

Risk equation, landslide hazard and susceptibility

- Pierluigi Confuorto (Earth Science Department, University of Florence)

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Who I am

Pierluigi Confuorto

Department of Earth Sciences - UNIFI

Researcher in Physical Geography and Geomorphology

pierluigi.confuorto@unifi.it



 Currently a fixed-term researcher at the Earth Science Department of the University of Florence in Physical Geography and Geomorphology.

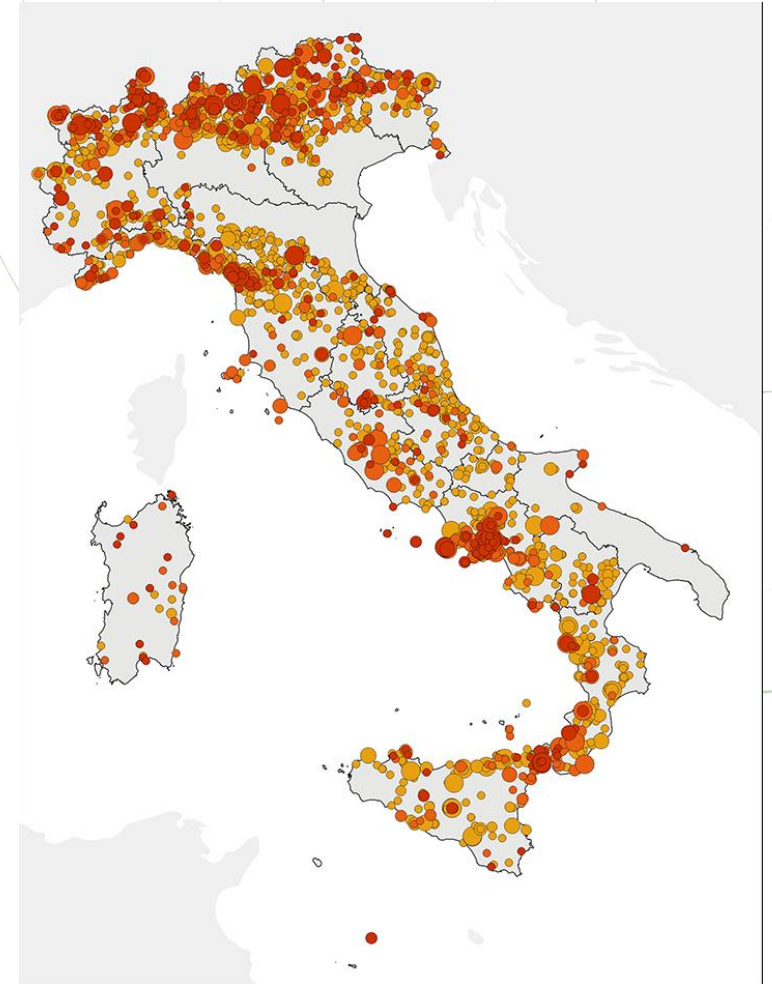
- Graduated in 2012 and PhD in Analysis of Environmental Systems in 2016 at the Federico II University of Naples (Italy).
- Visiting student at the German Aerospace Center (DLR) and at the Technical University of Munich (TUM) in 2014 and 2015
- Since 2019, post-doc researcher at the Earth Science Department of the University of Florence.
- Main researches topics: landslide and subsidence monitoring by spaceborne remote sensing methods (DInSAR, multi- and hyper-spectral imagery), landslide and soil erosion susceptibility assessment through ML methods.

What's going on in Italy

2 victims and
5 injuries due
to landslides
in Italy in the
first semester
of 2024



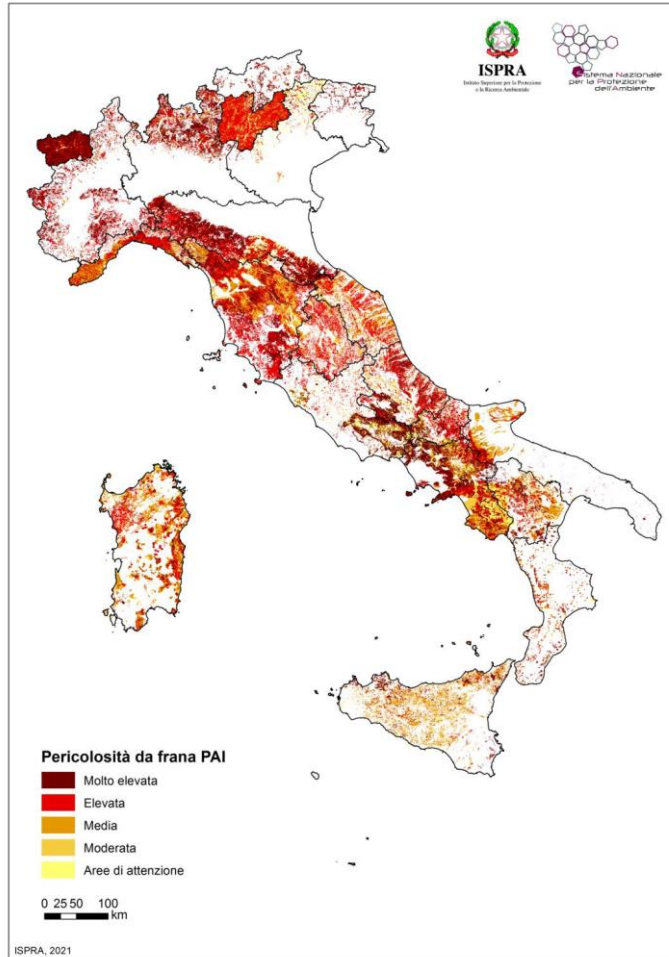
1060 victims
and 1442
injuries due to
landslides in
Italy in the last
50 years



Source: IRPI Polaris

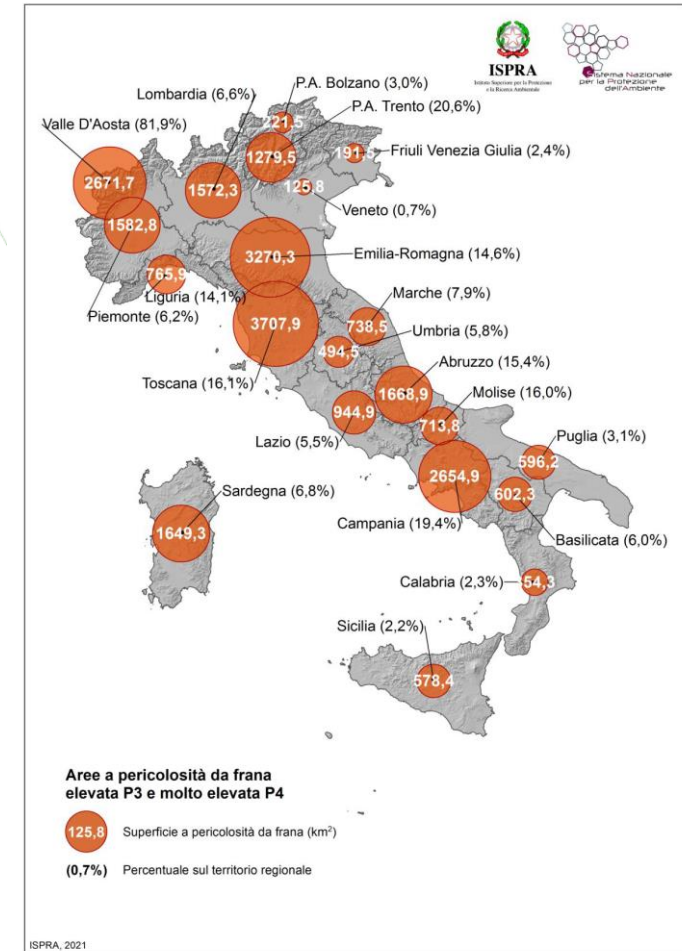
What's going on in Italy

60'481 km² (20% of the national territory) is the total extent of hazardous areas in Italy



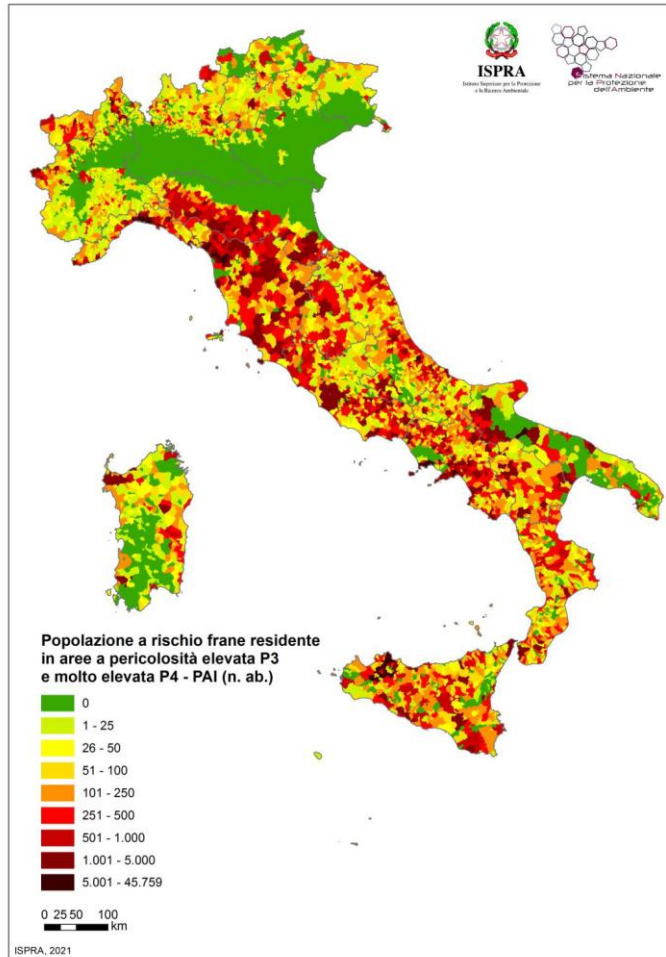
Tuscany, Emilia-Romagna, Valle d'Aosta, Campania regions have the higher extent of high and very high hazardous areas to landslides

Source: ISPRA



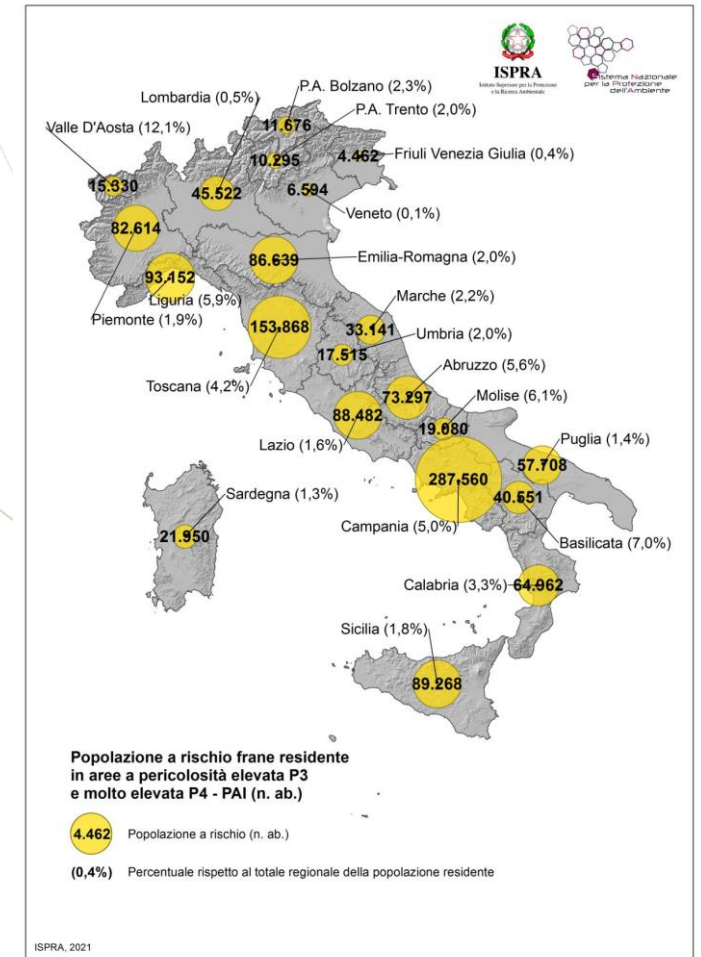
What's going on in Italy

5.7 millions of people lives in landslide risk area. Of these, 500k in very high hazardous areas

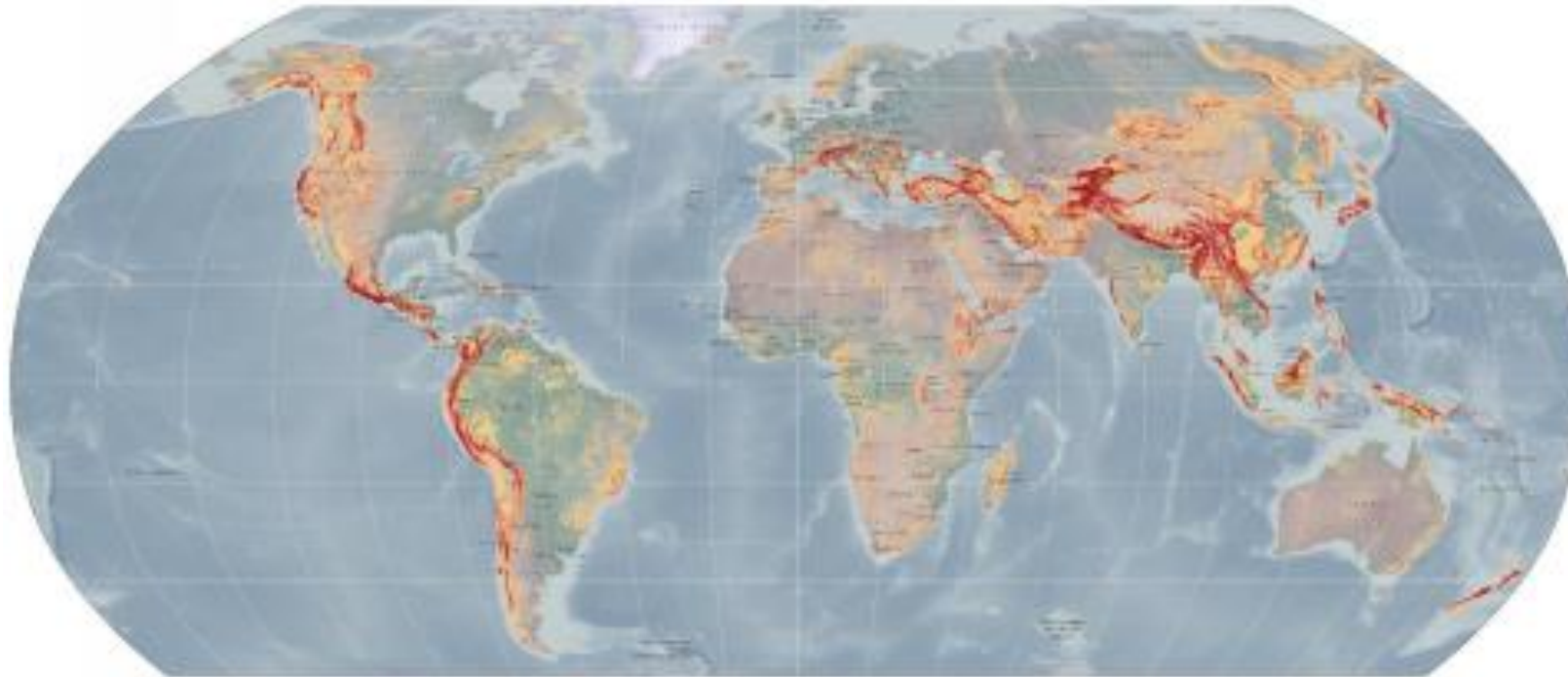


Campania, Tuscany, Liguria and Sicily regions have the highest number of people exposed to landslide risk

Source: ISPRA



Landslide hazard in the world



Exec Table 1 – Estimated average annual number of significant rainfall-triggered landslides (1980-2018)

| Country | Country code | Estimated average annual number of significant rainfall-triggered landslides (1980-2018) |
|--------------------------|--------------|--|
| United States of America | 259 | 36,150 |
| China | 147295 | 35,280 |
| India | 115 | 31,430 |
| Philippines | 196 | 23,110 |
| Indonesia | 116 | 22,220 |
| Russian Federation | 204 | 18,340 |
| Myanmar | 171 | 15,080 |
| Brazil | 37 | 13,360 |
| Canada | 46 | 11,780 |
| Vietnam | 264 | 11,490 |

Exec Table 3 – Estimated average annual number of significant earthquake-triggered landslides

| Country | Country code | Estimated average annual number of significant earthquake-triggered landslides |
|--------------------------|--------------|--|
| China | 147295 | 20,950 |
| Kyrgyz Republic | 138 | 11,070 |
| United States of America | 259 | 10,710 |
| Turkey | 249 | 9,270 |
| Mexico | 162 | 7,510 |
| Islamic Republic of Iran | 117 | 6,580 |
| Russian Federation | 204 | 6,290 |
| Tajikistan | 239 | 5,810 |
| Afghanistan | 1 | 4,990 |
| Nepal | 175 | 4,550 |

Source: World Bank

$$R = H \cdot V \cdot E$$

Risk =
expected loss

Hazard =
probability of
occurrence

Vulnerability =
loss degree

Elements at risk
=
value

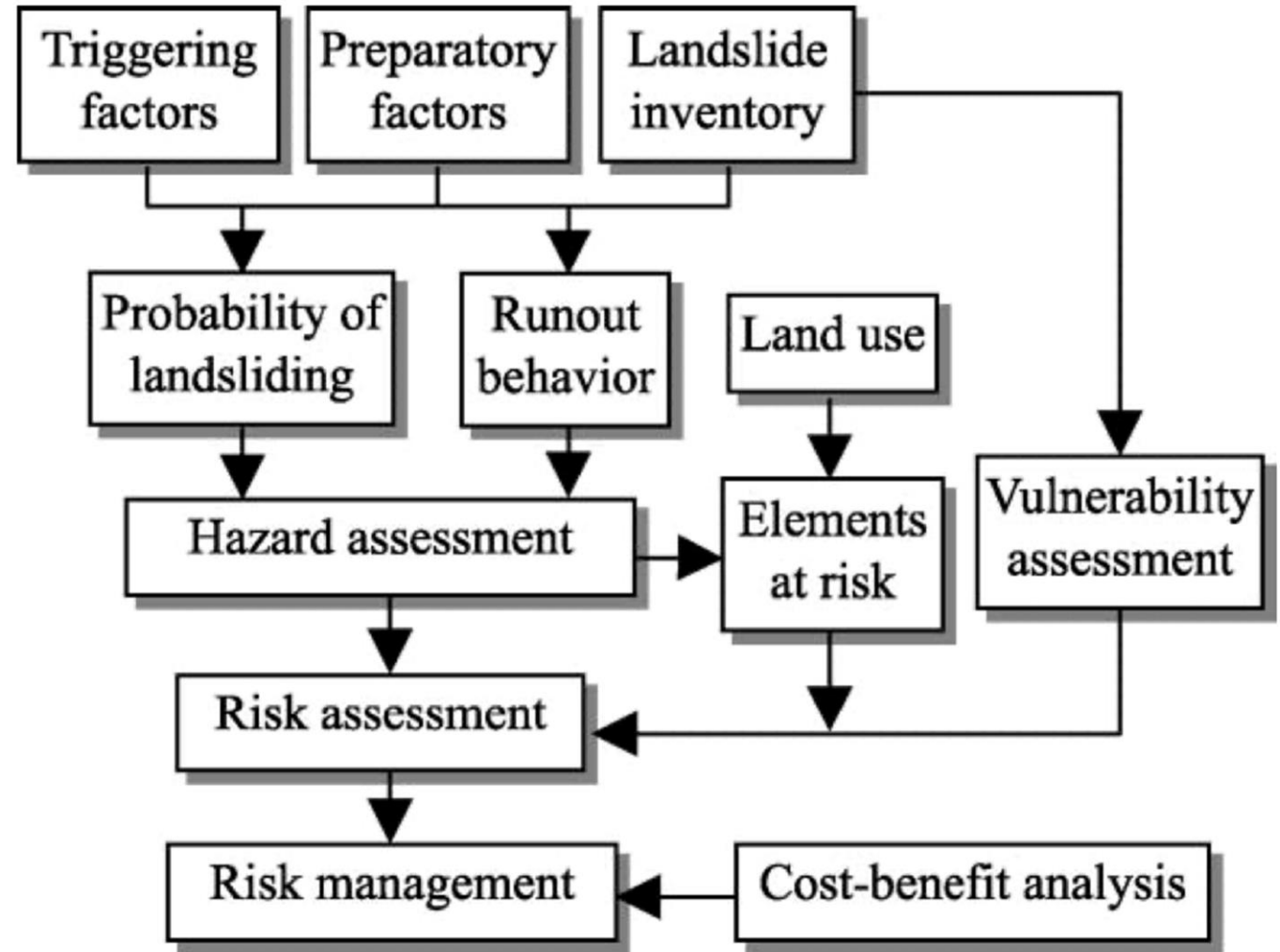
- 🌐 **Total risk (R)**: expected loss, i.e. expected number of lives lost, persons injured, damage to property, disruption of economic activity due a particular phenomenon, and is therefore the product of specific risk R_s and elements at risk E
- 🌐 **Hazard (H)**: probability of occurrence within a specified period of time and within a given area of a potentially damaging phenomenon of given intensity
- 🌐 **Vulnerability (V)**: degree of loss to a given element or set of elements at risk resulting from the occurrence of a natural phenomenon of given intensity. It is expressed on a scale from 0 (no damage) to 1 (total loss)
- 🌐 **Element at risk (E)**: population, properties, economic activities, including public services etc. at risk in a given area
- 🌐 **Specific risk (R_s)**: expected degree of loss due to a particular natural phenomenon. It may be expressed by the product of H times V

Varnes & IAEG (1984) modified

Risk framework



Dai et al. (2002)



 **Qualitative methods:** probability and losses expressed in qualitative terms

 **Semi-quantitative methods:** indicative probability, qualitative terms

 **Quantitative methods (QRA):** probability and losses quantified

Depends on the desired accuracy of the outcome and the nature of the problem, and should be compatible with the quality and quantity of available data

$$R = H \cdot V \cdot E$$

Risk =
expected loss

Hazard =
probability of
occurrence

Vulnerability =
loss degree

Elements at risk
=
value

Hazard H

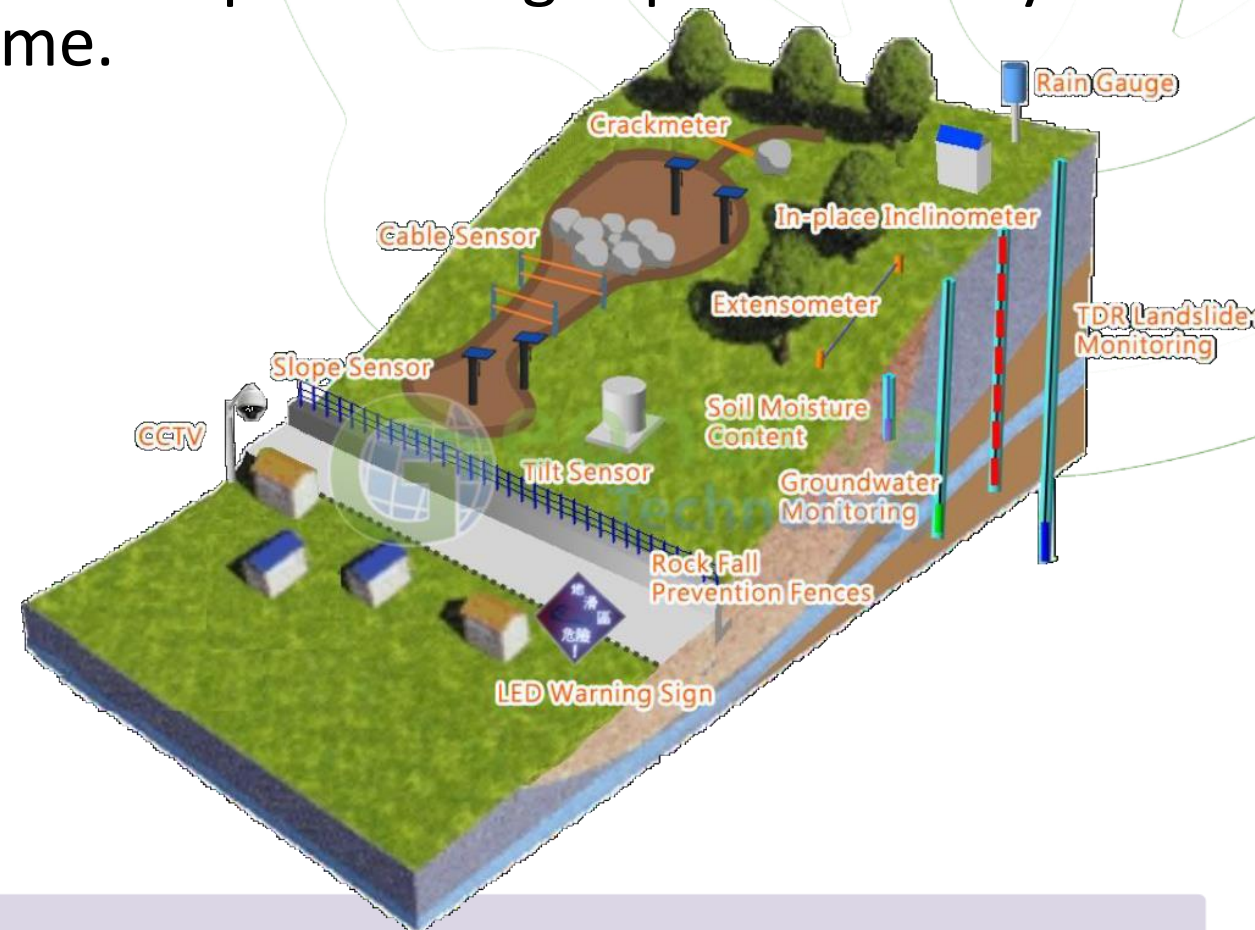
- 🌐 **Hazard** is defined as the probability of occurrence of a geomorphological process with intensity I on a given area in a given time span.
- 🌐 Hazard prediction is made difficult by the fact that most of the underlying processes are only partially known, and systems are not deterministic in behavior.
- 🌐 For the most part, the starting point is the study of the recent past to understand which processes are taking place and why. It is clear that a good database of the past process is an area that may lead to good predictions and vice versa for a poor database
- 🌐 Hazard prediction may be of various types: **typological**, **spatial**, **temporal**, **intensity**, and of the **runout**.

Slope scale vs Basin scale

For landslide analyses at the slope scale, a geomorphic process is easy to control due to the many available monitoring tools and modeling methods. It is not difficult to inspect carefully the entire slope with high spatial density and high frequency of observations in time.

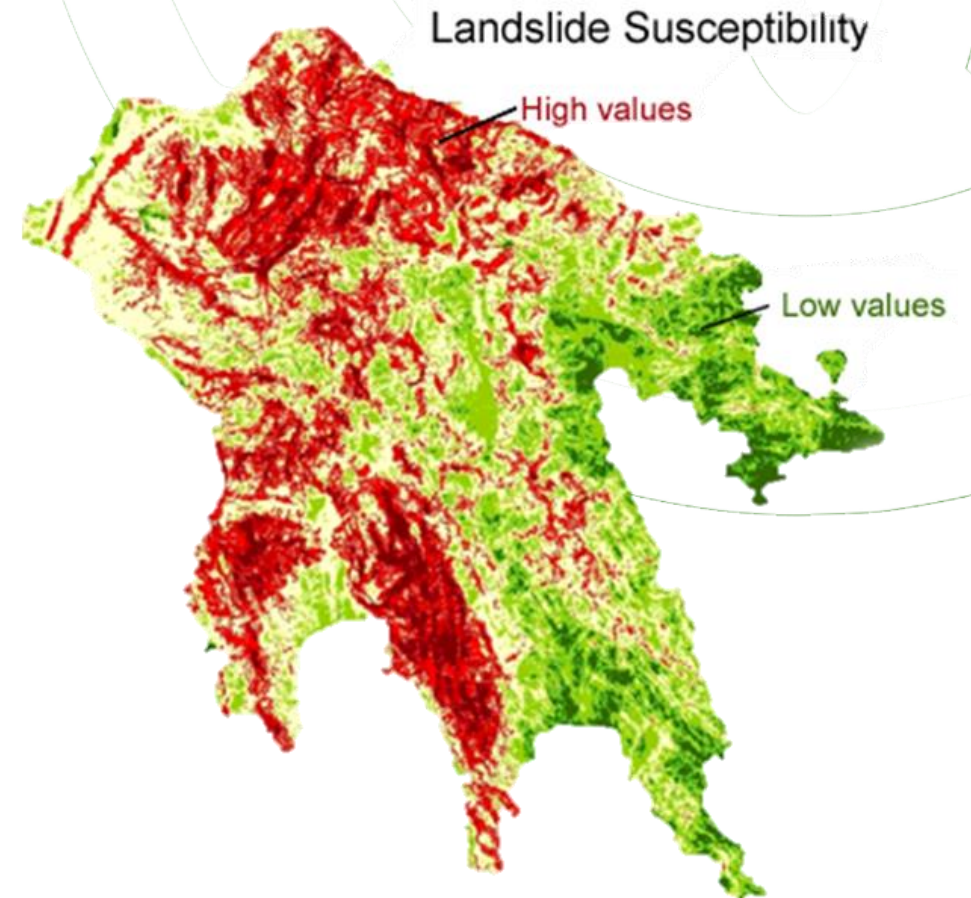
Most of the terrain parameters are all directly measurable by recurring to specific tools with costs compatible with results in case we have elements at risk exposed and impending failure.

What if we have 100 situations like this?



Hazard at Basin scale

- 🌐 To work at a much larger scale we need to start from basic knowledge of the region, by collecting data on the state of the nature.
- 🌐 Some of the required basic documents for this are the geological maps, the landcover maps, the river network, the topographical maps or DEM, the rainfall distribution (in both space and time), the geomorphological map.
- 🌐 In the geomorphological map, in particular, we must have a good quality inventory of the known occurrences of the target process we want to be able to forecast (e.g., a landslide inventory map). This map will represent our known observable.



Susceptibility vs Hazard

🌐 The term hazard refers to the probability that one or more landslides of a certain intensity will trigger in a given time interval and at a specific location.

🌐 What size?

🌐 When?

🌐 Where?



Susceptibility

Susceptibility definition

🌐 Landslide susceptibility is the likelihood of a landslide occurring in an area on the basis of local terrain conditions (Brabb, 1984)

🌐 As reported in Reichenbach et al. (2018)...

“Susceptibility does not consider the size e.g., the length, width, depth, area, or volume of the landslides, but susceptibility assessments can be prepared for different-sized landslides (Carrara et al., 1995). We note that the definition of landslide susceptibility adopted in this work differs from the definition given by Fell et al. (2008a).”

🌐 In mathematical language, landslide susceptibility can be defined as the probability of spatial occurrence of slope failures, given a set of geo-environmental conditions (Guzzetti et al., 2005). Susceptibility measures the degree to which terrain can be affected by future slope movements. In other words, it is an estimate of “where” landslides are likely to occur (Guzzetti, 2006).

🌐 Susceptibility evaluation represents the first step towards a hazard and risk assessment, but can also coincide with an end product for spatial planning or environmental impact studies.



Susceptibility estimation

- 🌐 The basic principle of hazard analysis is that the causes that produced a process in the past are likely the same that will produce the process in the future. This is only valid if processes are in equilibrium with the landscape and for short time frames in geological terms.
- 🌐 For example, it is not correct to predict a glacial erosion process in a mountain valley in the Apennines since the glacial landforms we see today are only relics of a past climate.
- 🌐 It is correct, instead, to predict that the Arno river could flood Florence since the same as happened only a few decades ago, which is quite no time, in geological terms.



Susceptibility estimation

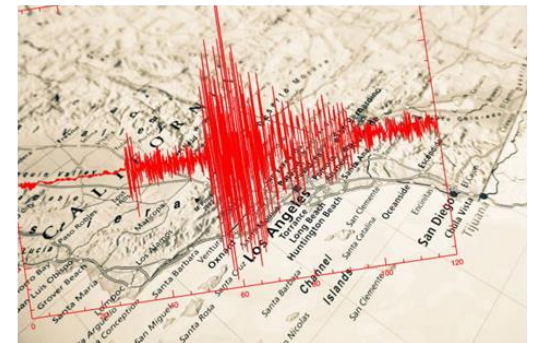
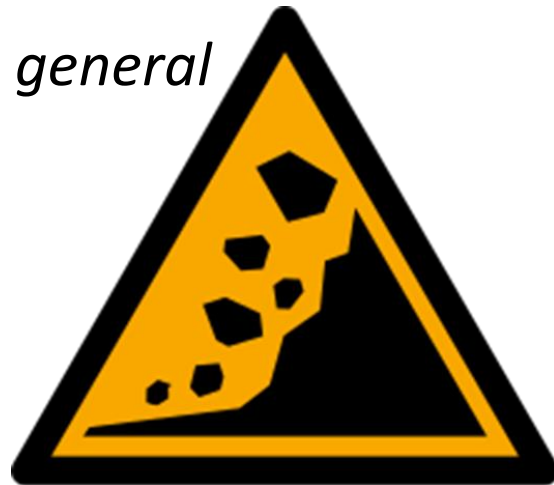
The first step is therefore to understand which are the possible causes of recent landslides or active processes. Then, we collect maps and data relative to such causes, at the best possible resolution and accuracy.

Causes may be of two types:

- **Predisposing**: causes that made the slope susceptible to mass wasting and that are necessary (but not sufficient) to develop slope instability.

- **Triggering**: causes that actually are responsible of the actual failure or, in any case, able to bring the impending process to start or to change its kinematics. Typical triggering causes for slope processes are:

1. *Rainfall, water-related in general*
2. *Earthquakes*
3. *Human activity*



Susceptibility scale

| Scale description | Indicative range of scales | Examples of zoning application | Typical area of zoning |
|-------------------|----------------------------|---|---|
| Small | < 1:100,000 | Landslide inventory and susceptibility to inform policy makers and the general public. | >10,000 square kilometres |
| Medium | 1:100,000 to 1:25,000 | Landslide inventory and susceptibility zoning for regional development or very large scale engineering projects. Preliminary level hazard mapping for local areas | 1000 – 10,000 square kilometres |
| Large | 1:25,000 to 1:5,000 | Landslide inventory, susceptibility and hazard zoning for local areas. Intermediate to advanced level hazard zoning for regional development. Preliminary to intermediate level risk zoning for local areas and the advanced stages of planning for large engineering structures, roads and railways. | 10-1000 square kilometres |
| Detailed | > 5,000 | Intermediate and advanced level hazard and risk zoning for local and site specific areas and for the design phase of large engineering structures, roads and railways. | Several hectares to tens of square kilometres |

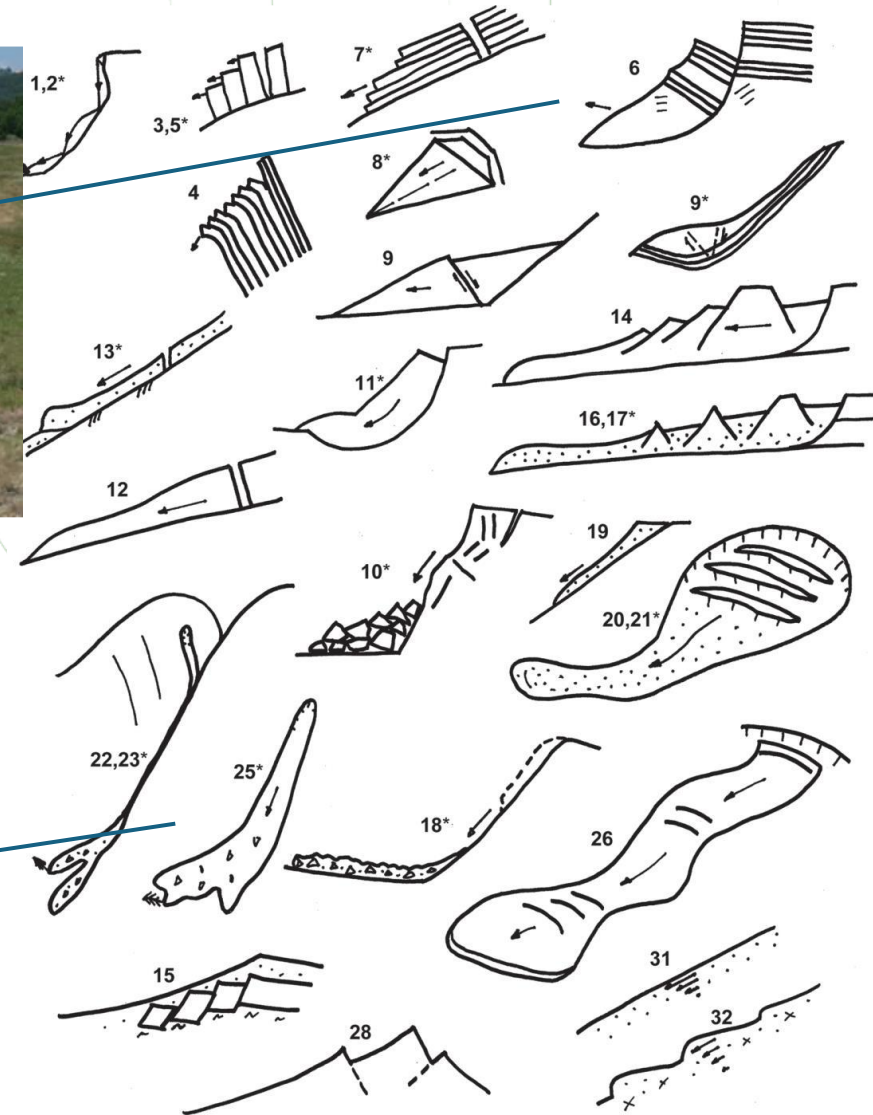
Fell et al., 2008

Susceptibility – type of landslide

There is **no unique procedure** capable of estimating the potential of failure of each type of landslide and its expected travel distance.

In fact, the conditioning factors (i.e., slope angle, lithology, groundwater conditions, ...) are specific for each landslide mechanism. Because of this, it will often be necessary to assess separately susceptibility, hazard, and risk, for the **different types of landslides** affecting the area (i.e. for rockfalls, small shallow landslides, and deep-seated large landslides) and to present the results in **specific zoning maps** as the recommendations of the statutory obligations to mitigate the risk might differ for the different landslide types.

These maps may be **combined into one map**. In this case, it must be taken into account that, for instance, the same hazard level may be obtained from different combinations of landslide types, volumes, intensities and frequencies. It may also be necessary to produce separate maps for landslides from natural slopes and constructed slopes.



Susceptibility – Starting point

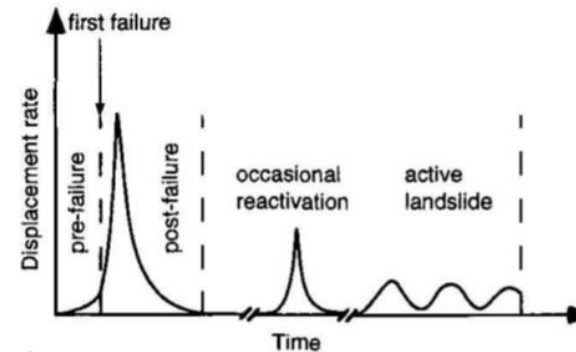
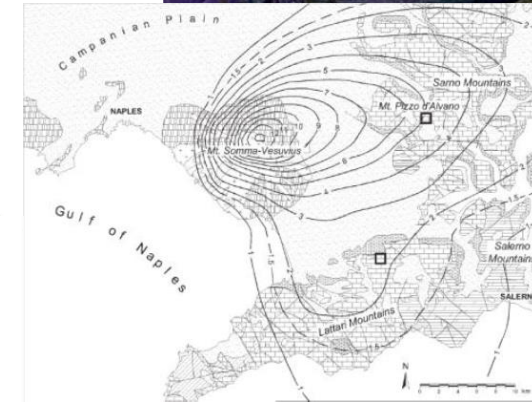
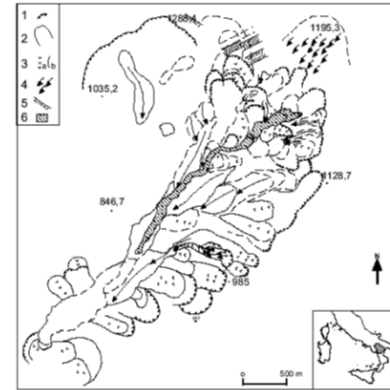
🌐 Individuation of the area where first-failure phenomenon or landslide reactivation can occur

🌐 Geomorphological sketch-map

🌐 Knowledge of the territory

🌐 State of activity of landslides

🌐 Classification, areal extent and volume



Susceptibility – Starting point – Landslide inventory

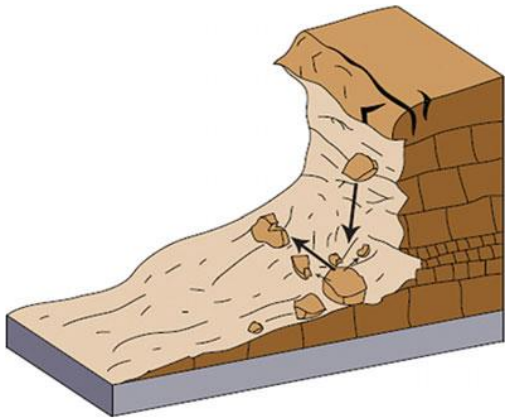
🌐 Know your inventory!

Who did it and how?

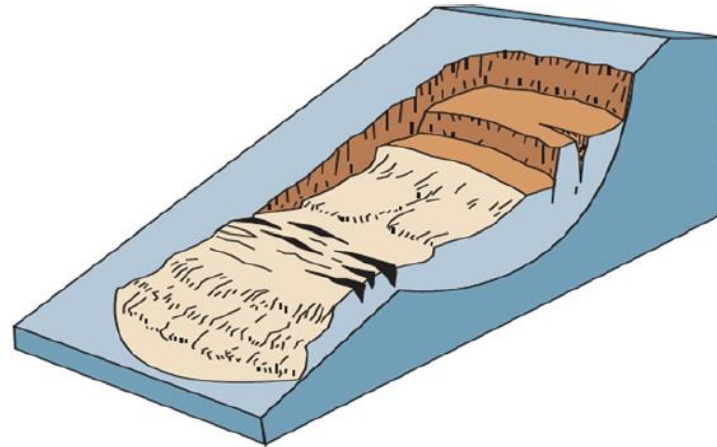
What landslide types?

Different landslide types have different predisposing factors

In a good LSM, it is mandatory that only a specific landslide type is considered



Falls

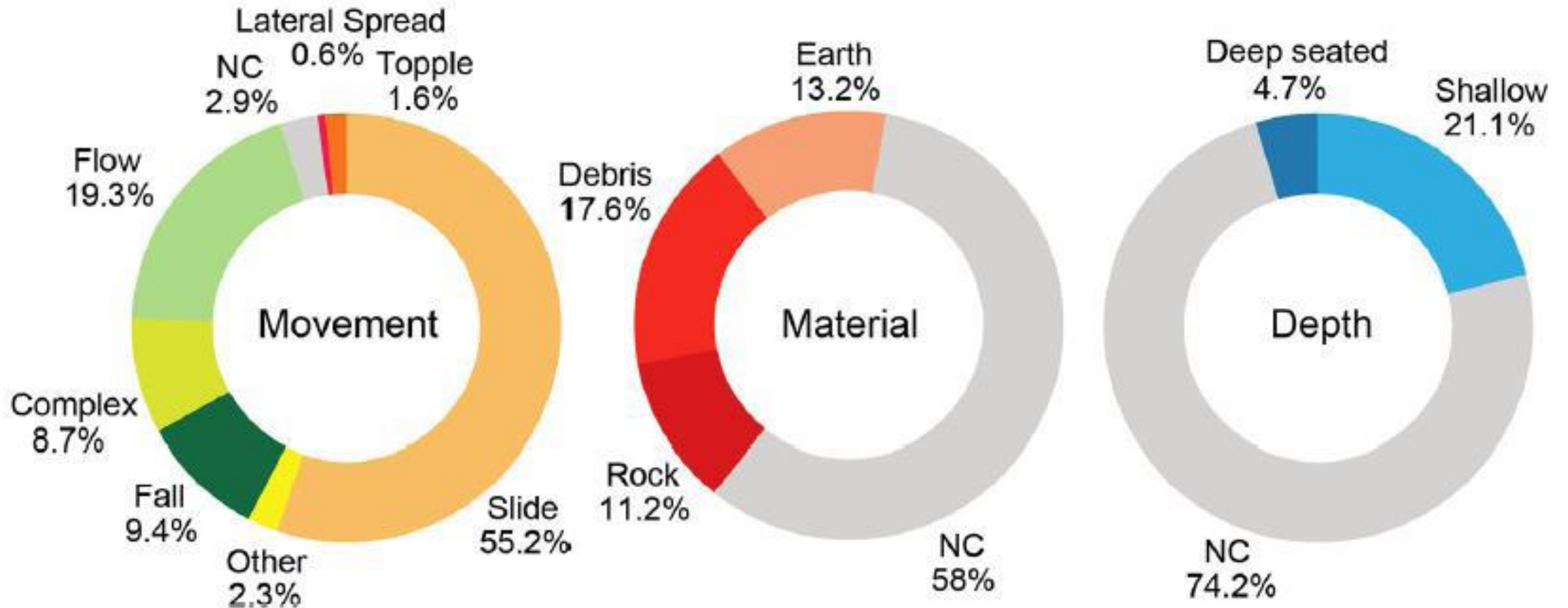


Slides



Flows

Susceptibility – Starting point – type of landslide



Reichenbach et al., 2018

Susceptibility – Starting point – Landslide inventory

🌐 Know your inventory!

Who did it and how?

What landslide types?

How mapped?

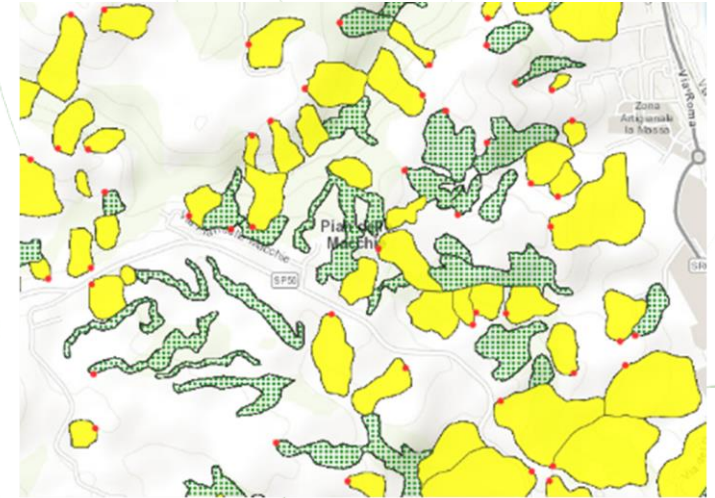
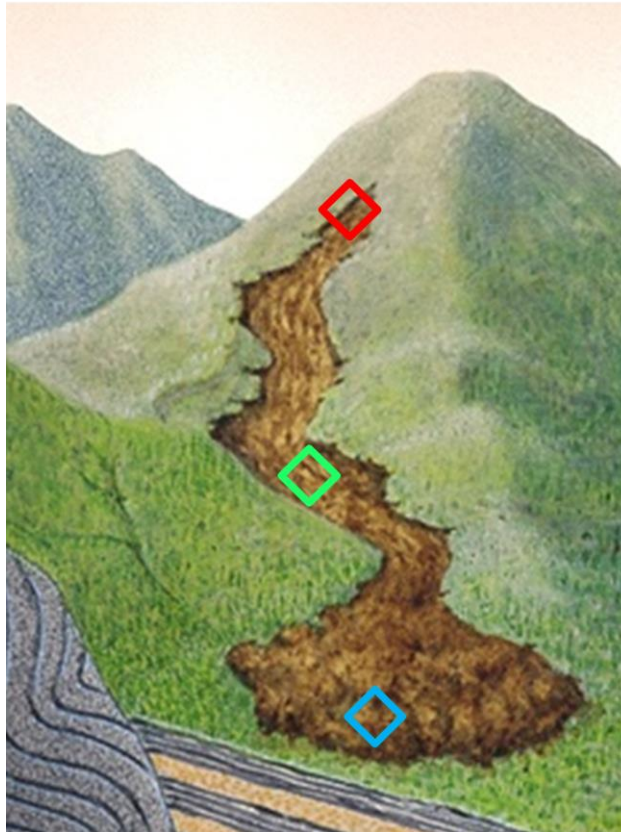
🌐 Polygon

🌐 Point

source area

centroid

Impact point



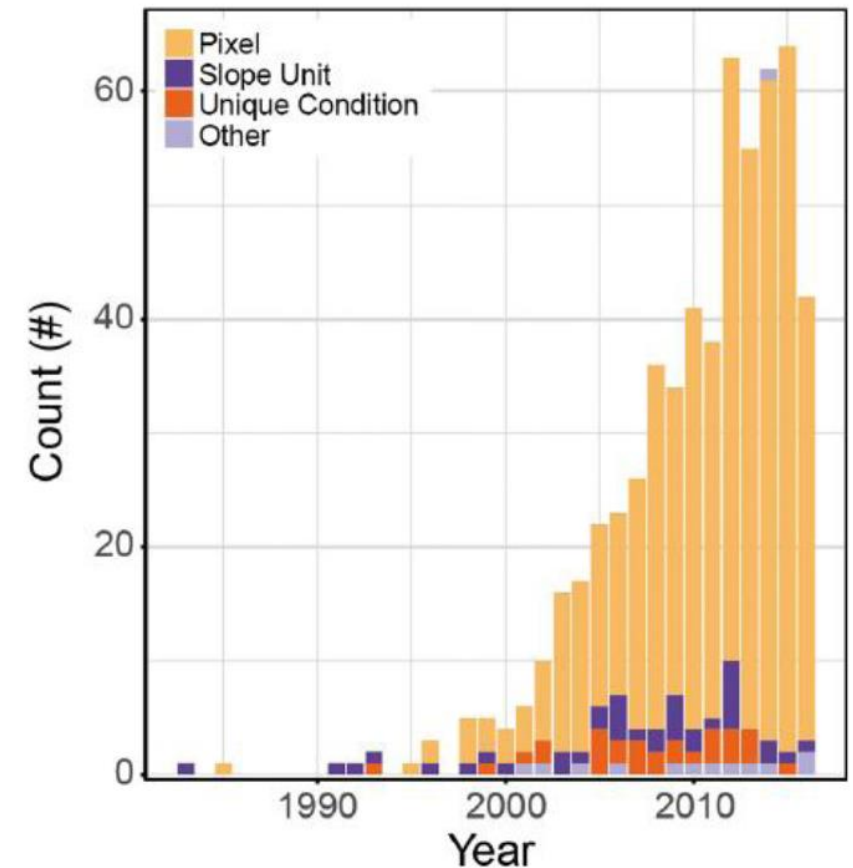
<https://idrogeo.isprambiente.it/app/>

Susceptibility – Starting point - Terrain units

A terrain unit (or “mapping unit”) is a portion of the land surface characterized by a set of ground conditions that differ from the adjacent units across distinct boundaries (Hansen, 1984). At the scale of the analysis, a mapping unit is a geographical domain that maximizes the unit internal homogeneity and the between-unit heterogeneity (Guzzetti, 2006).

All the mapping units proposed in the literature for landslide susceptibility assessment fall into one of the following seven groups (Reichenbach et al., 2018)

- (i) Grid cells (“pixels”)
- (ii) Terrain units
- (iii) Unique condition units
- (iv) Slope units
- (v) Geo-hydrological units
- (vi) Topographic units
- (vii) Political or administrative units.



Susceptibility – Starting point - Terrain units

The main ones are:

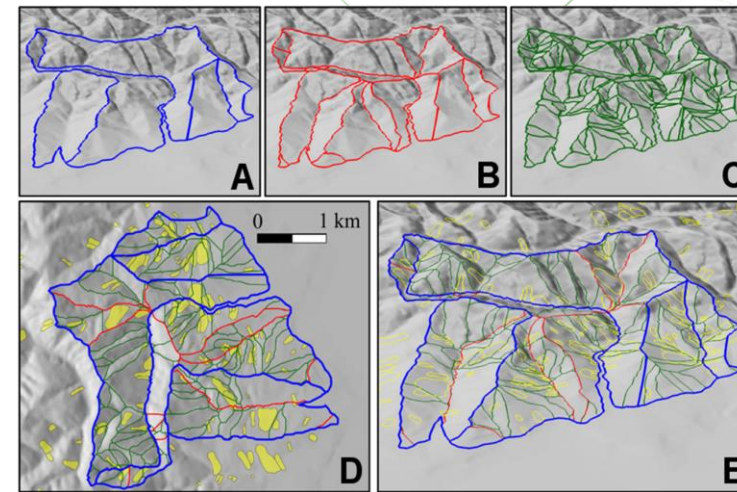
- regular cells: provide very accurate information on predisposing factors (high spatial resolution), but do not take into account the geomorphological context
- slope units: have a coarser resolution, but outline the geomorphological context. They can represent single slopes or groups of slopes.

CELLE REGOLARI

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 2 | 4 | 6 | 7 |
| 1 | 3 | 3 | 2 | 5 | 6 | 6 | 7 | 8 |
| 1 | 1 | 3 | 2 | 2 | 2 | 4 | 5 | 6 |
| 1 | 2 | 2 | 2 | 2 | 4 | 4 | 5 | 6 |
| 1 | | 1 | 2 | 2 | 2 | 4 | 5 | 6 |
| 1 | | 1 | 2 | 2 | 3 | 4 | 5 | 6 |
| 1 | 1 | 1 | 1 | 1 | 2 | 3 | 4 | 5 |
| 0 | 0 | 1 | 1 | 1 | 2 | 4 | 4 | 5 |
| 0 | 1 | 1 | 1 | 1 | 2 | 3 | 4 | 4 |

<https://desktop.arcgis.com/>

SLOPE UNITS



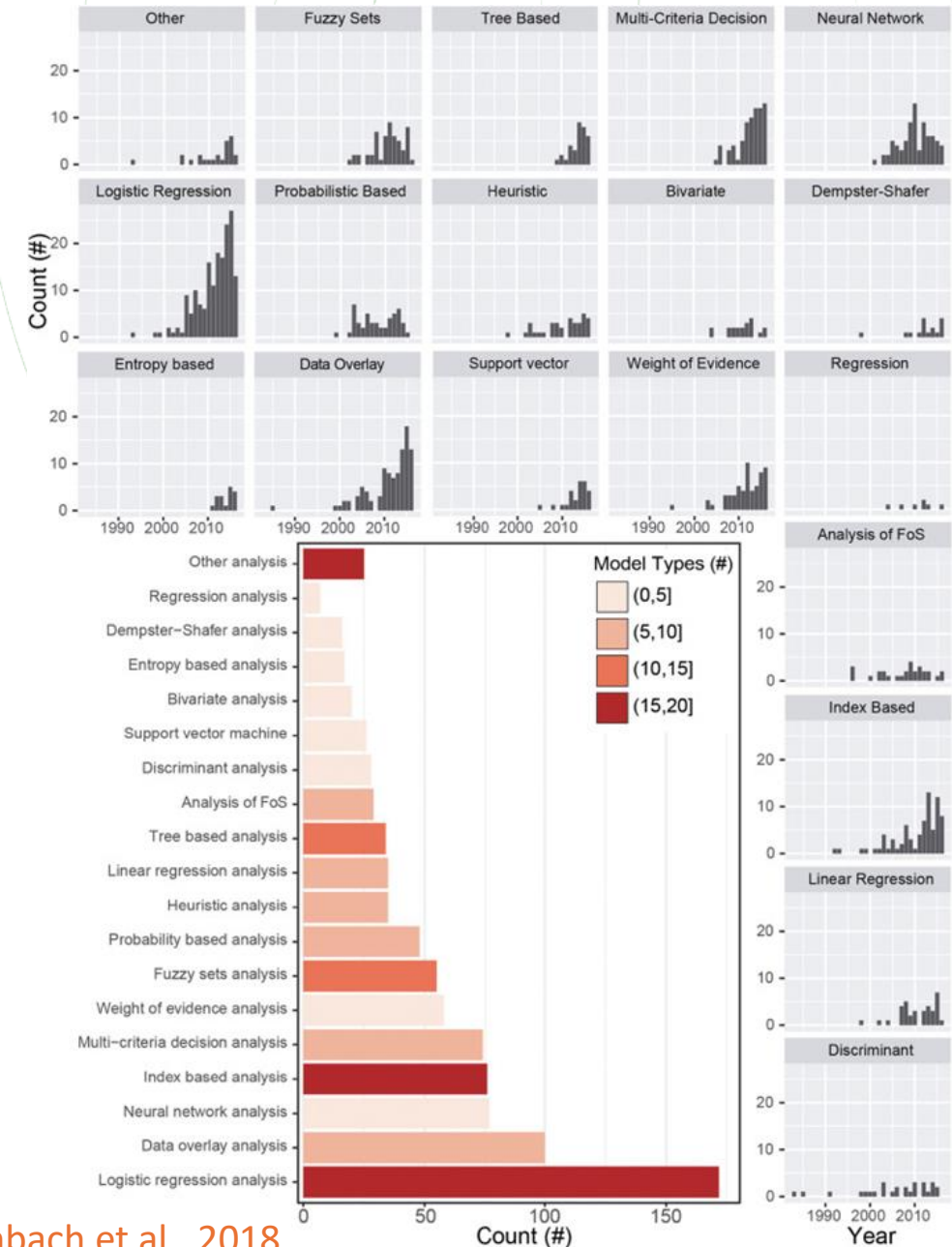
<https://www.irpi.cnr.it/focus/slope-units/>

Statistical methods

Statistically-based landslide susceptibility models are constructed to describe the functional (statistical) relationship between instability factors, described by sets of geo-environmental (independent) variables, and the known distribution of landslides, taken as the dependent model variable. The functional relationship is then used to ascertain the propensity of the terrain to generate landslides and to predict susceptibility.

In the literature, the majority of the models employs one of several possible classification methods that can be clustered into six main groups:

1. Classical statistics (e.g., logistic regression, discriminant analysis, linear regression)
2. Index-based (e.g., weight-of-evidence)
3. Machine learning (e.g., fuzzy logic systems, support vector machines, forest trees)
4. Neural networks
5. Multicriteria decision analysis
6. Other statistics



Reichenbach et al., 2018

Maps and data for statistical susceptibility

🌐 Main information to collect to build a reliable susceptibility map for slope instability processes.

🌐 Independent variables X (predisposing factors or landslide conditioning variables):

- Geological map (better if contains any lithological or geo-mechanical information)
- Land cover or land use map (a plus if with vegetation type)
- Topographic map (better if derived from DEM)
- Hydrographic network (if not available, can be derived from DEM)
- Structural map (faulting, joints)
- Rainfall maps (from ground stations, weather radars, satellites or models)

🌐 Dependent variable Y (slope process density, probability, likelihood)

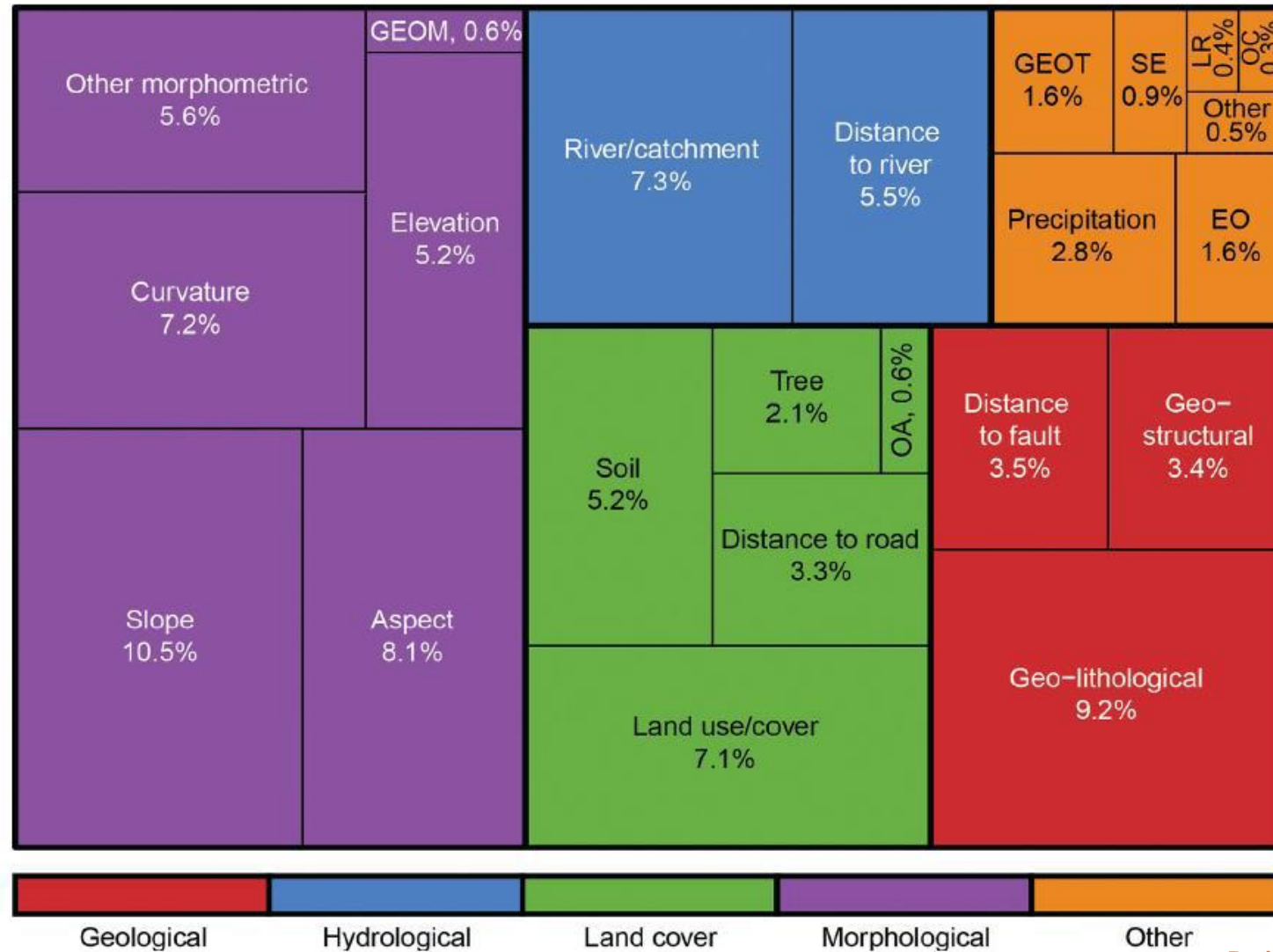
Map of slope processes (polygon of the landslides, point of the highest peak in a landslide, indications on the state of activity, etc.)

The comparison (often statistical) between effects (dependent variable) and causes (independent variables) is the key to understanding the process and forecasting it.

The basic method is to simply analyze the bivariate relationship between Y and X_i . Then we go to multi-variate analysis and then to model design, training, and testing. The final step is the validation.

Predisposing factors

Among dozens of possible parameters, how to select the optimal number? How to identify the most effective ones?



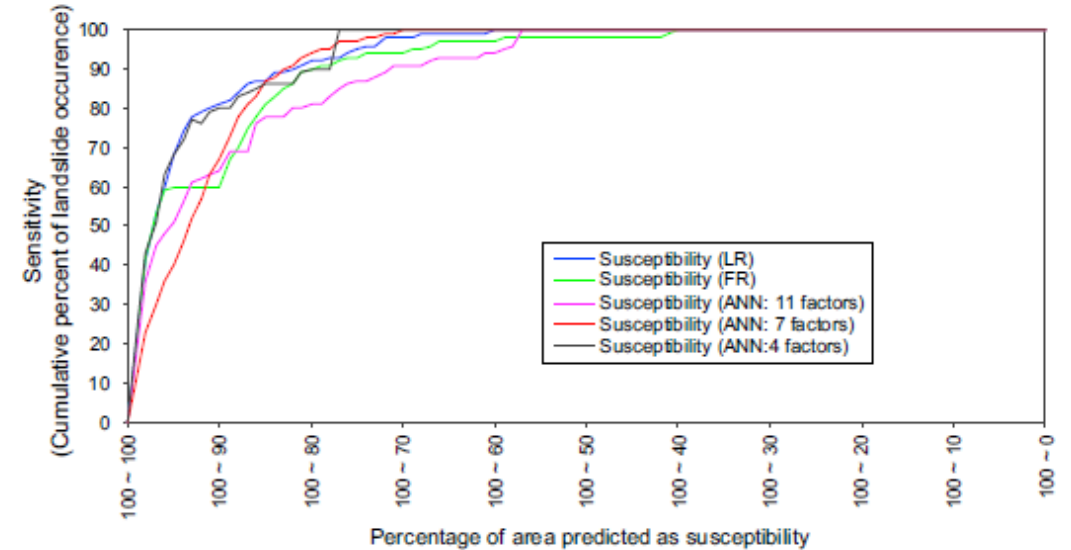
Reichenbach et al., 2018

Predisposing factors - selection

🌐 The more, the better? Not always true!

| Model configuration | AUC logistic regression | |
|---------------------|-------------------------|---------------------------------------|
| Three parameters | 0.73 | Slope gradient, lithology, land cover |
| Four parameters | 0.78 | Three parameters + CN |
| Five parameters | 0.79 | Four parameters + I_a |
| Six parameters | 0.77 | Five parameters + aspect |
| Seven parameters | 0.76 | Six parameters + flow accumulation |
| Eight parameters | 0.76 | Seven parameters + profile curvature |

Manzo et al., 2012



Pradhan and Lee, 2010

🌐 Model complexity may lead to worse predictions

🌐 Some models work better with simple configurations

🌐 Complex models may have other problems (e.g. overfitting issues)

Predisposing factors - selection

Expert evaluation

| Predisposing factors | VIF |
|----------------------|--------|
| Altitude | 2.424 |
| Aspect | 1.183 |
| Built-up areas | 1.136 |
| Curvature | 42.569 |
| Fault | 1.140 |
| Geomorphology | 1.625 |
| LULC | 1.167 |
| Lithology | 1.104 |
| Plan curvature | 17.828 |
| Profile curvature | 14.828 |
| Road | 1.149 |
| Slope | 2.334 |
| Soil Texture | 1.476 |
| Soil bulk density | 2.649 |
| Soil clay density | 2.761 |
| Stream | 1.364 |
| TRI | 2.072 |
| TWI | 2.463 |

Removed 3 factors (Curvature, plan curvature, profile curvature) since VIF value is above 10

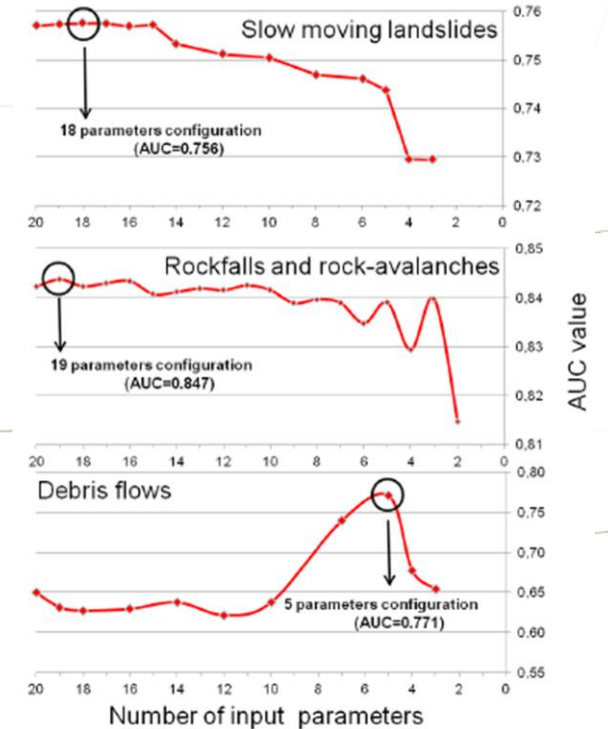
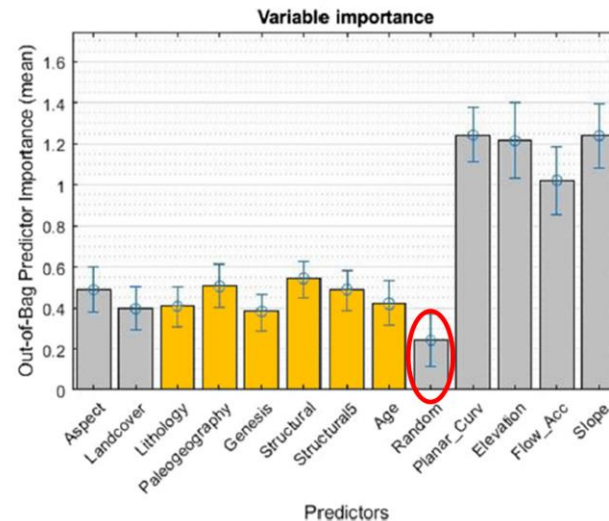
Collinearity tests

(e.g., Correlation matrix or VIF)

Forward selection

(Based on the final results or on the importance score)

Random variable



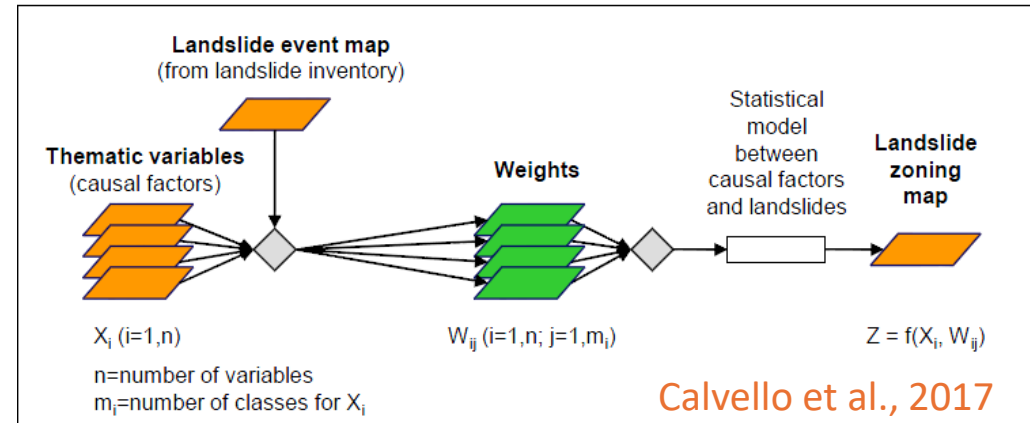
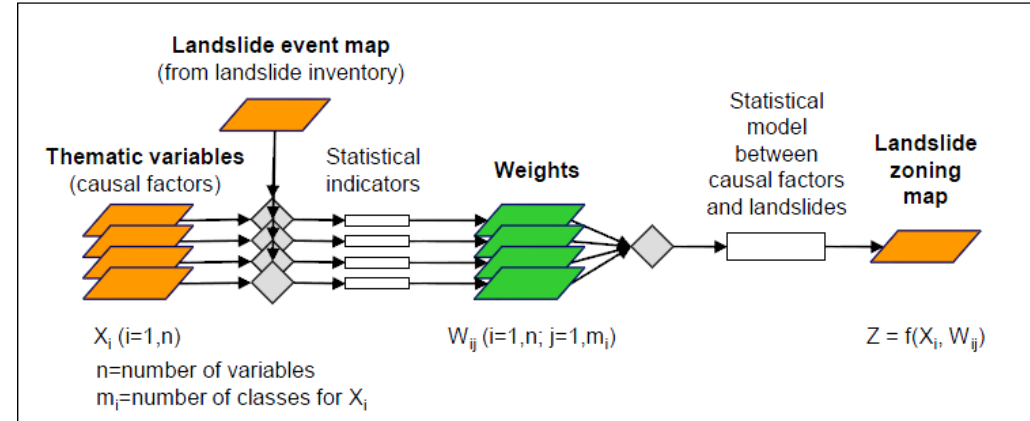
Segoni et al., 2020

Bivariate statistics

Weights of evidence
Information value
Etc.


Multivariate statistics


Logistic regression
Discriminant analysis
Cluster analysis
Artificial Neural Networks
Etc.



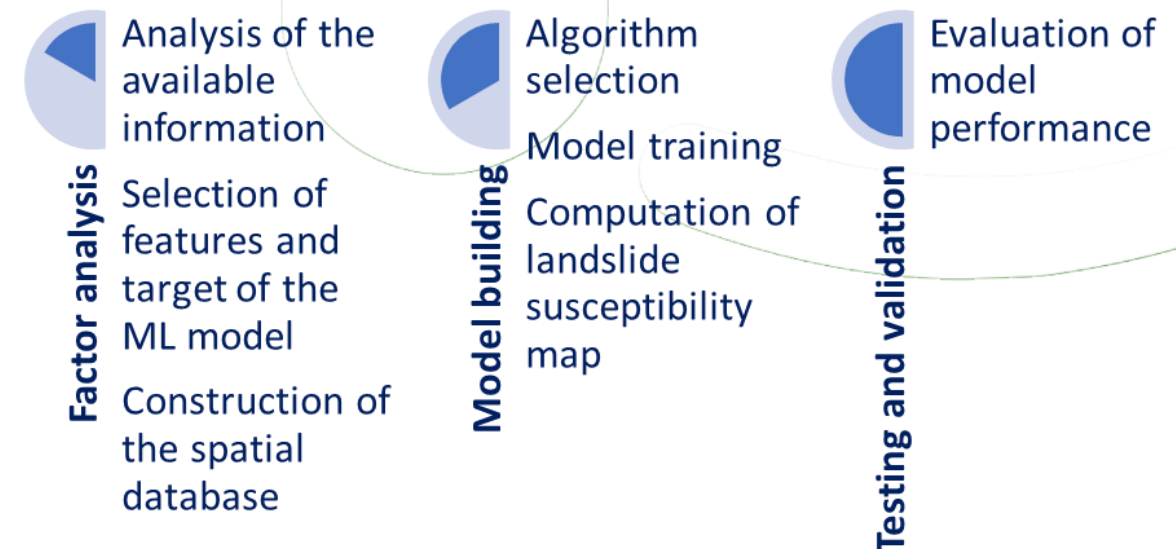
Both types of analysis rely on the information provided by a landslide event map derived from a landslide inventory, which acts in the analyses as the only dependent variable; several thematic independent variables are pre-identified as possible causal factors for landslide events. Weights are computed and assigned to the independent variables considering their statistical importance, both in absolute and relative terms, for detecting landslide events in the study area.

Machine Learning

 Differently from statistical analyses, ML algorithms are able to learn the association between landslide occurrences and landslide conditioning factors without necessarily assuming a structural model in the data.

 The learning aspect of these methods is to develop sequences of commands or algorithms that search, in a process of iterative and gradual refinement, for associations in the data that basic descriptive statistics and the human eye may not readily detect as such (Korus and Stolle, 2014).

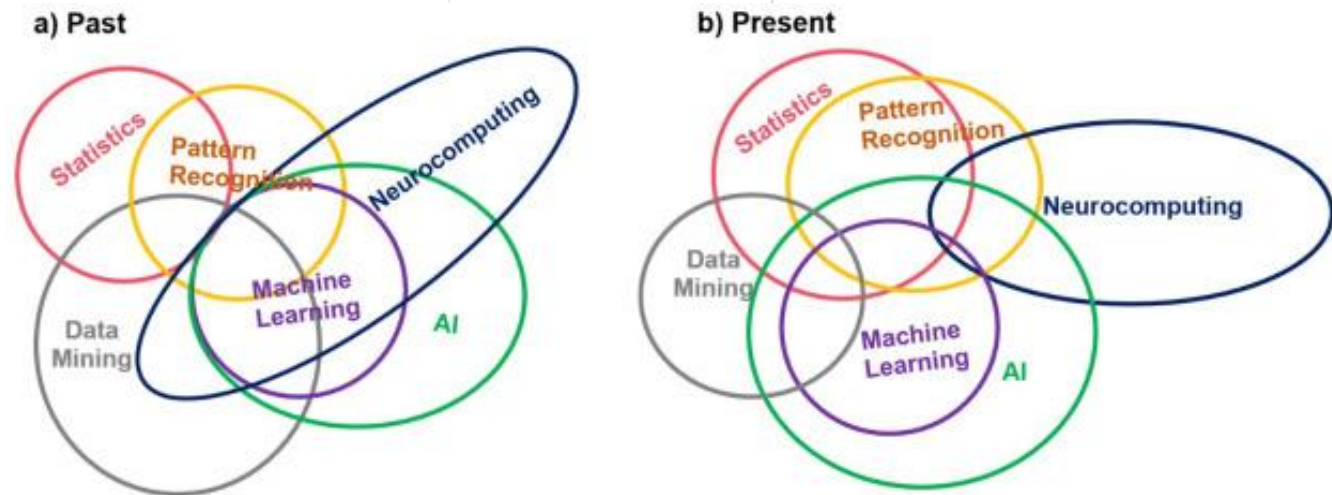
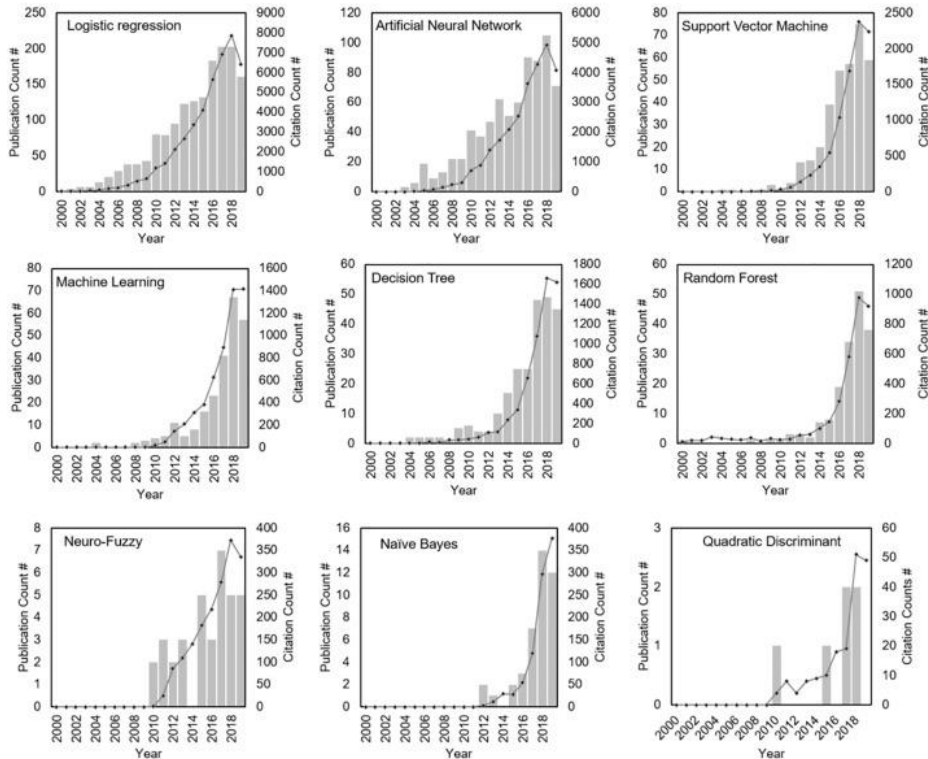
Three main common phases of analysis may be recognized in each ML procedure for landslide susceptibility modeling



Statistical methods – Methods and algorithms

Why Machine Learning

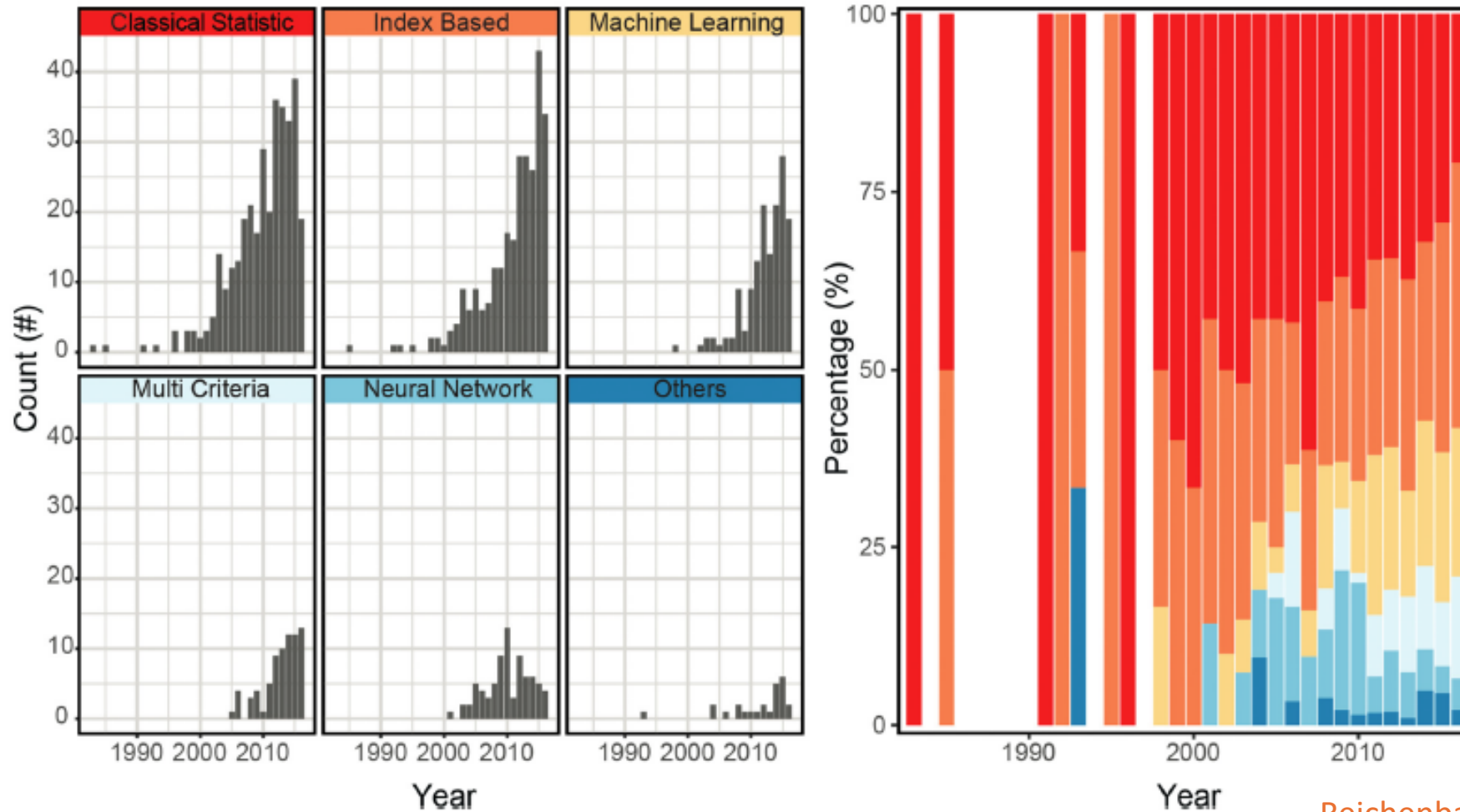
By definition, ML learns from data without banking on rules-based functions, whereas statistical modeling streamlines relationships between variables in the data by means of mathematical equations



Merghadi et al., 2020

Statistical methods – Methods and algorithms

Which one to choose?

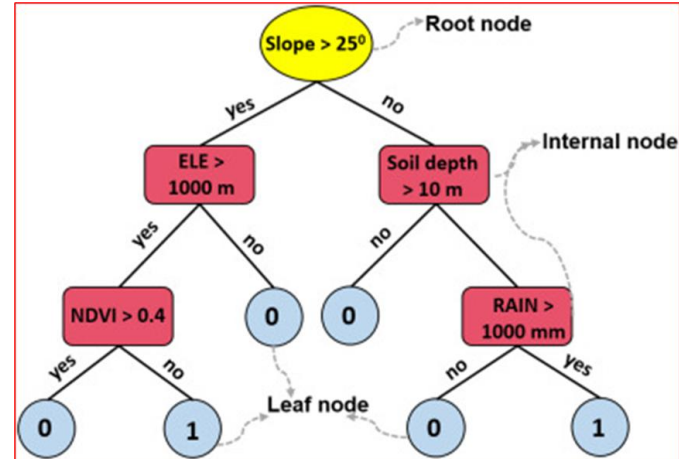


Reichenbach et al., 2018

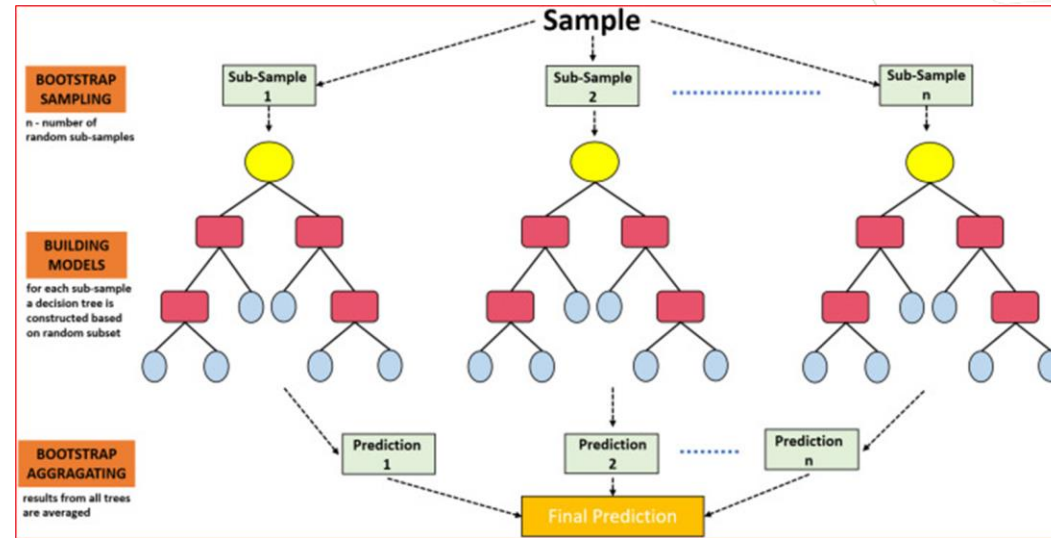
Statistical methods – Methods and algorithms

Which one to choose?

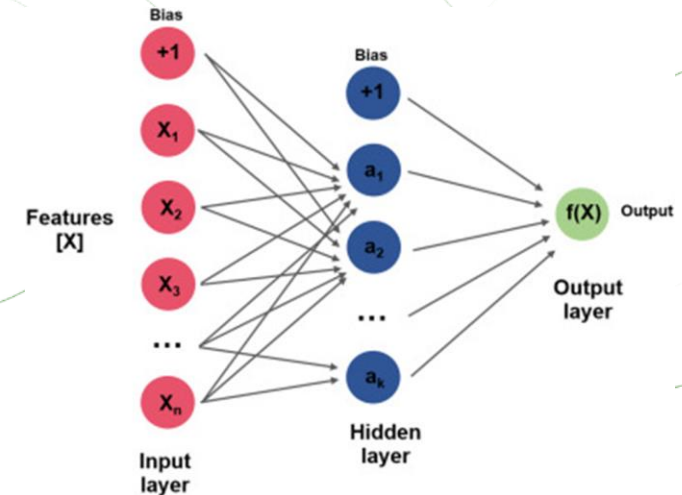
Most methods are classification/regression algorithms to be used in programming software (Matlab, R, Python...)



Decision tree



Random Forest

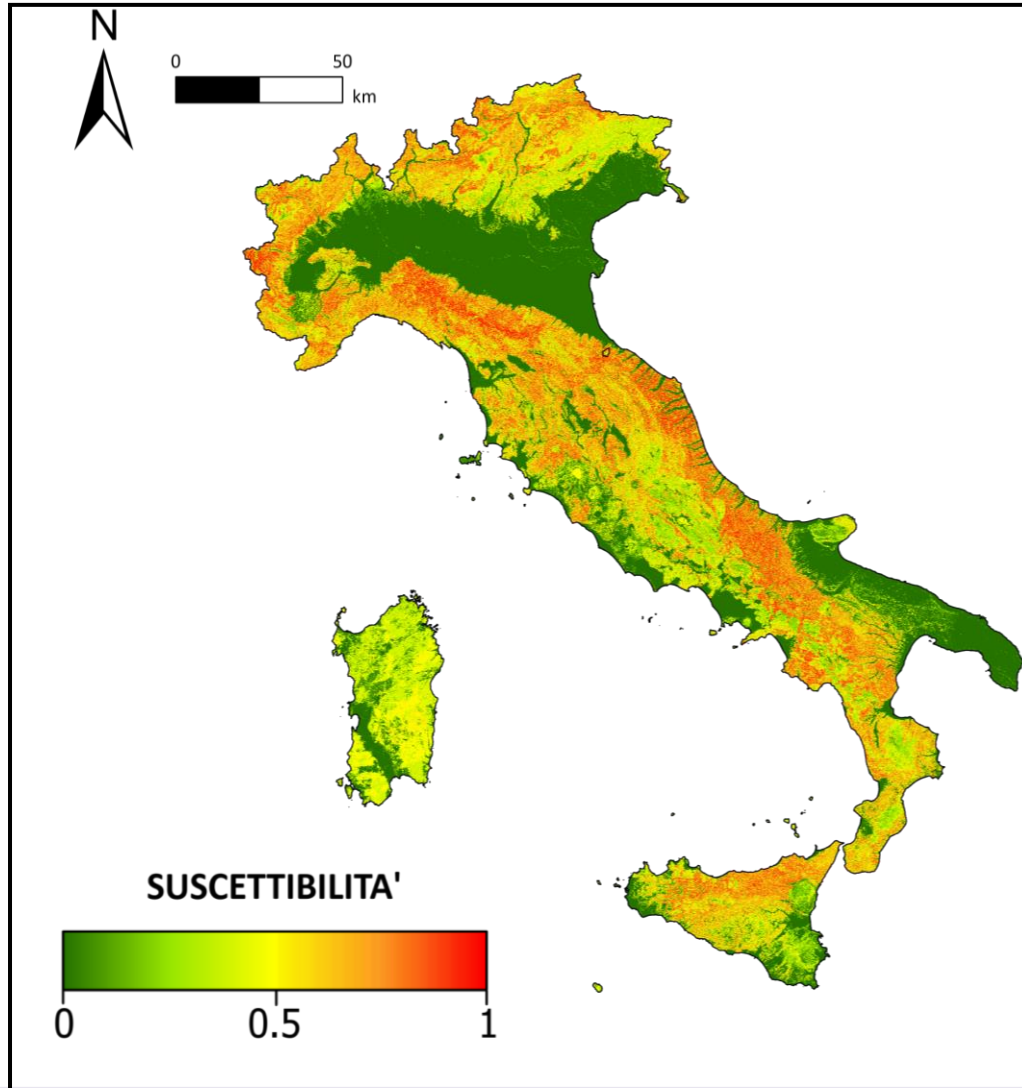


Simple multi-layer Artificial Neural Network

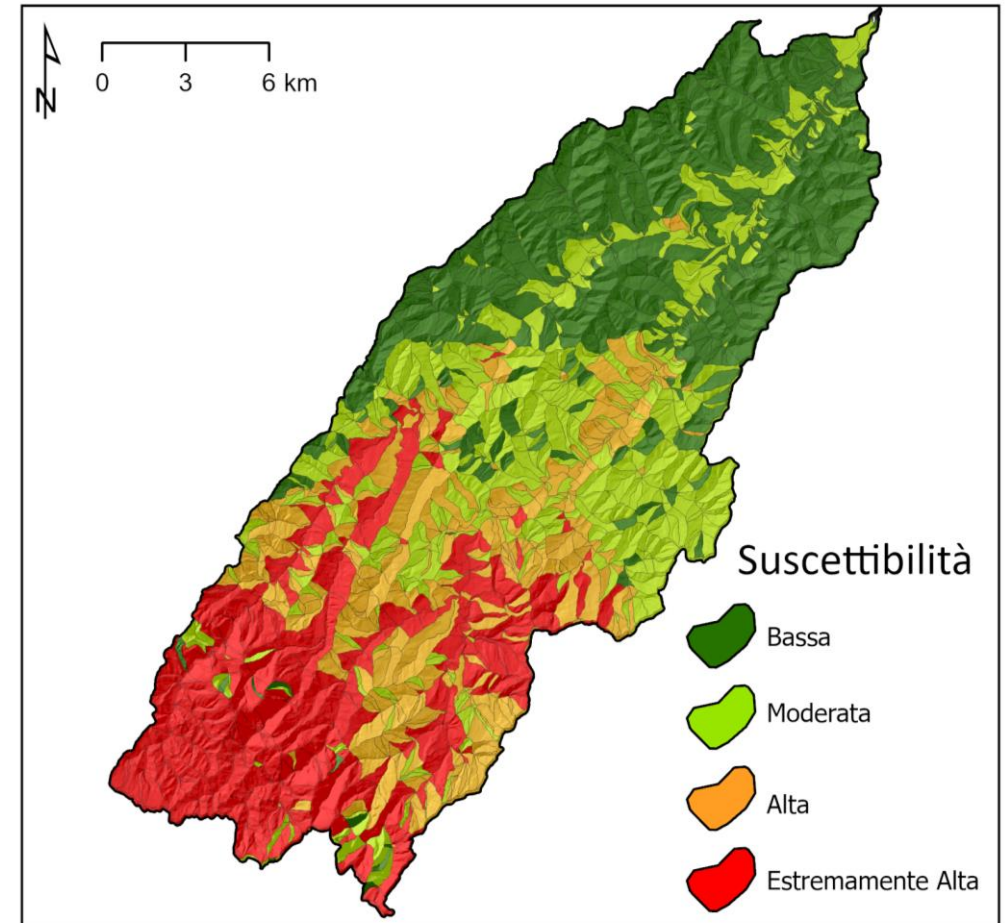
Merghadi et al., 2020

Susceptibility maps

Continuous values



Classes



Manzo et al., 2012

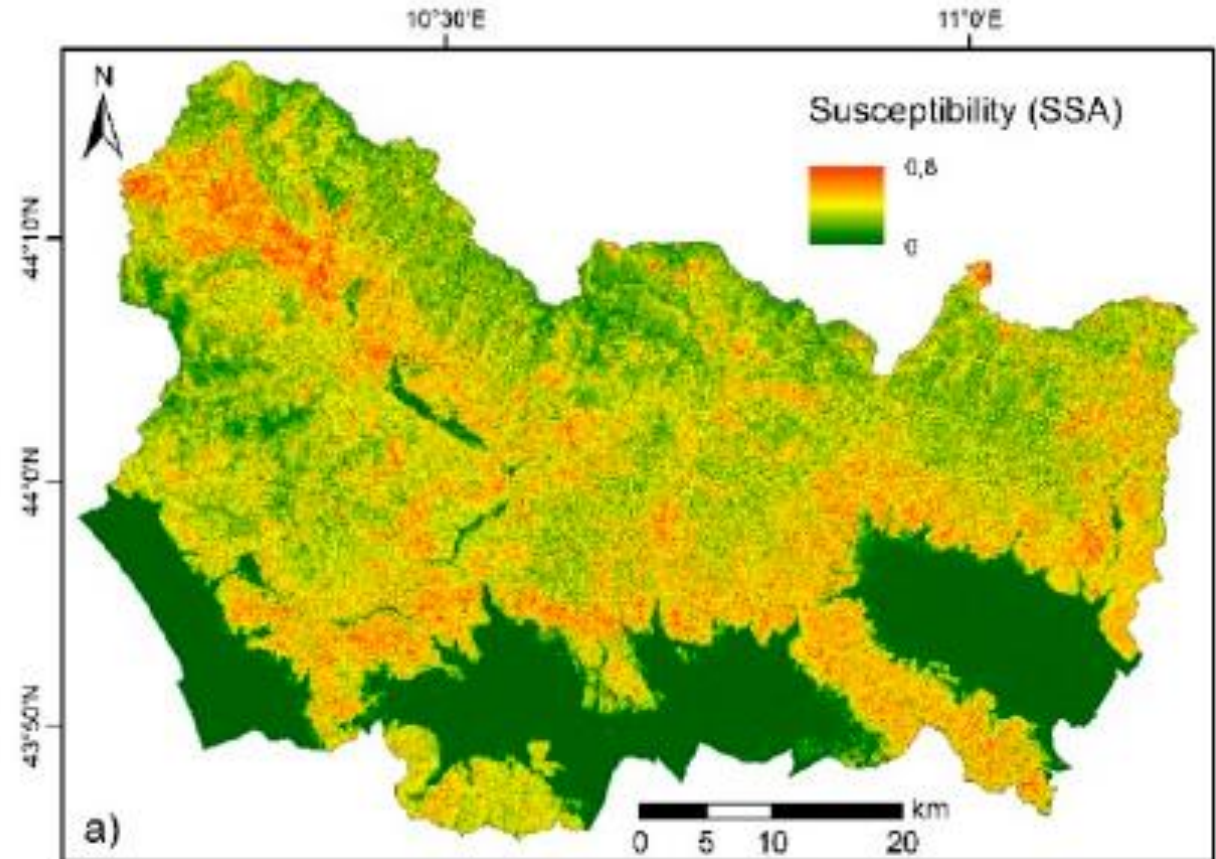
Susceptibility maps

RAW MODEL OUTPUTS

Depending on the model:

 probability [0 - 1]

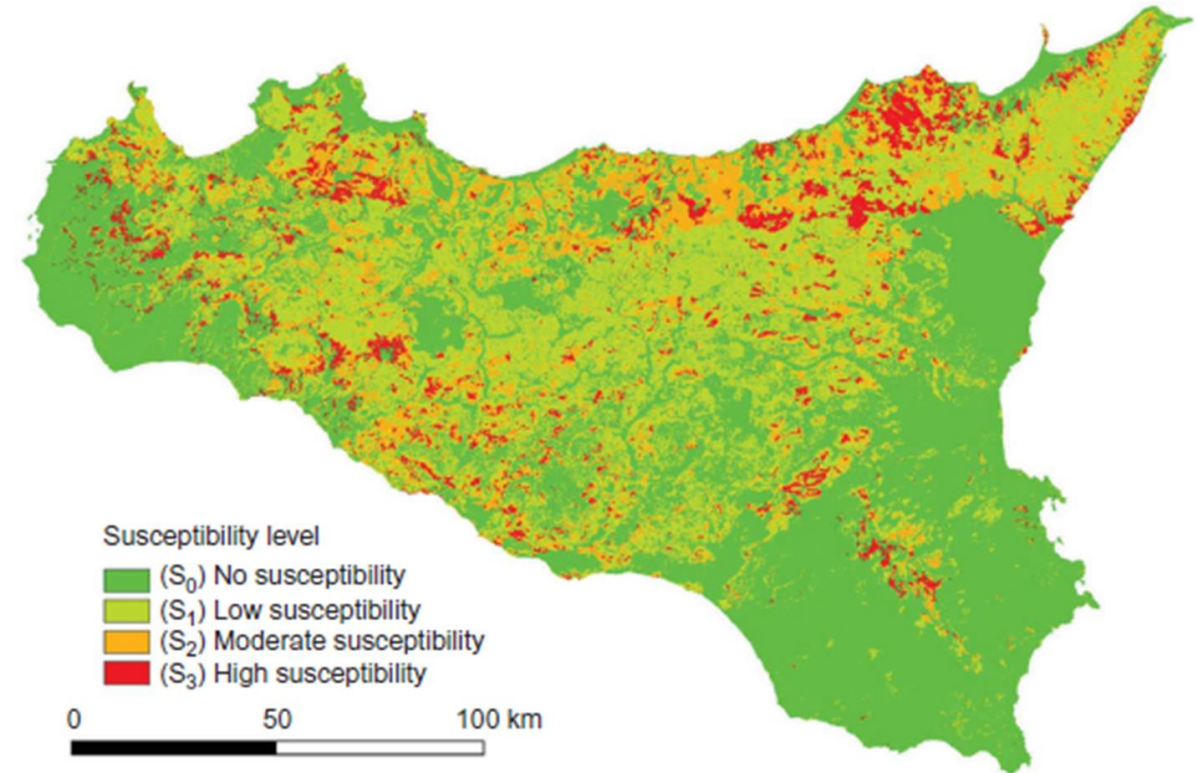
 adimensional index



Luti et al., 2020

RECLASSIFIED MAP

- 🌐 Decide the number of classes
- 🌐 Define a method to break the raw susceptibility values into classes
 - Natural breaks (Jenks)
 - Relative difference of derivatives
 - Equal intervals
 - ...



Manzo et al., 2012

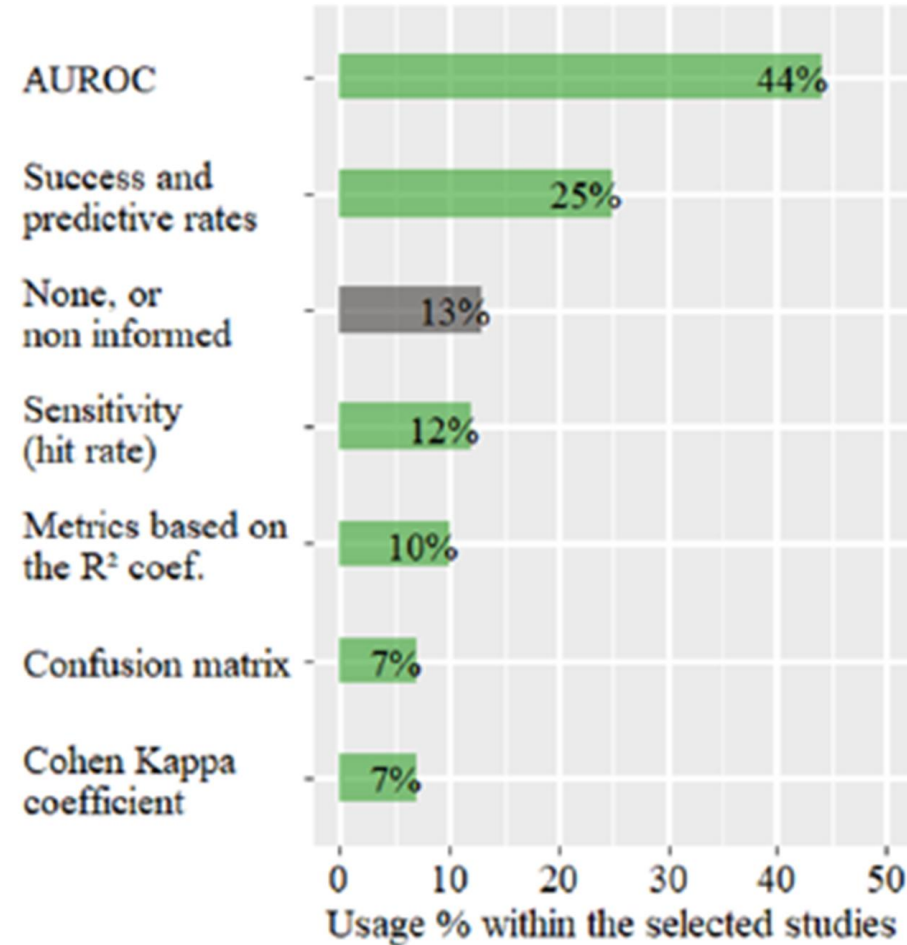
Performance indicators

🌐 Accuracy = $(TP + TN) / (TP + FP + TN + FN)$

🌐 RMSE, R2, ...

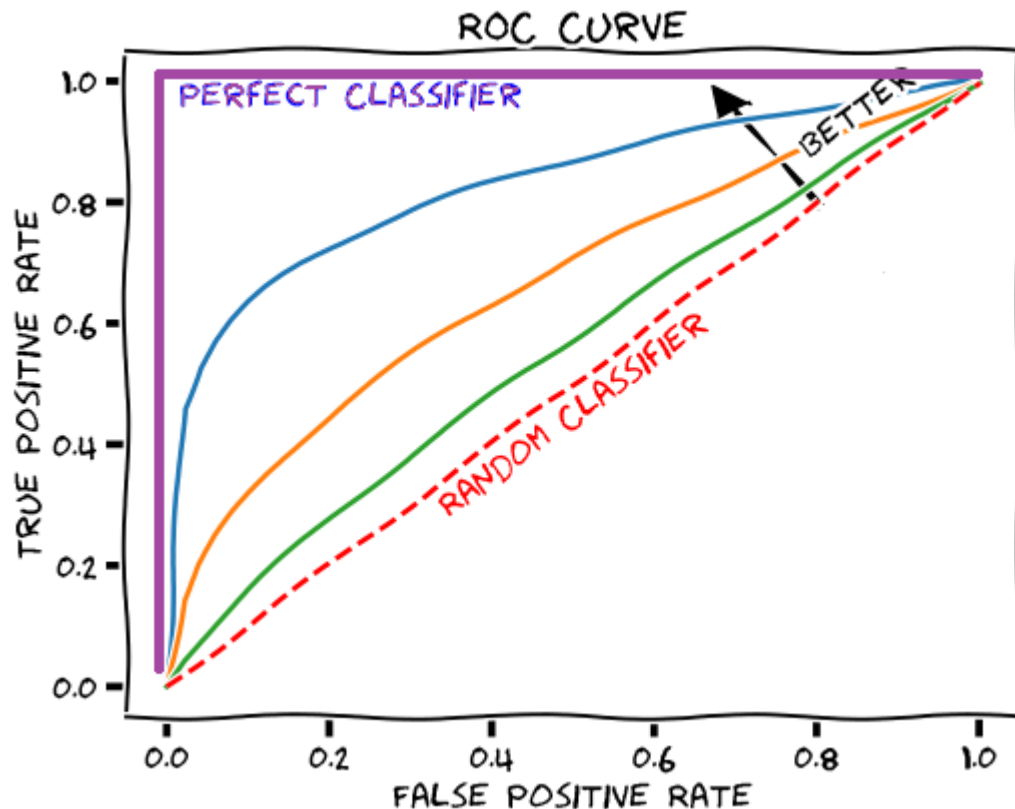
🌐 K index

🌐 ...



F_w Fig. 13 Most used validation error measure techniques within the selected studies.

AUC (Area Under Receiving-Operator Curve)



A **ROC curve (receiver operating characteristic curve)** is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

True Positive Rate
False Positive Rate

True Positive Rate (TPR) is a synonym for recall and is therefore defined as follows:

$$\text{TPR} = \text{TP} / (\text{TP} + \text{FN})$$

False Positive Rate (FPR) is defined as follows:

$$\text{FPR} = \text{FP} / (\text{FP} + \text{TN})$$

A ROC curve plots TPR vs. FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives. The following figure shows a typical ROC curve. AUC stands for "Area under the ROC Curve." That is, AUC measures the entire two-dimensional area underneath the entire ROC curve (think integral calculus) from (0,0) to (1,1).

AUC (Area Under Receiving-Operator Curve)

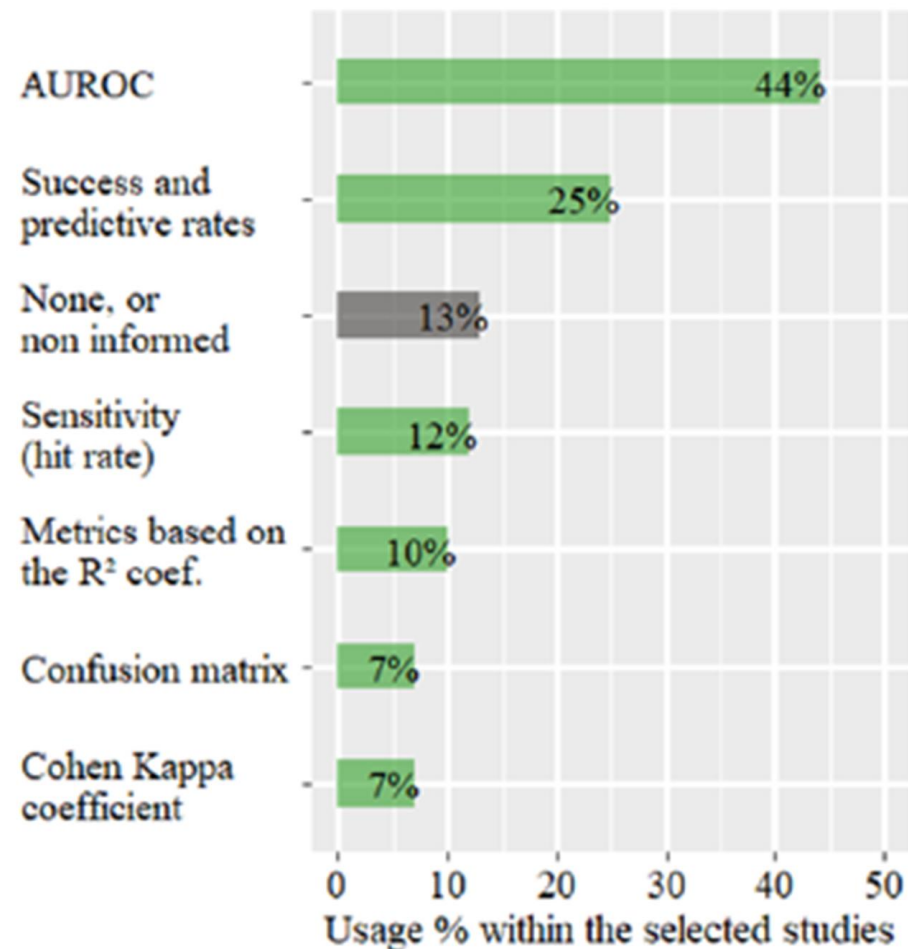
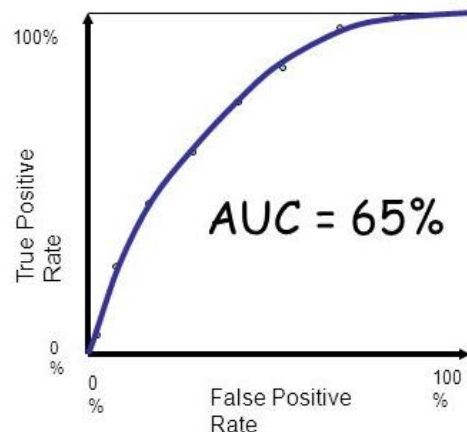
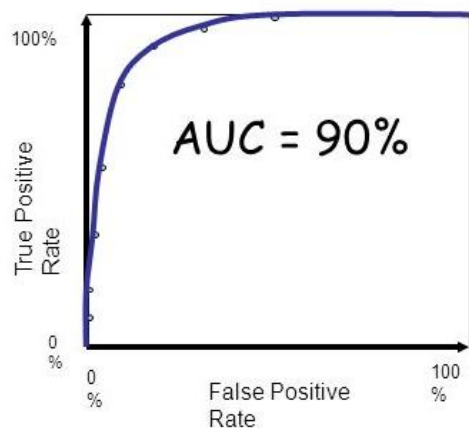
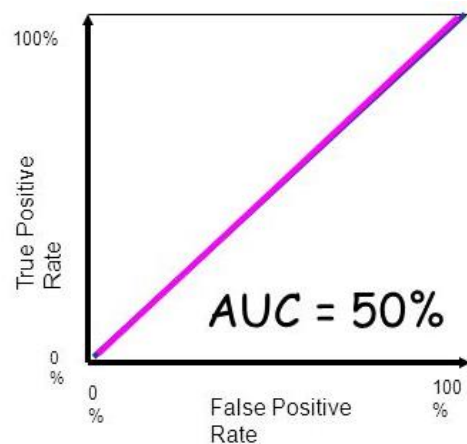
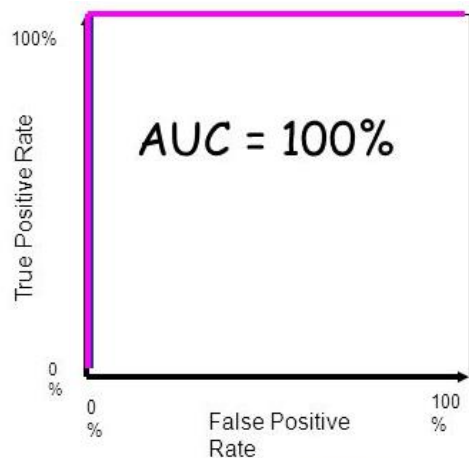


Fig. 13 Most used validation error measure techniques within the selected studies.

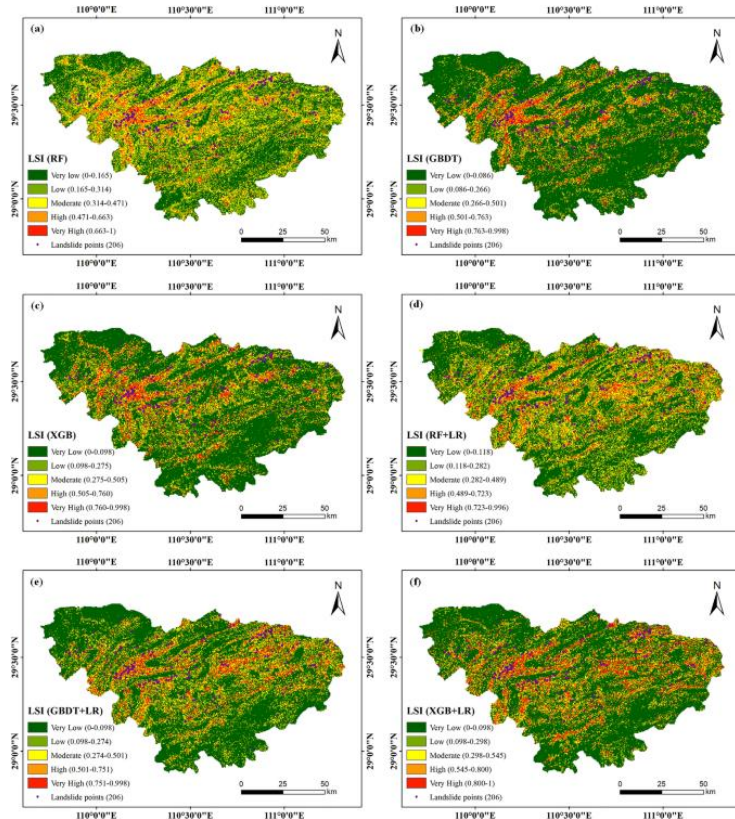
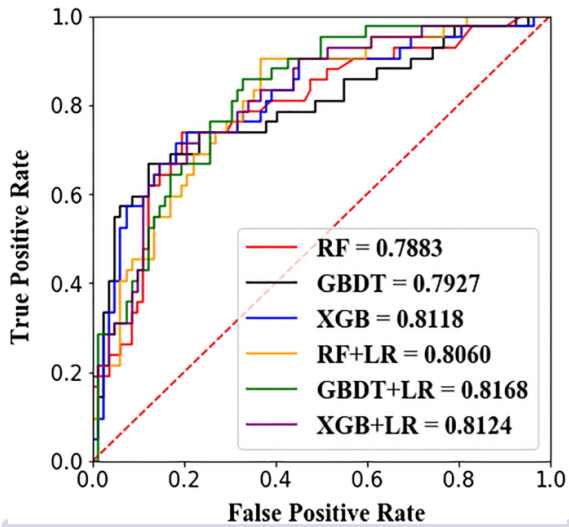
Comparison

Different models or Different configurations of the same model

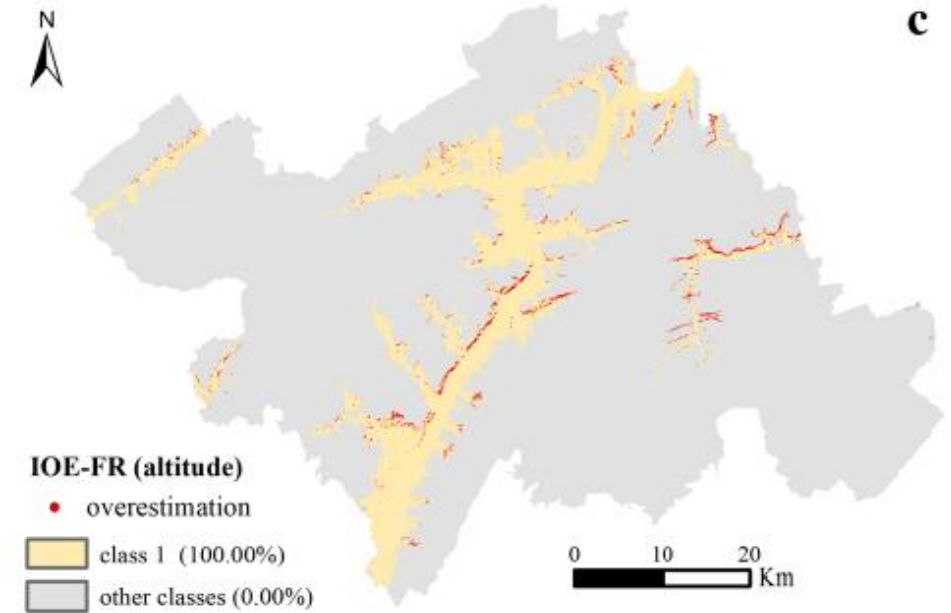
In terms of indicators (AUC)

Spatial patterns of differences

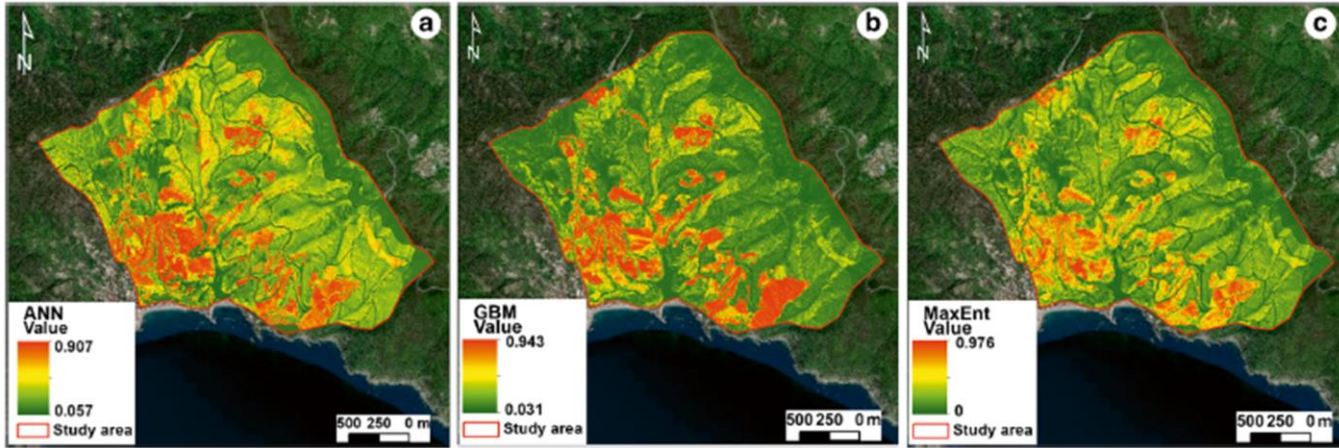
Huan et al., 2023



Xiao et al., 2020



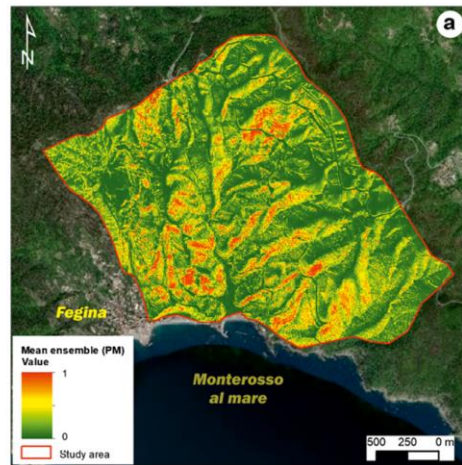
Ensembling



From **n** maps

to a **single**, comprehensive, map

(mean, median, maximum, or more complex stacking methods)



Di Napoli et al., 2020


$$R = H \cdot V \cdot E$$

Risk =
expected loss

Hazard =
probability of
occurrence

Vulnerability =
loss degree

Elements at risk
=
value


$$R = P \times V(I) \times E$$

V (Vulnerability): degree of loss, that is, the propensity of an exposed element to suffer damage as a result of the occurrence of an event of a certain **intensity (I)**

Intensity

Landslide intensity A set of spatially distributed parameters related to the destructive power of a landslide. The parameters may be described quantitatively or qualitatively, and may include maximum movement velocity, total displacement, differential displacement, depth of the moving mass, peak discharge per unit width or kinetic energy per unit area.

Landslide magnitude The measure of the landslide size. It may be quantitatively described by its volume or (indirectly) by its area. The latter descriptors may refer to the landslide scar, the landslide deposit, or both.

| Process | Intensity | | |
|--|------------|----------------|------------|
| | Low | Medium | High |
| Rock falls | | | |
| Kinetic energy | <30 kJ | 30 · 300 kJ | >300 kJ |
| Slides | | | |
| Mean annual velocity | <2 cm/year | 2 · 10 cm/year | >0.1 m/day |
| Displacement | – | – | >1 m/event |
| Debris flow | | | |
| Debris front thickness | – | <1 m | >1 m |
| Debris flow velocity | – | <1 m/s | >1 m/s |
| Depth of soil material (potential debris flows) | 0.5 m | 0.5 · 2 m | >2 m |

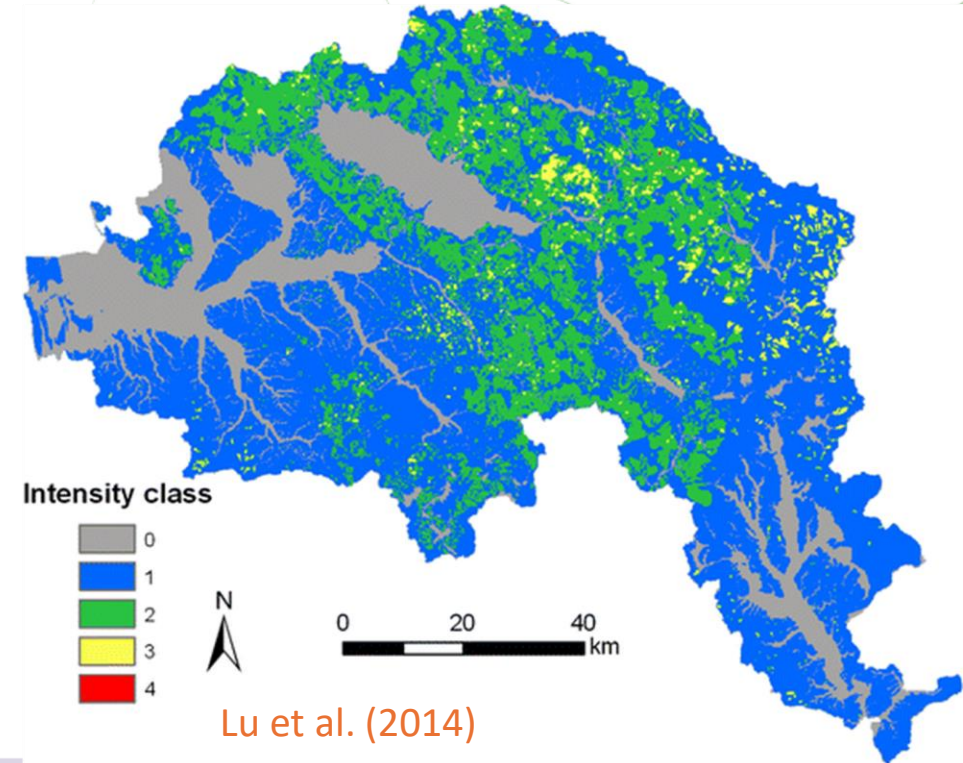
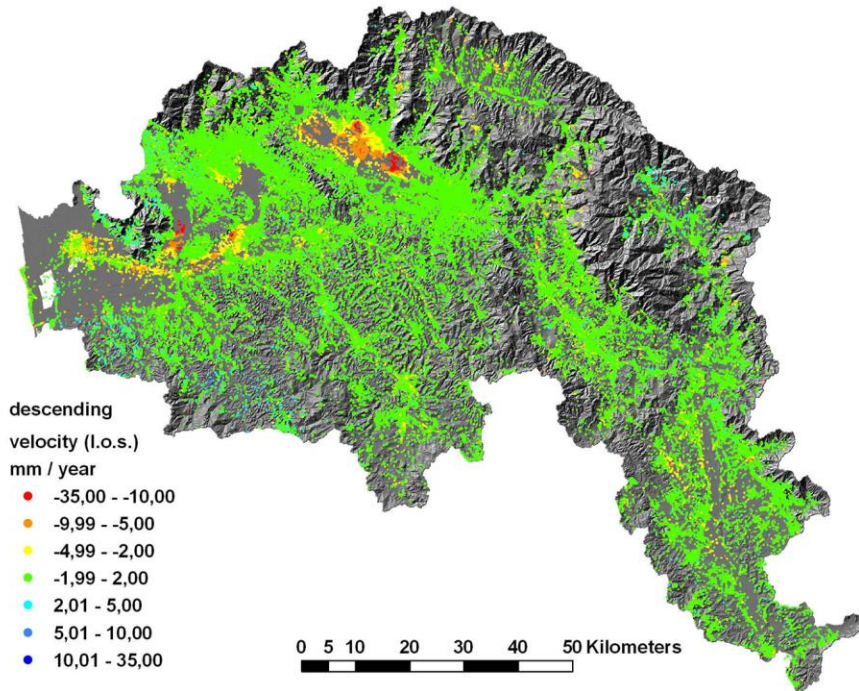
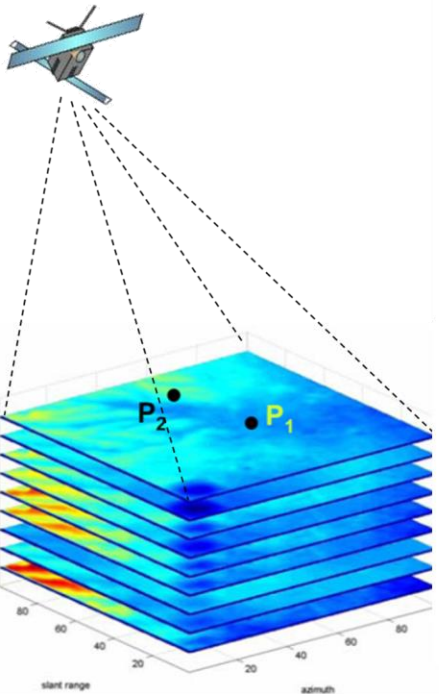
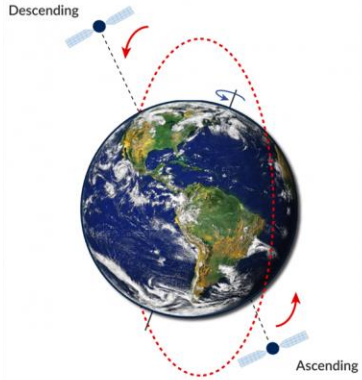
Lateltin et al. (2005)

Intensity assessment at regional scale

SAR interferometry

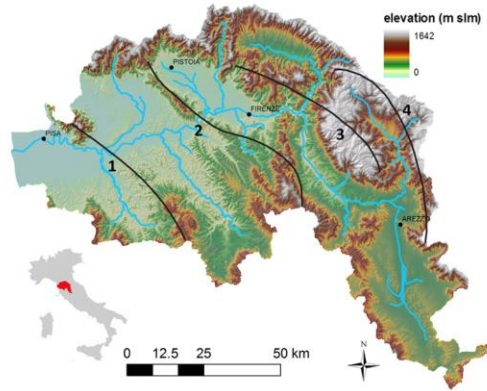
From velocity

To intensity classification



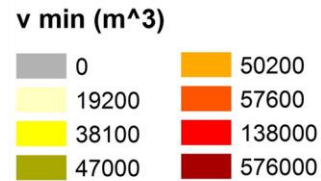
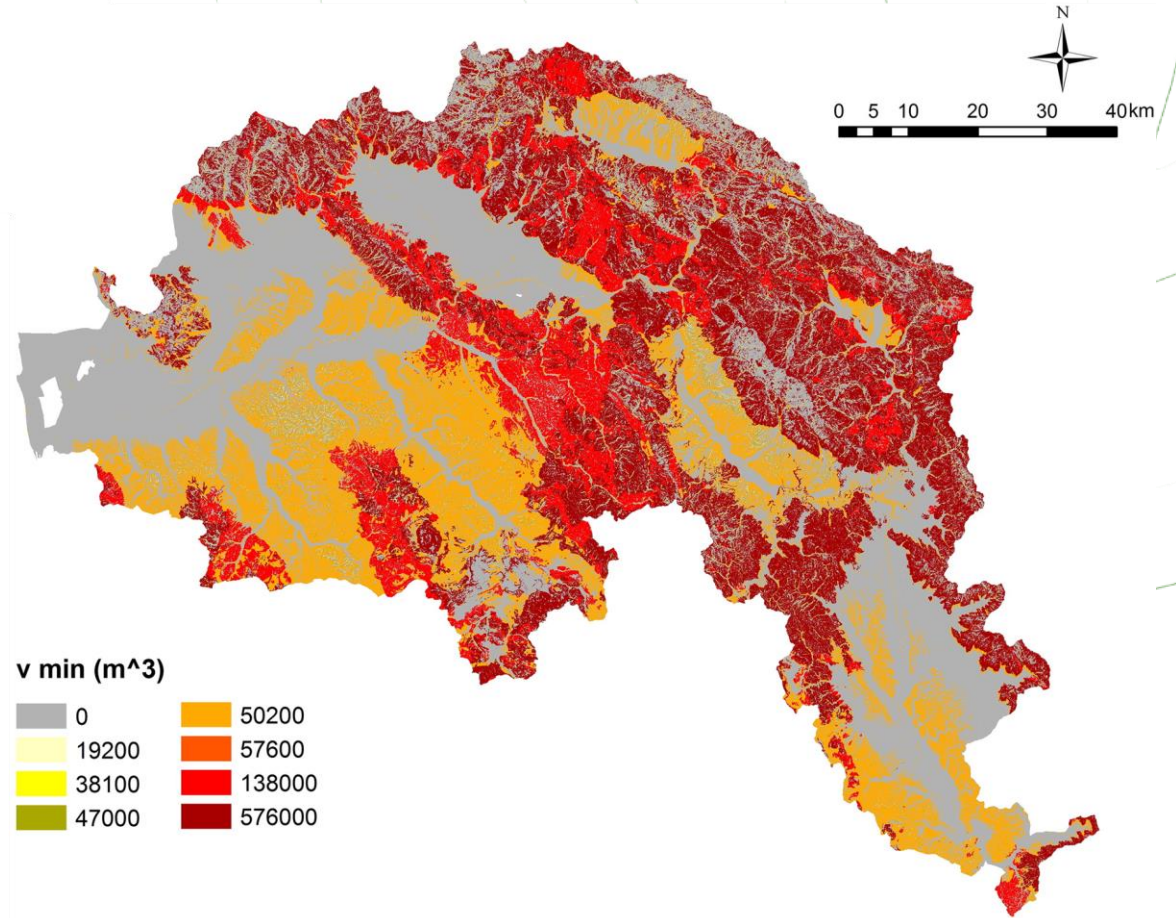
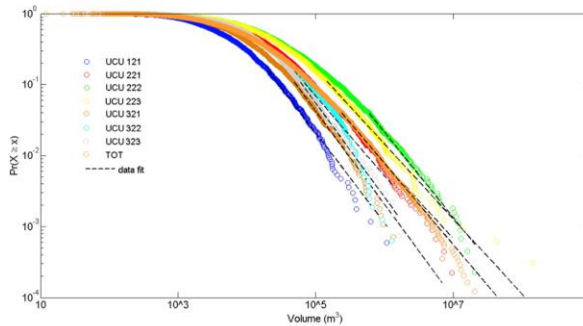
Lu et al. (2014)

Intensity assessment at regional scale



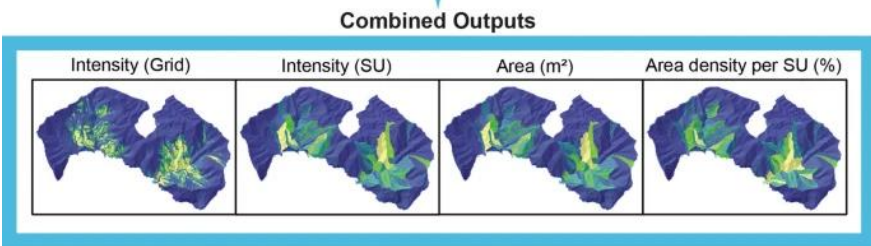
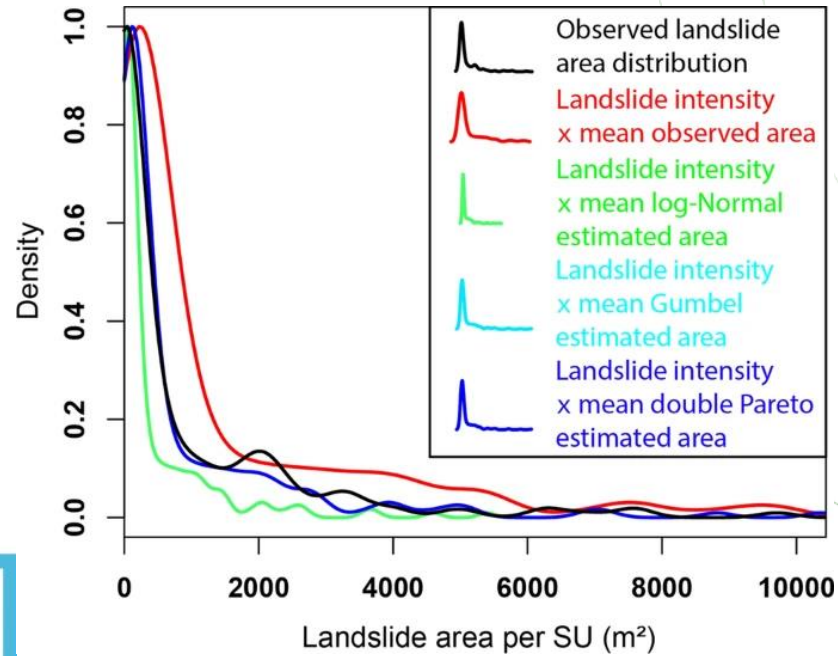
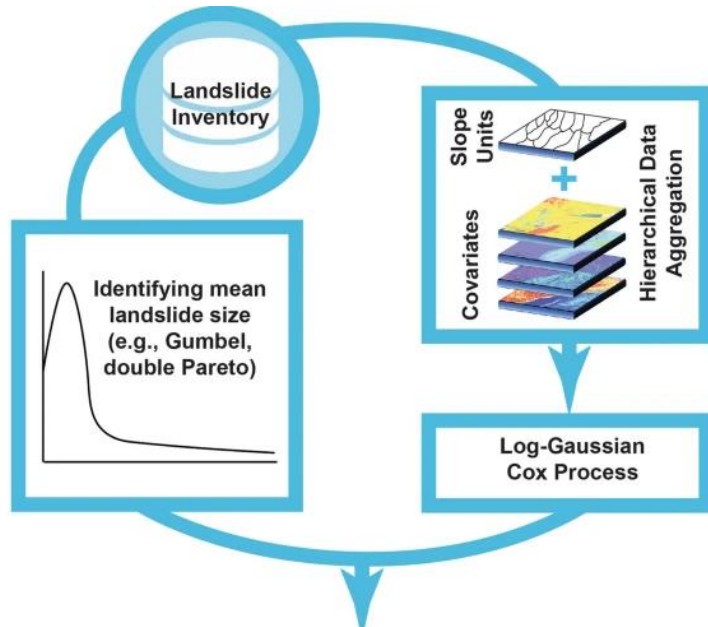
$$V = \frac{1}{6} \pi D_r W_r L_r$$

| UCU | Profile curvature | Slope (°) | Lithology | Area (km²) | Landslide # | Area landslide/area UCU |
|-------|-------------------|-----------|-----------|------------|-------------|-------------------------|
| 1.1.1 | Concave | 0-5 | GCS | 10.58 | 127 | 0.120 |
| 1.1.2 | Concave | 0-5 | HR | 9.61 | 18 | 0.010 |
| 1.1.3 | Concave | 0-5 | SR | 1.79 | 16 | 0.050 |
| 1.2.1 | Concave | 5-25 | GCS | 21.79 | 1694 | 0.880 |
| 1.2.2 | Concave | 5-25 | HR | 42.14 | 958 | 0.300 |
| 1.2.3 | Concave | 5-25 | SR | 4.34 | 608 | 0.170 |
| 1.3.1 | Concave | >25 | GCS | 5.10 | 312 | 0.470 |
| 1.3.2 | Concave | >25 | HR | 22.33 | 312 | 0.160 |
| 1.3.3 | Concave | >25 | SR | 1.23 | 41 | 0.270 |
| 2.1.1 | Planar | 0-5 | GCS | 2612.85 | 208 | 0.002 |
| 2.1.2 | Planar | 0-5 | HR | 184.32 | 24 | 0.002 |
| 2.1.3 | Planar | 0-5 | SR | 103.47 | 19 | 0.092 |
| 2.2.1 | Planar | 5-25 | GCS | 1735.95 | 4486 | 0.070 |
| 2.2.2 | Planar | 5-25 | HR | 2312.46 | 4430 | 0.090 |
| 2.2.3 | Planar | 5-25 | SR | 911.63 | 3249 | 0.150 |
| 2.3.1 | Planar | >25 | GCS | 103.19 | 360 | 0.020 |
| 2.3.2 | Planar | >25 | HR | 750.36 | 857 | 0.030 |
| 2.3.3 | Planar | >25 | SR | 50.65 | 76 | 0.020 |
| 3.1.1 | Convex | 0-5 | GCS | 11.29 | 189 | 0.190 |
| 3.1.2 | Convex | 0-5 | HR | 8.30 | 20 | 0.008 |
| 3.1.3 | Convex | 0-5 | SR | 2.44 | 27 | 0.060 |
| 3.2.1 | Convex | 5-25 | GCS | 39.85 | 2803 | 0.760 |
| 3.2.2 | Convex | 5-25 | HR | 85.05 | 1601 | 0.440 |
| 3.2.3 | Convex | 5-25 | SR | 13.73 | 1359 | 0.170 |
| 3.3.1 | Convex | >25 | GCS | 10.53 | 170 | 0.210 |
| 3.3.2 | Convex | >25 | HR | 55.31 | 374 | 0.100 |
| 3.3.3 | Convex | >25 | SR | 3.74 | 47 | 0.100 |



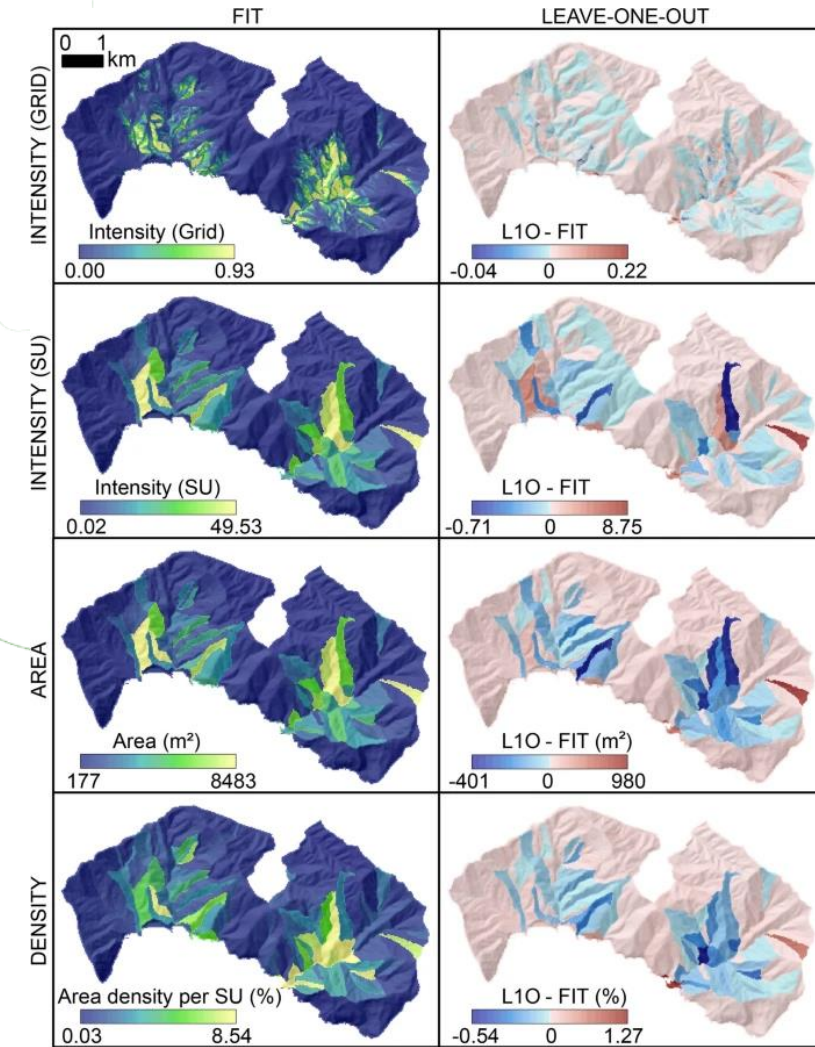
Catani et al. (2018)

Intensity assessment at regional scale



From number of landslides per Slope Unit

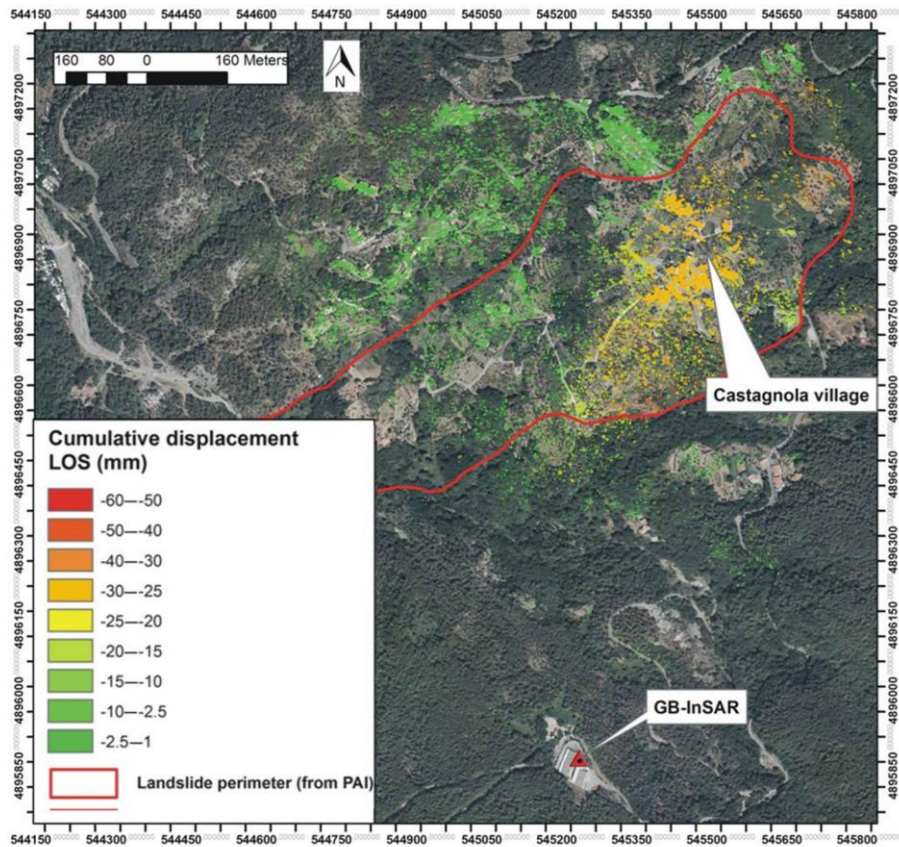
To intensity mapping



Di Napoli et al. (2023)

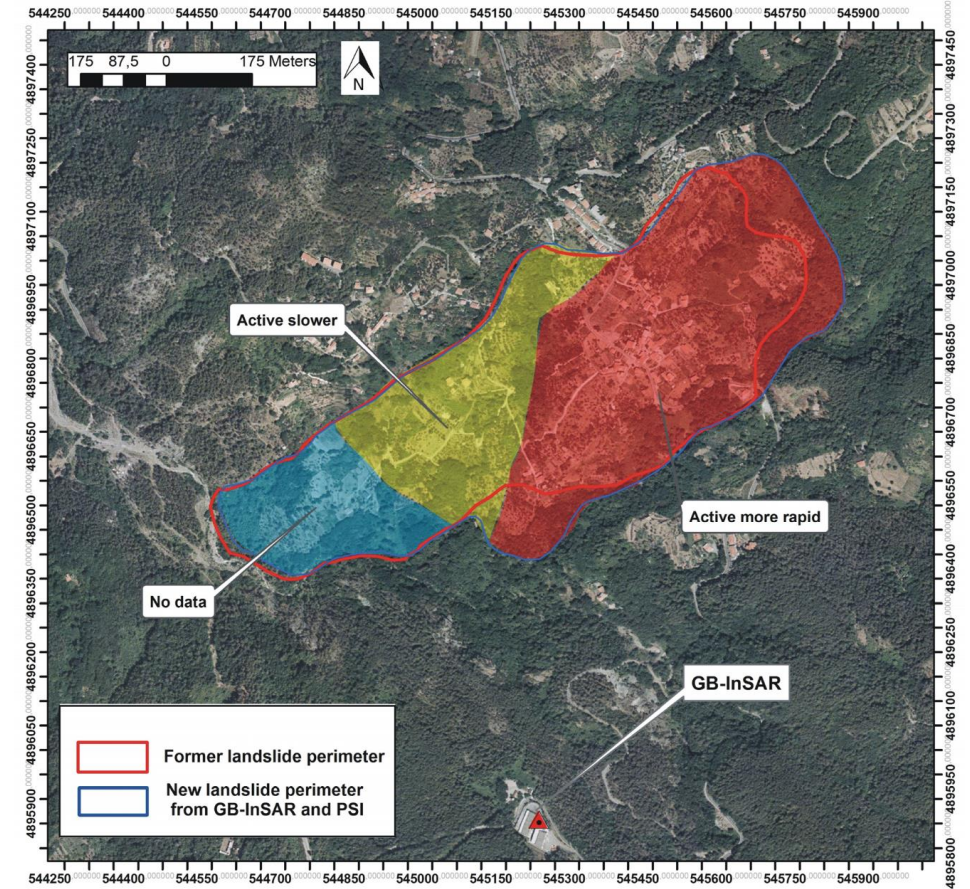
Intensity assessment at slope scale

From velocity




Tofani et al. (2014)

To intensity classification



Vulnerability

 **Vulnerability** The degree of loss of a given element or set of elements exposed to the occurrence of a landslide of a given magnitude/intensity. It is expressed on a scale of 0 (no loss) to 1 (total loss).

Physical vulnerability

impact on buildings, infrastructures and utilities



Social vulnerability

determines whether a landslide event will cause injuries or fatalities

Environmental vulnerability

Direct impact on natural environment (forests, animal, plants, water)



Economic vulnerability

Indirect impact of the phenomenon on various activities

Buildings vulnerability

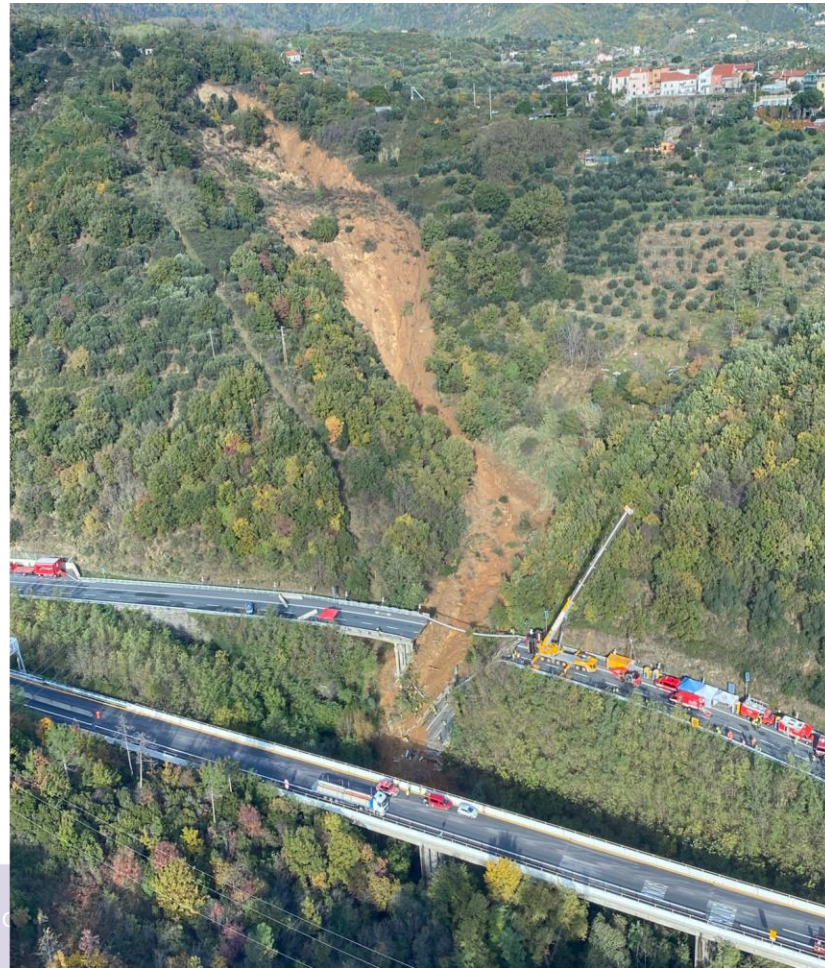
Depends on:

- 🌐 characteristics of the building
- 🌐 the landslide mechanism
- 🌐 magnitude and intensity



Infrastructure vulnerability

Partial or complete blockage of the road or track as well as structural damage, including damage to the surfacing, which is associated with the level of serviceability



Physical vulnerability assessment

Vulnerability indices

Qualitative risk assessment

| I | Building typology | Observed Damages | VULNERABILITY |
|---------------|----------------------|------------------|-----------------|
| HIGH | All | Not considered | HIGH |
| MEDIUM | Strategical building | Not considered | HIGH |
| | Common building | YES | |
| | Common building | NOT | MEDIUM |
| LOW | Strategical building | Not considered | MODERATE |
| | Common building | YES | |
| | Common building | NOT | LOW |

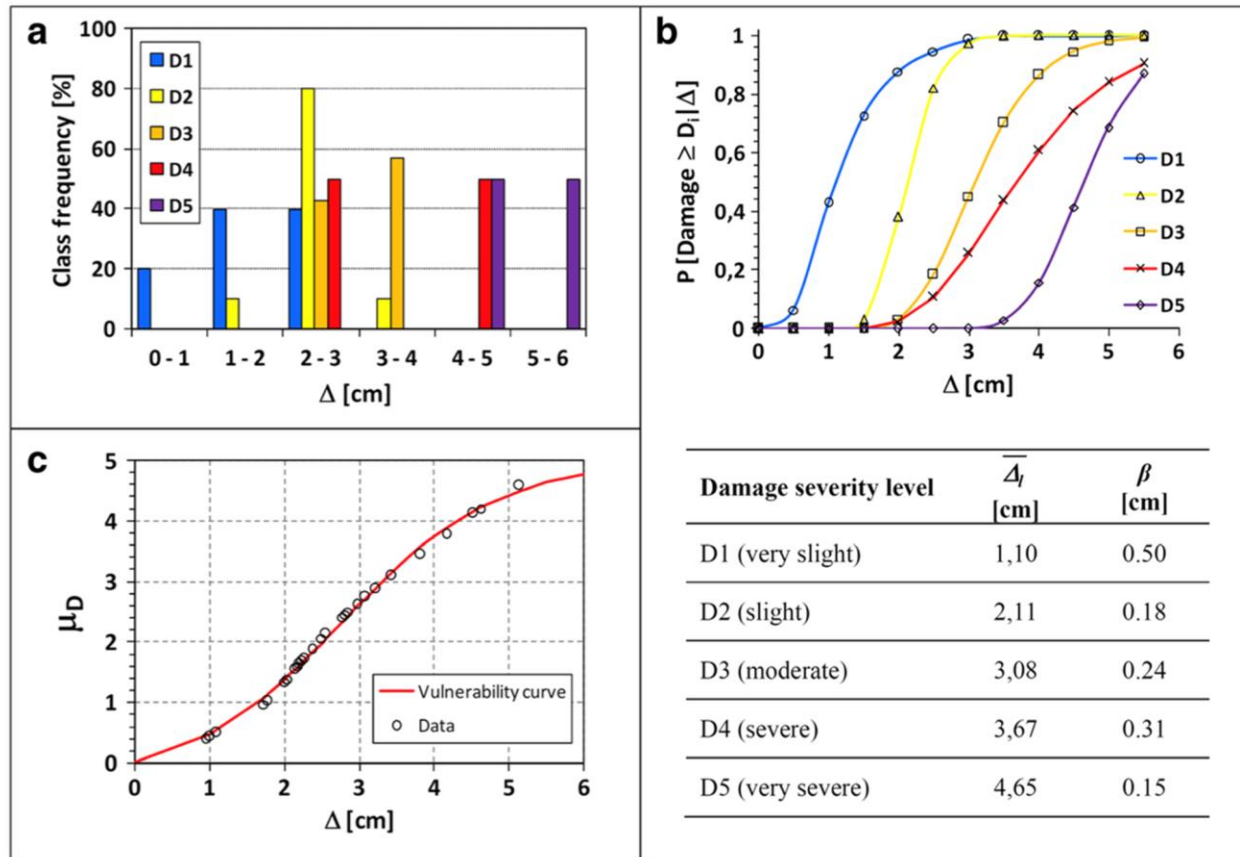
Cascini et al., 2005

Quantitative risk assessment

| Code | Description | Exposure (euro/m ²) | Vulnerability (% loss) as a function of intensity I | | | |
|------|---|---------------------------------|---|----------|----------|----------|
| | | | V (I=I0) | V (I=I1) | V (I=I2) | V (I=I3) |
| 201 | PUBLIC/SOCIAL/ADMINISTRATIVE BUILDING | 3000 | 5 | 10 | 30 | 60 |
| 202 | INDUSTRIAL/COMMERCIAL BUILDING-FACTORY | 1000 | 5 | 10 | 20 | 50 |
| 203 | RELIGIOUS BUILDING/BELLTOWER/TABERNACLE | 4000 | 5 | 15 | 30 | 60 |
| 204 | BUILDING UNDER CONSTRUCTION | 100 | 5 | 15 | 30 | 40 |
| 205 | ABANDONED/RUINED BUILDING | 10 | 5 | 20 | 50 | 60 |
| 206 | PROJECTING BODY/PORTICO/LOGGIA | 100 | 5 | 10 | 20 | 40 |
| 207 | SHED/KIOSK | 100 | 5 | 15 | 50 | 60 |
| 208 | AWNING//DORMER WINDOW | 10 | 5 | 10 | 20 | 40 |
| 209 | PRESSURIZED DOME | 10 | 5 | 20 | 50 | 60 |
| 210 | PERMANENT GREENHOUSE | 10 | 5 | 20 | 40 | 60 |
| 211 | TOLLGATE/RAILWAY STATION/STOPS | 2000 | 5 | 10 | 30 | 50 |
| 212 | POWER STATION/POWER SUBSTATION/POWER SHED | 2000 | 5 | 10 | 20 | 50 |
| 213 | MONUMENT | 100 | 5 | 15 | 40 | 50 |
| 215 | NURSERY GREENHOUSE | 10 | 5 | 20 | 40 | 60 |
| 216 | STABLE/BARN/BREEDING FARM | 10 | 5 | 15 | 40 | 60 |
| 217 | TOWER/CHIMNEY | 100 | 5 | 15 | 40 | 50 |
| 218 | SILO | 10 | 5 | 15 | 40 | 50 |
| 219 | CROSS/TABERNACLE | 10 | 5 | 10 | 40 | 40 |
| 223 | HOSPITAL COMPLEX | 4000 | 5 | 10 | 50 | 70 |
| 224 | SCHOOL COMPLEX | 4000 | 5 | 20 | 50 | 70 |
| 225 | SPORT FACILITIES | 100 | 5 | 10 | 25 | 50 |
| 226 | RELIGIOUS BUILDING COMPLEX | 4000 | 5 | 15 | 50 | 70 |
| 227 | CIVIL COMPLEX | 4000 | 5 | 15 | 30 | 50 |
| 228 | CEMETARIAL COMPLEX | 100 | 5 | 10 | 30 | 50 |
| 229 | CAMPGROUND/RESORT | 100 | 5 | 20 | 50 | 80 |
| 301 | TOLLROAD/HIGHWAY | 200 | 5 | 30 | 50 | 80 |
| 302 | STATE HIGHWAY/PROVINCIAL HIGHWAY | 100 | 5 | 40 | 60 | 100 |
| 303 | PROVINCIAL ROAD | 50 | 5 | 50 | 80 | 100 |
| 304 | LOCAL ROAD | 50 | 5 | 60 | 80 | 100 |

Catani et al., 2005

Vulnerability/fragility curves



Peduto et al., 2017

Structural resistance

$$R_{STR} = (\xi_{sfd} \cdot \xi_{sty} \cdot \xi_{smn} \cdot \xi_{sht})^{\frac{1}{4}}$$

| Structural typology | Field name | ξ_{sty} |
|---|------------|-------------|
| Lightest structures (simple timber constructions) | LT | 0.10 |
| Light structure | LS | 0.20 |
| Mixed structure (concrete and timber) | MS | 0.40 |
| Brick walls, concrete | BC | 0.80 |
| Reinforced concrete | RC | 1.30 |
| Reinforced | RF | 1.50 |

| State of maintenance | Field name | ξ_{smn} |
|----------------------|------------|-------------|
| Very poor | VP | 0.10 |
| Poor | P | 0.40 |
| Medium | M | 0.80 |
| Good | G | 1.20 |
| Very good | VG | 1.50 |

| Height | Field name | Number of storey | ξ_{sht} |
|----------------------|------------|------------------|-------------|
| Single-storey | S | 1 | 0.10 |
| Low-rise building | L | 2 | 0.40 |
| Medium-rise building | M | 3,4,5 | 0.90 |
| High-rise building | H | 6+ | 1.50 |

Li et al., 2010

$$R = H \cdot V \cdot E$$

Risk =
expected loss

Hazard =
probability of
occurrence

Vulnerability =
loss degree

Elements at risk
=
value

Exposure of elements at risk

- 🌐 The exposure of an element is determined by its position relative to the path of the landslide, which varies depending on the landslide kinematics
- 🌐 **Population exposure**: the quantification is based on the number of human lives exposed
- 🌐 **Physical assets** (buildings, infrastructure, or agricultural areas): exposure is determined by their monetary value

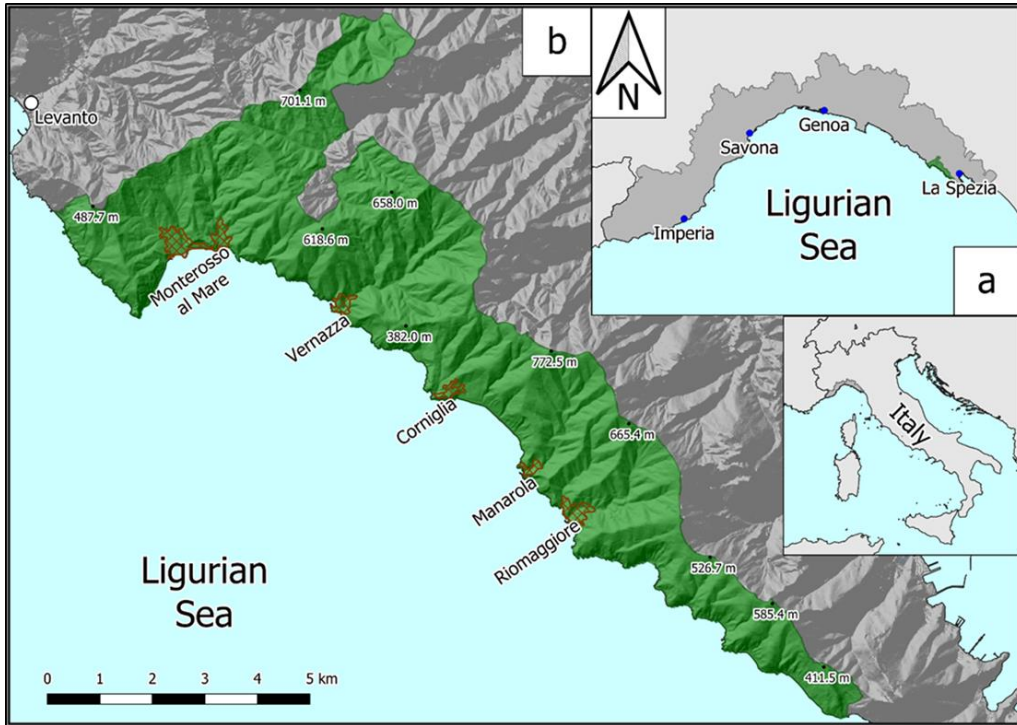
Case studies

 Susceptibility analysis

 Risk analysis at regional scale

 Risk analysis at national scale

Case studies –Landslide susceptibility



Cinque Terre National Park

- 🌐 Area: 38.44 km²
- 🌐 5 hamlets (Monterosso, Vernazza, Corniglia, Manarola, Riomaggiore)
- 🌐 Residents: 4373
- 🌐 Millions of tourists visit the Cinque Terre every year



Di Napoli et al., 2021



Case study – Cinque Terre – Machine learning

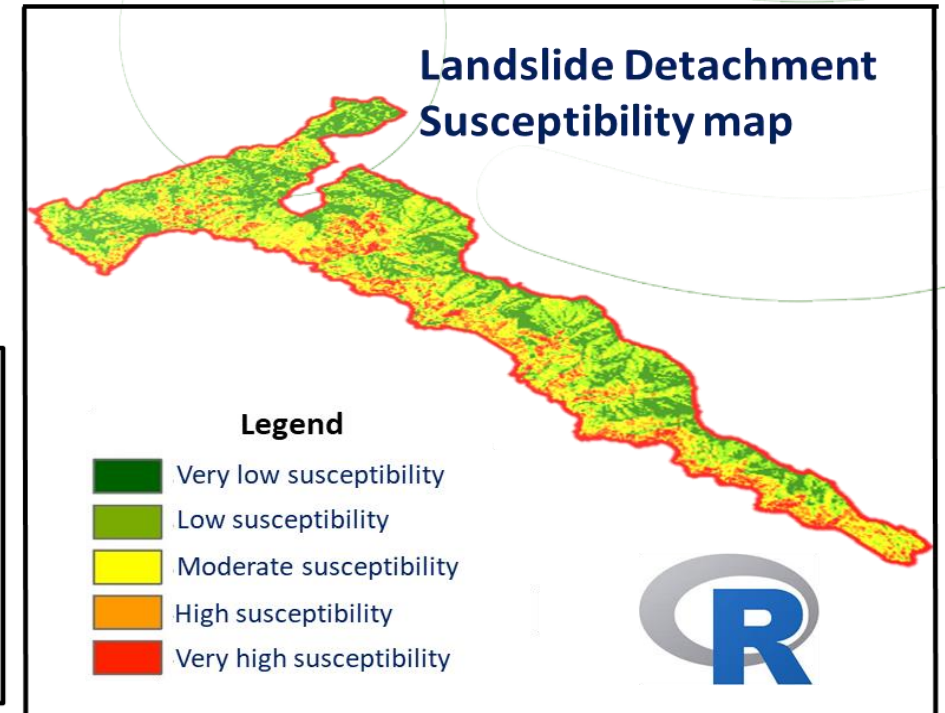
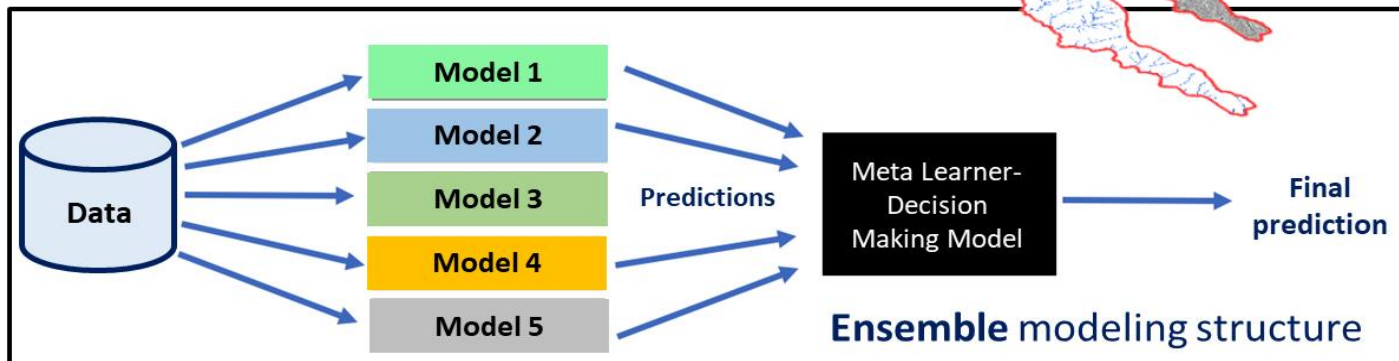
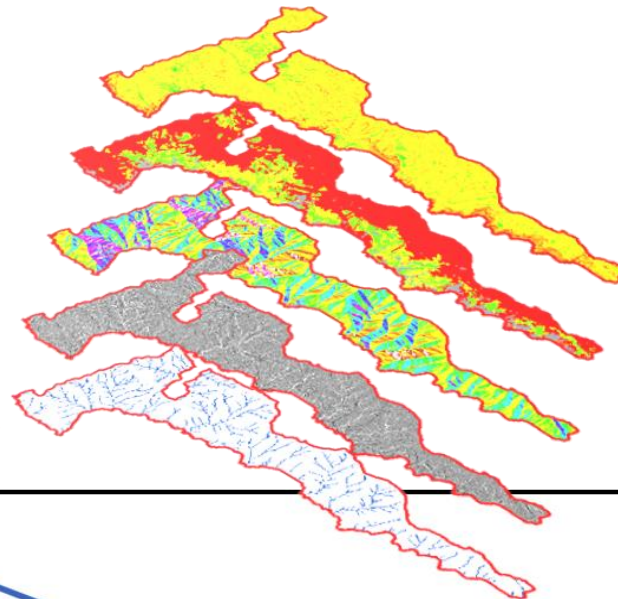
Y = Response or dependent variable (landslide inventory map)



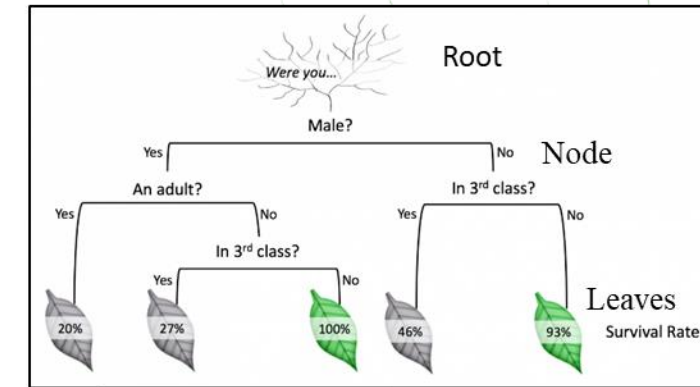
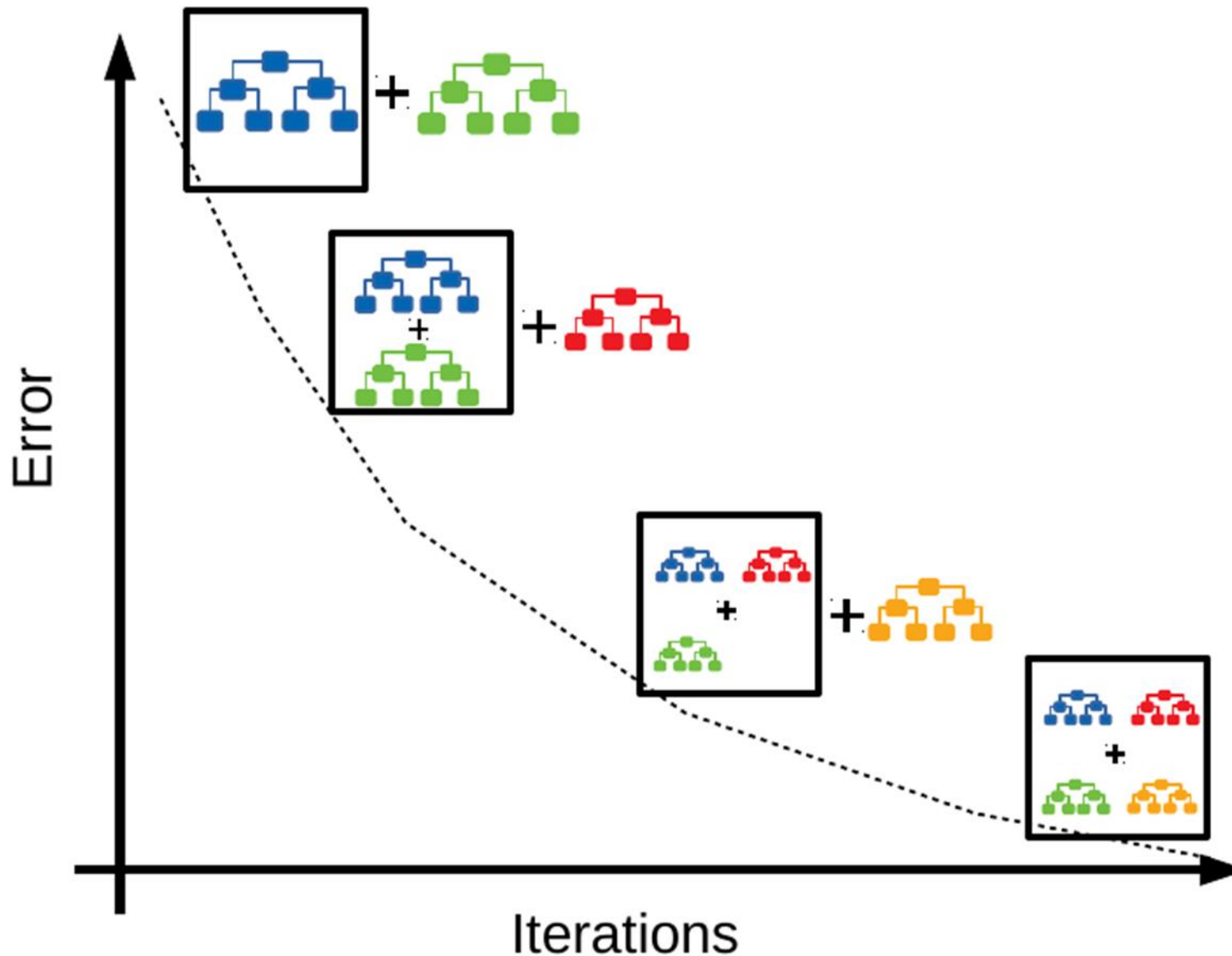
X = Independent or predisposing variable (slope, aspect, drainage density, soil moisture index, degree of abandonment of agricultural terraces)




- Machine Learning models:
- Generalized Boosting Model
- Artificial Neural Network
- Maximum Entropy (MaxEnt)

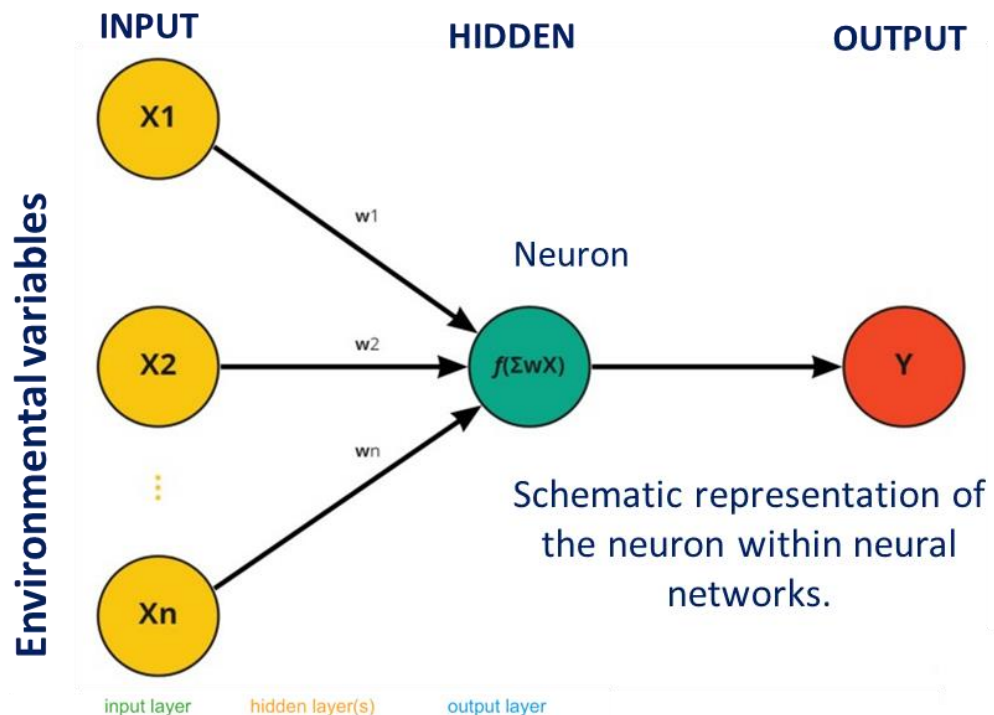


Case study – Cinque Terre – GBM



 Generalized Boosting Models repeatedly fit many decision trees to improve the accuracy of the model.

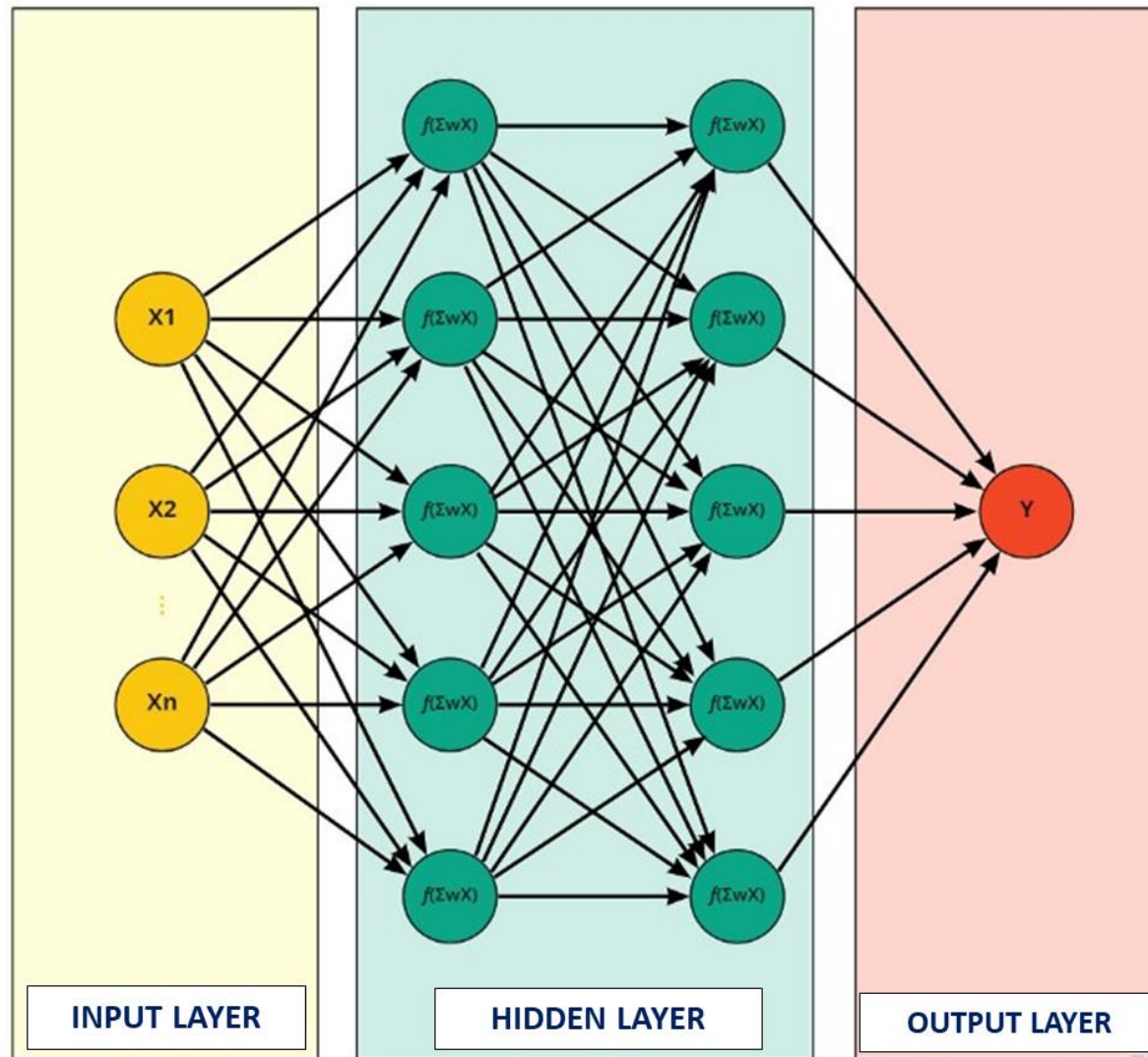
Case study – Cinque Terre – ANN



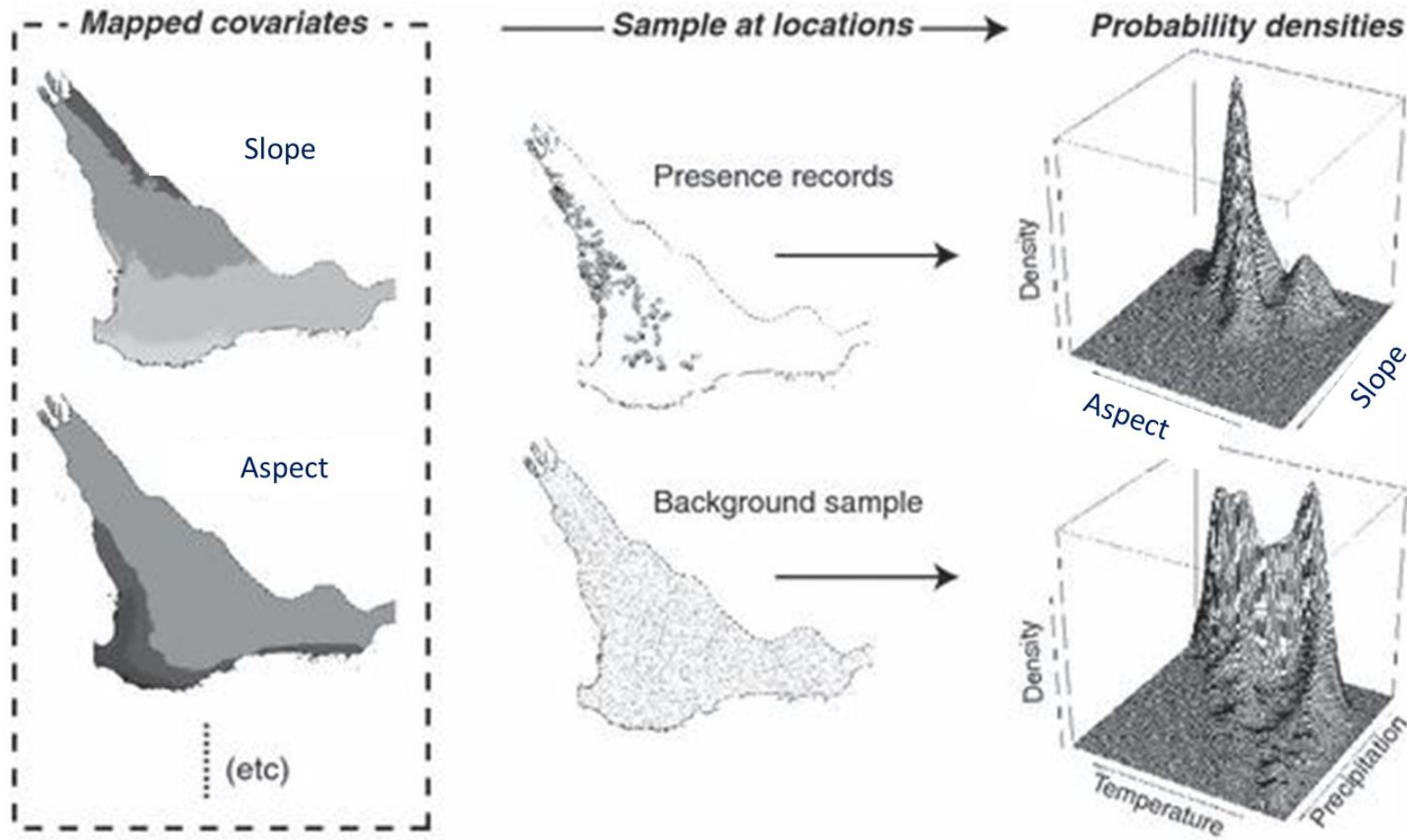
Schematic representation of the neuron within neural networks.




Neural network structure.

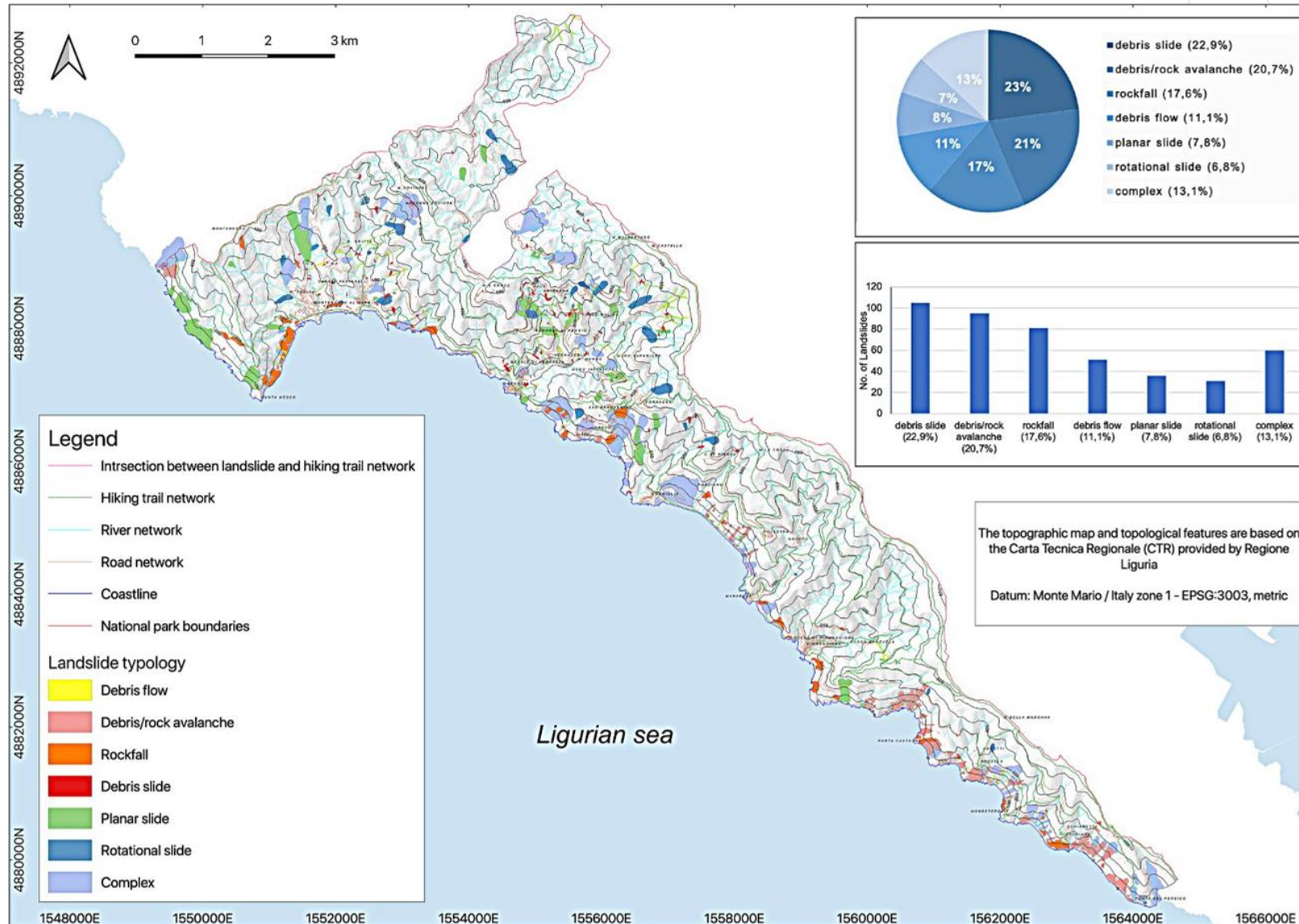


Case study – Cinque Terre – MAXENT



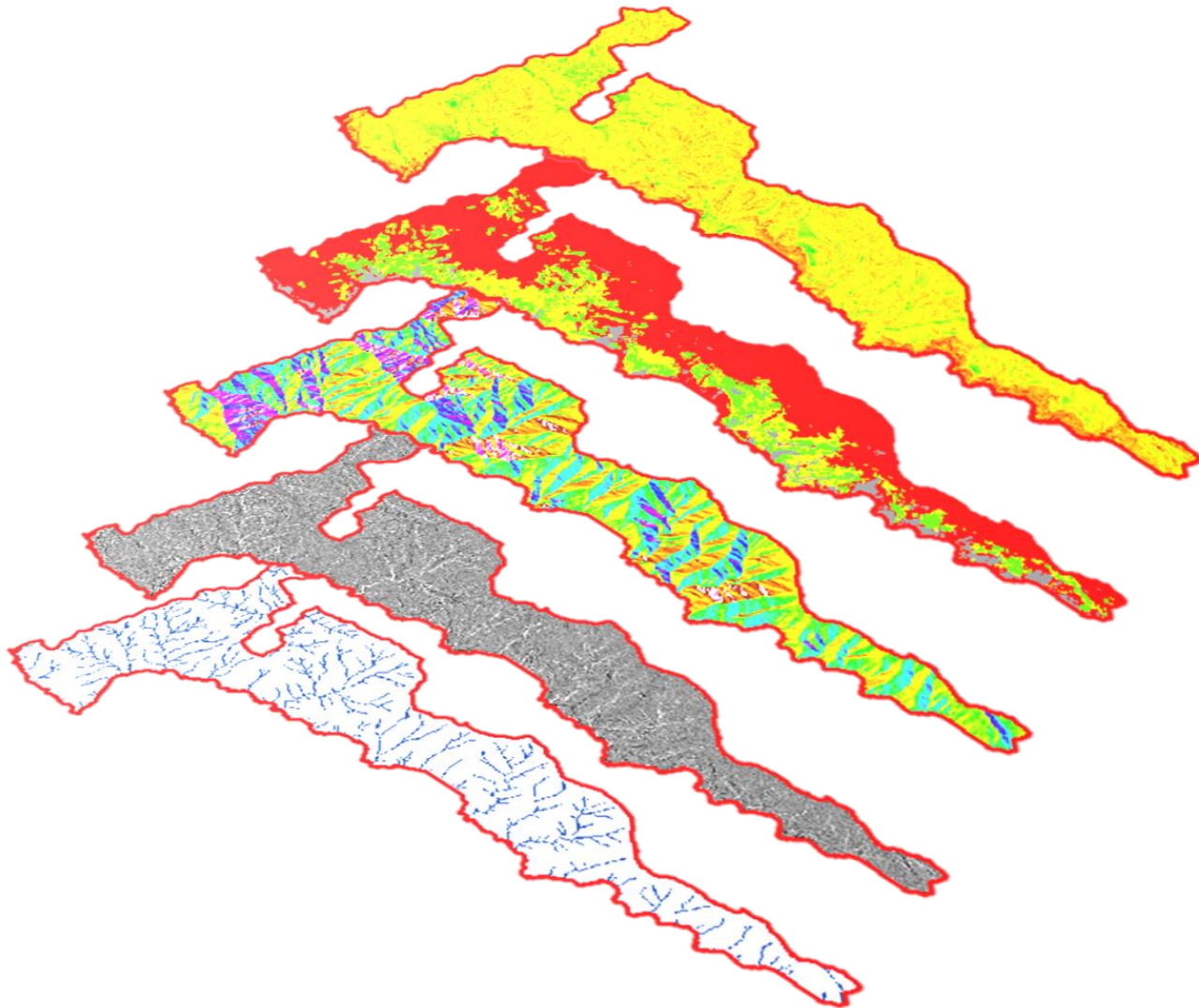
 Schematic representation of the MaxEnt algorithm.

Case study – Cinque Terre – Landslide Inventory












Landslide inventory of the Cinque Terre National Park and diagrams showing the percentage of catalogued landslides for each typology (from [Raso et al. 2019](#)).

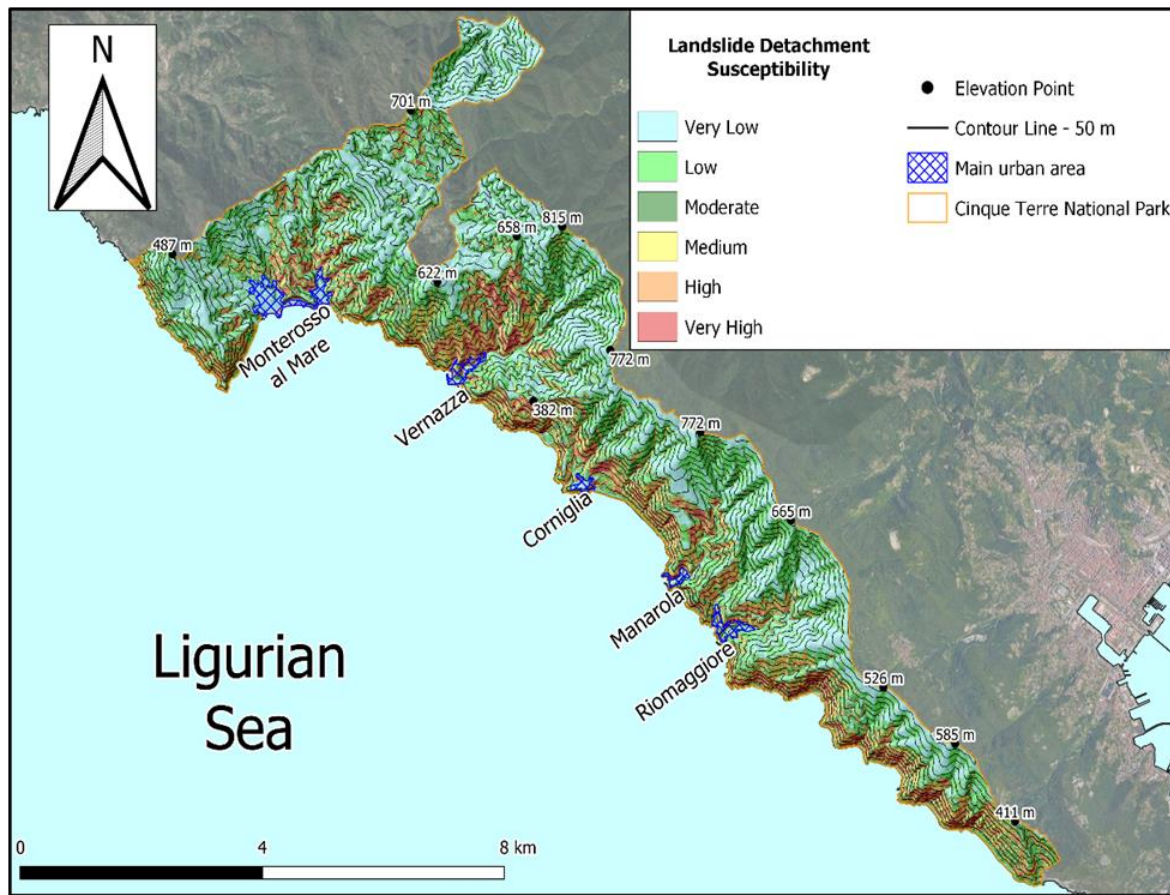
Case study – Cinque Terre – Predisposing factor



Predisposing factors:

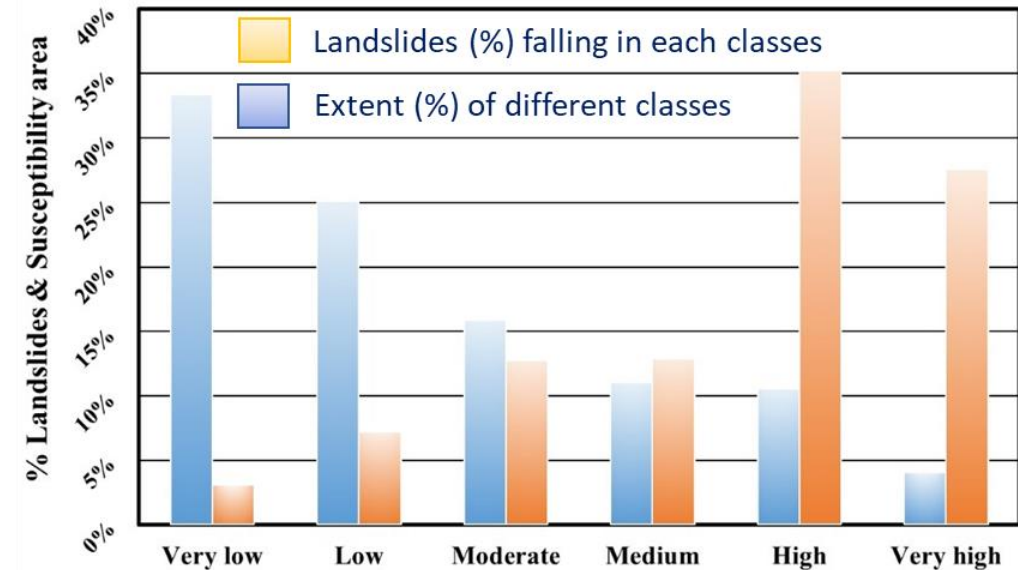
-  Slope angle;
-  Slope aspect;
-  Planform curvature;
-  Profile curvature;
-  Distance to roads;
-  Distance to streams;
-  Agricultural terraces state of activity;
-  Land use;
-  Geolithological map.

Case study – Cinque Terre – Ensembled map



Landslide Detachment Susceptibility (LDS) map of the Cinque Terre National Park obtained with Machine Learning algorithms

Results of the statistical analysis (Ensemble Weighted mean method)



| Stand-alone methods | AUC |
|---------------------|------|
| GBM | 0.78 |
| ANN | 0.74 |
| MaxEnt | 0.80 |
| Ensemble methods | AUC |
| Mean | 0.89 |
| CA | 0.86 |
| Median | 0.87 |
| Wmean | 0.90 |

AUC values for Machine Learning algorithms used for both stand-alone and ensemble methods

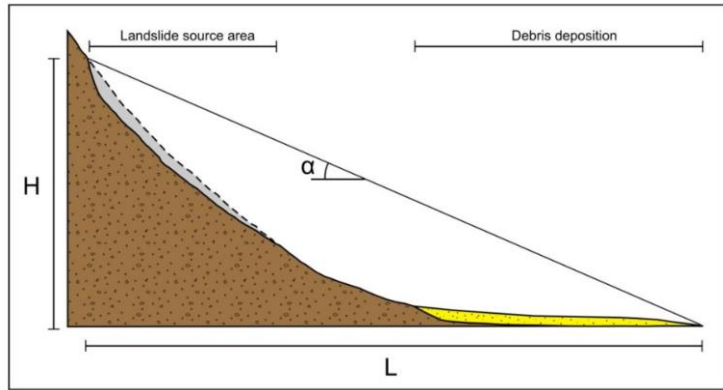
Case study – Cinque Terre – Variable importance

| | | Stand-alone models | | |
|----------------------|------------|--------------------|------|--------|
| | | GBM | ANN | MaxEnt |
| Predisposing factors | aspect | 0.23 | 0.4 | 0.25 |
| | plan_curv | 0.11 | 0.2 | 0.13 |
| | prof_curv | 0.032 | 0.11 | 0.07 |
| | slope | 0.24 | 0.28 | 0.23 |
| | geological | 0.035 | 0.07 | 0.08 |
| | terraces | 0.38 | 0.37 | 0.31 |
| | land_use | 0.087 | 0.11 | 0.06 |
| | streams | 0 | 0.03 | 0.02 |
| | roads | 0 | 0.01 | 0.012 |

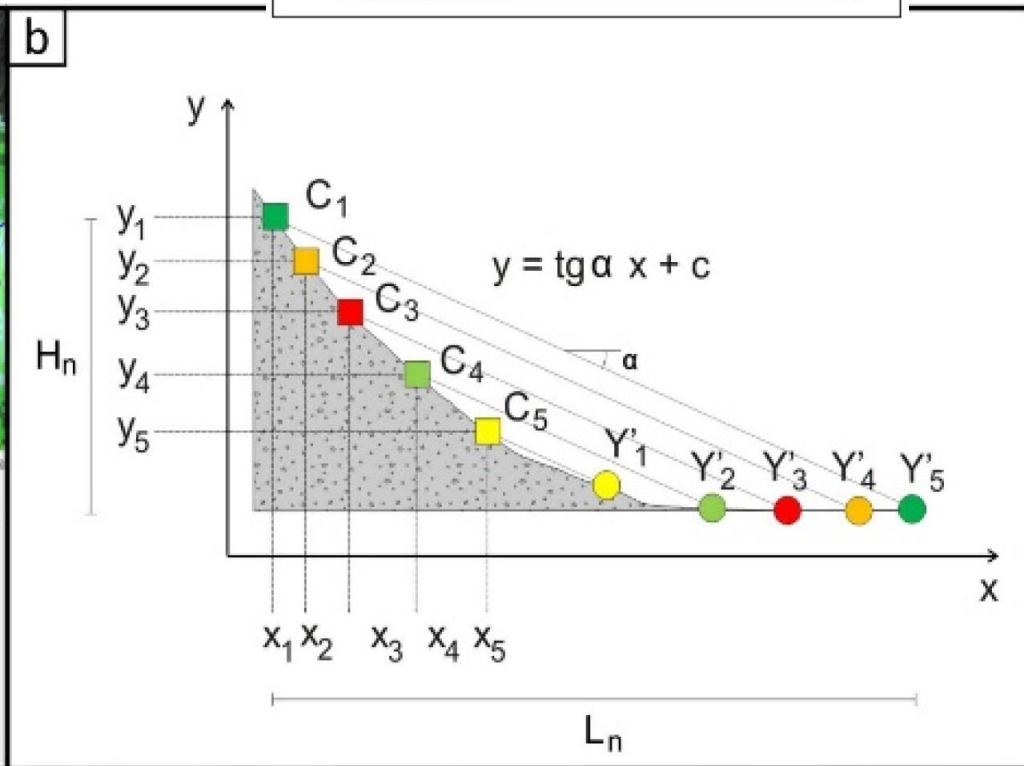
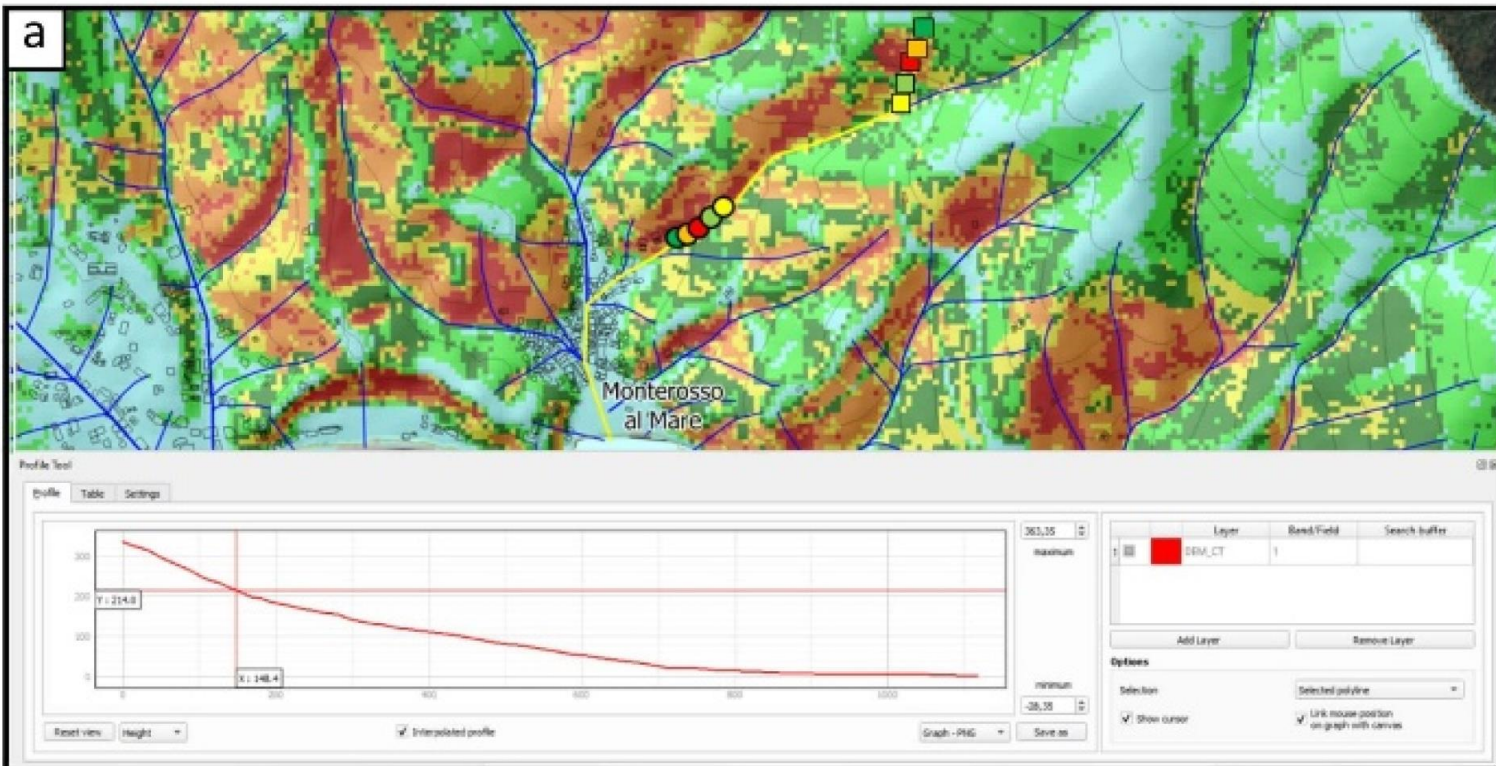
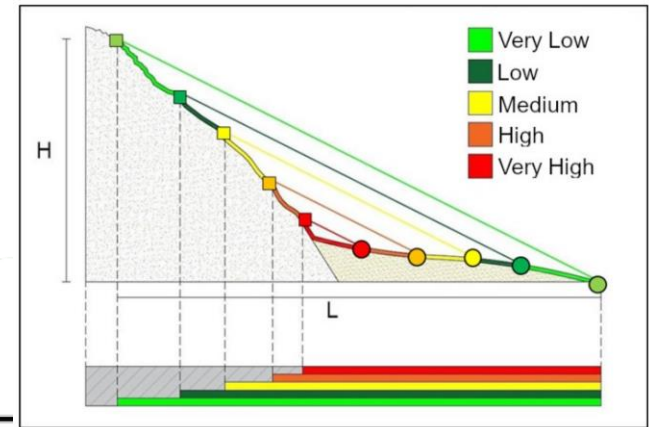
| | | Ensemble models | | |
|----------------------|------------|-----------------|-------|--------|
| | | Mean | Wmean | Median |
| Predisposing factors | aspect | 0.24 | 0.24 | 0.25 |
| | plan_curv | 0.12 | 0.12 | 0.12 |
| | prof_curv | 0.04 | 0.04 | 0.04 |
| | slope | 0.22 | 0.22 | 0.245 |
| | geological | 0.04 | 0.04 | 0.05 |
| | terraces | 0.38 | 0.38 | 0.37 |
| | land_use | 0.06 | 0.06 | 0.06 |
| | streams | 0 | 0 | 0 |
| | roads | 0 | 0 | 0 |

 Variables' importance values of stand-alone and ensemble models.

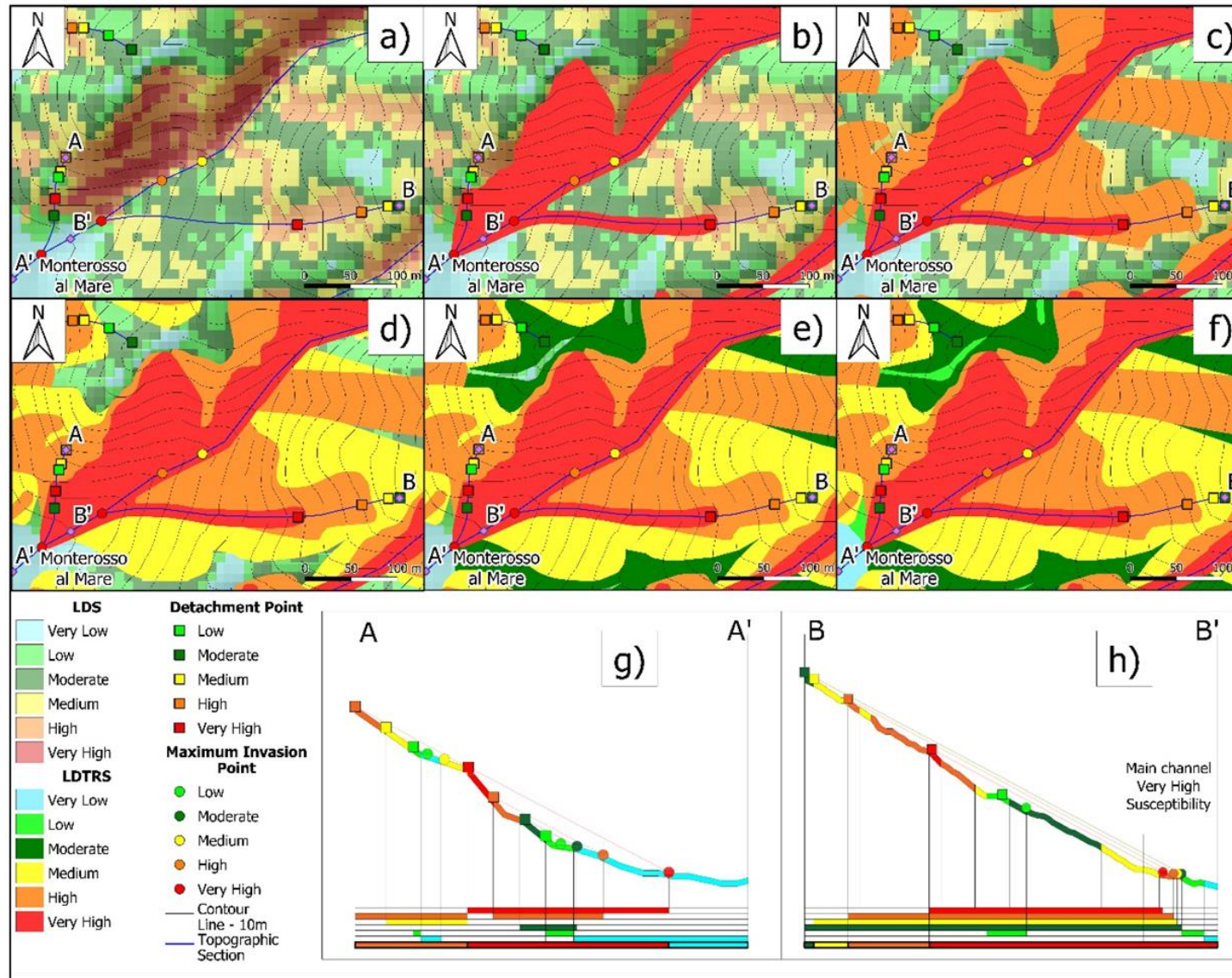
Case study – Cinque Terre – Run-out estimation



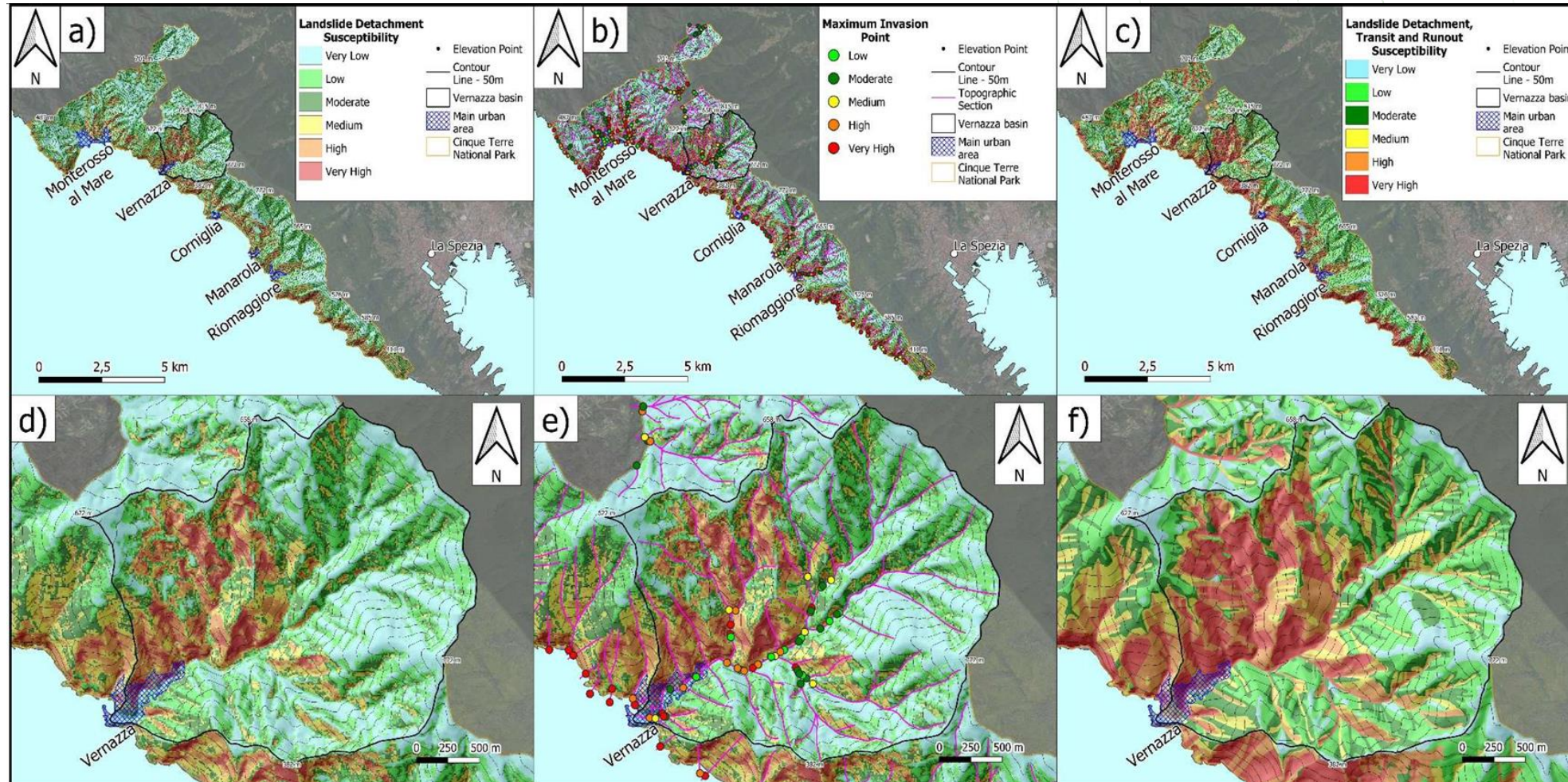
Reach angle method



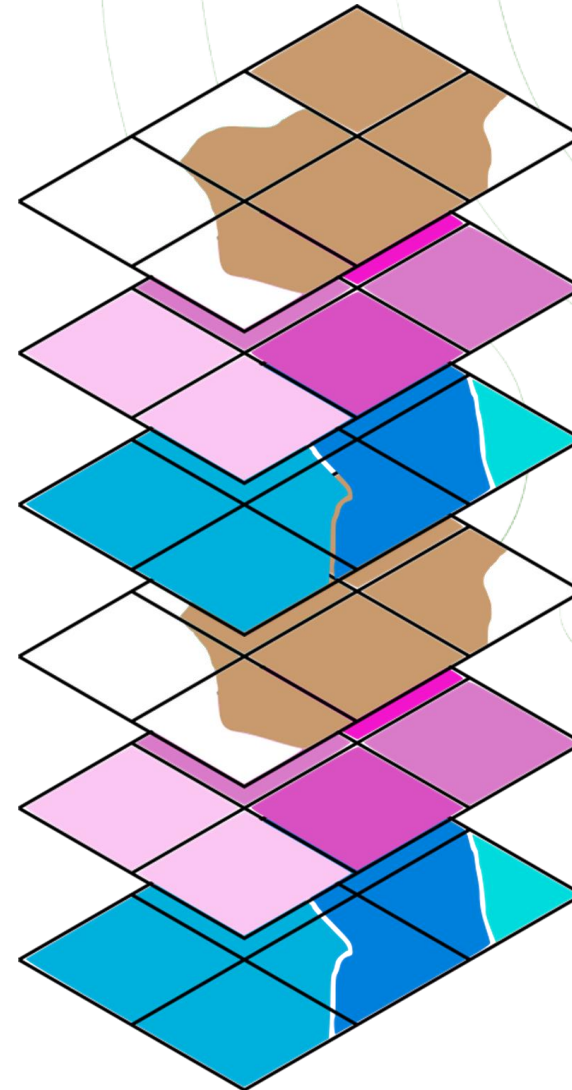
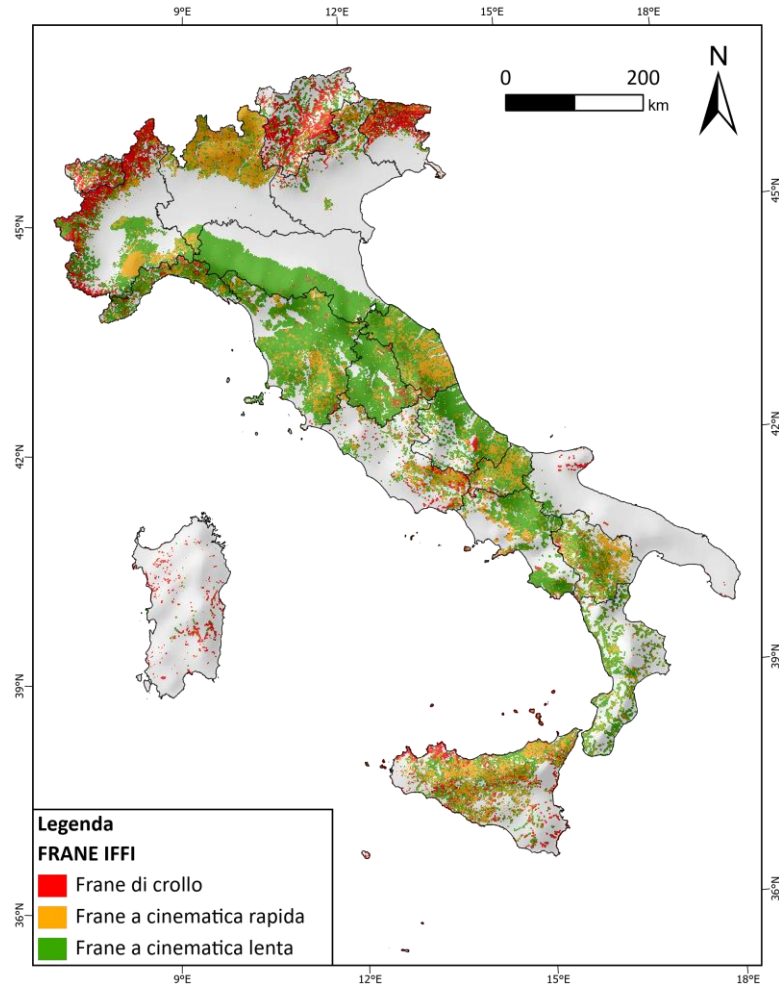
Case study – Cinque Terre – Run-out estimation




Case study – Cinque Terre – Run-out estimation



Landslide susceptibility and risk at national scale



 QRA at basin scale
Italy
Caleca et al. 2022



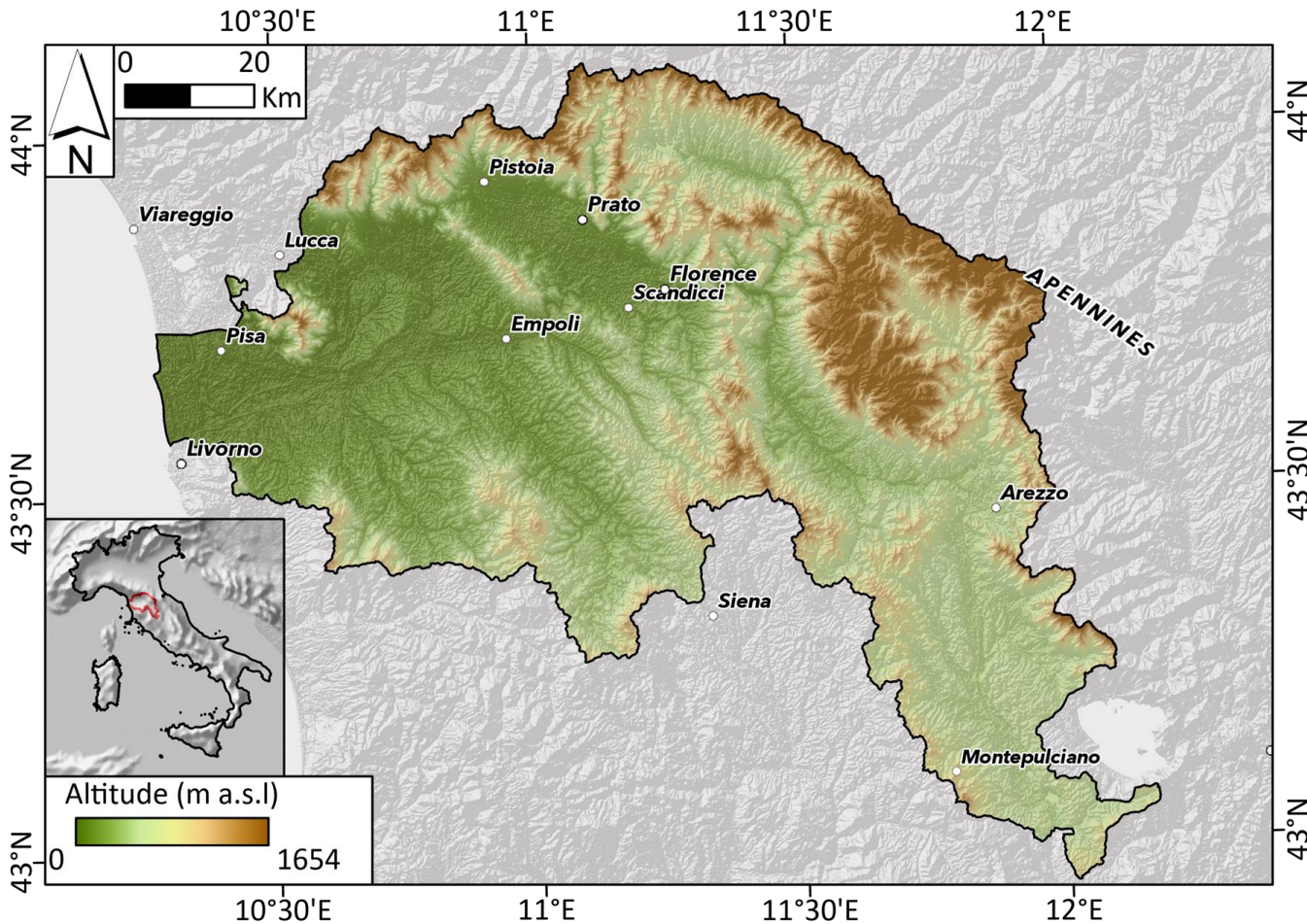
Objectives

- 🌐 Implement an approach to quantitatively assess risk for slow-moving landslides in terms of possible economic losses to buildings and land use
- 🌐 Define a replicable nationwide (Italy) methodology
- 🌐 Verify the soundness of outcomes

Motivation and research question

- 🌐 Risk assessment is a powerful tool for measuring the severity of landslides to properties and population, allocate resources and define priorities of intervention
- 🌐 QRA studies are generally focused on site specific or limited area cases
- 🌐 Can we go beyond this “limit” of the scale of analysis?

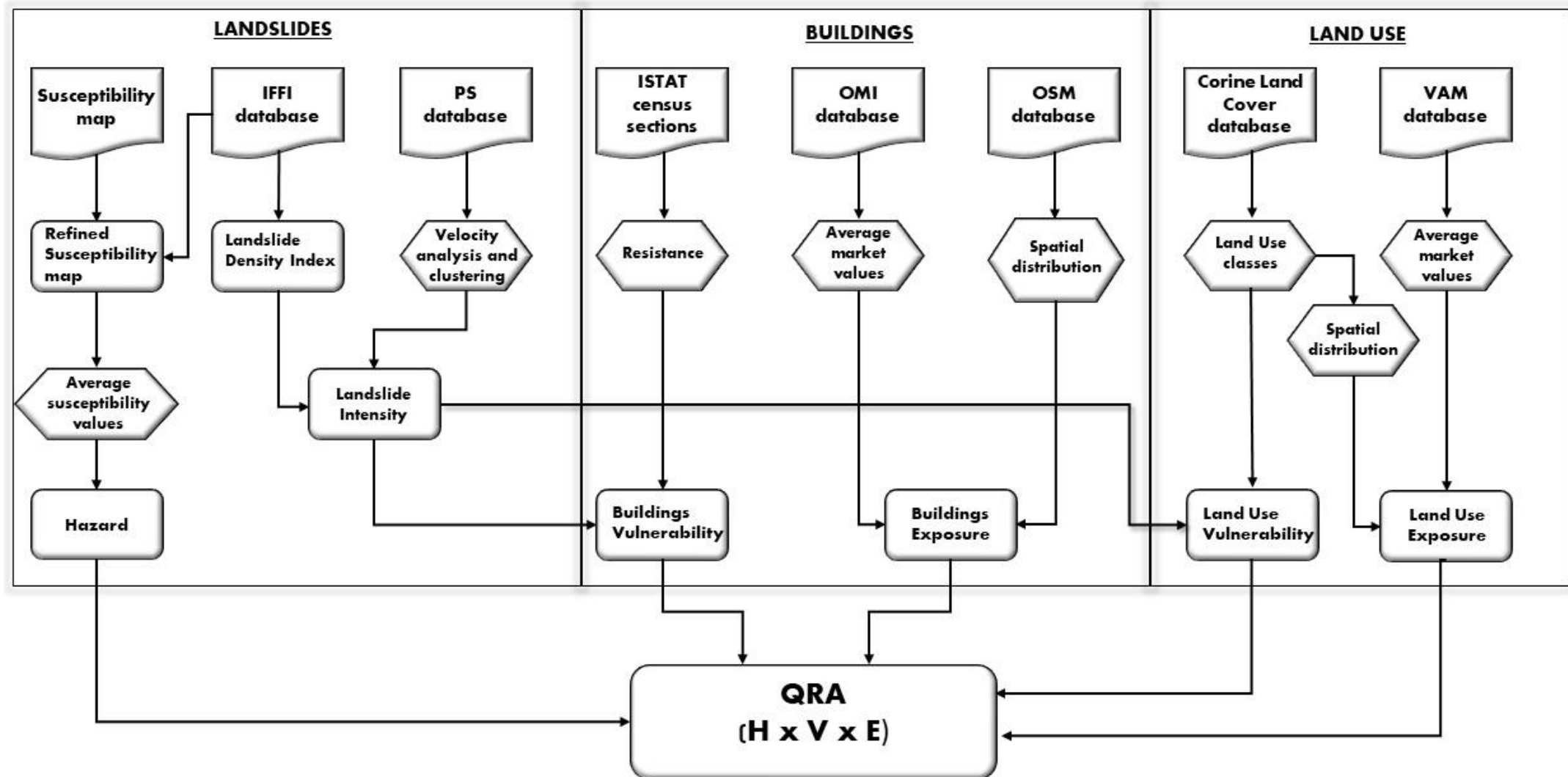
Arno basin case study



Arno River basin (9100 km²)

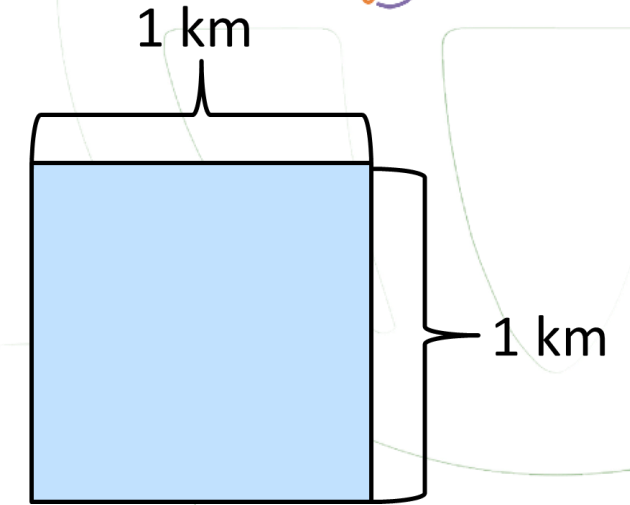
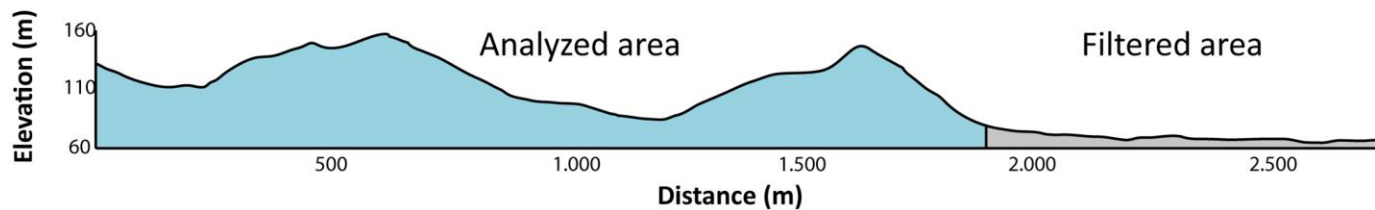
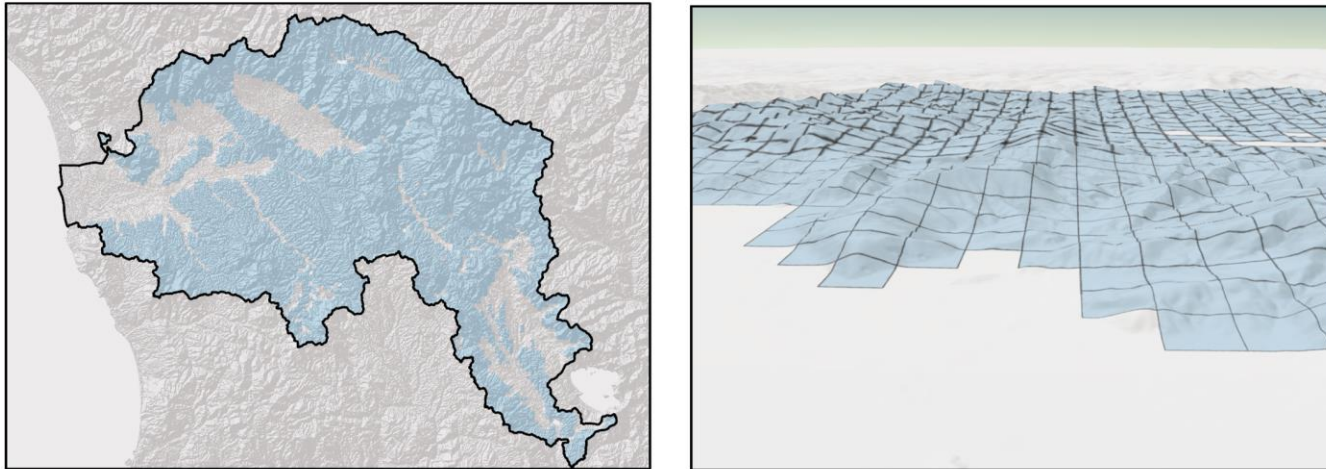
| Input data | Parameter |
|---------------------------------------|--|
| DTM (10m) | Grid analysis |
| Italian landslide inventory (IFFI) | Hazard and Intensity |
| Landslide susceptibility map of Italy | Hazard |
| Satellite InSAR data | Intensity |
| ISTAT census sections | Building structural resistance – Building Vulnerability |
| Real estate market observatory (OMI) | Building values (€) – Building Exposure |
| Open Street Map | Building footprint – Building Exposure |
| CORINE Land Cover | Land use spatial distribution – Land use Vulnerability and Exposure |
| Mean Agricultural Values (VAM) | Land use values (€) – Land use Exposure |

Arno basin case study – Methodology



Arno basin case study – Mapping unit

- Regular grid with 1 km² spatial resolution
- Flat areas removed

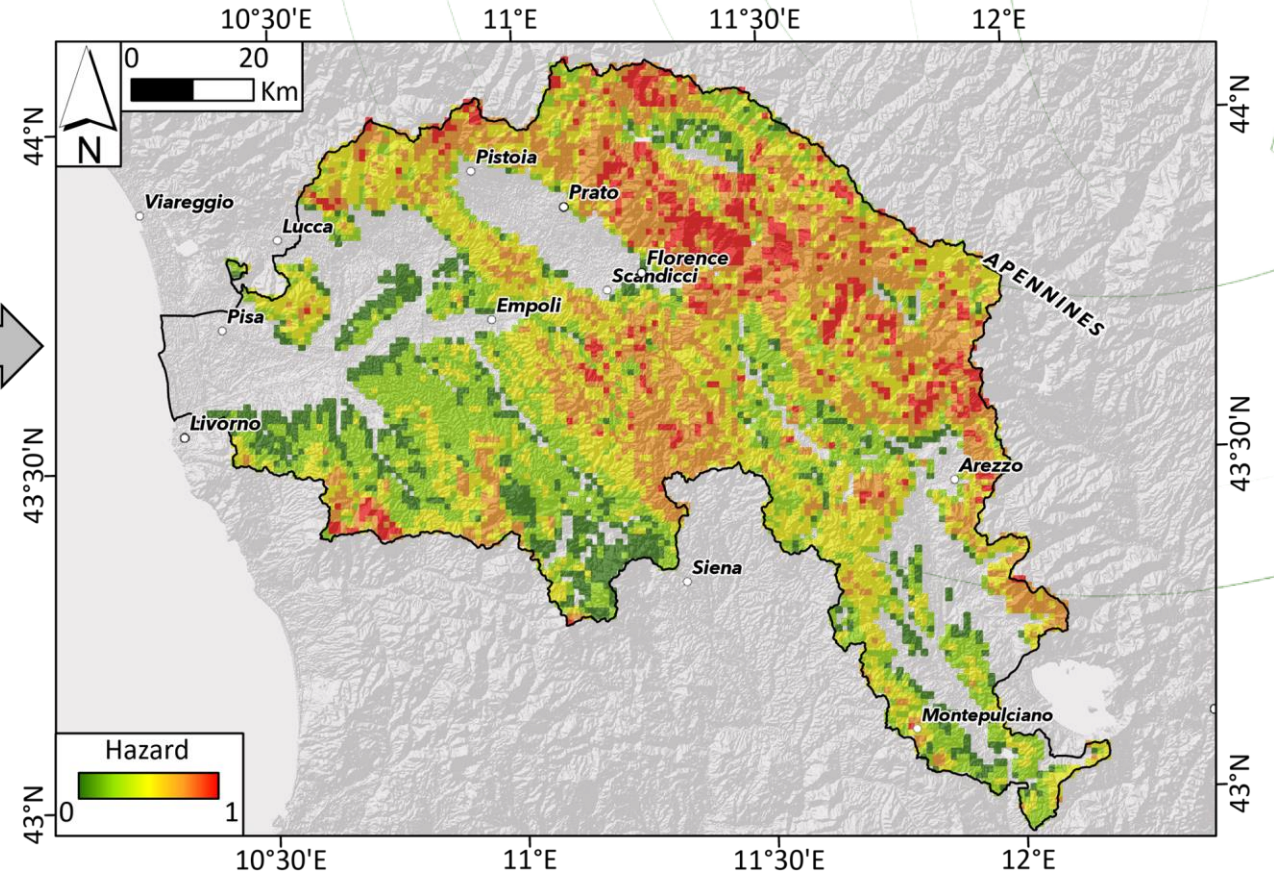
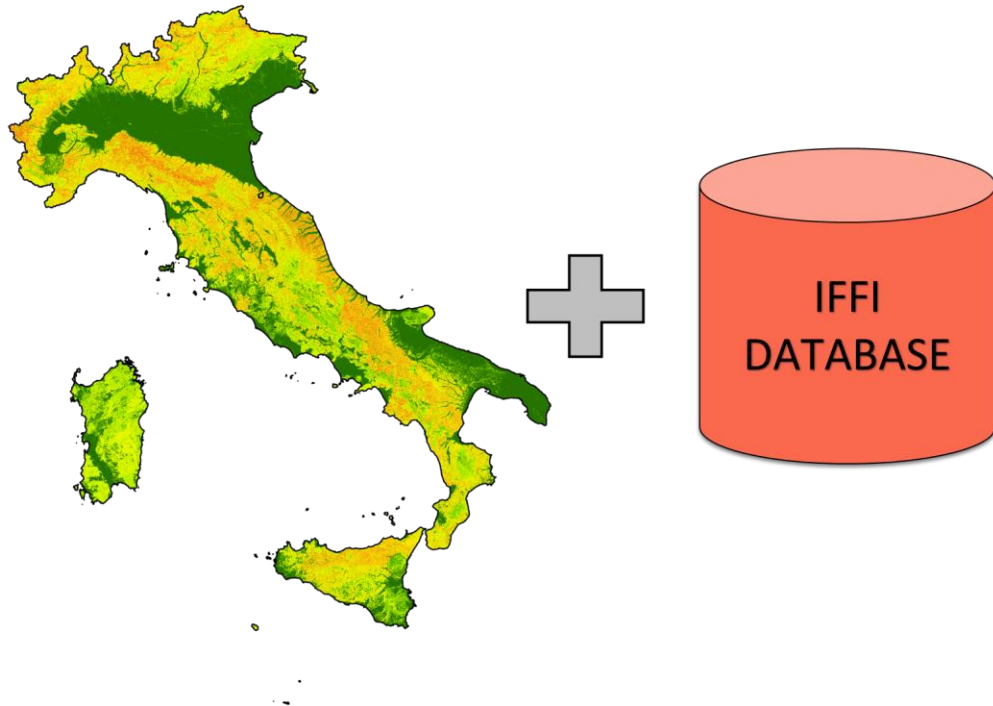


$$\text{Risk} = H \times V(I) \times E$$

H = Hazard
V = Vulnerability
I = Intensity
E = Exposure

Arno basin case study – Hazard

Hazard was approximated to Susceptibility.

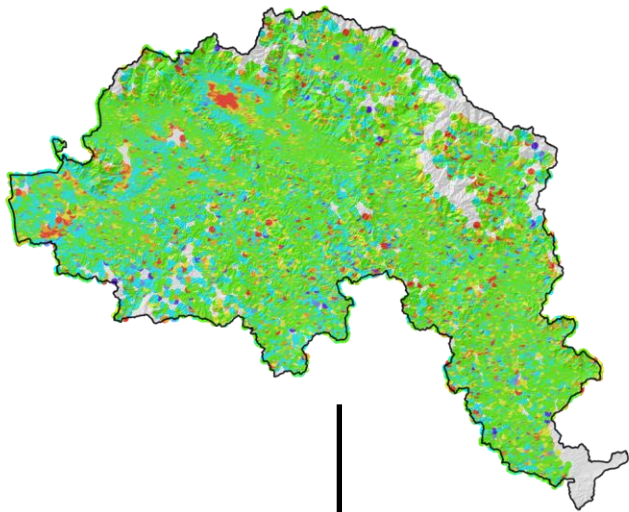


Map from [Trigila et al. \(2013\)](#)

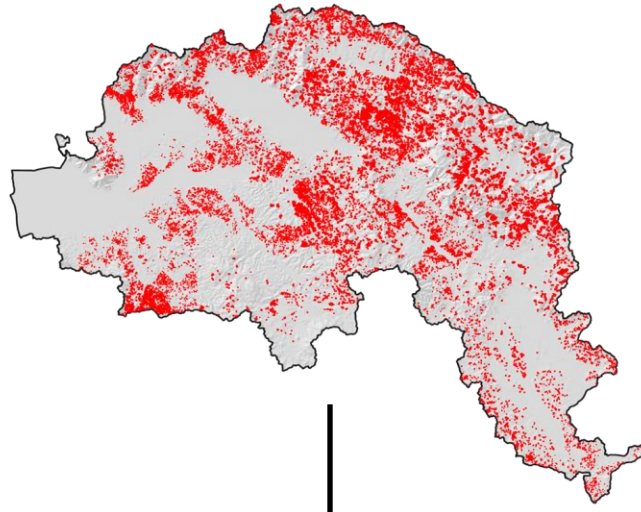
Arno basin case study – Vulnerability – Landslide Intensity

Vulnerability = f (Landslide Intensity, Response of exposed element)

- where **Landslide Intensity** = f (Landslide Area, Landslide Velocity)

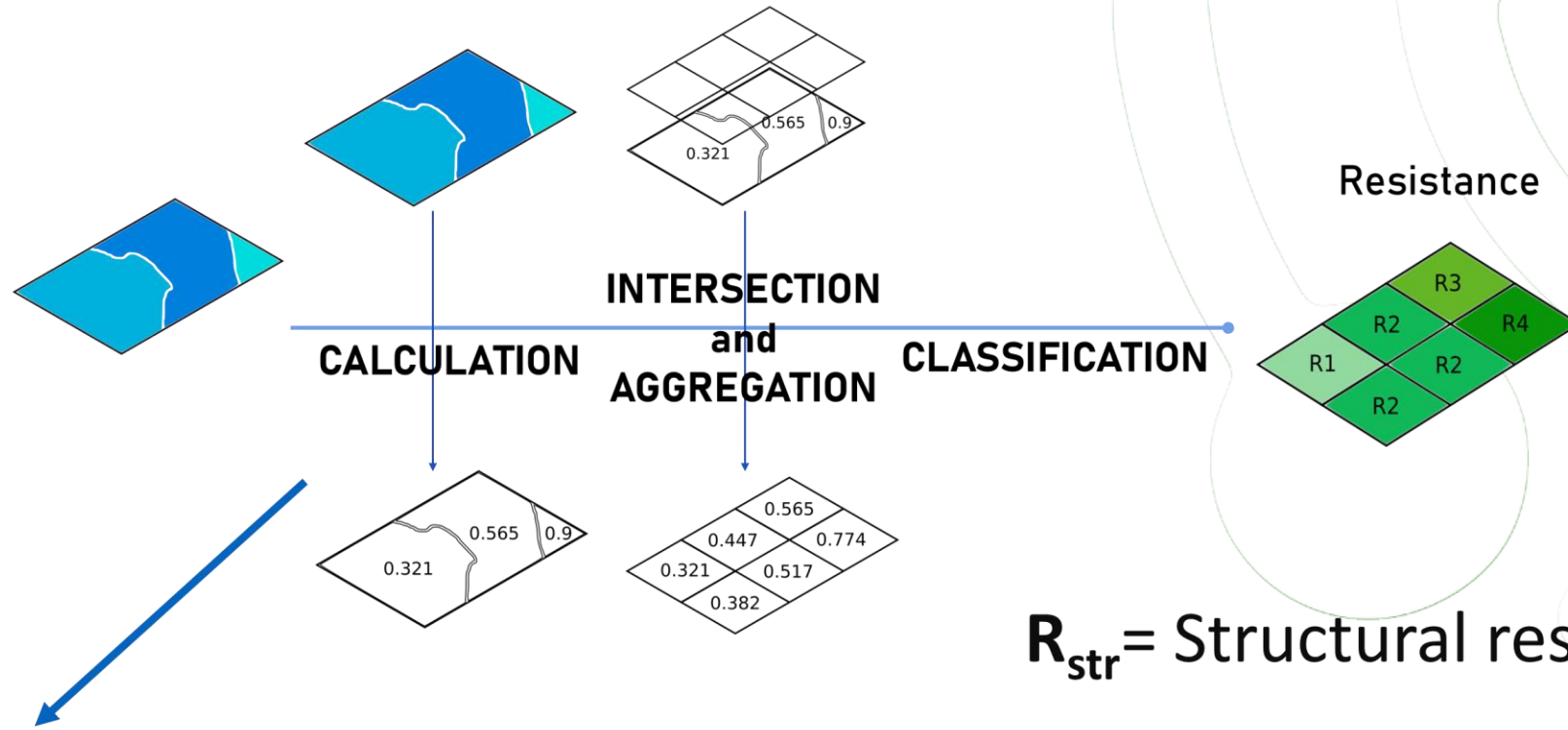


Ground deformation velocity



Landslide area

| | Vel < 4mm/yr | 4mm/yr < Vel < 16mm/yr | Vel > 16mm/yr | No Vel |
|----|--------------|------------------------|---------------|--------|
| A0 | I0 | I1 | I2 | I0 |
| A1 | I1 | I2 | I3 | I1 |
| A2 | I2 | I3 | I4 | I2 |
| A3 | I3 | I4 | I4 | I3 |



$$R_{str} = (\epsilon_{sty} \cdot \epsilon_{sht} \cdot \epsilon_{smn})^{1/3}$$

Modified from Li et al., 2010

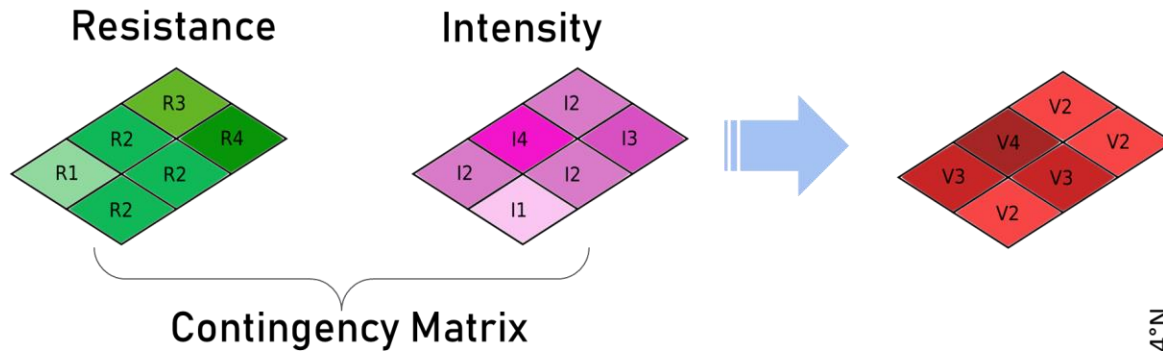
R_{str} = Structural resistance

ϵ_{sty} = type of material construction

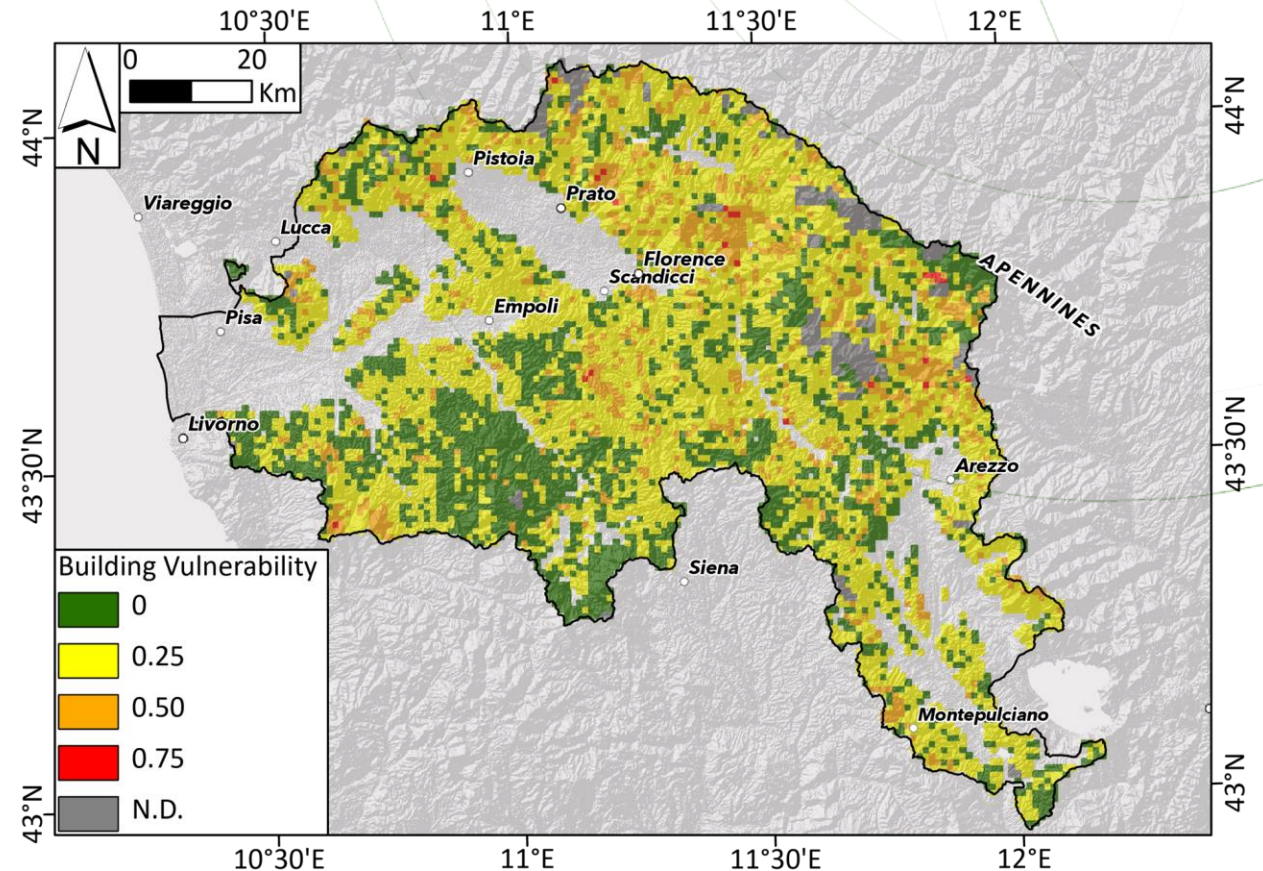
ϵ_{sht} = number of floors

ϵ_{smn} = maintenance state

Arno basin case study – Building Vulnerability



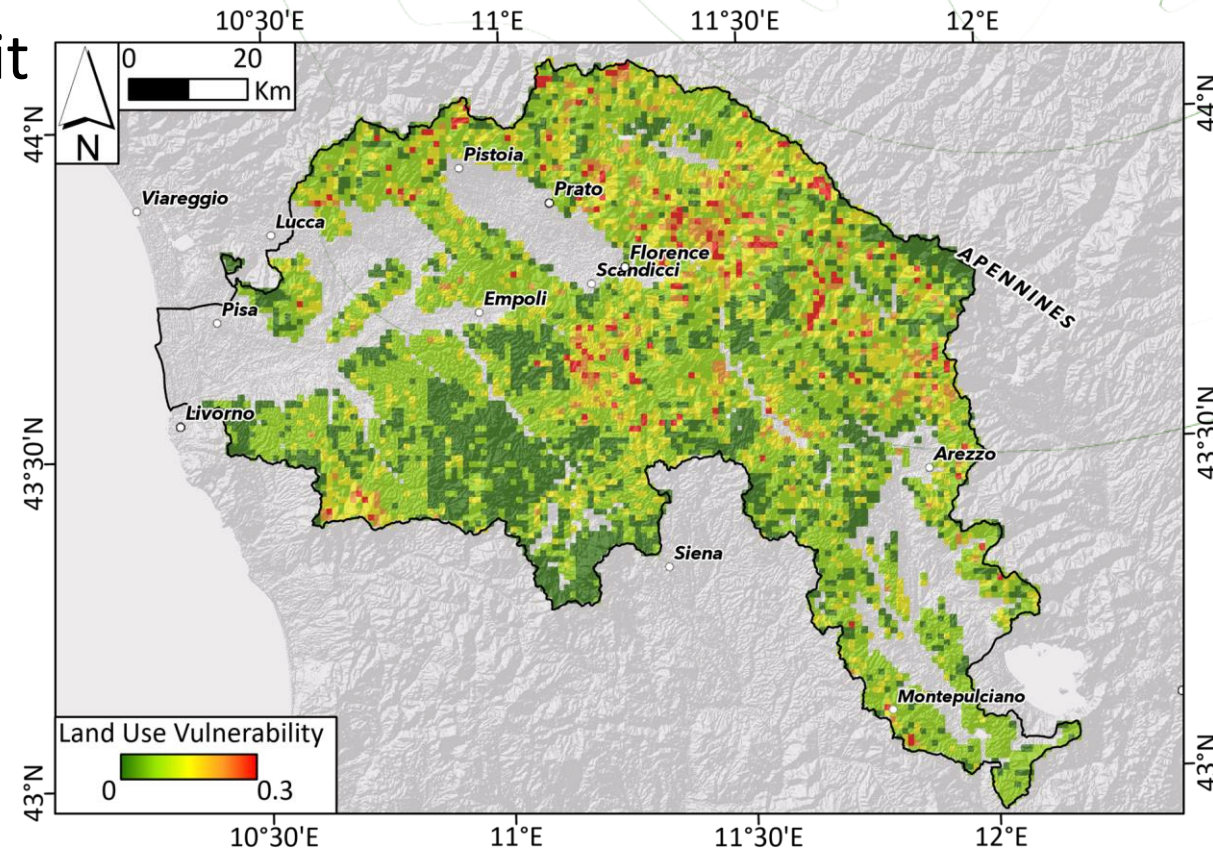
| | I0 | I1 | I2 | I3 | I4 |
|------|------|------|------|------|------|
| R4 | 0 | 0.25 | 0.25 | 0.50 | 0.75 |
| R3 | 0 | 0.25 | 0.50 | 0.75 | 1 |
| R2 | 0 | 0.50 | 0.75 | 0.75 | 1 |
| R1 | 0 | 0.50 | 0.75 | 1 | 1 |
| R0 | 0 | 0.75 | 1 | 1 | 1 |
| N.D. | N.D. | N.D. | N.D. | N.D. | N.D. |



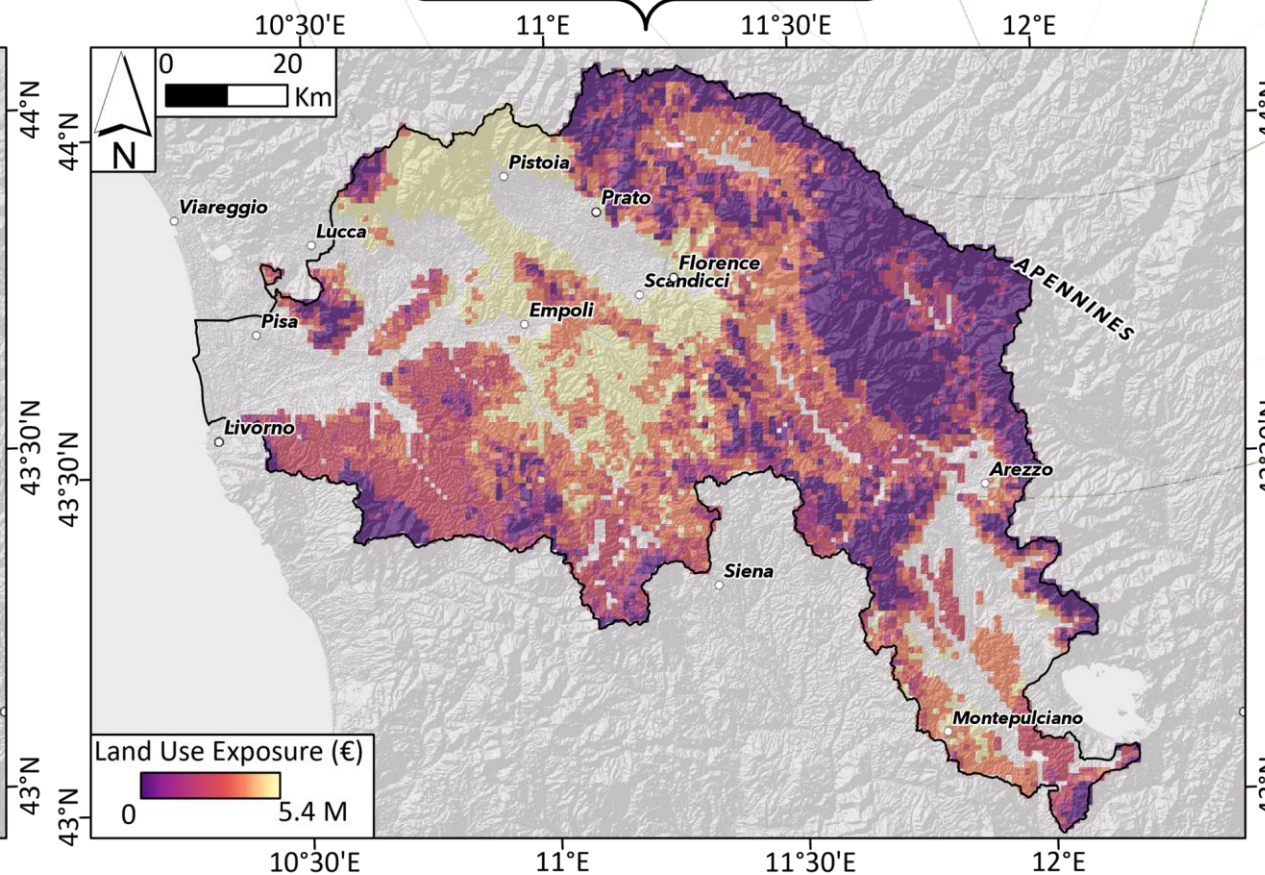
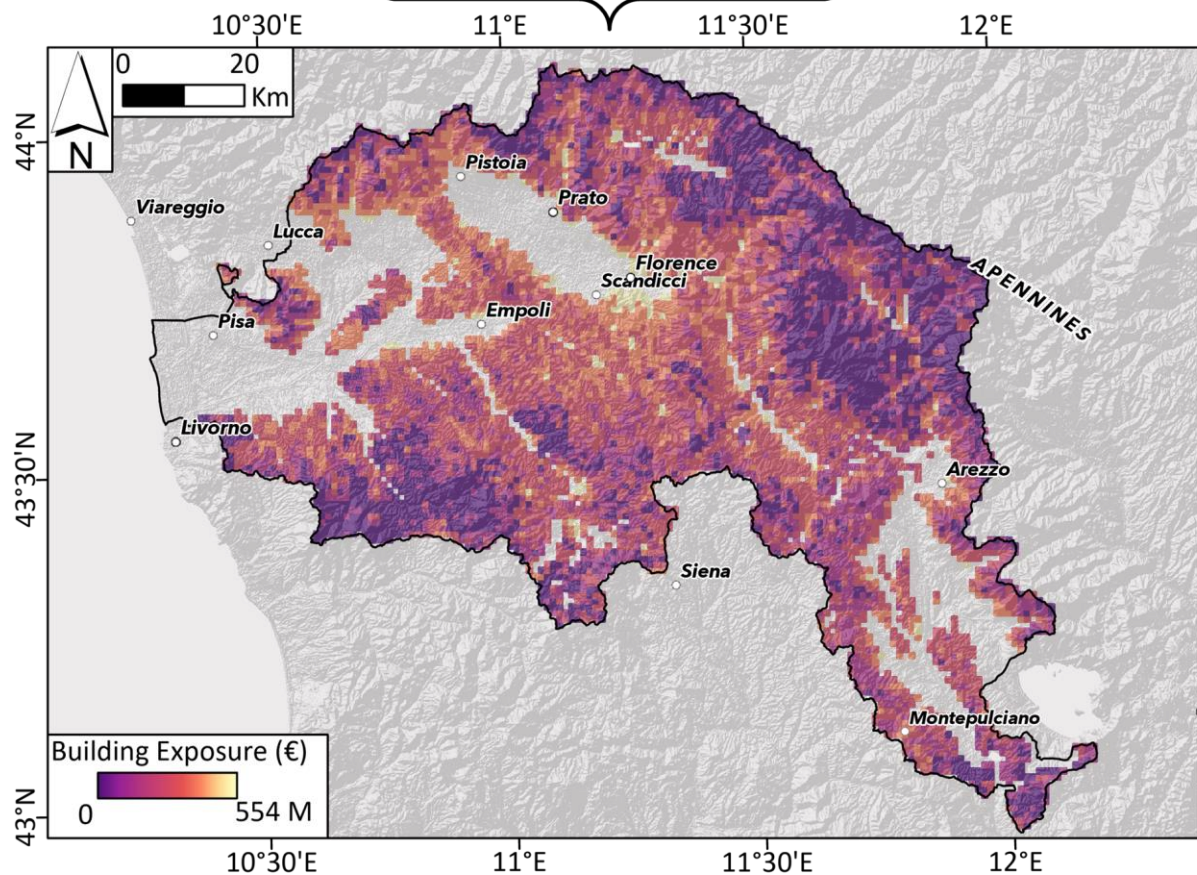
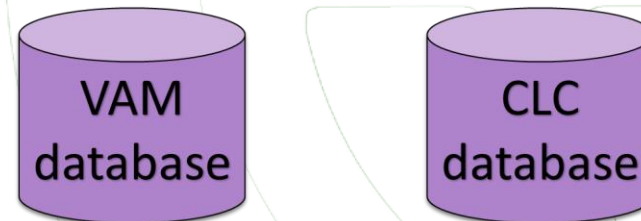
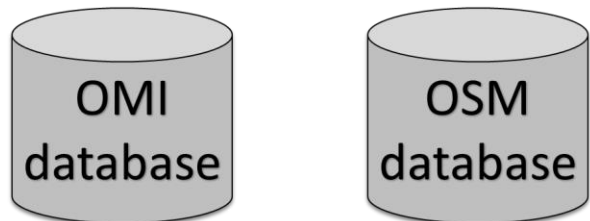
Arno basin case study – Land Use Vulnerability

- Reclassification CORINE Land Cover into 6 classes
- Definition of a vulnerability value for each class
- Vulnerability of land use within mapping unit

| | I0 | I1 | I2 | I3 | I4 |
|--------------------|----|------|------|------|------|
| Agricultural Areas | 0 | 0.05 | 0.15 | 0.2 | 0.25 |
| Permanent Crops | 0 | 0.05 | 0.1 | 0.2 | 0.3 |
| Grasslands | 0 | 0.05 | 0.1 | 0.15 | 0.2 |
| Woods | 0 | 0.05 | 0.1 | 0.2 | 0.3 |
| Shrubs | 0 | 0 | 0 | 0.05 | 0.1 |
| Water | 0 | 0 | 0 | 0.05 | 0.1 |



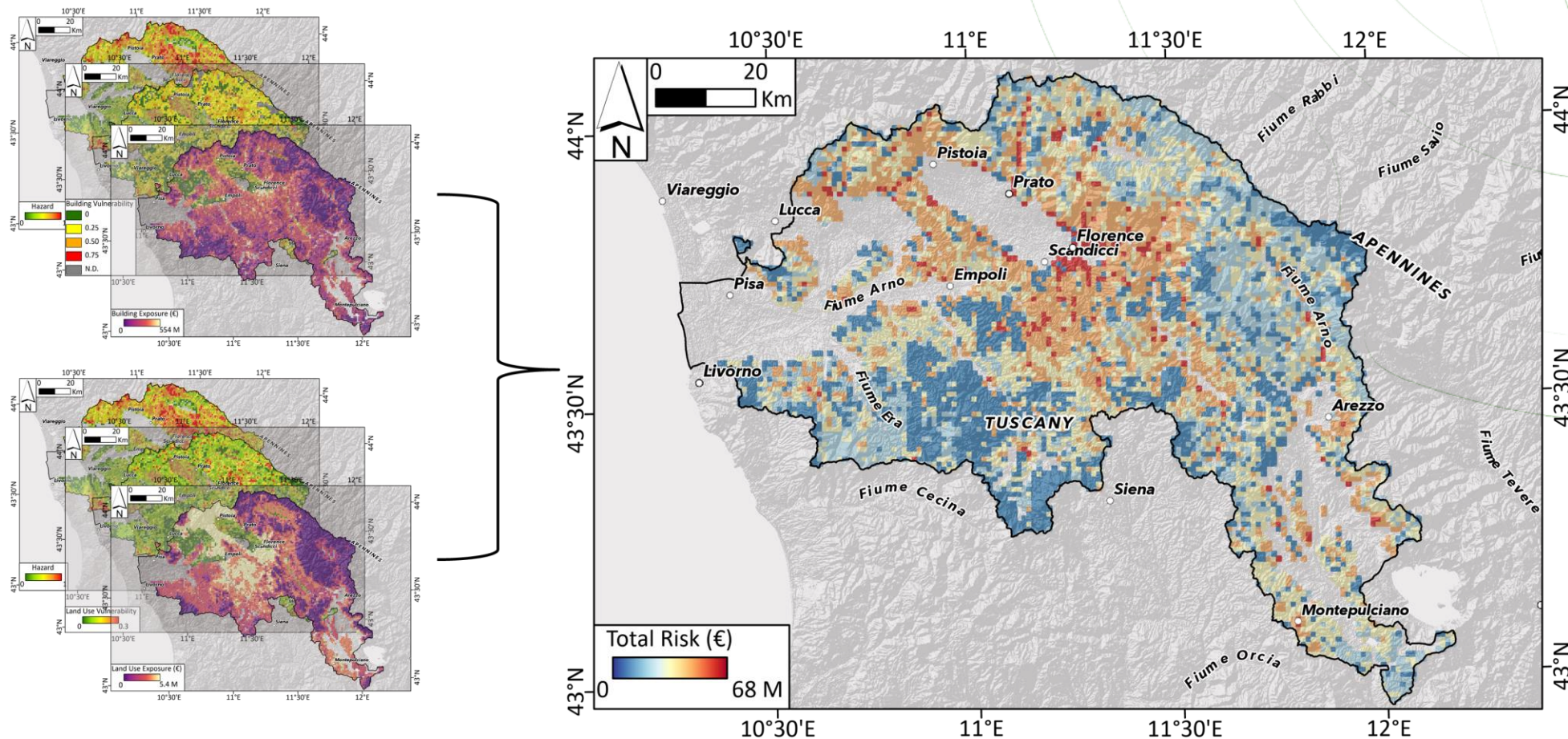
Arno basin case study – Exposure



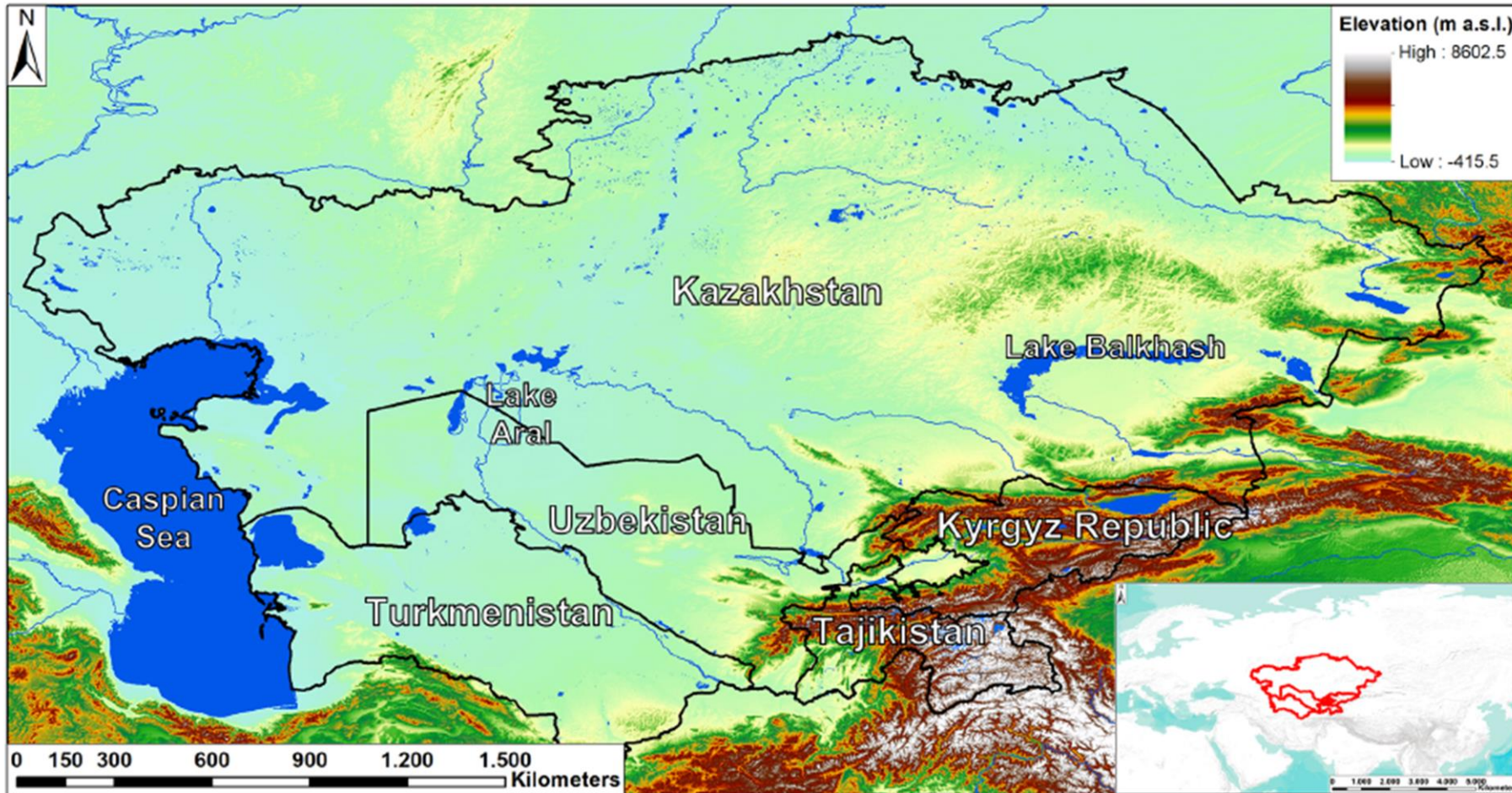
Arno basin case study – Risk

Risk (element) = Hazard x Vulnerability (element) x Exposure (element)

Total Risk (€) = Building Risk (€) + Land use Risk (€)



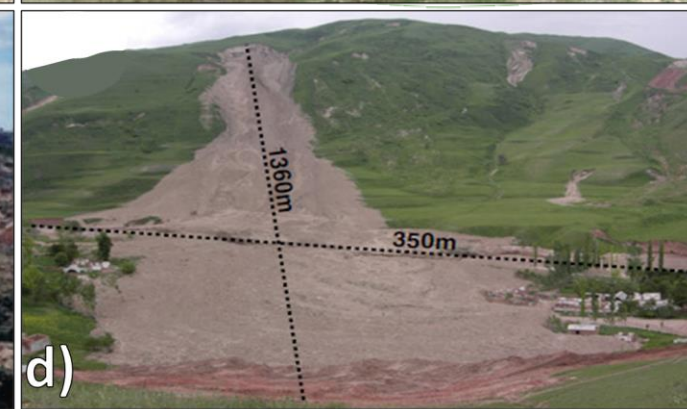
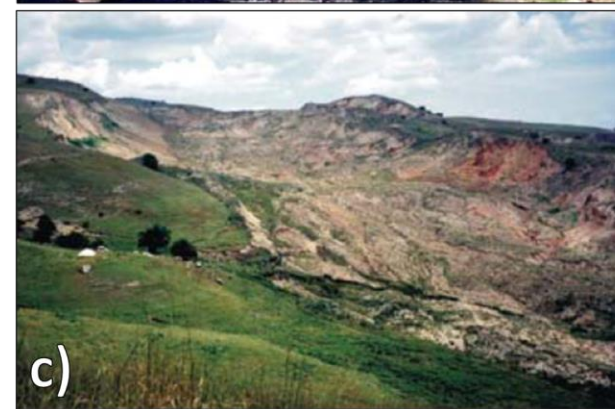
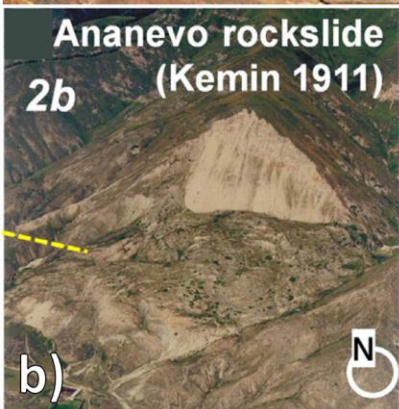
Central Asia - Case study



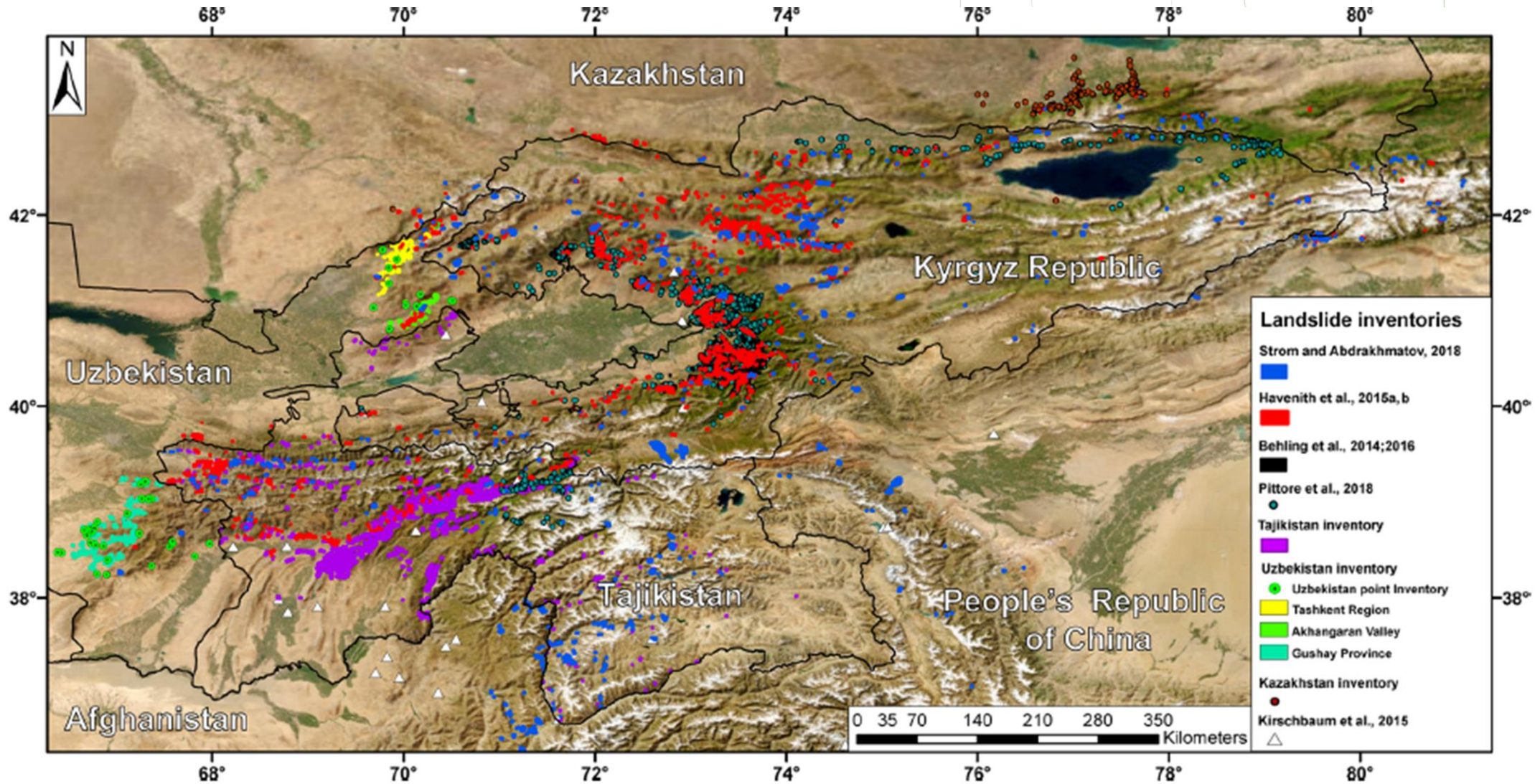
Caleca et al. (2023)

Central Asia - Case study

- In CA landslide phenomena are triggered by natural events such as earthquakes, floods, rainfall and snowmelt
- In the past few decades, the number and intensity of landslides have grown owing to climate change and the increase of the anthropic pressure (uncontrolled land and water use, rising of the water tables due to the increase of irrigation, deforestation, mining and excavation activities).



Central Asia - Landslide inventories

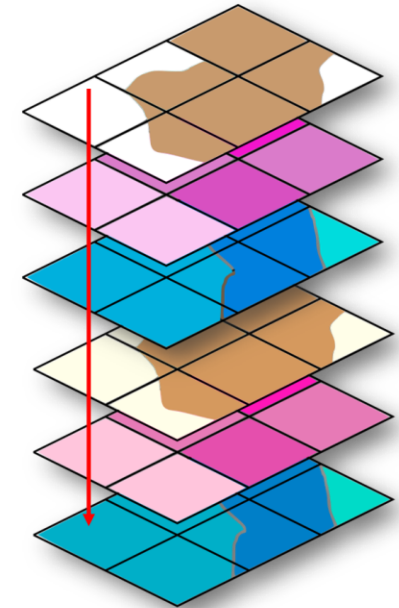


Central Asia - Landslide susceptibility

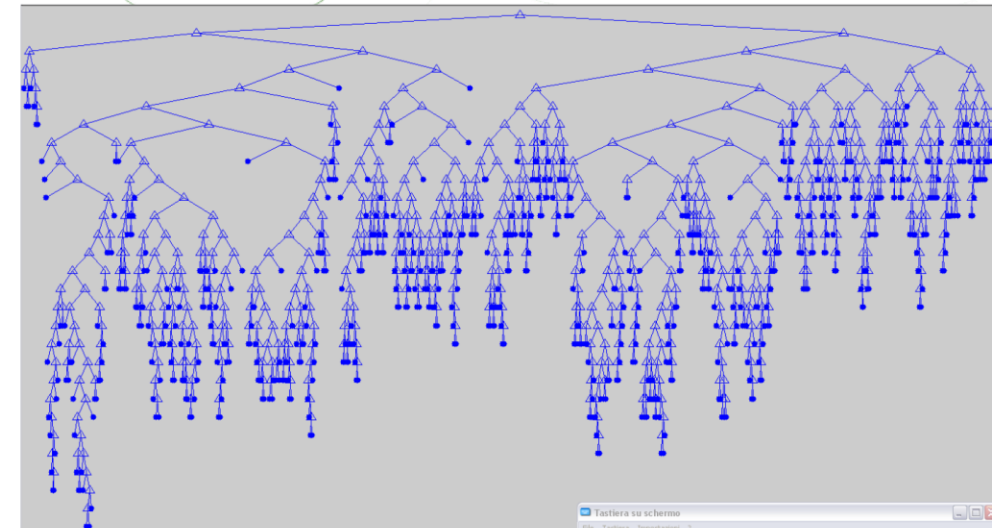
🌐 Random forest model

Strong Points:

- Both categorical and numerical variables can be used
- No assumption about the statistical distribution of the data
- It accounts for interactions and nonlinearities between variables
- Avoid overfitting
- It allows exploring a large number of explanatory variables at the same time
- It's unambiguous and objective



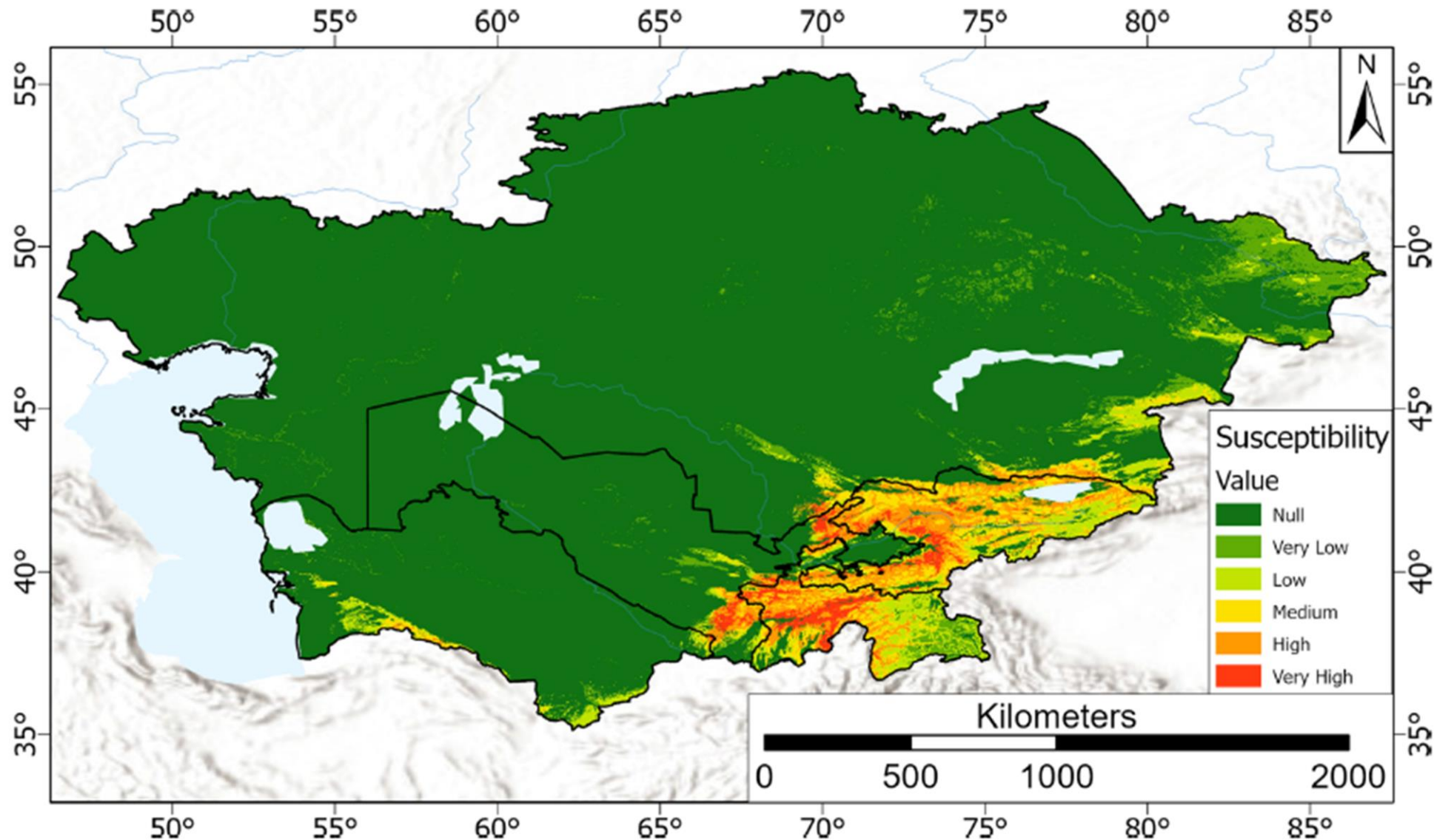
- pixel- based approach
- pixel size: 70 m
- about $2.2 * 10^9$ pixels analyzed



Central Asia - Landslide susceptibility

- 🌐 MERIT DEM and DEM-derived products. This includes aspect, slope gradient, total curvature, profile curvature, planar curvature, flow accumulation, topographic wetness index (TWI), stream power index (SPI), and topographic position index (TPI).
- 🌐 Lithology. This is derived from the geological map of the former Soviet Union made by the USGS (Persits et al., 1997).
- 🌐 Soil-type map. This is taken from the Digital Soil Map of the World (DSMW) database (Copernicus land use; <https://land.copernicus.eu/>, last access: 27 July 2022).
- 🌐 Distance from faults. It is the minimum distance, in meters, between each landslide and the nearest fault. The fault database is derived from the AFEAD catalogue (Styron and Pagani, 2020) and was modified after Poggi et al. (2023a).
- 🌐 Distance from roads. It is the minimum distance, in meters, between each landslide and the nearest road. The road database is derived from Scaini et al. (2023).
- 🌐 Distance from rivers. It is the minimum distance, in meters, between each landslide and the nearest river. The river network database is derived from Coccia et al. (2023).
- 🌐 Distance from hypocenters. It is the minimum distance, in meters, between each landslide and the nearest earthquake hypocenter with a magnitude greater than 6.5 (following the methodology adopted by Havenith et al., 2015a). The hypocenter database was provided by Poggi et al. (2023a).
- 🌐 Peak ground acceleration (PGA). Four kinds of PGA maps according to different return times (475 and 1000 years) and different materials (soil layers and bedrock) to which it refers were created (Poggi et al., 2023b).
- 🌐 Rainfall distribution maps . Derived from ERA5 database

Central Asia - Landslide susceptibility



 Elements at risks: population , buildings and transportation systems

Population exposure

Source: high-resolution global-scale dataset + national census data

Output : total number of inhabitants in each cell (100 m resolution)

Building exposure

Source: literature

Type of buildings: residential and commercial

Output : economic value of both residential and commercial buildings at 200 m resolution

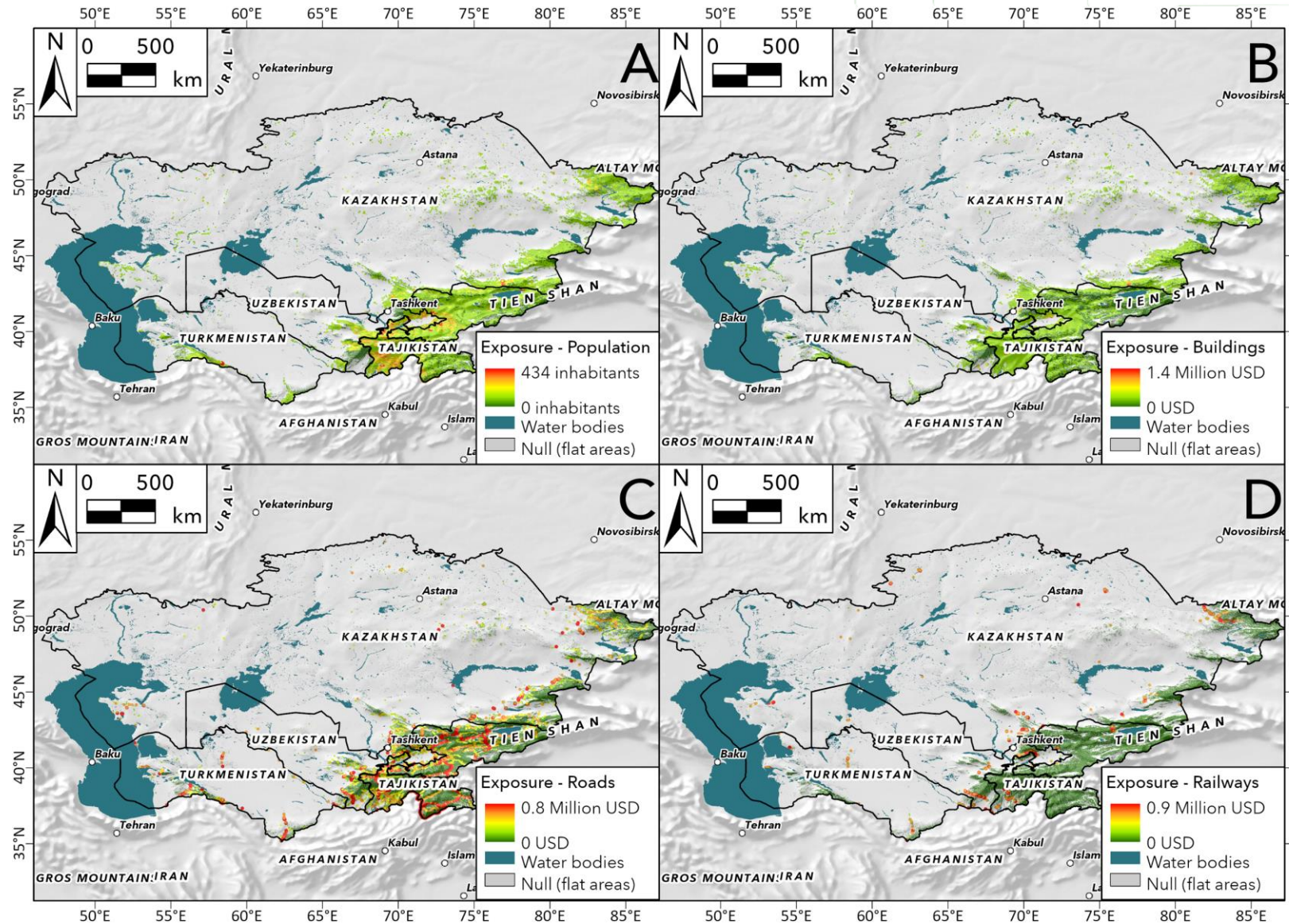
Trasportation exposure

Source: Open Street Map data + reconstruction costs

Type of transportation: roads and railways

Output : total reconstruction cost is defined for each linear infrastructure sub-type by multiplying its length and reconstruction cost (USD/m) within each cell at 200m resolution

Central Asia - Exposure



Central Asia -QRA

Hazard= Susceptibility

Vulnerability = 1

Spatial resolution = 200-m grid

Population risk

$$R_p = H \times P$$

R_p is the number of lives potentially at risk,

H is hazard

P is the mean number of inhabitants within each cell of the grid analysis.

Total risk

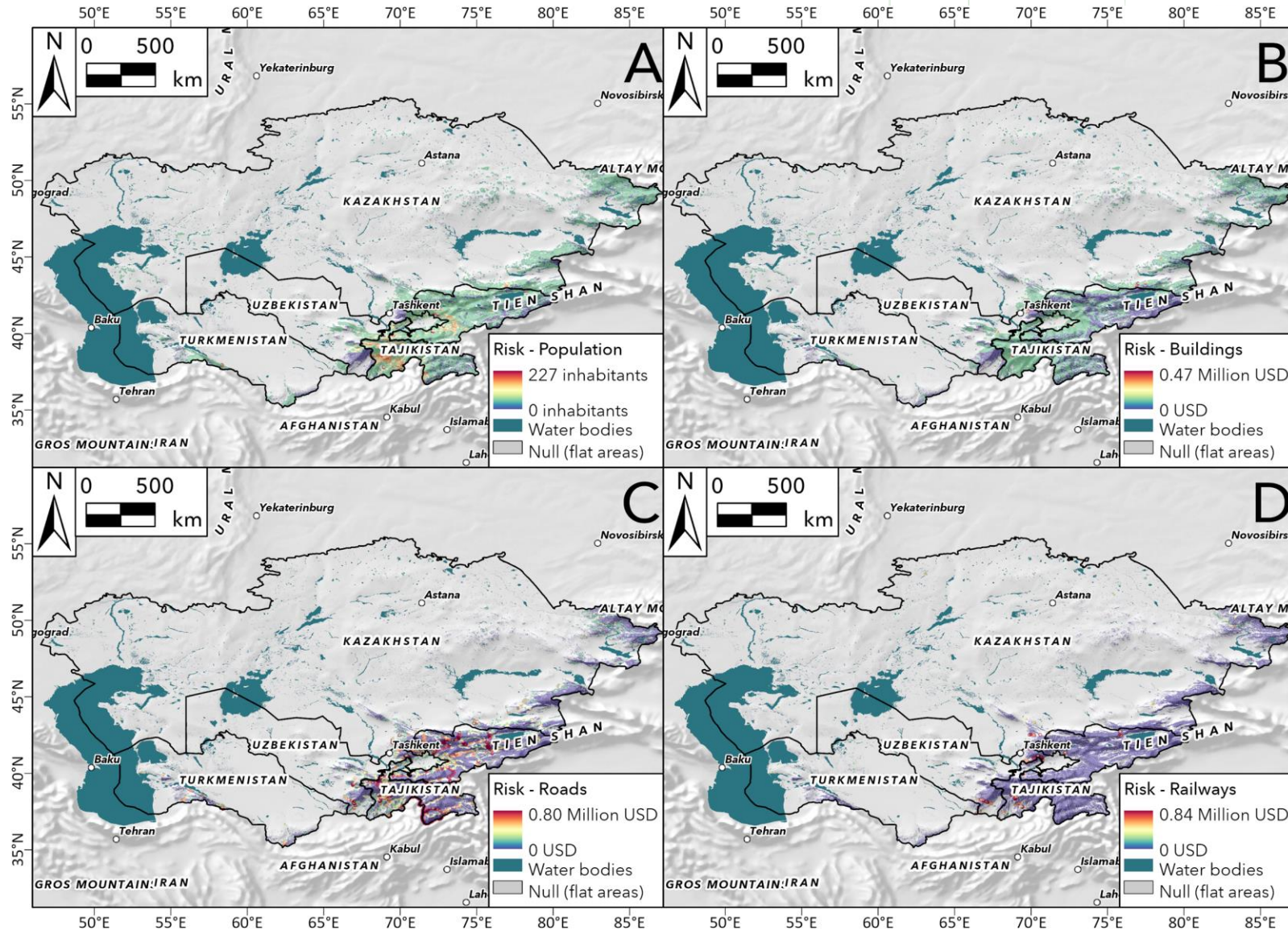
$$R_{tot} = R_b + R_{ro} + R_{ra}$$

R_b risk of building

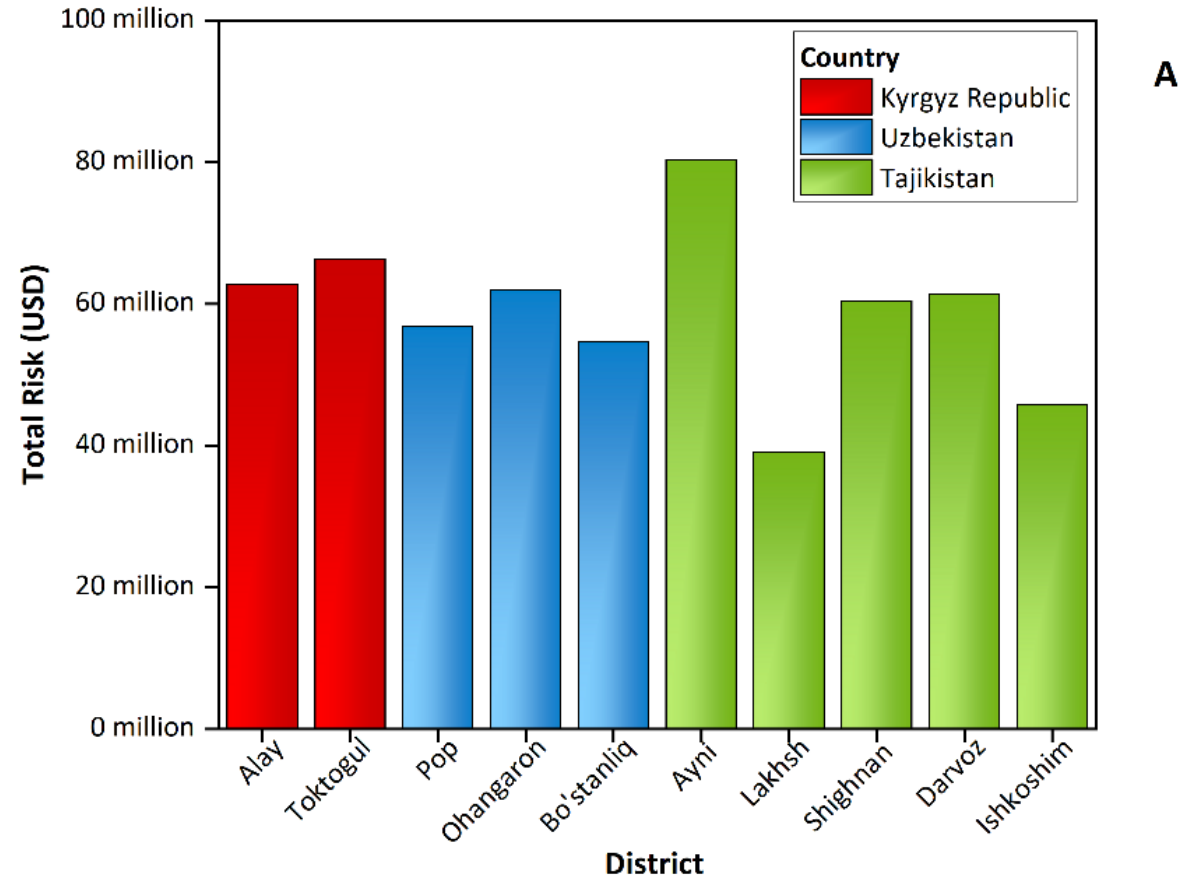
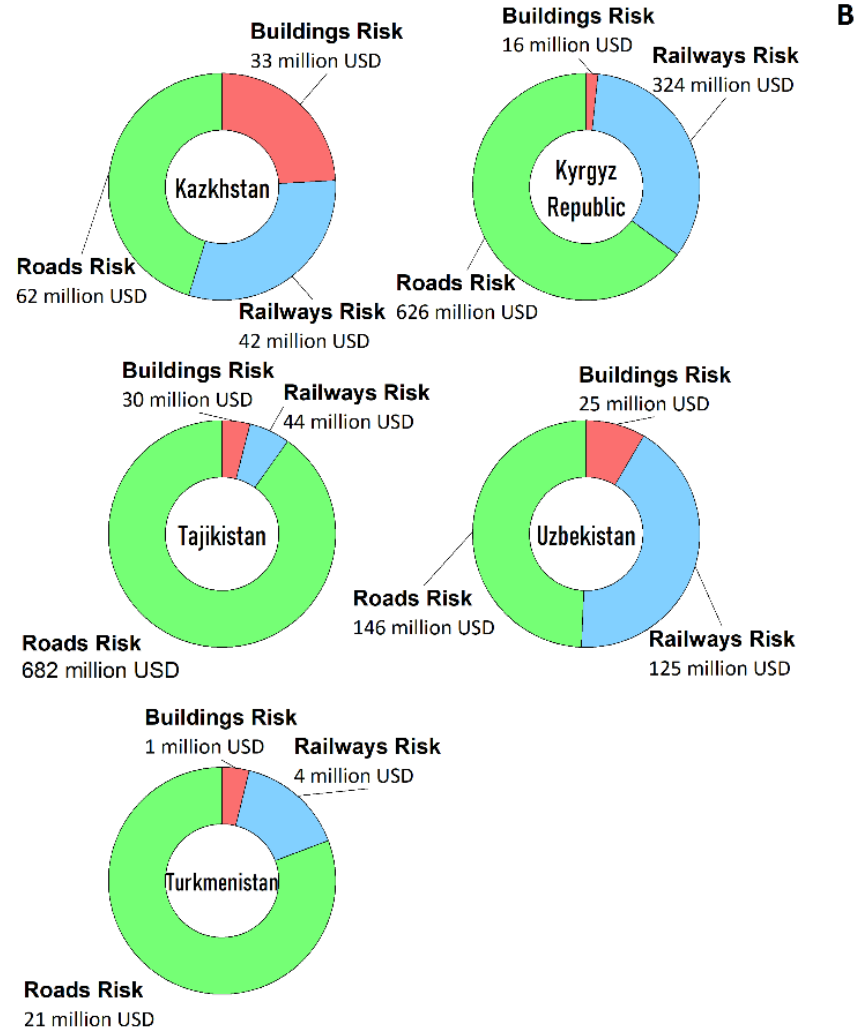
R_{ro} risk of roads

R_{ra} risk of railways

Central Asia -QRA



Central Asia -QRA



Next challenges

From susceptibility to hazard:

TIME BECOMES A FACTOR:

- Additional analyses
- More input data needed, with better quality
- Setting precise objectives

TRIGGERING FACTORS

• *Rainfall*

Establishing critical rainfall conditions for landslides of target magnitude

Probabilistic analysis to assess temporal probability of exceedance

CLIMATE CHANGE involved!

• *Earthquakes*

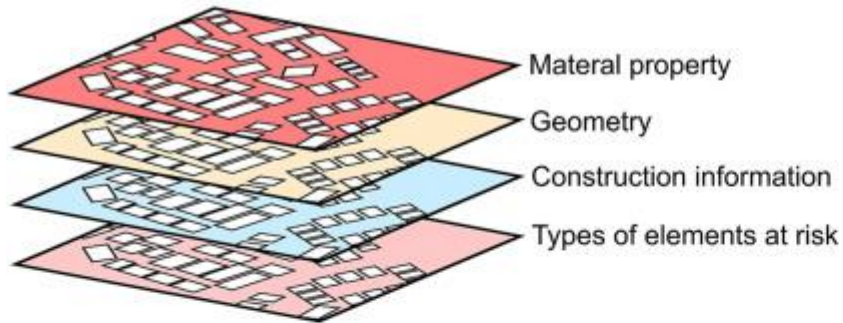
Establishing critical earthquake magnitude for landslides of target magnitude

Probabilistic analysis to assess temporal probability of exceedance

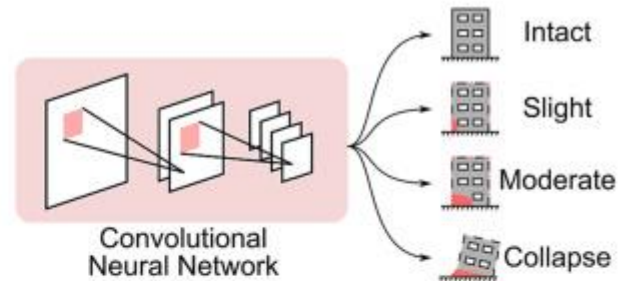
Next challenges

Risk analyses:

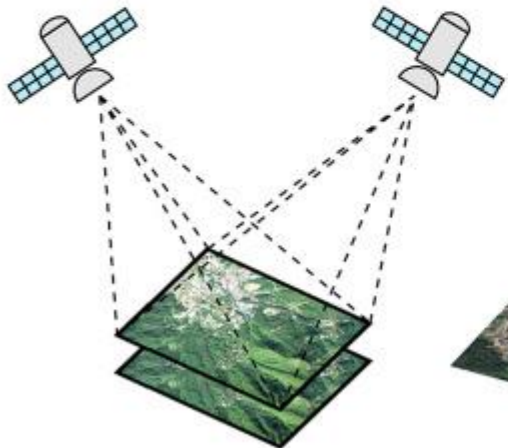
Elements at risk database



AI powered vulnerability study



Space-Air-Ground multi-sources post disaster data



Multitemporal stereopair



Unmanned aerial vehicle (UAV)



Damage document

- Enhanced Elements at risk and post disaster database
- Precise building damage evaluation
- Multi-vulnerability assessment due to frequently occurring cascading hazards



THANKS!

IR0000032 – ITINERIS, Italian Integrated Environmental Research Infrastructures System
(D.D. n. 130/2022 - CUP B53C22002150006) Funded by EU - Next Generation EU PNRR-
Mission 4 "Education and Research" - Component 2: "From research to business" - Investment
3.1: "Fund for the realisation of an integrated system of research and innovation infrastructures"

