Assessing the Influence of Temperature on Slope Stability in a Temperate Climate: A Nationwide Spatial Probability Analysis in Italy

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Abstract

Among the factors controlling the stability of slopes, the role of temperature remains poorly understood, especially in temperate climates. Experiments reveal the coupled thermo-hydro-mechanical (THM) nature of clay behaviours; however, field evidence of thermally-induced landslides is scarce. The complexity of THM processes hinders the construction of a temperature-related variable, usable in modelling at multiple scales. We conducted spatial modelling for areas in Italy featuring shallow clay landslides moving on gentle slopes. We used the Italian National Inventory (IFFI), which discriminates among different landslide types. We employed a slope unit-based Generalised Additive Model (GAM) and utilised Land Surface Temperature (LST) data from MODIS, accessible in Google Earth Engine. We found a positive correlation between landslide occurrence and LST in Southern Italy, where creep/shallow phenomena are common. This aligns with the known decline in soil/water viscosity as temperature rises, resulting in enhanced creep rates.

Highlights

- Temperature influences the stability of gentle clay slopes in temperate climate.
- Slope unit-based statistical modelling reveals a role of land surface temperature.
- A small set of covariates ensures explainability with small performance loss.
- Spatial homogeneity in model subsets supports the identification of thermal effects.

Keywords: land surface temperature, generalized additive model, landslide susceptibility, thermo-hydro-mechanical coupling, slope unit, clay.

Software & data availability

The data and code for this study are available, respectively, at the following links: https://bit.ly/3tEer4N and https://bit.ly/47oASsn. Data analysis was conducted in R environment. The software is freely available at https://www.r-project.org/. An introduction to r.corrplot can be found here: https://cran.r-project.org/web/packages/corrplot/vignettes/corrplot-intro.html. The package r.slopeunits can be downloaded here: https://geomorphology.irpi.cnr.it/tools/slope-units. Maps were produced in GIS environment using Grass GIS 8.3.1, freely available here: https://grass.osgeo.org/download/windows/; and ArcGIS Online, available through subscription here: https://www.arcgis.com/index.html. Input data were freely downloaded from Google Earth Engine: https://earthengine.google.com/ and the IFFI Catalogue: https://idrogeo.isprambiente.it/app/.

1. Introduction

In the modern age, our planet is experiencing an acceleration of surface warming. This rapid change is altering natural equilibria on a human timescale, and within this, a range of geohazards has emerged as a formidable agent reshaping the frequencies, magnitudes, patterns, and consequences of various geological phenomena. However, when we embark on the mission to forecast the ramifications of climate change on soil slopes in temperate and warm climates, our attention is often drawn to shifts in precipitation patterns and the broader interplay between the atmosphere and the Earth's surface (Gariano and Guzzetti, 2016). Traditionally, temperature does not occupy a central role in our considerations, unless we are specifically investigating freeze-thaw dynamics (Mithan et al., 2021). Yet, it is crucial to acknowledge that temperature exerts a profound influence on the strength, compressibility, and viscosity of soil (Mitchell, 1969; Scaringi and Loche, 2022), even though these geotechnical parameters are categorically discarded by geostatistical models.

The findings of experimental research and field observations underscore the direct impact of temperature on the hydro-mechanical behaviour of geomaterials, even within the typical temperature ranges experienced near the ground surface (e.g., 0° to 40°C). Pioneering studies have described the complex interplay between the thermal expansion of water and soil minerals, alterations in interparticle forces, and their consequences on volume and pore water pressure in saturated soils (e.g., Villar and Lloret, 2004). Drained cycles of heating and cooling have also been investigated to induce net shrinkage and stiffening, creating an apparent preconsolidation effect, a phenomenon also witnessed in unsaturated soils (Mitchell, 1969). Moreover, soil compressibility, governed by stress and temperature, is known to increase with higher temperatures, leading to larger compressibility and creep strains, yet reduced plasticity due to the decreased viscosity of pore water. In undrained conditions, a mere 20°C rise in temperature can trigger a significant 30% reduction in shear resistance in clays, while in drained conditions, elevated temperatures can promote softening (Loche and Scaringi, 2023). Recent research has unveiled the intricacies of this relationship, indicating that temperature's effect on shear resistance varies depending on mineralogy, shear rate, and stress-thermal history (Loche and Scaringi, 2023; Shibasaki et al., 2017). A close association between temperature, mineral composition (particularly smectite content), and shear rate effects has been noted, exerting control over the potential for landslides (Shibasaki et al., 2016).

At the scale of slopes, the combined influence of thermal and hydraulic forces is a well-recognised driver of weathering in rocks, a phenomenon that extends to stiff and swelling clays Nigrelli et al., 2022; Paranunzio et al., 2016). Discontinuities in geological materials can transmit changes in pore water pressure to considerable depths and also facilitate heat transfer through water flow or air convection. As a result, the fracturing, softening, and enhanced weathering of deforming geological bodies may lead to distinct thermal properties and surface temperatures when compared to adjacent areas (Elia et al., 2017; Tagarelli and Cotecchia, 2020). The absence of vegetation can accentuate these temperature differences. Temperature also interacts with soil moisture and evapotranspiration, impacting the precipitation thresholds that trigger landslides. Notably, at the slope scale, the effect of thermal forcing in natural soil slopes is less documented than in rock slopes. Possibly, the most scrutinised case in the literature of a landslide whose activity was tied to temperature variations was the Touge landslide (Shibasaki et al., 2016). The kinematics of this landslide was found to be influenced by the temperature in the slip zone, through a correlation supported by experiments entailing a 13% reduction in available strength upon cooling from 25°C to 9°C. In this precise perspective of assessing future landslide susceptibility, hazard, and risk under the influence of climate change (direct temperature increase), our traditional approaches may fall short if they neglect the direct impact of temperature on soil hydro-mechanics. The role of temperature in slope stability in temperate climates is an underexplored area of study, compounded by the lack of a suitable variable to represent this effect. Nevertheless, with the increasing availability of thermal information at catchment and regional scales through thermal remote sensing products, an opportunity emerges to explore the intricate relationship between temperature and landslide susceptibility.

The objective of this study was to craft a representative thermal variable suitable for catchment and regional-scale analyses. Land Surface Temperature (LST), accessible through Google Earth Engine (GEE), can be seamlessly integrated into Landslide Susceptibility Models (LSM). In doing so, we intend to uncover the role of temperature in slope stability and explore its dynamic interaction. In light of these considerations, we have developed a LSM workflow utilising a Generalized Additive Model (GAM) framework with slope unit (SU) partitioning. Leveraging the computational capabilities and data resources of GEE, our model accommodates thermal effects through LST data derived from MODIS (Ebrahimy et al., 2021; Shiff et al., 2021; Yu et al., 2022). This approach allowed us to explore how the average temperature-driven effects evolve over space in a rapidly changing landscape abundant with landslides. Furthermore, by shifting the focus from rainfall-induced landslides to the broader domain of temperature's influence on clay reactivation of landslides, our study aims to bridge the gap in understanding this pivotal factor's role in slope stability, especially in the context of a changing climate. This introduction lays the foundation for a comprehensive exploration of the intricate interplay between temperature, soil mechanics, and landslide susceptibility in temperate climates.

2. Data and methods

2.1. Background

Upscaling physically-based models to entire catchments is difficult as strong simplifications in boundary conditions, parameters, and models are necessary. Fully coupled thermo-hydro-mechanical (THM) models have not been implemented at this scale, although partial or sequential coupling has been attempted (Loche et al., 2022b). In this perspective, geostatistical modelling is currently the only viable tool for evaluating the non-straightforward but direct effect of temperature on landslide patterns at the catchment scale (Lombardo and Mai, 2018; Steger et al., 2016). Experiments have pointed the accent on the THM response in expansive soils and selected landslides have shown signs of thermally-induced activity. This has sparked the need to delve into how thermal behaviours connect with geomechanical parameters and morphological processes, offering a fresh perspective on landscape evolution. From this perspective, shreds of evidence from the laboratory are striking even though with some complications. Evidence fades as the scale increases, owing to forced simplifications in frameworks in parallel with increasing complexities and heterogeneities of the landscape (Scaringi and Loche, 2022). For instance, **Figure 1** shows a possible distinct behaviour between a very active and a less active clay under the effect of temperature. However, at the slope-scale, little evidence is observed. The unique example of the Touge landslide showed the very same relationship between temperature changes and the activity of the landslide (**Figure 2**).

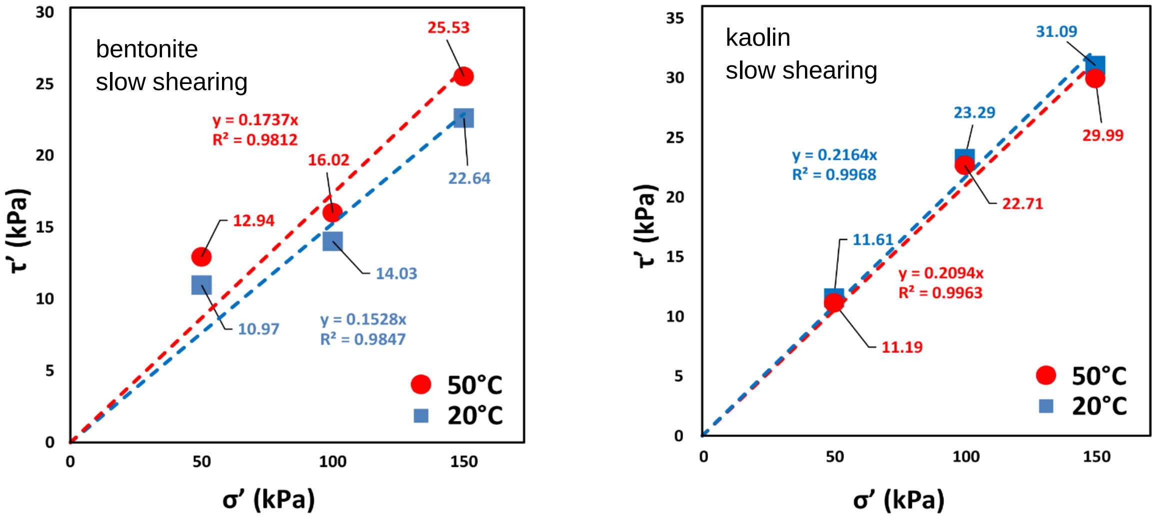

Figure 1. Evidence of thermal effect on the residual shear strength of two clays under slow shearing and typical landslide stress levels (mod. from Loche and Scaringi, 2023).

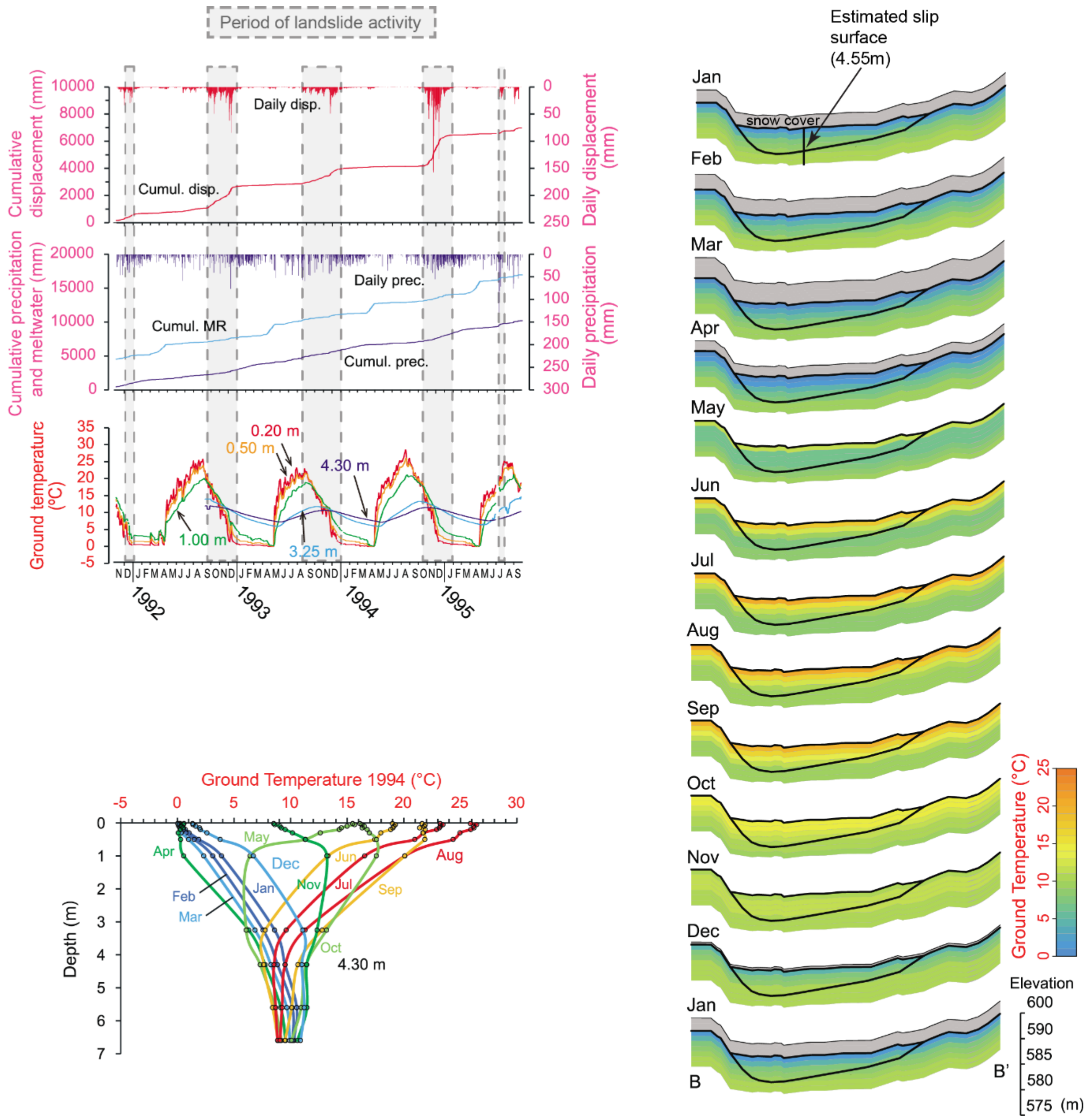

Figure 2. Example of landslide activity affected by temperature changes (mod. from Shibasaki et al., 2016).

As aforementioned, at catchment scale, a knowledge gap concerning the direct effect of temperature has been identified. Few authors tackled this point using a statistical approach. In one study, we correlated landsliding and temperature after the 2008 Wenchuan earthquake, finding that higher surface temperatures corresponded to prolonged post-earthquake landsliding (Loche et al., 2022b). Unfortunately, different climates, different lithologies and diverse landslide processes do not allow us to fully understand the process. Thus, to constrain the recent approaches, we decided to focus on solely clay materials to align the laboratory tests and to explore the complicated large Italian regions.

2.2. Inventory and mapping units

The geomorphology of Italy is extremely complex (e.g., Soldati and Marchetti**,** 2017). The large-scale geomorphological and geological settings of the country are represented by the Apennine and the Alps. The great variety of morphological features is the result of an active geodynamic environment (Bosellini, 2017), which determines a considerable variety in terms of outcropping lithologies (Bucci et al., 2022; Marchesini et al., 2015). Our study area comprises all clay formations according to the geological map of Italy (Bucci et al., 2022) (**Figure 3a**). Within the area, only the shallow landslides have been considered. These are, in fact, continuous movements in which displacements typically occur within a thick zone of distributed shear stresses. We specifically focused on shallow landslides because they are often associated with creep movements and the velocity distribution in the moving mass can be compared to that of viscous fluids. Earthflows predominantly occur within clayey and structurally complex formations (Hungr et al., 2014). Shallow landslides are characterised in the Italian national inventory (IFFI) (Loche et al., 2022a; Triglia et al., 2010) as having low speed and involving soils with a high clay content and comparatively low water content. These phenomena are well distinct in the national inventory and are carefully discerned from translational, rapid flow, and slow flow movements. Shallow phenomena mainly affect not-very-steep slopes made up of stiff clays or weathered clay rocks.

To investigate these processes, a geographical subdivision of the study area using r.slopeunits software (Alvioli et al., 2016) was performed. As a result, we detected 3293 shallow landslide presences in clay materials and 33838 Slope Units (SUs). The choice of spatial partitioning is of particular interest in our geostatistical modelling. While most studies adopt pixel-based subdivisions (Reichenbach et al., 2018), we deviate from the norm by relying on Sus. These physical entities are shaped by geomorphological processes and hold promise for providing valuable insights into the occurrence of landslides, despite being an aspect that has received limited attention in previous research. Thermal boundary conditions (e.g., solar irradiation, air temperature) are influenced by slope orientation and surface morphology, which are intrinsic characteristics of the SUs. Therefore, working with SUs rather than with pixel-based partitions seems the most practical and reasonable approach. Specifically, the calculations to produce SUs allowed us to obtain a spatial partition uniquely associated with theoretically susceptible zones to landslides and with objects with geomorphological meaning in slope stability analysis. Then, we intersected the SUs with the inventory to construct the landslide presence/absence dataset, which we took as the target variable in LSM (**Figure 3b**). As the inventory contains landslide polygons, we identified a single point for each polygon which corresponds to the highest location along the landslide scarp. All these procedures have been described in Loche at al. (2022a), to which the dataset belongs.

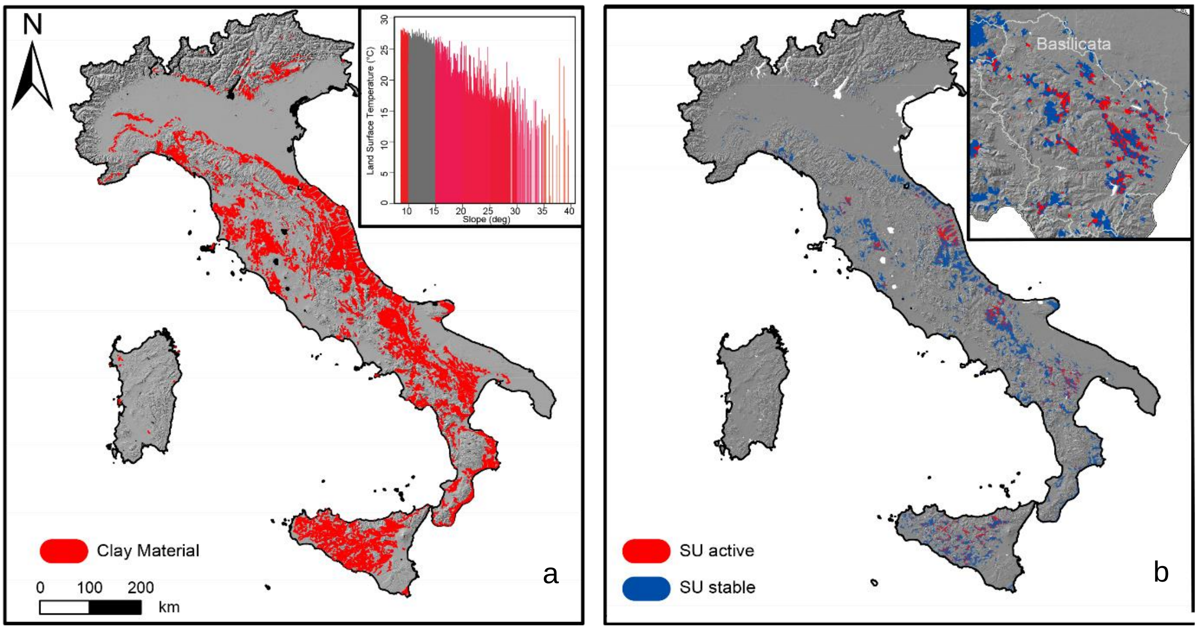

Figure 3. Normalised shallow landslides within SUs containing clay materials (a) and distinction between SUs containing or not containing active movements (b). Flat areas have been cropped from the model. The inset in (a) displays a relationship between average slope angle in clay slopes and surface temperature. The inset in (b) exemplifies the distinction between active and non-active SUs in Basilicata, a region in southern Italy. Total count of landslides: 16530; binarized SUs: 5572.

Notably, **Figure 3** shows an abundance of SUs. Among them, landslides of the shallow type are featured, with 595 presences in the Basilicata region (**Figure 3b, inset**). Indeed, we conducted our analysis on the whole Italian territory as well as in a subset of data of our interest, in which a sufficient number for statistical modelling is present. We believe that the shallow landslides are particularly appropriate for highlighting the role of LST through LSM. Notably, although the area features slopes of variable size and shape, the variability in most covariates is not excessive. Especially precipitation patterns over such a long period are relatively homogeneous, and so are the gentle slope angles and the elevation of the ridges based on the clay mechanical response. A clear increase in temperature can be observed moving from North to South, in which at the same time we can highlight a slight change of morphology, where a gentler typology of slope is present. It is also true that in the same Apennine formation, we can observe different morphologies moving between pre-Apennine and pure Apennine, where the valleys in conjunction with the sea have a softer morphology.

What stands out in **Figure 3a (inset)** is how the temperature is higher in gentle slopes, but it is also true that a gentle slope in the north of Italy can be hardly related to a gentle slope in the south or on islands owing to the different geology. So, being the correlation still visible merging all these slopes (SUs), we can suggest that a thermal signal may have an effect on the stability of clay formations by allowing a decrease in viscosity and permitting more moveability in a sort of flow. These clay materials are not able to sustain a steep slope and their critical and residual friction angles can be attested around 25° and 5-10°, respectively. Moreover, these different slopes in Italy have to behave physically in the same way, but the average temperature is certainly changing moving from North towards South. An example of interest comprises the Basento and Bradano valleys in Basilicata. These are some explanatory examples of a quite unstable morphology, in which old landslides are as well represented in the area. The erosion in this type of condition can guarantee an acceleration in the process of instability. Furthermore, southern Italy does not feature too remarkable mineralogical changes in the clay material, and we can attest to the value aforementioned as a reference (smectite, illite). In Sicily, on the other hand, we may observe a huge spread of clays but in this case of clear volcanic origin.

2.3. Model setup and covariates

We used a simple logistic regression assuming that landslide patterns can be explained with a Bernoulli exponential family of distributions and that the influence of the covariates can be captured via a Generalized Additive Model (GAM). This is for exploring landslide spatial probability through nonparametric smoothing functions (Petschko et al., 2012; Steger et al., 2016). We utilised this approach to describe a minimalistic slope unit-based spatial model for the Italian clay areas following this very same formulation:

$$\eta P = \beta_0 + f_1(X_{SLP\mu}) + f_2(X_{TWI\mu}) + f_3(X_{LST\mu}) + f_4(X_{LST\sigma}) + f_5(X_{NRT\mu}) + f_6(X_{EST\mu}) + f_7(X_{MD}) + f_8(X_{DA}) + f_8(X_{RAIN\mu})$$

where P is the probability of landslide occurrence, η is the logit link and f_1 to f_9 represent the nonlinear functions mentioned above, for each covariate under consideration. GAMs have proven to be highly useful in susceptibility modelling as they allow the inclusion of non-linear relations between the response (landslides) and quantitative predictors while maintaining a high generalization capacity and interpretability (Loche et al., 2022b). Especially, the interpretability is at the base of this study. Indeed, we used a small set of basic morphometric variables together with thermal and rainfall variables (**Table 1**) to perform the susceptibility analysis neglecting any type of variable influence. Specifically, we have done this by computing the morphometrical covariates using the 25-m digital elevation model (DEM) and we computed the average and standard deviation within the units (Loche et al., 2022a). We also accounted for the rainfall covering an interval of ten years (2008-2018) (obtained from the GEE and TRMM data), which reasonably represents the main hydraulic changes in the area. Additionally, we accounted for the shape of the SUs through the maximum distance from the highest to the lowest point along a SU boundary and we computed the elongation index as the maximum distance divided by the square root of the SU area. This index represents large SUs when the ratio returns small values and depicts elongated SU as the ratio increases. Finally, we computed the thermal variable (Land Surface Temperature – LST), which defines how hot the surface is. This has been done using GEE and data from the Infrared band of MODIS. To add additional constraints that avoid multicollinearity effects or variable mixture problems, we did not consider the Normalised Difference Vegetation Index (NDVI) as the LST already contains information on vegetation coverage and aspect (in its continuous form through Eastness and Northness), as specified in the very same formulation of LST (Jaber, 2023).

Table 1. List of covariates and their usage in modelling. The nonlinear representations are smoothing spline with five degrees of freedom. Mean and standard deviation (μ, ς) values always are referred to within a SU.

Name	**Abbreviation**
Mean slope within the SU	SLPμ
Topographic Wetness Index	TWIμ
Mean land surface temperature	LSTμ
SD of land surface temperature	LSTς
Mean Northness	NRTμ
Mean Eastness	ESTμ
Maximum distance within the SU	MD
Max distance/√(SU area)	DA
Rainfall	RAINμ

2.4. Land surface temperature

Particular attention was paid to the computational part of the temperature variable. To guarantee the maximum computational information, averaged LST data have been downloaded over the interval of 10 years between successive image acquisitions. The time-averaged LST was further averaged over the SUs, as it was the standard deviation of it. Finally, the 2008–2018 average and standard deviation (MODIS data) over each slope unit was the main possible solution for a decent long-term trend investigation. From 2008 until 2018, the year of the last update of the IFFI inventory in the regions of interest (i.e., Basilicata), the variable showed reasonable spatial and temporal trends. The choice of the Moderate Resolution Imaging Spectroradiometer (MODIS) to compute the LST (**Figure 4**) was dictated by the temporal resolution, which is preferable for discriminating temporal features associated with climate change. MODIS has longer revisit times (2 days) compared with other satellites (e.g., LANDSAT). This time, we preferred the high revisit time as we used averaged data over considerable intervals in our model. Methodological frameworks for deriving LST data from MODIS data series are well codified and implemented in GEE (Ermida et al., 2020; Meng et al., 2019; Zhang et al., 2021). A necessary data correction is available in the aforementioned codes, taking into account water vapour content from NCEP/NCAR, emissivity from the ASTER GEDv3, and NDVI-based correction for vegetation (Ermida et al., 2020; Jaber, 2023).

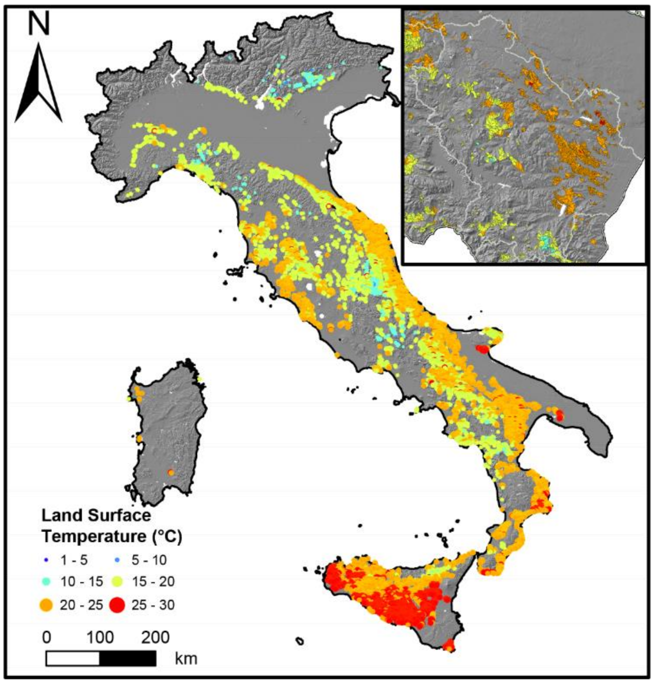

Figure 4. LST bubble map for the entire domain of clay materials over the Italian territory averaged over ten years of image acquisitions. The inset presents the focus of the Basilicata region with the defined SUs.

2.5. Multicollinearity and fitting

To validate our hypothesis of no variable interaction and increase the pure effect of the covariates we used the R package corrplot to evaluate multicollinearity issues (Mela and Kopalle, 2002). **Figure 5** displays the computed coefficient for each of the independent variables and produces a graphical display of a correlation matrix. The multicollinearity, by definition, is a potential problem when the coefficient is greater than 0.75, and a serious problem when it is greater than 0.9. After this stage, we used the whole dataset for each single subset to perform a within-sample fitting, and no cross-validation (CV) (out-of-sample), has been attempted, not being the purpose of the work predicting but solely evaluating the variables impact.

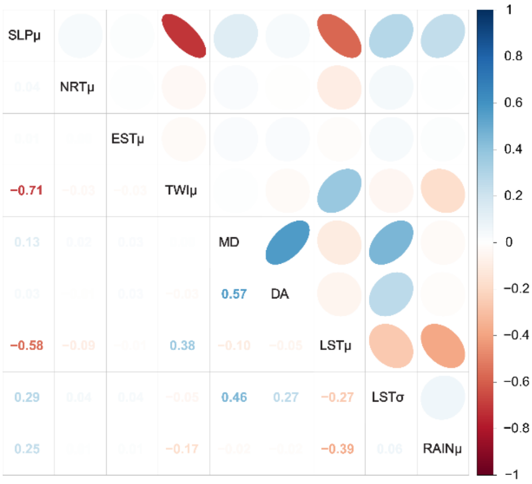

Figure 5. Multicollinearity matrix. See **Table 1** for the meaning of the abbreviations. We used the R package corrplot to evaluate multicollinearity issues.

3. Results and Discussion

3.1. Within-sample fitting

The fitting procedure returns satisfactory results from acceptable to excellent performances in terms of receiver operating characteristic (ROC) curves and their integral, the area under the ROC curve (AUC), with values around 0.78-0.81 (**Table 2, Figure 7**) (Hosmer and Lemeshow, 2000). Interestingly, the values of performance using Precision Recall Curves (PRC) showed clearly very low performance (Sofaer et al., 2019). Probably, the model performance is affected by the number of variables, which was intentionally kept low to ease the Interpretation and keep the model as simple as possible, decreasing the possible potential performances. However, interestingly, each model class is predicted with an average AUC which corresponds to Excellent performances even with these small and unconventional variables.

Table 2. Model performance in terms of ROC curves and AUCs and PRC for the complete study area (Italy, ITA) and two subsets: Basilicata (BAS) and Basilicata slope<20° (BAS20).

	Model performance		
Procedure	**Italy (ITA)**	**Basilicata (BAS)**	**Basilicata slope<20° (BAS20)**
Model fit AUC	0.787	0.818	0.817
Model fit PRC	0.296	0.563	0.563

3.2. Variables effects

Aiming at an interpretable model, the number of variables was kept minimal. Here, we analysed one by one the effects allowing to capture variation and the uncertainty of the variables (Steger et al., 2016; Tong et al., 2023) (**Figure 6**). Variables such as slope (SLT*μ*) and rainfall (*RAINμ*) are fundamental, respectively because represent the gravitative process and a hydraulic trigger. However, LST results are the reason for this work, and the main attention has be devoted to its behaviour. Additionally, SU morphometric characterisation of SU was added to the model to check the role of these. Reasonable behaviour is shown by the variables, as pointed out by the patterns of each covariate effect for each year (**Figure 6**).

Covariates responsible for the SU orientation (E*STμ* and N*RTμ*) demonstrated a quite small importance over the model, although a negative tendency has been observed in the model BAS and BAS20 for N*RTμ*. Across the model, which exponentially decreases the area extent of the analyses, what stands out is that the Italy model, the richest in landslides, is dominated by the Maximum distance, which expresses a strong positive effect, while LST also seems to play consistently in favour of instability. Here, we attempted to model the *SLTμ* and *RAINμ*, but a non-significant behaviour emerged. It is worth noting that the effect of both variables is nevertheless insignificant, compatible with the dominating role of the others. As regards *SLTμ* a maximum positive effect is just reached for slopes of 5–15°. This non-linear trend is marked by the decrease of counts. However, it remains a positive trend that can be highlighted. Steep slopes are more likely to produce landslides, but very steep slopes are unlikely to exist in clay materials. However, the model shows a gradual increase in linearity and positivity throughout time (**Figure 6**). The Maximum Distance of a SU and the roundness/elongation index presents the same behaviour throughout the models: a positive trend justifies how SUs with higher Maximum distance feature more landslides, whereas the elongation index shows how the larger SUs are more unstable. The absence of a statistically clear and positive effect of rainfall in the model is not surprising considering the small (large-scale) variability of rainfall over the studied area. Indeed, we evaluate a non-significant effect in each model. Conversely, the Mean rain covariate shows a kind of positive effect, where however we can observe a high influence of uncertainty, thus the patterns stay in the non-significant field, and we cannot assume any positive or negative effect. Finally, in the whole Italy model, we observe a non-linear effect of the Mean LST and Mean Slope, which is gradually getting linear as we discuss in the next section. In BAS, the Mean Slope acquires a more positive effect, even though is strongly uncertain in the tail given the small data population. A non-linear correlation between slope and landsliding is reasonable, particularly in a clay material context, as the one defined a priori. In BAS20, it is possible to note that Mean LST exhibits a strongly positive trend (s(1.5)), suggesting that higher mean surface temperatures are conducive to more landsliding. Overall, Mean LST shows a strong non-linear behaviour (s(3.71)) for mean surface temperatures in the Italy models, which increases toward a positive trend BAS and strongly linear and positive in BAS20 (1.5), showing how high temperatures correlate with instability and a thermal weakening behaviour (**Figure 6b**). Remarkably, the simultaneous increase in Mean LST linearity is coupled with the increasing spatial relationship between gentle slope and temperature (**Figure 7, 8**).

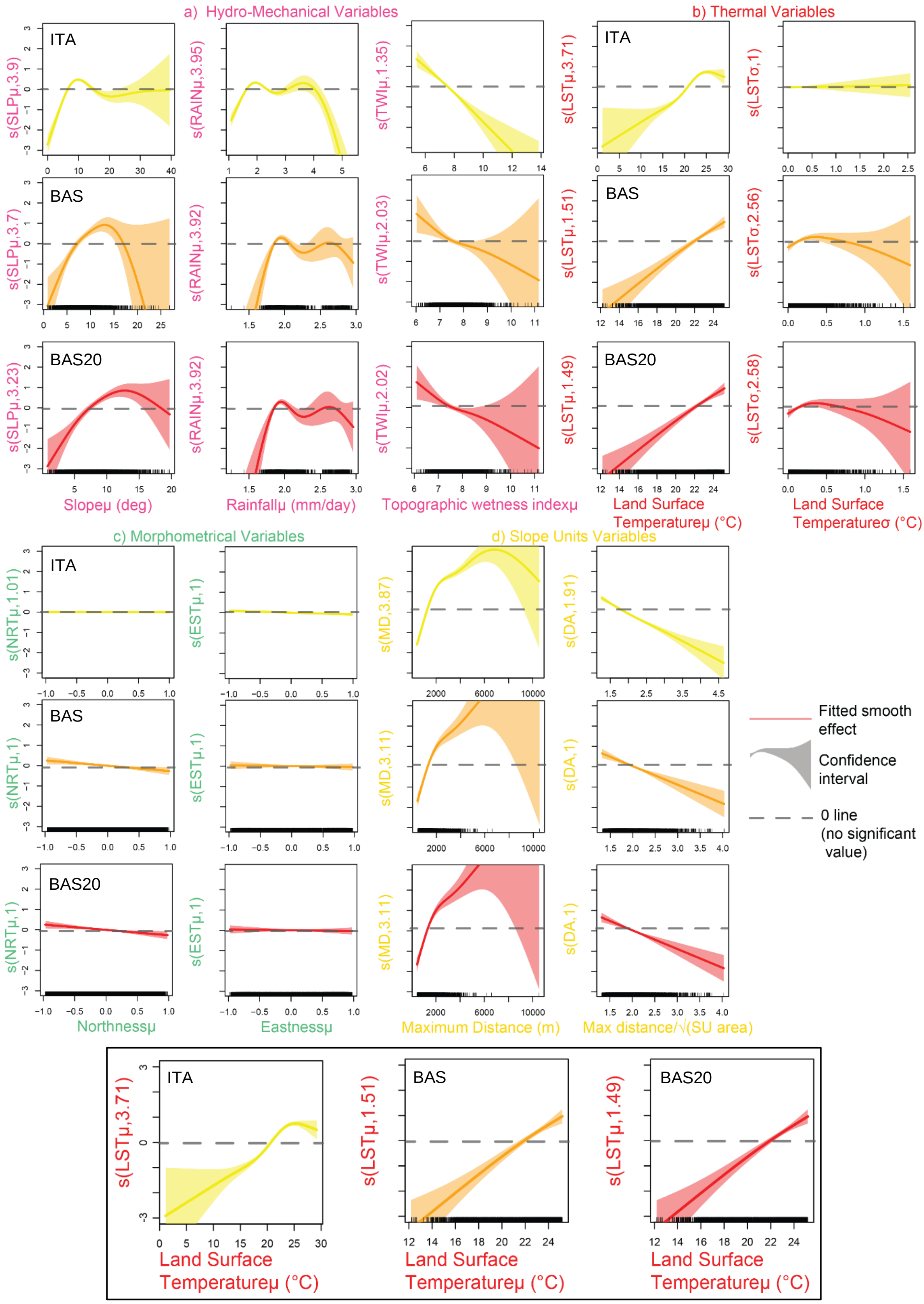

Figure 6. (Top) Variables effects displayed as component smooth functions and confidence bands (95%) during the years. Effect of (a) Hydro-"mechanical", (b) thermal, (c) morphometrical and (d) SU variables are displayed as component smooth functions. The first line relates to the model for Italy, the second only for Basilicata, and the third only for

gentle slopes (<20°) in Basilicata. The shaded areas represent 95% confidence bands. The numbers on the vertical axes are the effective degrees of freedom. (Bottom, framed) Summary of the behaviours of the Mean LST throughout the models, reducing the area and increasing the linearity (left: Italy (ITA), centre: Basilicata (BAS), right: Basilicata <20° (BAS20)).

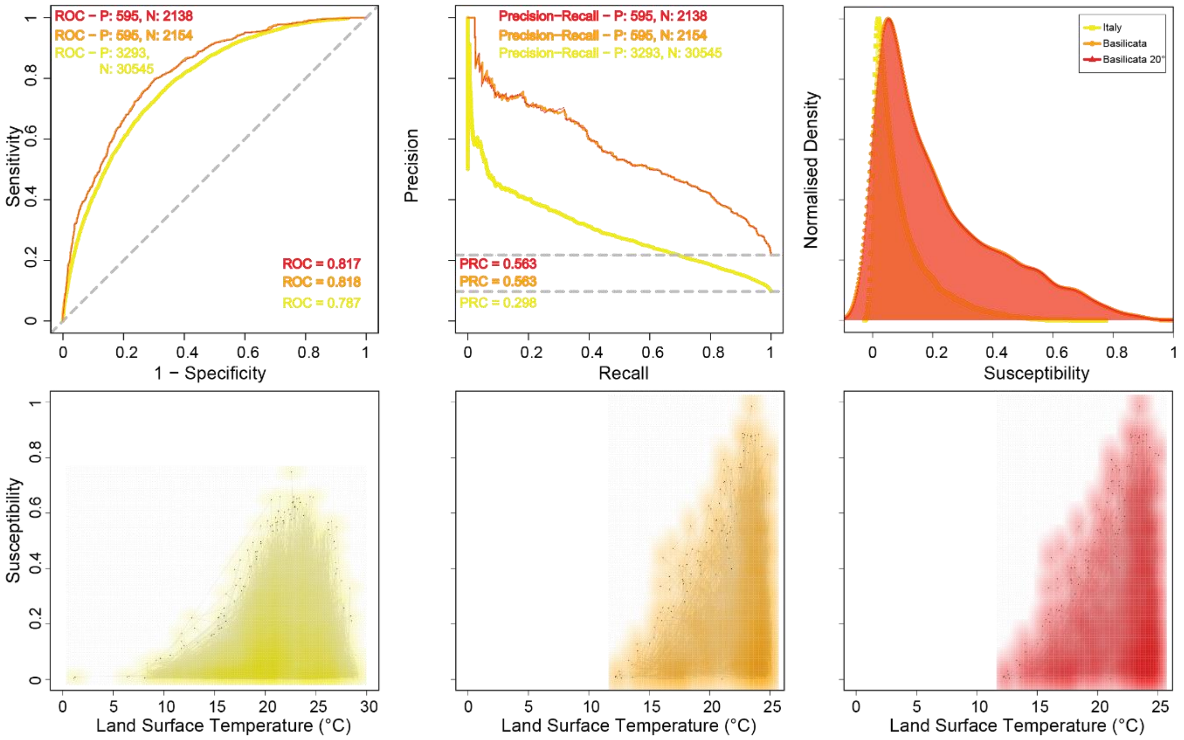

Figure 7. AUC and PRC curves, and probability density functions of landslide susceptibility for the current models. Smooth plots of LST and Susceptibility and their distribution of the susceptibility over the models (yellow: ITA; orange: BAS; red: BAS20 model).

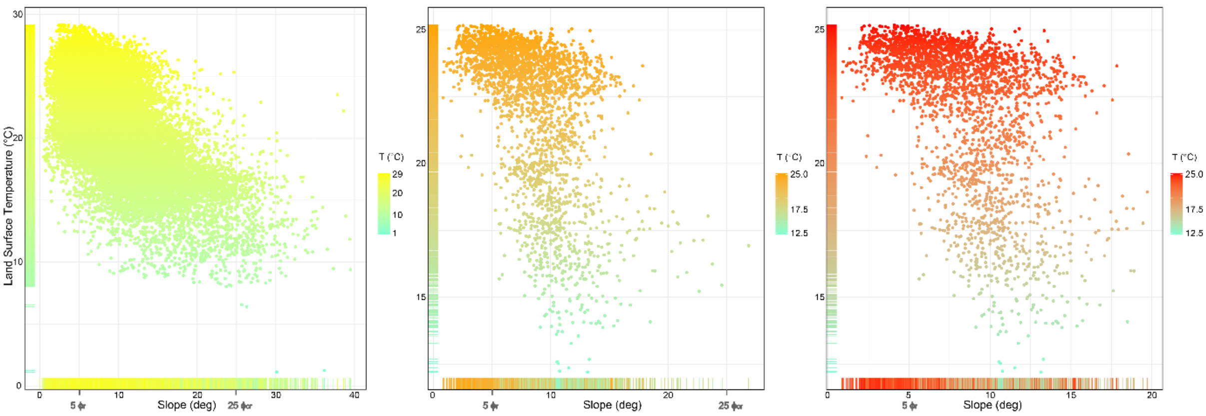

Figure 8. Land Surface Temperature vs Slope within each slope unit (left: ITA; centre: BAS; right: BAS20 model).

The distribution of susceptibility over the model can be a useful tool to figure out the processes of instability mentioned above. The susceptibility distribution in the whole of Italy shows lower values (mean close to 0.5), while by decreasing the area extent we can observe the increasing of the values where in conclusion we can assess a mean value close to 0.9 for BAS20 (**Figure 9d**). The main changes in the stability effects may be highlighted for a very small range of specific values between BAS and BAS20, and this is not particularly evident at first sight. This is peculiar but not unreasonable considering that we are observing already a very similar area extent, in which the cut at 20° removed just a few slope units. However, thanks to this action, the thermal controlling role gained informativity across the area and the result is the progressive increase in the linear variable behaviour (**Figure 8**).

Spatially, the pattern presented in **Figure 9** can be better appreciated in the insets relative to the same region (Basilicata). The susceptibility in the Italy model is evenly distributed in all areas and increases toward the south, interestingly with a gradual appearance of the thermal and susceptible signal (**Figure 4**). Another interesting point is the understanding of the signal increase across **Figure 9c-d** which presents similar patterns. The difference between BAS and BAS20 presented low variability, with some differences in the central part of the study area. Overall, the constrained models showed an increase in the susceptibility values, showing a general trend of the SUs that we can consider active. These considerations highlight a possible relation between the thermal behaviour and the landslide-prone areas in clay materials and gentle slopes.

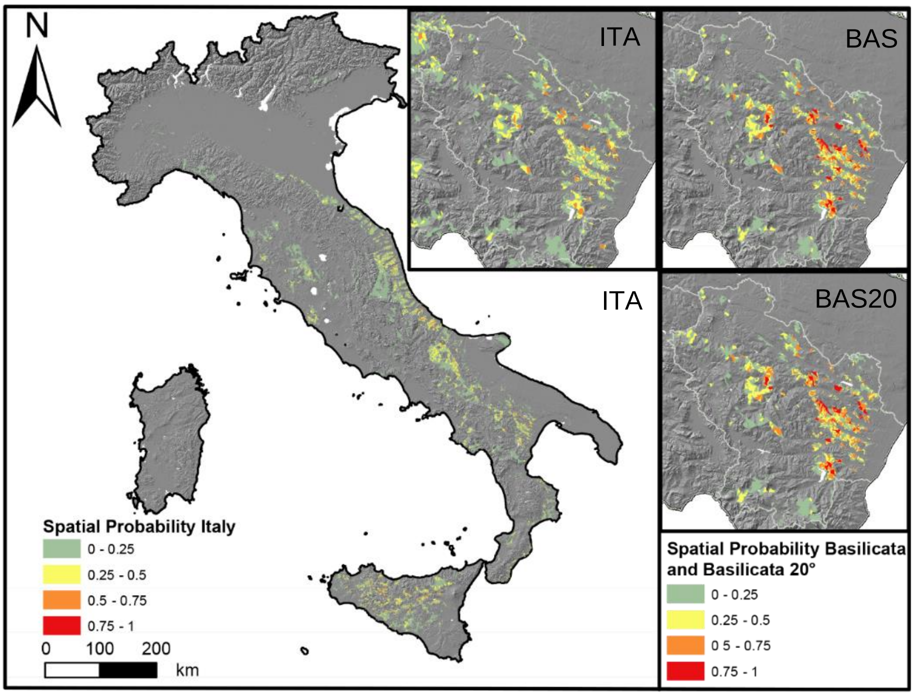

Figure 9. Susceptibility maps for different models (ITA, BAS, BAS20). We can observe some dissimilarity between the susceptibility maps of Italy and those constructed on a smaller area extent. This confirms the non-linear analysis done numerically.

4. Conclusion

By performing a SU-based LSM over clay deposits in Italy and focusing on a single class of landslides, we choose to aim for an explanatory model to describe the effect of a small set of covariates. We demonstrated that temperature, a typically neglected variable in slope stability modelling, does play an important role (as LST) in controlling landslide spatial patterns. What is more, we showed that this role changes in the different segmented models (**Figure 6**), from being remarkably nonlinear (s(3.7)) in the Italian model to exhibiting a strong, positive, and linear correlation once the model is constrained in a single region (s(1.5)). The final, positive, and linear correlation in the constrained models (BAS, BAS20) is consistent with experimental observations on the thermal effect on the residual shear strength of clay soils (especially those poor in smectites) (Loche and Scaringi, 2023; Shibasaki et al., 2017). It also seems consistent with a process of temperature-enhanced consolidation, typical of poorly consolidated materials (Campanella and Mitchell, 1968), as shallow landslide deposits can be. Exposure of slopes to higher temperatures (resulting from direct solar irradiation) could promote crack formation, especially upon cyclic thermal forcing (Rosone et al., 2018; Yalcin, 2007). However, the main progressive destabilisation should result from an increase in water content or pore water pressure, that should dominate over other processes in the future of gentle clay slopes (consolidation, revegetation). Therefore, the fine soil fraction, which may be affected by temperature changes, implies the accounting of temperature as a preparatory factor which should be related to the slope angle as a direct derivation of friction angle. Thus, the fine fraction (selected in the study) that sufficiently controls the shear strength (Stark and Eid, 1994), would dominate not only latter but also its thermal sensitivity owing to their large temperature-dependent volume and strength changes, partly related to their larger water content (Loche et al., 2022b; Scaringi and Loche, 2022).

Explaining the thermal effects suggested by geostatistical modelling in terms of physical processes is challenging and requires further analyses in other contexts to look for consistent behaviours. Nevertheless, we believe that our approach, exploiting SU-based partitioning, GAM, and GEE, is simple but powerful and has a good potential for systematically investigating the contribution of LST (or other temperature-related variables) to slope instability. LST data, in particular, are freely and widely available thanks to spaceborne monitoring in the infrared band and can be downscaled by identifying relationships with higher-resolution aerial and ground-based observations. With these strongholds, we performed a purely spatial model of the portion of Italian territory featuring clay deposits. The use of a geo-lithological map of Italy and the Italian National Inventory (IFFI), which differentiates among landslide types, and the focus on shallow landslides, often associated with creep movements, were necessary to constrain our study.

Notably, our results showed a reasonable model performance despite the small set of covariates, thereby suggesting that LST could be used to capture possible thermo-hydro-mechanical controls on landslides at a large scale. As we invoked previously, THM coupling is well known in the literature in laboratory studies, but it has seldom been applied to slope stability analysis, particularly at the catchment scale. However, in the specific case study, improvements can come from considering the prevailing clay minerals, looking at activity and velocity of landslides, and more in general integrating spatial and temporal dimensions, essential for predicting trends under climate change scenarios. Furthermore, an integration of scales of investigation would be desirable and quantitative laboratory results may be considered to enhance physically-based slope models, which can be upscaled from slopes to catchments. Finally, capabilities of statistical and machine learning algorithms in identifying large-scale patterns and trends should be exploited.

CRediT statement

Marco Loche: conceptualization, methodology, software, formal analysis, data curation, writing – original draft, visualization. Gianvito Scaringi: conceptualization, resources, writing – review & editing, supervision, project administration, funding acquisition.

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