al., 2021). However, the unavailability of required geotechnical parameters mostly constrains their applicability to individual slopes or small catchment analyses. Data-driven approaches can by-pass the geotechnical requirements as long as a reliable multi-temporal landslide inventory is available (Guzzetti et al., 2012), together with a set of static and dynamic explanatory variables (Wang et al., 2021) capable of explaining landslide size distribution in space and time. Based on these considerations we propose a space-time landslide size model to estimate the planimetric landslide area in any given mapping and temporal unit. Specifically, we present the implementation of a Log-Gaussian generalized additive model (GAM), which assumes that landslide size follows a log-Gaussian distribution in the space-time domain. The spatio-temporal characteristics of landslide size are captured by incorporating a set of static and dynamic factors. The same model is constrained to treat mapping units that are close in space to behave more similarly compared to those that are far away, and the same is valid in time.

We tested this model with a dataset of the main island of Taiwan for the period from 2004 to 2018, during which tropical cyclones triggered many landslides. Earlier, we have implemented a space-time landslide susceptibility model for the same study area (Fang et al., 2022), which focused on the landslide space-time prediction. This present study aims at estimating probabilistically "how frequent" and "how large" landslides are expected within mapping units. We consider this a step forward towards a new generation of probabilistic landslide hazard assessment, beyond what is currently available in the literature.

2. Study area and data overview

2.1. Study area

We implemented the space-time landslide size modelling in the same study area as our previous study (Fang et al., 2022). The study area is located in the main island of Taiwan (**Fig. 1**) and extends over a total of 35,808 km^2. Taiwan is frequently affected by landslides triggered by typhoons and/or earthquakes, a unique condition owed to its geographical location within the Pacific Ring of Fire and in the path of tropical cyclones. For example, the 1999 Chi-Chi earthquake triggered more than 10,000 landslides in central Taiwan, with a total sliding area of exceeding 100 km^2 (Hung, 2000). Typhoon Morakot in 2009 brought an accumulated rainfall of 3059 mm and resulted in more than 22,705 landslides covering an total area of 274 km^2 (Lin et al., 2011).

2.2. Landslide inventory

The Forestry Bureau of Taiwan has produced a yearly landslide inventory for the whole Taiwan from 2004 to 2018 (Lin et al., 2013; Chen et al., 2019b), based on visual interpretation of Formosat-2 satellite images (2 m spatial resolution) collected between January and July for each year, and validated with aerial images (25 cm spatial resolution; Lin et al., 2013). These annual landslide maps do not distinguish new landslides that occurred in a specific year from those that were already present. Therefore, to isolate the contribution of new occurrences and/or reactivated failures, we calculated the difference of two subsequent yearly inventories to derive landslide expansion areas for each year under consideration. This preprocessing procedure for landslide maps is the same as our previous study, and further details are provided in Fang et al. (2022). As a result, we obtained 14 yearly landslide inventory maps (**Fig. 1**), with new or reactivated landslides between August 1st of the considered year to July 31st of the subsequent one.

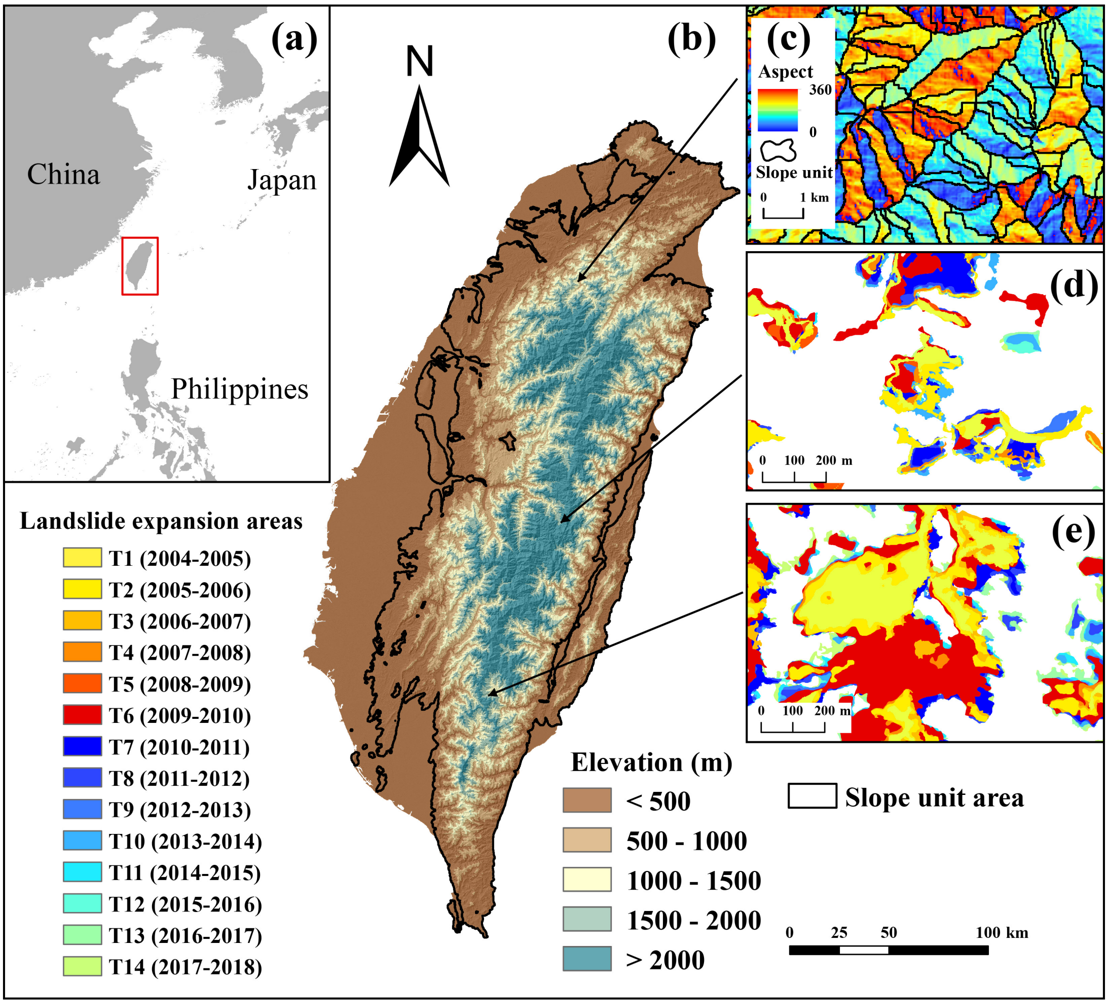


Fig. 1 (a) Location of the study area; (b) elevation distribution of Taiwan island; (c) a sub-region showing the slope units partition, and (d, f) spatial distribution of landslides in two sub-regions from 2004 to 2018. Landslides in each time period denotes the expansion area from August 1st of the current year to July 31st of the next year. This figure is modified from Fang et al. (2022).

2.3. Explanatory factors

In the context of a space-time modelling implemented, some landslide related factors can be simplified as constant properties, whereas others may exhibit some degrees of temporal variation on a daily, seasonally or yearly basis. For this reason, we prepared a set of static and dynamic factors to build our space-time model. Specifically, we derived eight static terrain attributes from SRTM DEM data, five of which have already been employed in Fang et al. (2022): slope, plan curvature, profile curvature, northness, and eastness. In the present study we also obtained three relief-related factors (intensity, range, and variance) to represent the gravitational potential energy across the terrain (Stepinski and Jasiewicz, 2011). Notably, the hillslope relief has appeared in a number of studies dedicated to landslide size (Medwedeff et al., 2020), and has proven to be a dominant covariate in landslide size predictive modelling (Lombardo et al., 2021). We also considered the variation in lithological conditions, expressed through 15 classes derived from a 1:250,000 scale geological map (see Appendix A for the descriptions). We also generated the Euclidean distance to faults, derived from a 1: 50,000 scale fault map. The above two geological factors can be accessed via the Central Geological Survey of Taiwan (https://www.geologycloud.tw/). Furthermore, we used slope units derived from the DEM as our basic terrain unit. We considered the dual interaction between longitude and latitude of each mapping unit centroid to represent the spatial structure of the Taiwan landscape. All the above factors belong to the stationary set of predictors we selected for our space-time modelling procedure.

As for the dynamic ones, we opted to include rainfall, normalized difference vegetation index (NDVI), and a yearly function of the timesteps between subsequent inventories. Our previous study showed that maximum daily rainfall is an appropriate dynamic factor in a yearly space-time landslide susceptibility model for Taiwan (Fang et al., 2022). Therefore, we collected the rainfall estimates from 188 meteorological stations and interpolated the yearly daily maximum rainfall via a cokriging routine, which used elevation as a parameter to represent the orographic effect on the precipitation patterns. To describe the effect of vegetation, we calculated the yearly maximum NDVI based on Landsat-7 images via the Google Earth Engine platform. Ultimately, the temporal effect on landslide sizes was brought into the model as a function of the timesteps between subsequent landslide occurrences, that is, we labeled each slope unit with an ID to indicate which yearly landslide inventor it belongs to .

3. Methodology

3.1. Mapping and temporal units

Determining appropriate mapping and temporal units is important for any space-time modelling. To geographically partition the landscape, we generated slope units (SUs) as our reference terrain units for they well reflect the slope morphodynamics (Guzzetti et al., 1999), and they cover the landscape units between sub-catchment divides and streams, making them particularly suitable for landslide modeling (Carrara, 1988). Since our study focuses on the whole main island of Taiwan which has extensive flat areas along the coasts, we used the r.geomorphon module (Jasiewicz and Stepinski, 2013) available in GRASS GIS to outline flat areas. In a subsequent step, we excluded them from the analysis performed by the r.slopeunits software (Alvioli et al., 2016), a tool to automatically delineate SUs on the basis of an aspect-homogeneity criterion. This resulted in 46,074 polygons with a mean SU area of 589,844 m^2 and a standard deviation of 395,973 m^2. As for the temporal dimension, we chose a temporal unit of one year (from August 1st of the current year to July 31st of the next year). The resulting space-time domain therefore featured 645,036 units, made of 46,074 SUs and repeated over the 14 temporal units. Further details on these aspects can be found in Fang et al. (2022).

Each of these units need to be assigned with a covariate value, for the covariates listed in Section 2.3 (see **Table 1**). The spatial extent of the SUs requires an upscaling step. In fact, a large number of grid-cells can be hosted in a SU, from which a distribution of potential values can be derived. Thus, to account for the associated intra-SU variability, we derived two statistical moments in the form of the mean and standard deviation for all terrain attributes, distance to faults, and NDVI. As for the lithological characterization of each SU, we extracted the class with the largest areal extent as representative for the whole SU. Because the maximum daily rainfall has a more even distribution over the SUs, we only extracted the mean precipitation value per SU, and not the standard deviation.

Unlike landslide susceptibility modelling where the focus is given to landslide presence/absence data, our size model requires an information on the planimetric landslide extent per SU. To estimate this extent and later use it as the response variable of our model, we computed the sum of all landslide areas falling within each SU and converting the resulting heavy-tailed distribution by using the logarithmic transformation. From this, we extracted the positive part of the landslide area distribution (removing the zeros or those units with no landslides) giving rise to a spatio-temporal domain made of 119,545 SUs (with a total landslide area of 1732.55 km^2).

Table 1 Summary of covariates used in the study.

Type	Covariates	Description
Static	Mean slope	Mean and standard deviation (SD) of morphological factors in each slope unit
	Slope-SD	
	Mean plan curvature	
	PlanCurv-SD	
	Mean profile curvature	
	ProfileCurv-SD	
	Mean northness	
	North-SD	
	Mean eastness	
	East-SD	
	Mean relief intensity	
	ReliefInt-SD	
	Mean relief range	
	ReliefRan-SD	
	Mean relief variance	
	ReliefVar-SD	
	Mean distance to faults	Mean of distance to faults in each slope unit
	FaultDis-SD	SD of distance to faults in each slope unit
	Lithology	Majority class in each slope unit.
	Slope unit area	Area of each slope unit
	Spatial location	longitude and latitude of the centroid in each SU
Dynamic	Maximum daily rainfall	Mean of rainfall per year in each slope unit
	Mean NDVI	Mean of NDVI per year in each slope unit
	NDVI-SD	SD of NDVI per year in each slope unit
	Time period	Time period ID for each slope unit

3.2. Generalized additive model

A generalized additive model (GAM) can estimate linear and nonlinear effects between explanatory and target variables (Goetz et al., 2011). As a result, these models can provide satisfying performance while maintaining flexibility and interpretability. GAMs have been successfully used in a number of spatially-explicit models for landslide occurrences, dedicated to landslide susceptibility (e.g., Steger et al., 2016; Titti et al., 2021) and intensity assessments (e.g., Lombardo et al., 2019). The same GAM framework has recently been used by Lombardo et al. (2021) through assuming that landslide planimetric area in a terrain unit follows a log-Gaussian distribution, which is the same assumption we will make in this manuscript. The difference resides in our extension of the same framework to the space-time domain. To do so, we fitted a space-time Log-Gaussian GAM by using the ‘mgcv’ R-package (Wood, 2011).

Notably, our GAM formulation can be denoted as follows:

$$\log(A_L) \sim \mathcal{N}(\mu, \sigma^2),$$
$$g(\mu) = \alpha + \sum_{i=1}^{m} S_i(x_i) + \sum_{j=1}^{n} \beta_j^{litho} x_j + S(lon, lat) + S(time) \tag{1}$$

where A_L is the cumulative landslide planimetric area in each slope unit, u and σ^2 are the mean and variance for Gaussian distribution respectively, g is the log link, α is the global intercept, S_i are the smooth function associated with a number of nonlinear covariates x_i (all covariates except lithology and spatial effect), β_j^{litho} is the regression coefficient for the lithology class x_j, $S(lon, lat)$ denotes the interaction smooth of longitude and latitude to account for the spatial structure. $S(time)$ represents the smooth function associated with temporal effect between subsequent landslide occurrences.

On a final note, the 119,545 Sus analyzed here do not represent the whole space-time domain expressed across the 14 examined years and the whole landscape of Taiwan. They are rather a subset of it corresponding to the positive part of the landslide size distribution. Because of this, we stress here that our modeling protocol will make us of the fitted model to extent the prediction over the remaining 525,491 SUs. We are aware that these SUs did not undergo any landsliding but we opted to graphically simulated over those units to get a full picture, albeit overestimated, of the expected landslide size distribution over the whole space-time domain.

3.3. Model evaluation

Below we describe the metrics and schemes to evaluate the model performance both in terms of goodness-of-fit and predictive performance. In both cases, three numerical metrics are considered namely, mean absolute error (MAE), root mean square error

(RMSE), and Person correlation coefficient (R). We recall here that we only use 119,545 SUs with mapped landslides for landslide size modelling. For the goodness-of-fit, we fitted an explanatory model with 100% of the dataset and interpreted the effects of covariates. Aside from above numerical metrics, we used three common graphical methods to assess the goodness-of-fit (Wood, 2006), namely, plot of observed versus fitted values, QQ plot, and histogram of residuals.

For the predictive performance, we used the above three numerical metrics and the plot of observed versus predicted values to evaluate the predictive performance. Moreover, four different cross-validation schemes were implemented for validation, namely, random 10-fold cross-validation (10fold-CV), spatial leave-one-out cross-validation (S-CV), temporal leave-one-out cross-validation (T-CV), and spatio-temporal leave-one-out cross-validation (ST-CV). Note that the four cross-validation procedures have been successfully used to model space-time landslide susceptibility in the same study area (Fang et al., 2022). We thus briefly introduced these validation procedures here. The 10fold-CV is the most common and conservative scheme to assess model performance. It randomly splits the original dataset into 10 equal-sized subsets and repeatedly fits the model with nine subsets and validates with the one left-out. The S-CV scheme first divides the whole dataset into 12 spatial subsets by considering the administrative partitioning of Taiwan, and then repeatedly leaves out one of the twelve subsets for validation and fits the model with the remaining subsets. Similar to S-CV, the T-CV is based on 14 temporal subsets and validated year by year. As for the ST-CV, it generates 168 subsets based on above 12 spatial partitioning and 14 time intervals, and then executes the leave-one-out validation procedure.

4. Results

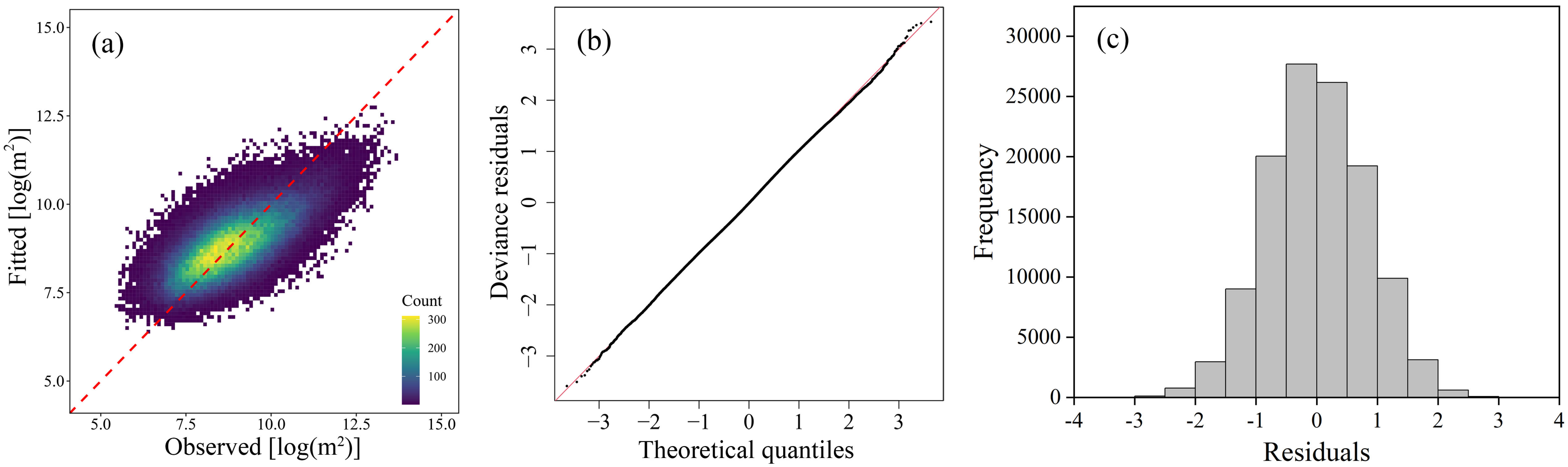
4.1. Model construction and goodness-of-fit

In the modelling process, we first implemented a forward-stepwise procedure to assess whether a given covariate would provide effective information for landslide size modelling. This covariate selection procedure relied on the Akaike information criterion (AIC; Akaike, 1974), where a lower AIC value is diagnostic of a better model. Specifically, we first ran all single-covariate models, from which we selected the covariate with the lowest AIC value. Then, we focused on selecting the best two-covariate model, then three-covariate one and so on, each time choosing the combination that has led to the minimum AIC. This process was then stopped when the decrease in AIC value fell below a threshold of 100. **Table 2** shows the overview of the forward-stepwise procedure described above. The final covariate set includes slope unit area, NDVI-SD, maximum daily rainfall, Mean NDVI, time periods, coordinate of slope units, mean profile curvature, mean slope, Slope-SD, mean eastness, lithology, ReliefVar-SD, and mean plan curvature.

Table 2 results of the forward-stepwise covariate selection

Step	Selected covariate	AIC	Improvement
1	Slope unit area	346734	/
2	NDVI-SD	317164	29570
3	Maximum daily rainfall	308237	8927
4	Mean NDVI	302228	6009
5	Time periods	297896	4332
6	Coordinate of slope units	296051	1845
7	Mean profile curvature	294976	1075
8	Mean slope	293829	1147
9	Slope-SD	293121	708
10	Mean eastness	292443	678
11	Lithology	292141	302
12	ReliefVar-SD	291894	247
13	Mean plan curvature	291722	172
14	Mean northness	291657	65

This covariate set was used as the base to construct an explanatory space-time model. **Fig. 2** shows an overview of the goodness-of-fit via three criteria, namely, observed versus fitted values, QQ plot, and histogram of residuals (all in log-scale). Inspection of **Fig. 2 (a)** shows that the model achieves a high degree of agreement between the observed and fitted landslide areas per slope unit. The QQ plot presents deviance residuals against theoretical quantiles of the deviance residuals distribution (Wood, 2006). In **Fig. 2 (b)** and **(c)**, we observe that the QQ plot is close to a straight line and the histogram of residuals is consistent with normality, indicating an excellent fitting performance. In addition, we also calculated the statistical criteria for fitting evaluation, that is, the MAE, RMSE, and R is 0.657, 0.817, and 0.673, respectively. Overall, our model thus shows a satisfying goodness-of-fit.



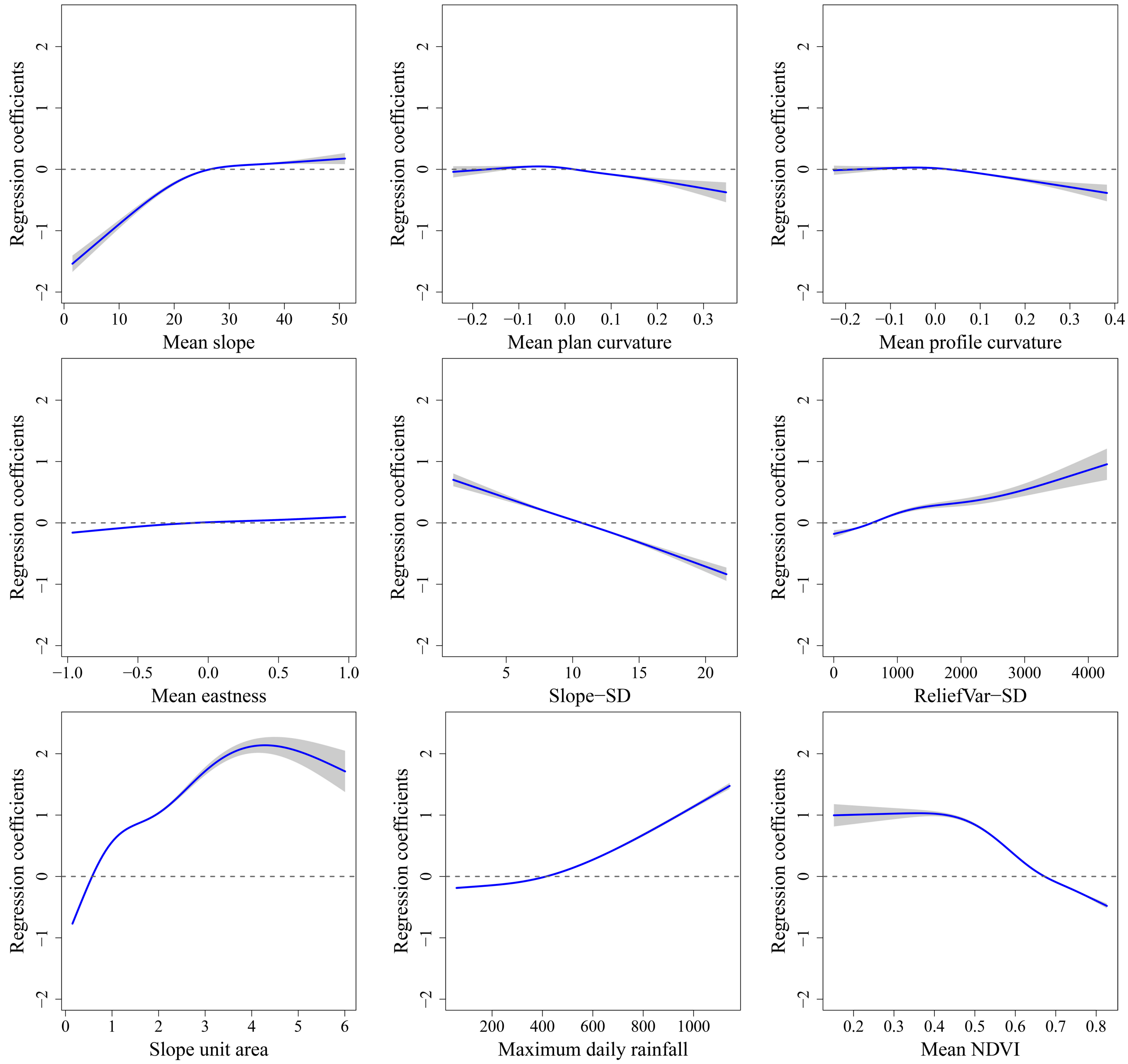
317 **Fig. 2** Goodness-of-fit of the model: (a) observed versus fitted plot (in log-scale), (b) QQ plot and (c) histogram of residuals.

4.2. Covariates' effect

The effects of all covariates with estimated 95% confidence intervals are shown in **Fig. 3**. Slope steepness, with a narrow confidence interval, has a positive effect on landslide size above 26º. Plan curvature and profile curvature show similar nonlinear effects on landslide size estimation, and maintain negative effects above 0.02 and 0.03, respectively. The effect of eastness indicates that slope units facing east are expected to have large landslide areas. Although we allowed the regression coefficients of all covariates to vary nonlinearly, the Slope-SD shows a linear effect on landslide size. We considered this as the best way to represent the effect of Slope-SD optimized by the smoothness selection procedure. The ReliefVar-SD has a positive effect on landslide size when the value is above 609. For the SU-Area, it maintains a negative effect on landslide size until the value reaches 5.6 km^2.

Rainfall is a key dynamic factor related to landslide occurrences. In our study, the maximum daily rainfall for each time period was selected for modelling. Inspection of **Fig. 3** shows that the maximum daily rainfall has very narrow confidence intervals and presents a positive effect with rainfall above 420 mm per day. And, the regression coefficient increases with the daily maximum rainfall. For the dynamic factor of NDVI, the mean NDVI maintains a positive effect on landslide size until 0.67, and then the regression coefficient decreases with the NDVI value. The NDVI-SD has a significant and positive effect on landslide size from 0.09 to 0.23. For the lithology covariate, 11 classes show significant and positive effects on landslide area estimation. Specifically, the class F (Mudstone intercalated with allochthonous material) has the highest positive effect, followed by the class N (Shale, siltstone, and sandstone) and class J (Sandstone, mudstone, and shale).

We recall here that we considered the temporal and spatial effects in the landslide size modelling through a function of time and a function that expresses the interaction of latitude and longitude, respectively. In **Fig. 3**, we observe that the temporal function shows a marked oscillation, with a “wavelength” of about 8 years. For the spatial effect (**Fig. 4**), some clusters emerged in certain regions. For example, the central and northeast parts show negative effects on landslide size, whereas the southwest and northwest fringe parts present positive effects.



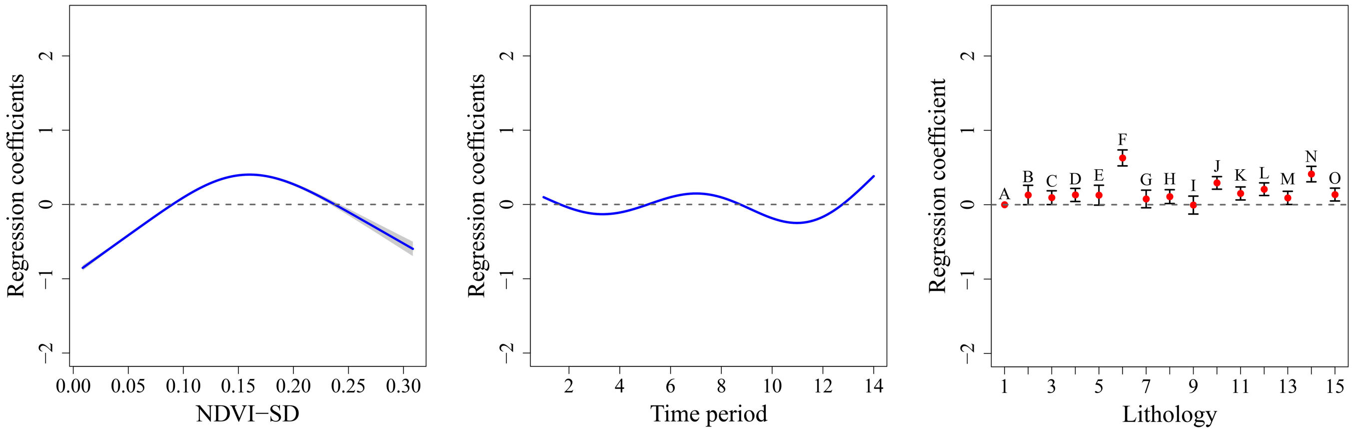


Fig. 3. Summary of effects of covariates. For lithology, the red dots show the regression coefficient, and the vertical segments are the 95% confidence intervals. For other nonlinear effects, the blue curves show the regression coefficient and the shadowed polygons denotes the 95% confidence intervals.

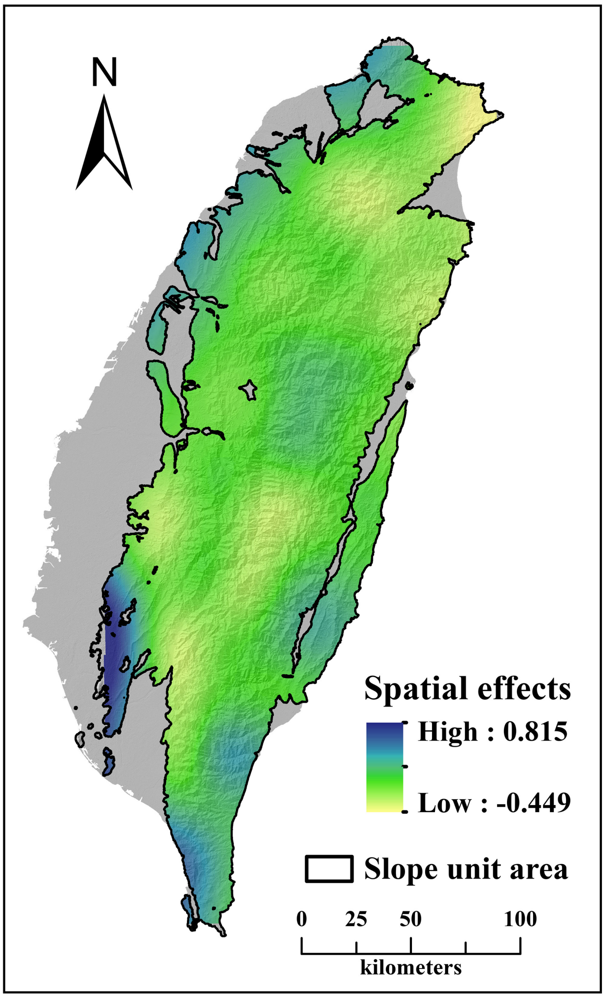


Fig. 4. Spatial effect in the space-time model

4.3. Space-time predictive performance

Aside from the goodness-of-fit assessment, it is also important to test whether the model predicts well "unknown" samples distributed both in space and time. Thus, we performed a suite of CV procedures to assess the predictive performance of the proposed model in different perspectives, namely, 10fold-CV, S-CV, T-CV, and ST-CV. Note that the space division for S-CV and ST-CV is based on the administrative unit of Taiwan, as shown in **Fig. 5**, and the description of different sub-regions is given to Appendix B. To maintain a comparable number of samples in each sub-region, we merged some small counties or cities.

The predictive performance of 10fold-CV, S-CV, and T-CV is presented in **Fig. 6**, measured via MAE, RMSE, and Pearson correlation coefficient (R). We observe that the 10fold-CV achieves the most stable results among the three CV schemes and its three evaluation indices do not vary significantly. This is because the 10fold-CV randomly selects validation samples from the whole space-time domain, thus limiting the spatial and temporal perturbation induced with respect to the original data distribution. Thus, we extended our validation scheme to incorporate S-CV and T-CV procedures. In **Fig. 6**, the T-CV shows larger metric fluctuations compared to S-CV, indicating that the temporal perturbation to the data distribution is more prominent than the spatial one, although our space-time model still returns good performance. To further investigate the predictive ability of our model across different time periods or geographical regions, we summarize the relative variations in performance in **Fig. 7**. There, we observe that the MAE and RMSE show similar fluctuations in the two CV procedures. This may be because both indices represent the error between the observed and predicted landslide areas. As for the R index, the S-CV returns the highest value while predicting over the sub-region 5, and achieves relatively low values of less than 0.6 while predicting over sub-region 1 and 2. For the T-CV procedure, the model has the highest R value in T6, and the lowest in T5.

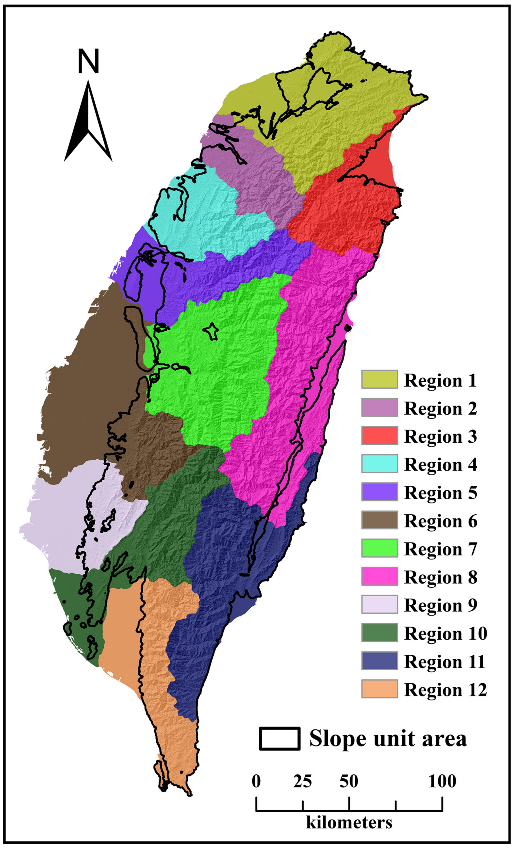


Fig. 5. Spatial sub-regions for validation.

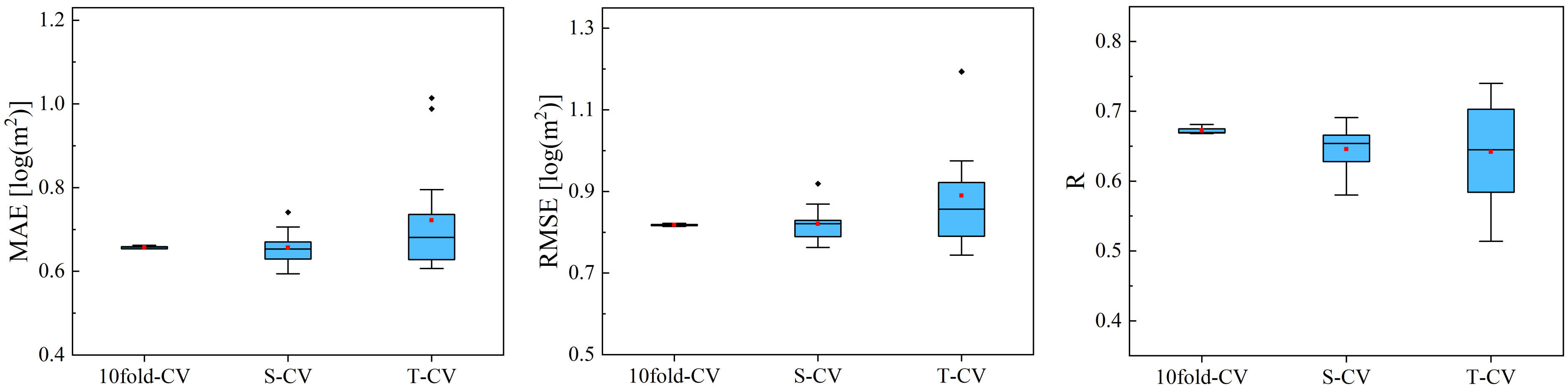


Fig. 6. Predictive performance of 10fold-CV, S-CV, and T-CV

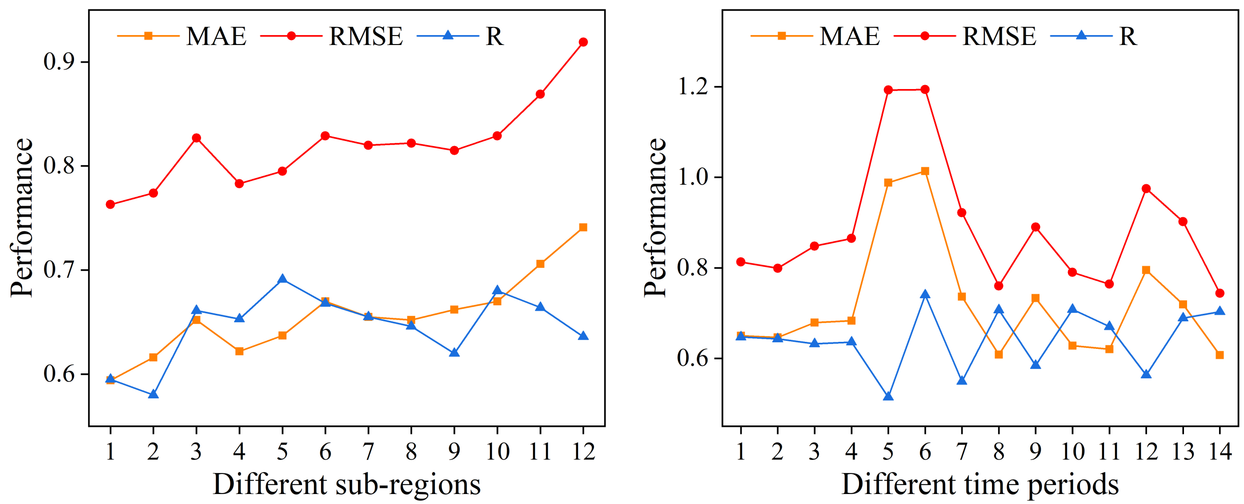


Fig. 7. Performance variations of different sub-regions and time periods.

Finally, we implemented a ST-CV procedure to contextually assess the size predictive performance in both spatial and temporal dimensions. We recall here that we divided the whole space-time domain into 168 parts with 12 spatial and 14 time intervals, and samples in each part were validated separately. **Fig. 8** shows the predictive performance of the ST-CV scheme. Note that each boxplot denotes the temporal variation in a given spatial sub-region. We observe that the model achieves a good prediction performance with mean MAE, RMSE, and R values of 0.661, 0.817, and 0.646, respectively. Inspection of the boxplots shows that three evaluation indexes have greater fluctuations in northern (sub-region 1 and 2) and southern (sub-region 11 and 12) parts of Taiwan than other sub-regions. Moreover, we can observe that the ST-CV scheme results in higher performance variations than 10-fold CV, S-CV, and T-CV, because this validation procedure exaggerates both spatial and temporal difference.

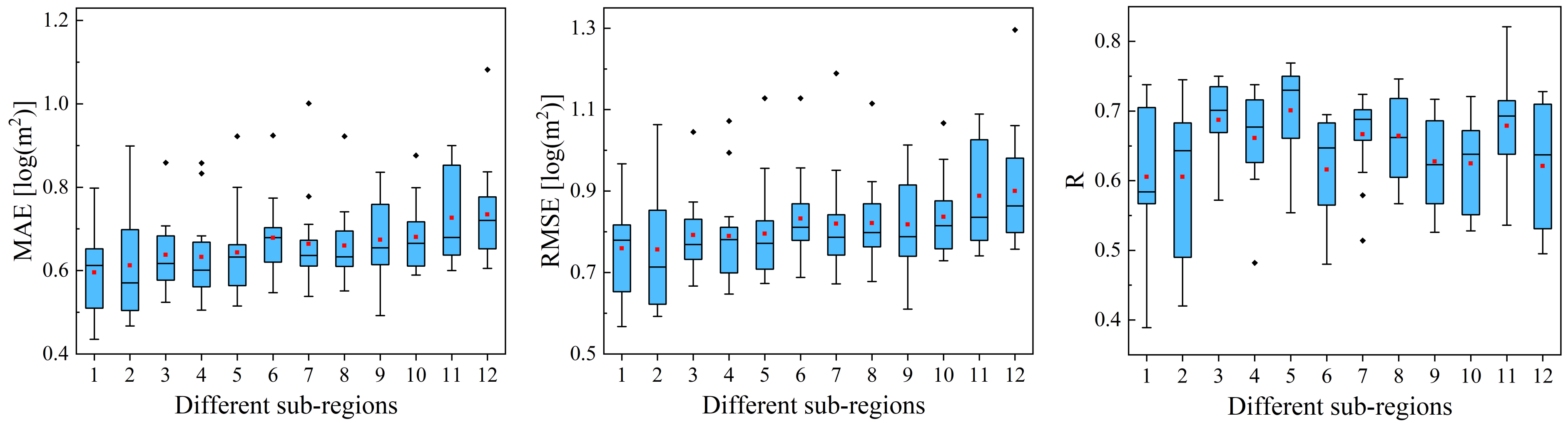


Fig. 8. Predictive performance of ST-CV

We also provide the scatter plots to show the visual agreement between observed and predicted landslide areas for different CV schemes (**Fig. 10**). One can see how much the predicted values agrees with the actual ones, for they roughly aligned with the 45° line. Inspection of **Fig. 10** shows that all models achieve reasonable predictive performance, and the 10fold-CV, S-CV, and ST-CV presents slightly better aligned spread along the 45° line than T-CV. Moreover, four models exhibit slightly overestimations in the left tail and underestimations in the right tail.

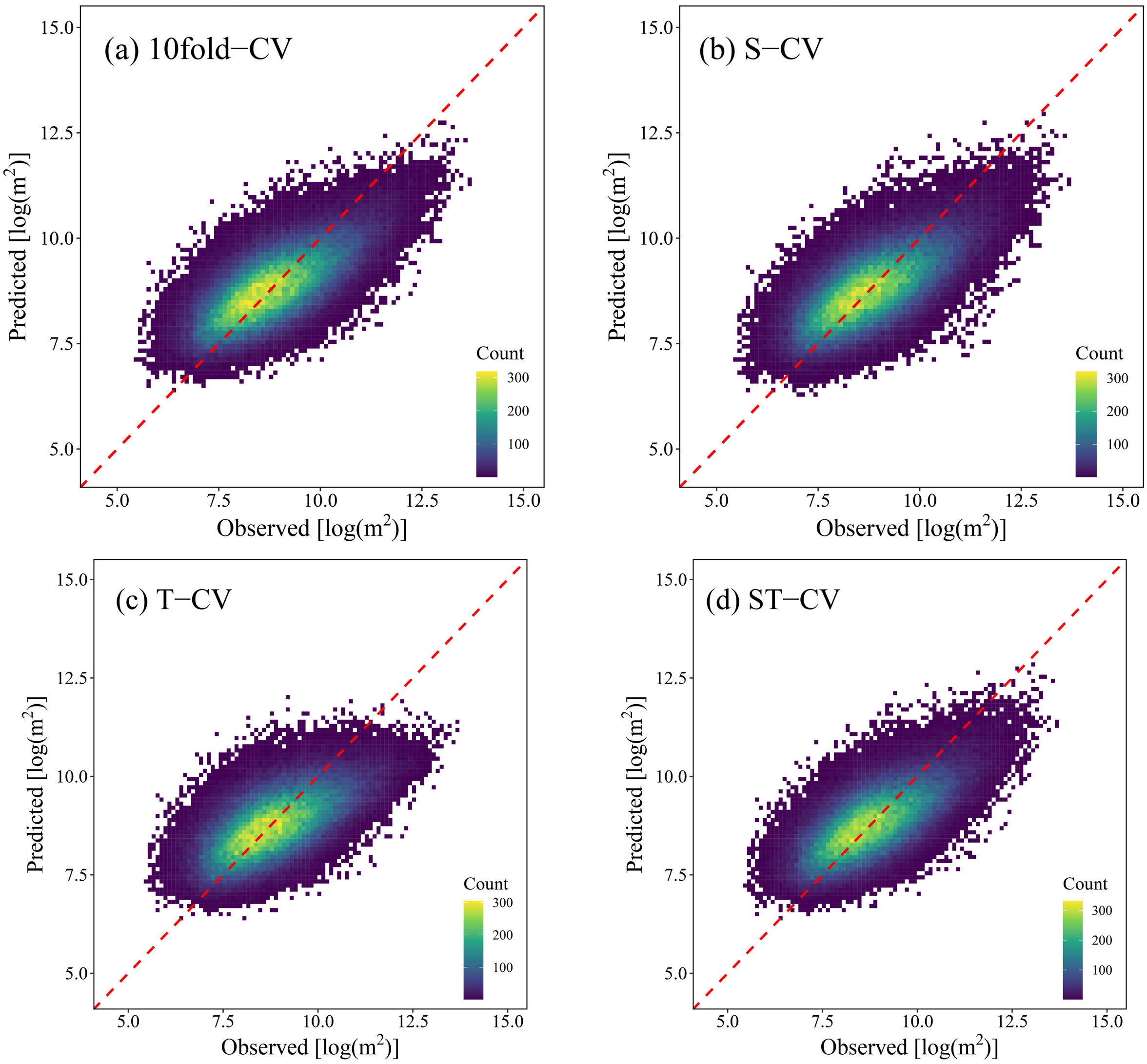


Fig. 9. Observed versus fitted plots (in log-scale) for different CV schemes.

4.4. Landslide size mapping

We used the T-CV procedure to predict the landslide size maps of the 14 time periods, as shown in **Fig. 10**. We also present the plot of predicted versus observed areas for each landslide size predictive map. We can observe that the 14 landslide size maps have strong spatial variations over time. A cluster of larger landslide areas in southern Taiwan can be seen, appearing in T6 (2009-2010), peaking at T7 (2010-2011), then gradually disappearing. Inspection of these scatter plots shows that the model obviously overestimates the landslide size in T5 (2008-2009), T9 (2012-2013), and T12 (2015-2016), and underestimates the landslide size in T6 (2009-2010), T10 (2013-2014), and T13 (2016-2017). Although the model predicts well and produces values aligned with the along the 45° line in other years, a slightly overestimation in the left tails, and underestimation in the right tails can be observed.

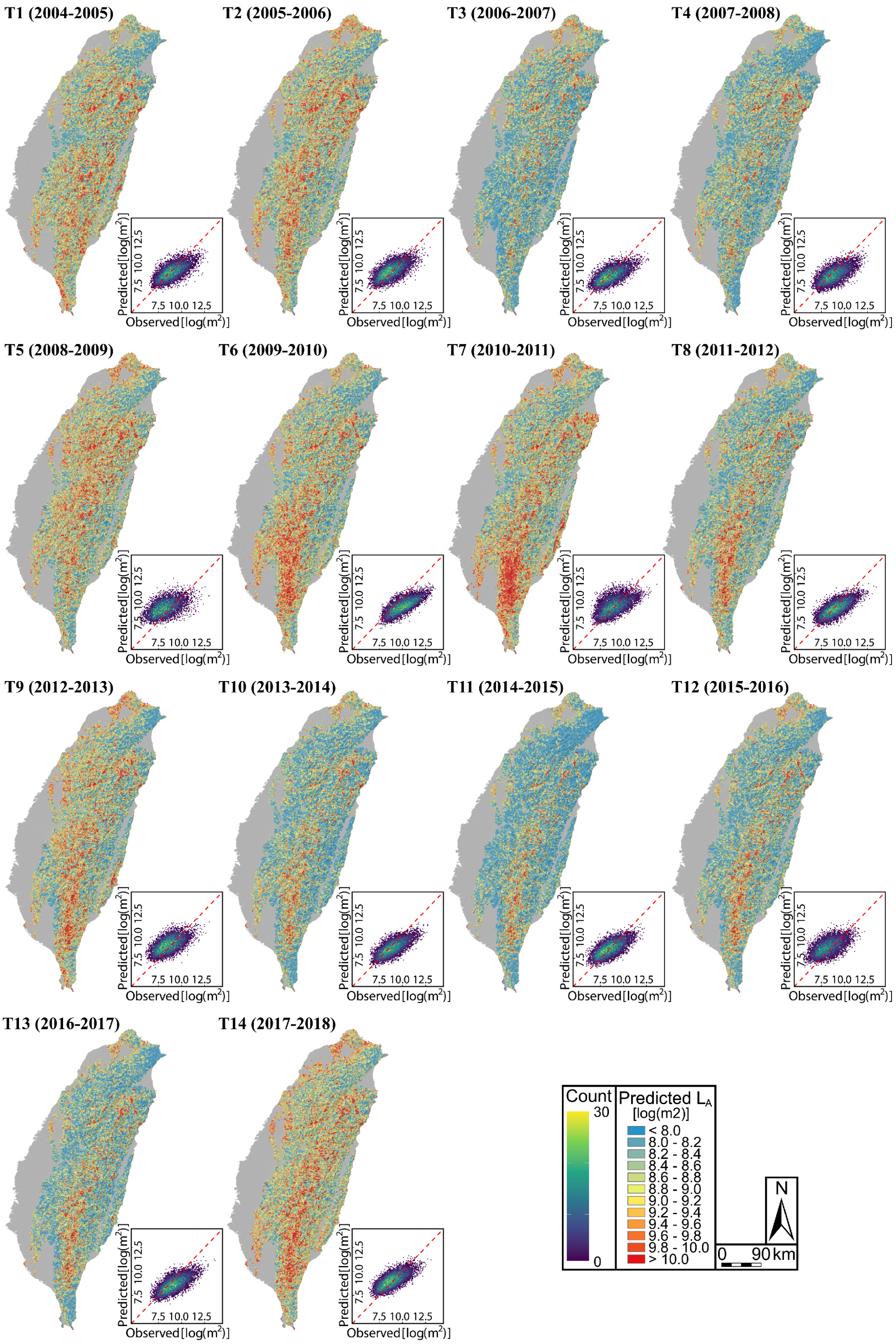


Fig. 10. Landslide size predictive maps in Taiwan from 2004 to 2018. Scatter plots shows the predictive versus observed landslide areas for each time period.

5. Discussion

5.1. Model performance

Our space-time-size model goes beyond the traditional susceptibility model to estimate the landslide planimetric areas across within SUs, and extend the spatially-explicit size model (Lombardo et al., 2021) into both spatial and temporal dimensions. Our explanatory model achieves a satisfying goodness-of-fit (**Fig. 2**) and is able to portray the effects of covariates in an interpretable manner (**Fig. 3**). Moreover, measuring the predictive performance of the size model is also important. Lombardo et al. (2021) implemented a general spatial validation, and Moreno et al. (2022) then extended it into a spatially explicit validation to evaluate the spatial transferability of the model across specific regions. However, as our model is contextually constructed over space and time, we need to explore the prediction ability across the whole space-time domain. We presented a full suite of cross-validation routines from the spatial, temporal, and spatio-temporal standpoints (see Section 3.3). Overall, the predictive performance estimated via different validation schemes achieves good results confirmed through numerical metrics (**Fig. 6** and **Fig. 8**) and graphical methods (**Fig. 9**). We stress here that another improvement in cross-validation process is the implementation of ST-CV. This can be viewed a complete spatio-temporal validation scheme capable of exploring the prediction ability of landslide size models over any time period and any geographic location.

However, there are still some limitations or some aspects can be further improved in this work. First, the landslide area is expressed on a logarithmic scale and is then assumed to follow a Gaussian distribution. Note that this logarithmic transformation is common used in landslide magnitude studies (Guzzetti et al., 2002; Malamud et al., 2004; Medwedeff et al., 2020). Although the logarithm function is monotonous increasing, the landslide area on such scale is hard to interpret for practical usage. On the other hand, converting the prediction results from logarithmic scale into actual expression (m^2) would exacerbate the difference in very low or very large areas (Lombardo et al., 2021). This is likely the result of the Gaussian likelihood choice, which struggles to predict well the behavior in the tail of a skewed distribution. This also stands out in our model results, where we can always observe a slight overestimation in the left tail and a slight underestimation in the right tail. This is valid not only in the predictions of all space-time domain (**Fig. 9**), but also when we look at specific temporal predictions (**Fig. 10**). We thus envision future efforts to test a more suitable probability distribution for space-time landslide size modelling. Second, the space-time domain in our size model is constrained by present and past situations. It lacks actual prediction for specific future time period. We envision this to be improved by simulating future scenarios of dynamic factors, following a simulation approach analogous to the scheme proposed by Lombardo and Tanyas (2021), in the context of earthquake scenarios for landslide susceptibility.

5.2. Interpretation of covariates

A good model should not only maintain high performance, but also need to be interpretable. Here, we discuss the effects of covariates on space-time size modelling from a geomorphological or statistical perspective (see **Fig. 3**). The terrain slope shows a monotone trend with the regression coefficient, indicating that steeper landscapes are expected to generate larger mass movements. This observation is line with Katz et al. (2014) who performed numerical simulations to study the controls on landslide size. The authors concluded that the detachment of material from steeper slopes largely disintegrates while propagating downhill, thus covering a larger planimetric area upon arrest. The plan curvature and profile curvature negligibly contribute to explaining the landslide size approximately up to 0, and the two covariates show negative effects on landslide size from the threshold onward. It may be because landslide materials are difficult to converge into the sidewardly convex terrain, and the erosion may not prevail in upwardly concave terrain (Ohlmacher, 2007). Furthermore, some studies find that east-facing slopes in Taiwan region have a high correlation with landslide occurrences (Lee, 2013; Chen et al., 2019a; Fang et al., 2022), we extended this relationship into landslide size in this study. As for Slope-SD, this can be considered a proxy to represent the topographical roughness across a give SU. It shows a completely linear effect with landslide size and its effect decreases as the SD value increase. This may be because the SU with a low standard deviation of slope has a smooth and homogeneous landscape, and a large amount of materials will mobilize once the landslide occurs. Or an alternative explanation may have to do with rock mass strength. In fact, strong materials tend to produce rougher landscapes, i.e., large steepness variations. Conversely, softer or unconsolidated material can loosely drape over the bedrock, giving raise to large failures. In this work, we also selected the relief variance (ReliefVar-SD) to describe the variability of elevation information in a circle, because a higher locations intrinsically have a larger gravitational potential energy to be converted into landslide kinematics and thus into overall planimetric extent (Lombardo et al., 2021). This initial hypothesis is confirmed in the ReliefVar-SD plot, where this parameter positively contributes to the increase of landslide sizes. The slope unit area shows a negative effect on very small SUs, while the contribution appears to positive on larger SUs, which is associated with previous study (Bryce et al., 2022). For lithology, the class F (Mudstone intercalated with allochthonous material) has the highest positive effect on landslide size. The Class F often coincides with badland landscapes in Taiwan, which are prone to landsliding, debris flows, and fluvial erosion (Yang et al., 2021). The class N (Shale, siltstone, and sandstone) and class J (Sandstone, mudstone, and shale) also show positive effects on landslide size, which is agreement with the observations made by Wu and Chen (2009), as the sandstone, shale and mudstone have been attributed by the authors with the highest landslide rates in central Taiwan.

Upon completing this overview of the contribution of static covariates, below we will summarize how the dynamic ones entered the landslide size estimation. Fang et al. (2022) discussed how to appropriately use rainfall-related covariates for landslide space-time susceptibility modelling in Taiwan, and concluded that the maximum daily rainfall is the most suitable by considering the landslide background, available rainfall data, and the involved spatio-temporal scale. In our study, we also used the maximum daily rainfall to express the climatic control over landslide sizes. We observe that the regression coefficient increases with the rainfall, with the maximum daily rainfall contribution becoming positive for values greater than 420 mm per day. This monotone increasing trend is surprisingly similar to the one shown in our space-time susceptibility model (Fang et al., 2022), although the rainfall threshold appears lower than the one retrieved for the susceptibility case (740 mm per day). Further studies in lines with the considerations above could open up discussion on rainfall thresholds models useful beyond the pure landslide occurrence case (Segoni et al., 2018; Monsieurs et al., 2019; Wang et al., 2021) and towards the size one instead.

NDVI was also used dynamically in time to reflect the effect of the surface vegetation condition. In **Fig. 3**, NDVI clearly maintains a positive effects on landslide size for low values and transitions to a negative regression coefficient for values above 0.67. This is reasonable because high vegetation cover could increase shallow soil shear strength and reduce erosion (Schwarz et al., 2010). As for the NDVI-SD, its contribution appears to be negative for low variation of NDVI within a SU. This effect transitions to positive for medium variations of the NDVI and goes back to negative for large variations within a SU. This is a complex behavior to interpret, but one explanation could be that a low NDVI-SD value indicates that the vegetation coverage in the SU is uniform, and this situation is likely to occur in SUs that are almost fully covered by vegetation or bare land. Conversely, a SU with high NDVI-SD value may denote a complex and heterogeneous landscape environment, whose contribution to the landslide size may be less straightforward to explain.

Aside from above environmental covariates, our model also considered the temporal and spatial relationship between SUs with different landslide areas. Specifically, we introduced and additional covariate, i.e., each SU was assigned a time period ID. We find that the temporal covariate shows significant oscillations. The two adjacent highest positive effects or lowest negative effects are separated approximately 8 years apart. This could indicate a return period for landslide size variation in time, or being diagnostic of a larger periodic effect due to harsher climatic conditions to which Taiwan may have been exposed in the past. As for the spatial effect, we considered the interaction between longitude and latitude to account for the spatial structure between SUs. In other words, this effect constrains close SU to behave more similarly as compared to SU that are far apart, in relation to the expected landslide size. In turn this can lead to clusters of landslide size, which the spatial effect denoted in specific regions of Taiwan.

5.3. Hazard considerations

The landslide hazard definition initially from Varnes (1984), and then improved by (Guzzetti et al., 2005), divides the probability assessment into three components of spatial probability (susceptibility), temporal probability, and size probability. Landslide susceptibility has been successfully estimated based on different methods (Reichenbach et al., 2018; Merghadi et al., 2020). In recent years, two components of spatial and temporal aspects are simultaneously modelled in landslide prediction studies. For example, Lombardo et al. (2020) is the first to build a Bayesian version of Poisson space-time GAM for landslide occurrences. They went beyond traditional susceptibility models to perform space-time estimation of the landslide counts. Wang et al. (2022) tested a space-time binomial generalized linear model for hydro-morphological process susceptibility across China. And, we recently implemented a Bayesian version of a binomial GAM to estimate the space-time susceptibility in Taiwan (Fang et al., 2022). However, the above space-time models neglect the landslide size, which is otherwise accounted for in this work. As a result, by estimating the planimetric area of mass movements per SUs in time we fulfill two components of the hazard definition. We therefore consider this improvement a step towards a next generation model where different aspects of the hazard definition will be estimated jointly.

6. Conclusions

We implemented a space-time size model in the main island of Taiwan from 2004 to 2018. The model corresponding to a Log-Gaussian GAM is capable to estimate landslide planimetric areas per slope unit across the whole space-time domain. We validated the predictive performance of the model based on a complete suite of cross-validation routines by considering the spatial, temporal, and spatio-temporal perspectives. The results indicate that the space-time characteristics of landslide size can be captured from stationary and dynamic factors, as well as the relationships between slope units that are close in space and time. This is a significant improvement that goes beyond the traditional susceptibility modelling to perform space-time estimation of landslide size. Moreover, this model is also an extension of space-time susceptibility model, which provide a promising step towards an operational use of landslide size estimation. However, our model does not fully satisfy the definition of hazard as it lacks the information on whether a slope is actually stable or unstable. For this reason, we envision our future efforts to be dedicated to a combinatory model where all requirements of the landslide hazard definition will be addressed in a single analytical protocol. If so, this could further provide the basis for an operational space-time risk model, where the expected loss due to landslides can be probabilistically simulated before reaching the emergency phase. Before reaching this stage though, another potential improvement to be explored could be finding a more suitable probability distribution to reduce the misestimates in the tails. Or even better, by directly modelling the landslide size in square meters instead of using a logarithmic transformation. Overall, we expect our space-time size prediction model to place a new brick in the landslide literature upon which laying the foundation for future advances in data-driven applications. This new data-driven prototype better portrays the overall landslide information across a given the landscape, and in the hope of triggering similar experiments within the geoscientific community.

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Data and codes availability statement

The data and codes that support the findings of this study can be accessed at:

https://doi.org/10.5281/zenodo.7005158.

Appendix A. Summary of lithology class

Class	Description
A	Alluvium
B	Andesite, basalt, and serpentine
C	Metamorphic limestone
D	Black schist, green schist, and sandy schist
E	Laterite, gravel, sand and clay
F	Mudstone intercalated with allochthon
G	Gneiss
H	Hard shale and sandstone
I	Agglomerate and tuffaceous sandstone
J	Sandstone, mudstone, and shale
K	Phyllite, slate, and sandstone
L	Sandstone, shale, and coaly shale
M	Quartzite, slate, and coaly shale
N	Shale, siltstone, and sandstone
O	Hard shale, slate, and Phyllite

Appendix B. Description of different sub-regions

Sub-region ID	Description
1	New Taipei City, Taipei City, Keelung City, Taoyuan County
2	Hsinchu City, Hsinchu County
3	Yilan County
4	Miaoli County
5	Taichung City
6	Chiayi County, Chiayi City, Yunlin County, Changhua County
7	Nantou County
8	Hualien County
9	Tainan City
10	Kaohsiung City
11	Taitung County
12	Pingtung County

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