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SUSCEPTIBILITY MAPS OF ANTHROPOGENIC SINKHOLES IN URBAN AREAS BY USING GEOSPATIAL ANALYSIS



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Anthropogenic sinkhole in urban areas



Over the last decades an increase in the occurrence of these collapses in urban centers determines risk conditions to citizenship, as well as to infrastructures (i.e, disruption of roads, buildings and underground networks, etc.).

Furthermore, the aspects related to cultural heritage preservation should be considered.

Anthropogenic sinkhole in urban areas



In Italy these collapses mainly occur in large urban centers, but some cases also characterised small towns and villages.

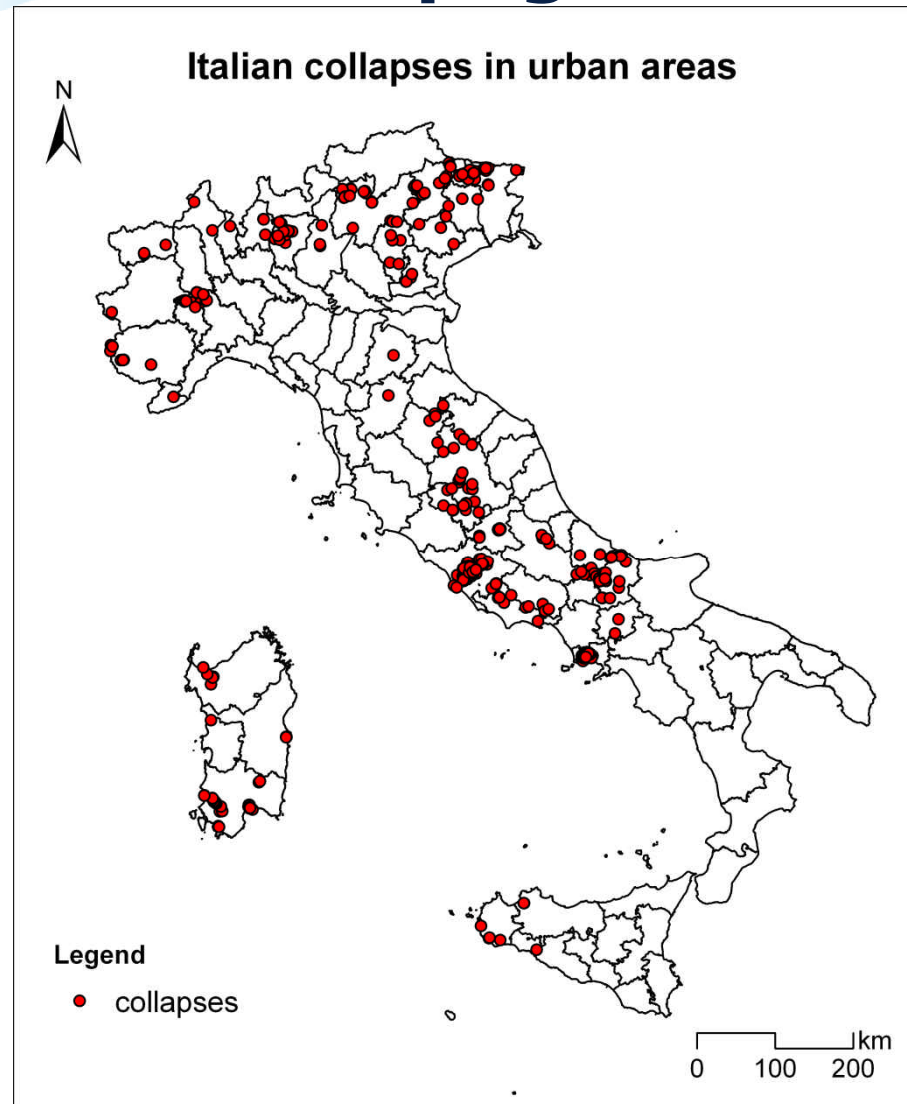


Anthropogenic sinkhole in urban areas



Generally collapses in urban areas are linked to anthropogenic causes due to the presence of underground cavities or sewer losses. Subordinately collapses could occur by natural causes, i.e., karst and liquefaction phenomena

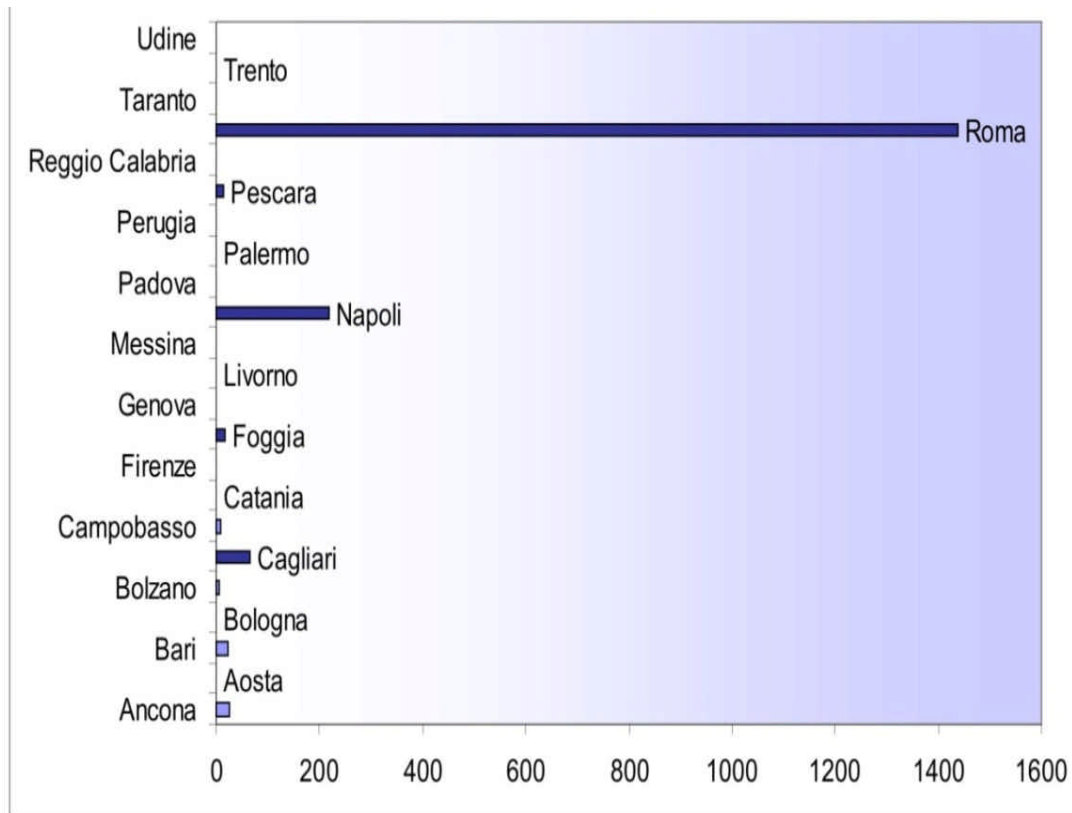
Anthropogenic sinkhole in urban areas



To date a complete database of collapses in urban areas for all the Italian territory is not present, whereas the first attempt includes data collected from the following catalogues:

- Catenacci, 1992
- AVI Project (NRC)
- IFFI Project (ISPRA)
- Census (National Civil Protection)
- Sinkhole project (ISPRA)

Anthropogenic sinkhole in urban areas



Results obtained from the database of collapse census in urban areas indicate that Rome constitutes the most important prone area (actually about 1900 events)

Objectives

In this work three methodologies by using geospatial analysis and multivariate statistics have been proposed and compared to construct susceptibility models to define anthropogenic sinkholes prone areas in urban centers.

The urban area of Rome has been selected as case study for the high frequency of these events.

Material & Methods

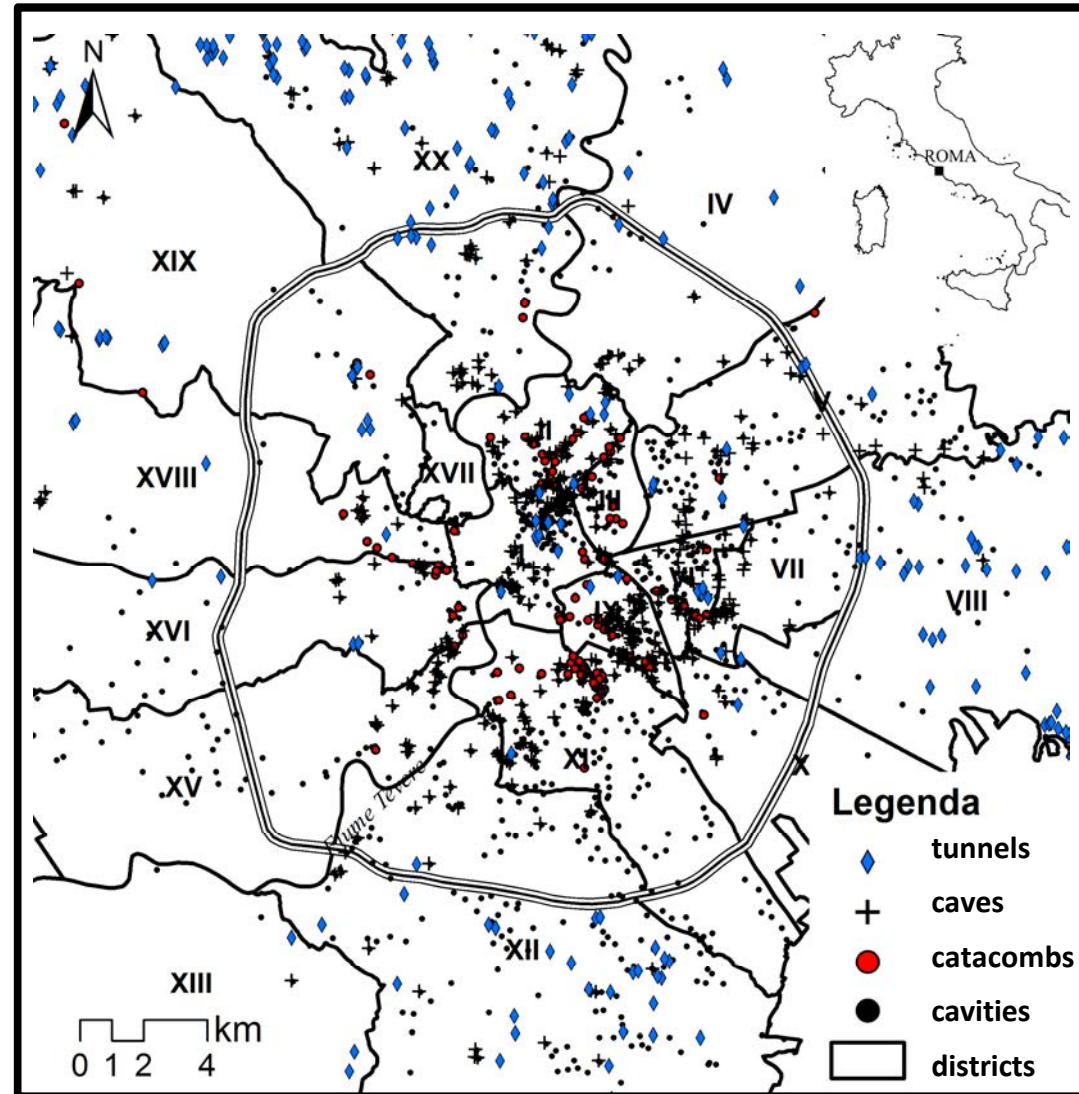
CONDUCTED WORK

- 1. Construction and analysis of collapse database**
- 2. Construction and analysis of a database regarding all known underground cavities (caves, tunnels, catacombs, etc.)**
- 3. Individuation, organization and analysis of conditioning factors**
- 4. Elaboration of susceptibility models**
 - Application of geospatial analysis techniques
 - Application of multivariate statistics

Causes of collapses in urban areas - Rome

Anthropogenic sinkholes in the urban area of Rome are mainly linked to the presence of a dense network of underground cavities that may easily trigger the collapse of the shallow or deeper layers from ground level:

- tunnels and caves of historical mining activities
- drainage tunnels
- catacombs



Causes of collapses in urban areas - Rome

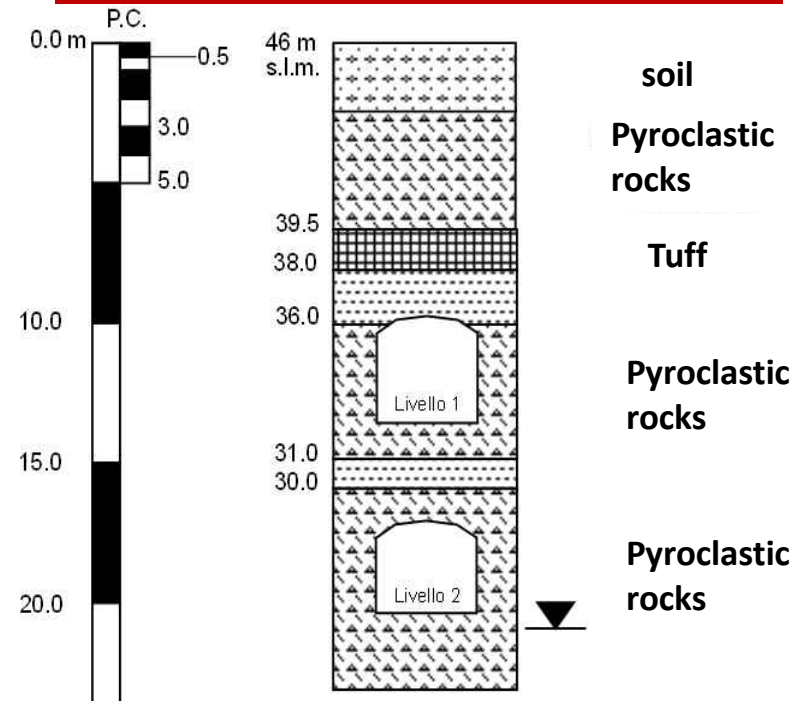


*Via delle Cave, Appio District
Rome*

After the Roman age an indiscriminate use of these cavities originated up to 4 overlapping levels of galleries about 20-25 meters below the surface.

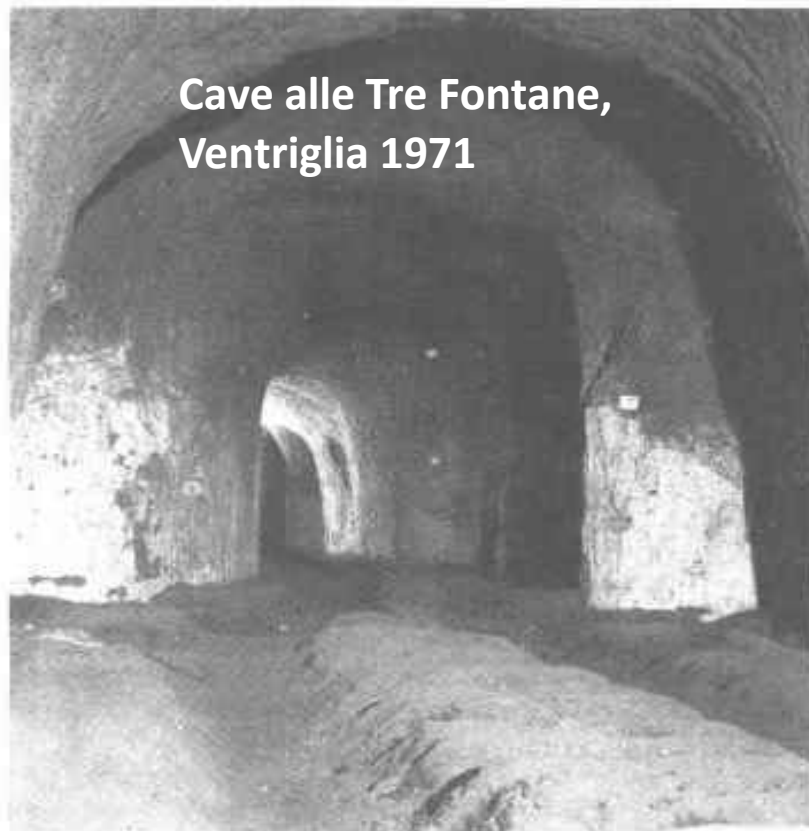
Underground cavities in Rome were used for mining activities (bricks) mainly in the eastern part of the city where volcanic terrain outcrops.

VILLA DE SANCTIS, District VI



Collapses at Rome

Surface effect of the presence of underground caves in the area of Tre Fontane, EUR, south Rome, District XII



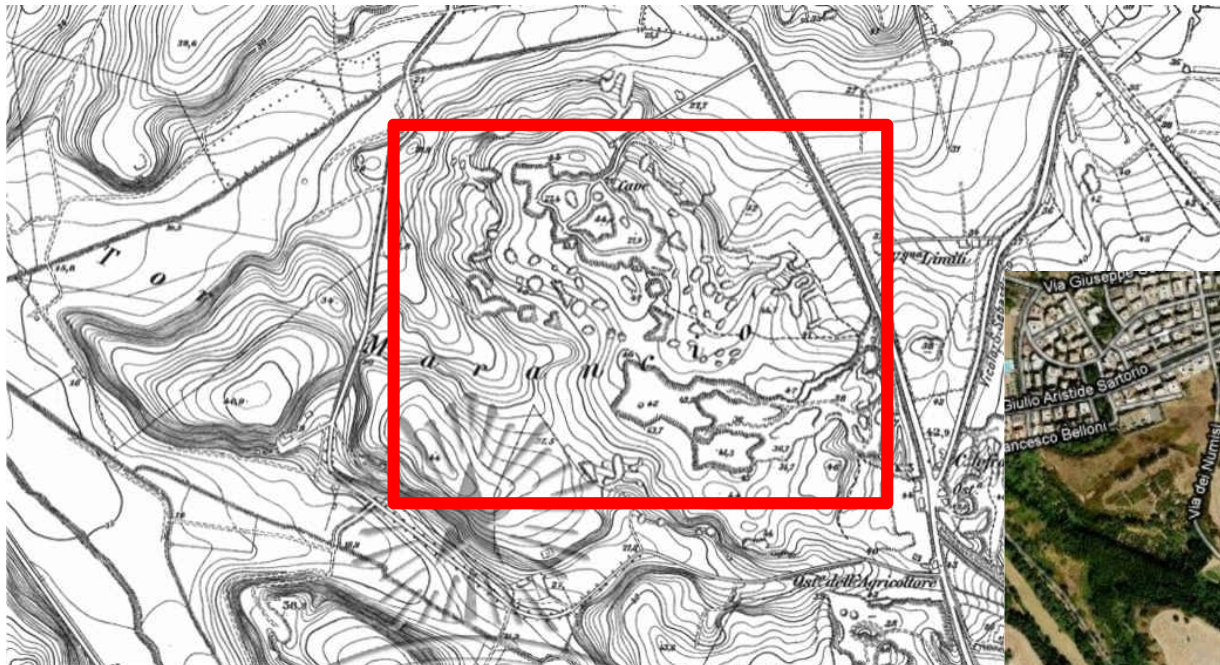
Collapses caused by the presence of underground cavities

The collapse database of Rome area has been increased by the analysis of the historical data and maps in which some typical morphological forms due to collapses of cavities has been recognised.



Topographic map 1884,
Via dell'Acqua Bullicante
(Prenestino-Casilino ,district VII)
East Rome

Collapses caused by the presence of underground cavities



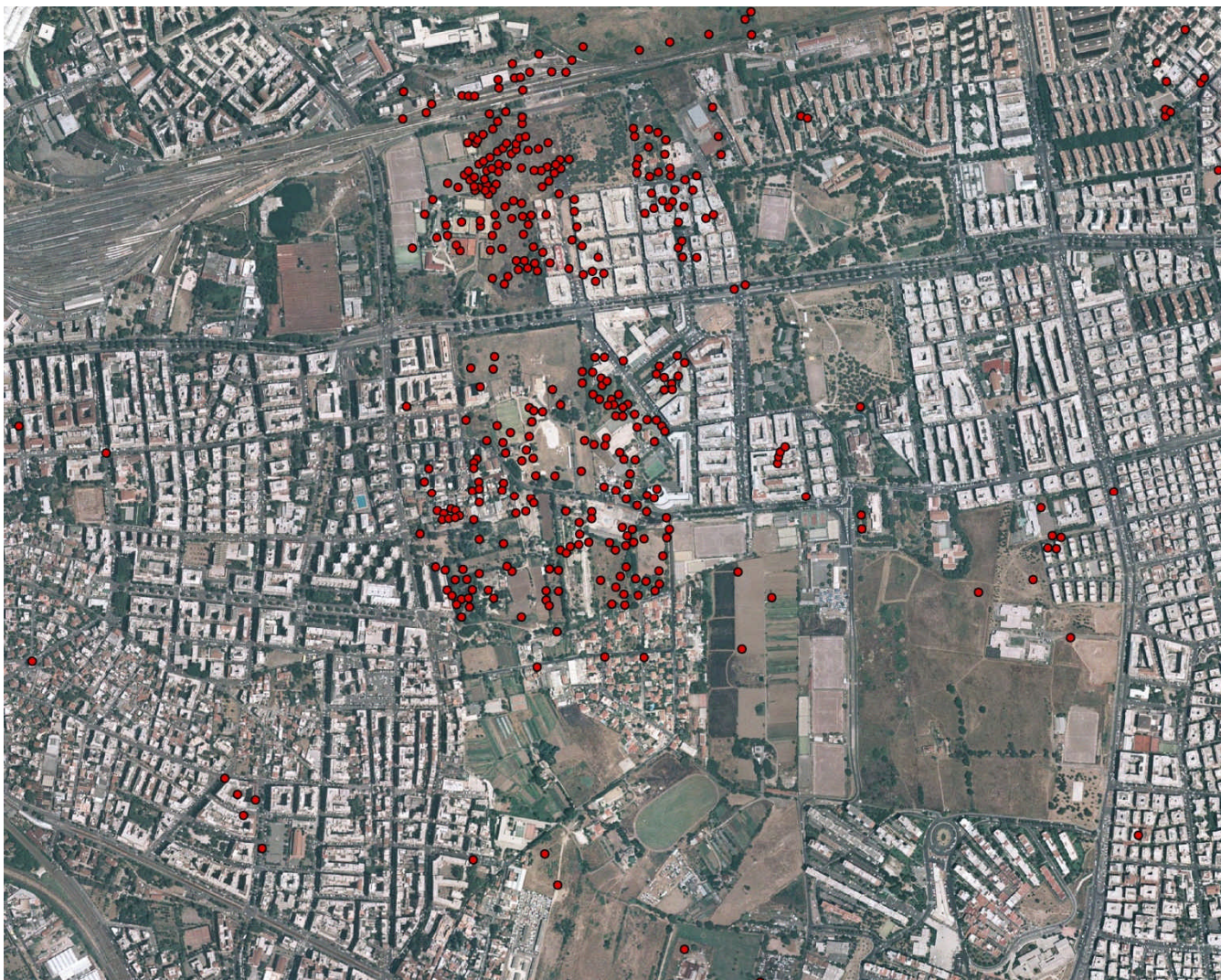
Map of 1907

Tor Marancio – Laurentino, district IX
(south Rome)



Google map of 2003

The risk of collapses in Rome



Prenestino-Casilino Districts V - VII

Collapse susceptibility concept

In these scenarios the evaluation of the associated risk is extremely difficult due to the lack of data about return times and specific characteristics of the site, and thus it is not possible to calculate probabilities of the event in a given time horizon.

The concept of risk has been replaced with the most generic concept of **susceptibility**, which defines the "potential" of an area in spatial terms only:

a collapse could occur in a certain area in an infinite time interval and an area has characteristics that facilitate a collapse.

Collapse susceptibility models

This could be obtained through three different levels of modeling:

1° LEVEL Geospatial Analysis

potential of an area based on the collapse occurrence at large scale, i.e., Density Model

2° LEVEL Probabilistic Approach

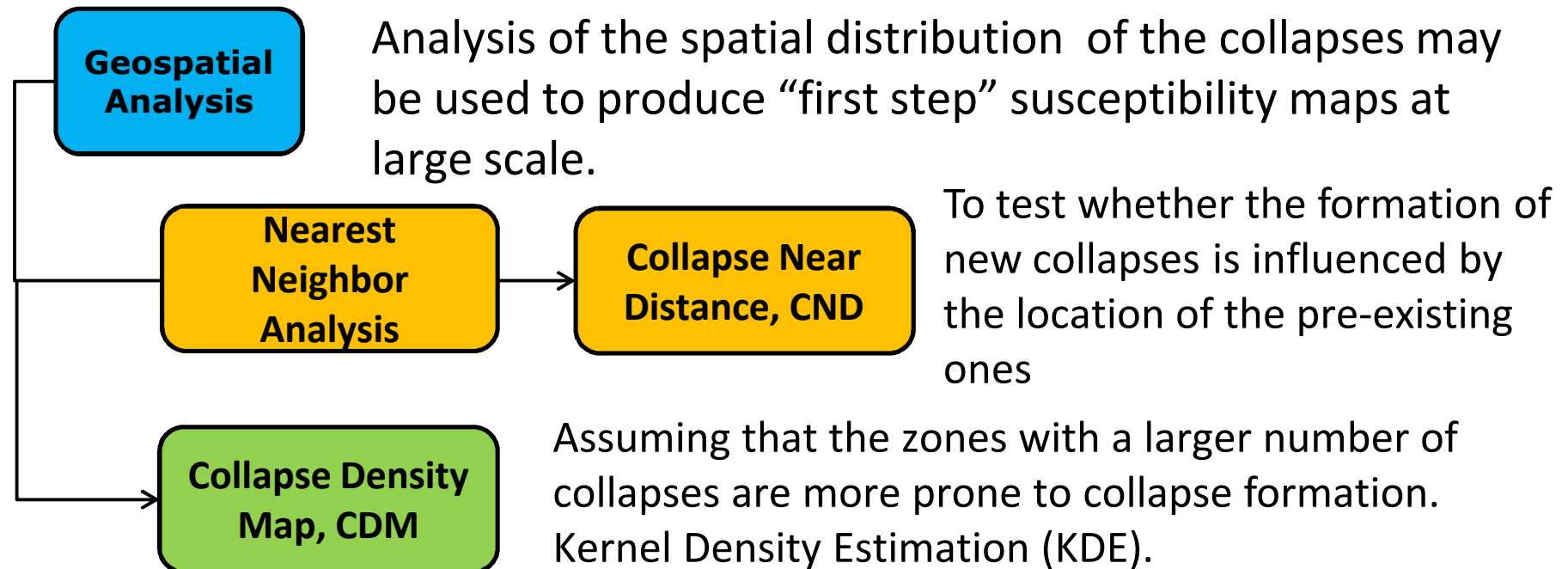
probabilistic model constructed by using the analysis of the statistical relationships between the presence of the collapses and a series of conditioning factors, i.e, Logistic Regression, Geographical Weighted Regression

3° LEVEL Numerical Model at site specific

Numerical models for the evaluation of site stability. Needs the knowledge and the collection of a lot of parameters and is difficult to apply to large areas.

Methodology – 1st level modeling

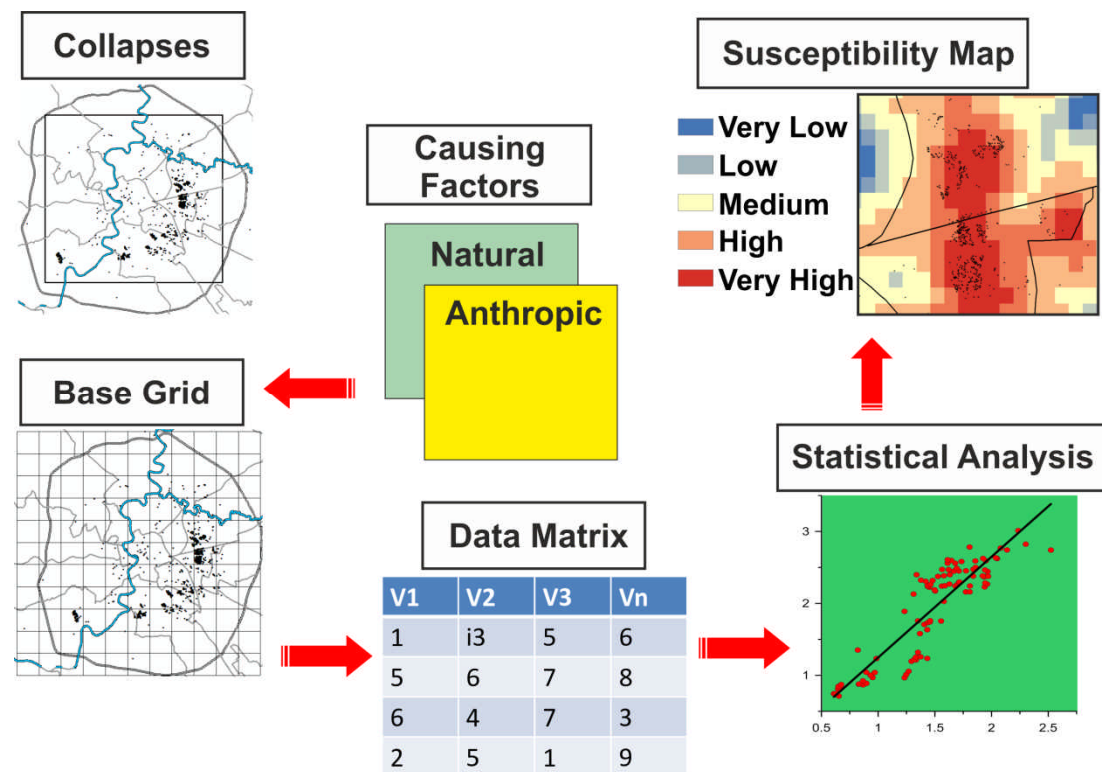
Strategies applied to address the spatial prediction of anthropogenic sinkholes.



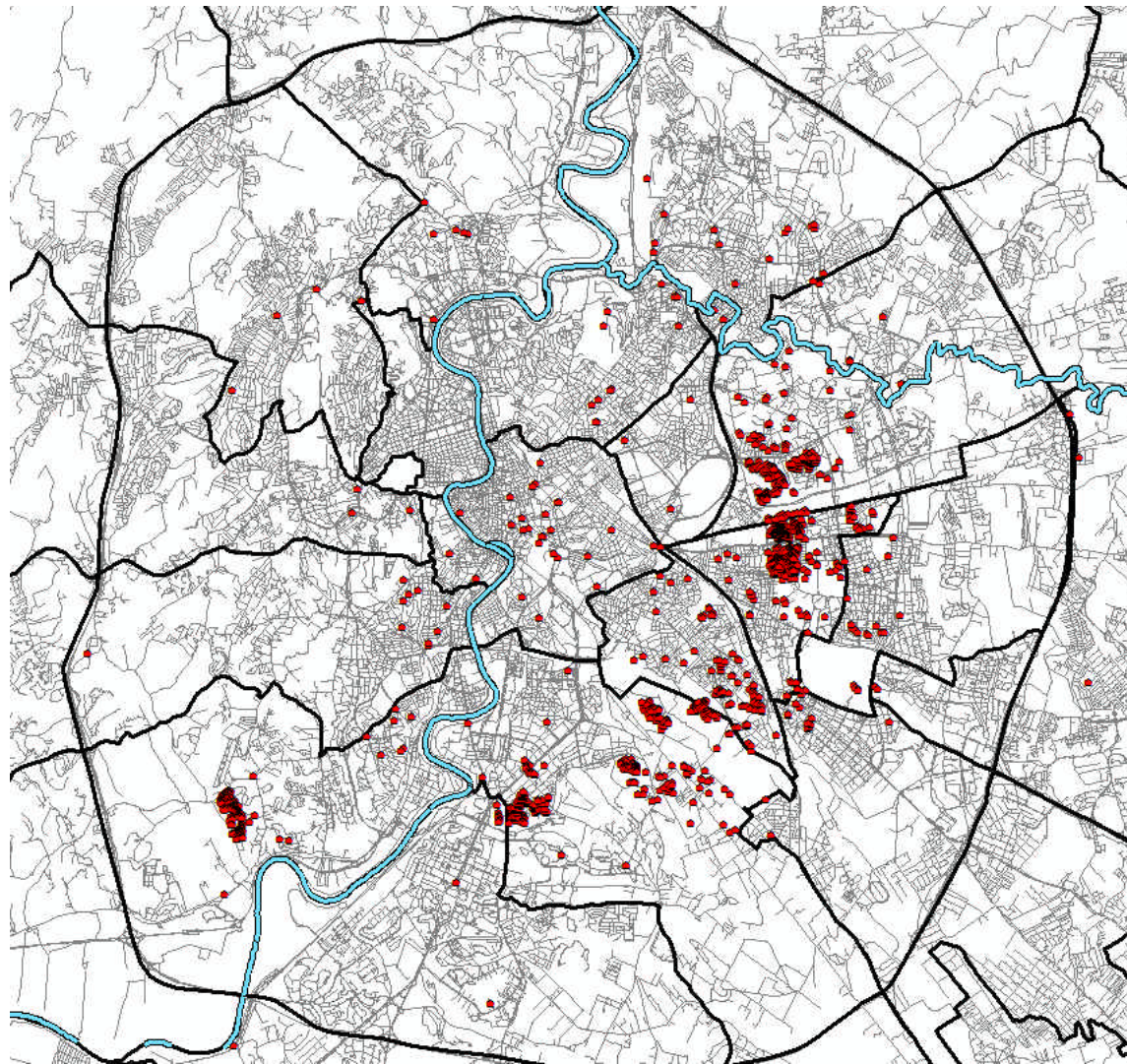
Methodology – 2nd level modeling

Elaboration of susceptibility zonation by the analysis of the statistical relationships between the known collapses (the “dependent” variable) and the available information on the conditioning factors (the “independent” variables) by using Logistic regression and GIS.

1. Selection of the study area and of the grid dimension (grid cell = 250m)
2. Collapse distribution map
3. Mapping of the conditioning factors and their raster transformation
4. Calculation of the factor weights (i.e., β coefficients of the Logistic regression)
5. Calculation of the susceptibility map by using map algebra
6. Goodness and comparison of the models (by Curva ROC)



Location of collapses in Rome urban area



DATA COLLECTION

Database ISPRA (about 1900 cases):

- Literature information
- Analysis of historical maps
- Analysis of aerial photos
- Archive of firefighters
- reports from Local Administrations, newspapers, internet, etc.

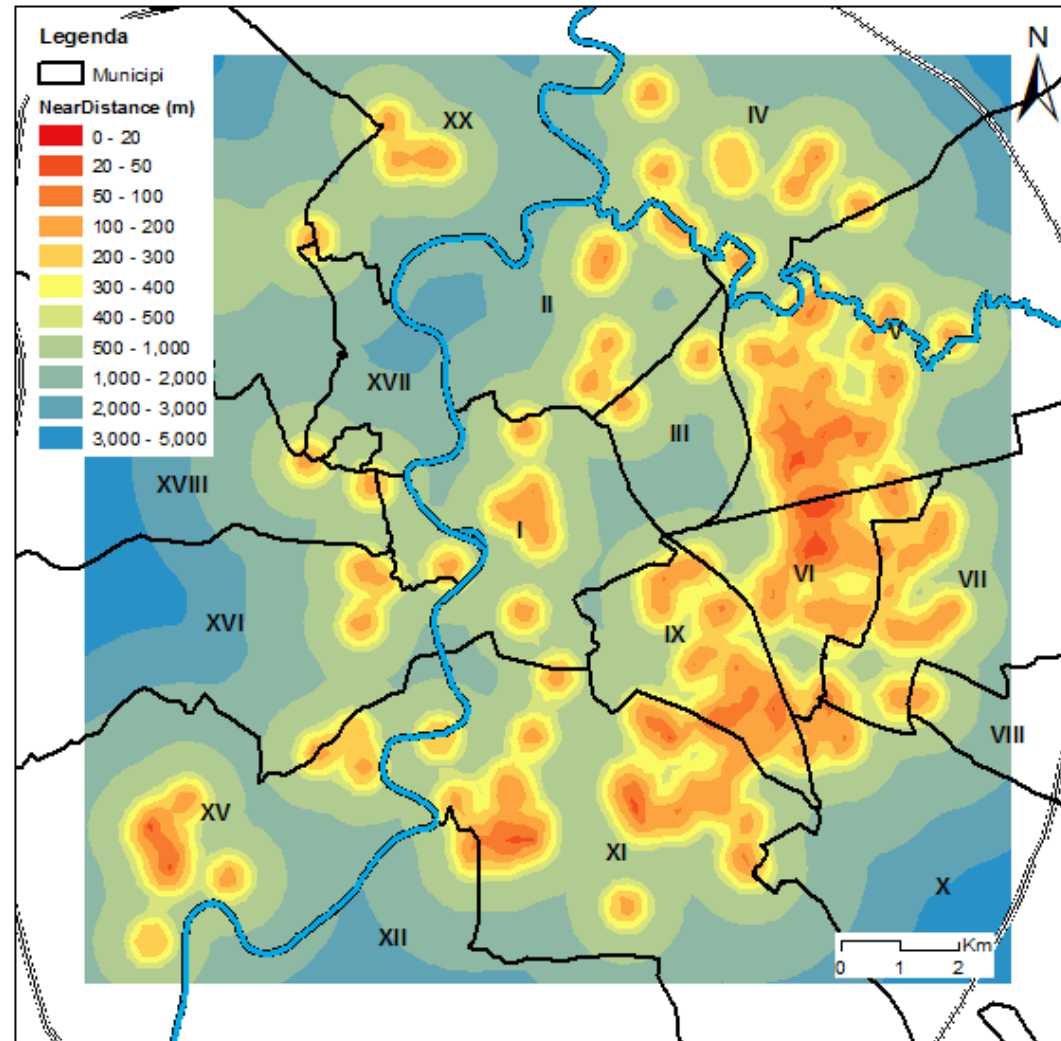
Contribution from:

- Database DPC (about 100 cases)
- Database AVI (about 30 cases)

First Level Modeling Nearest Neighbor Distance Map

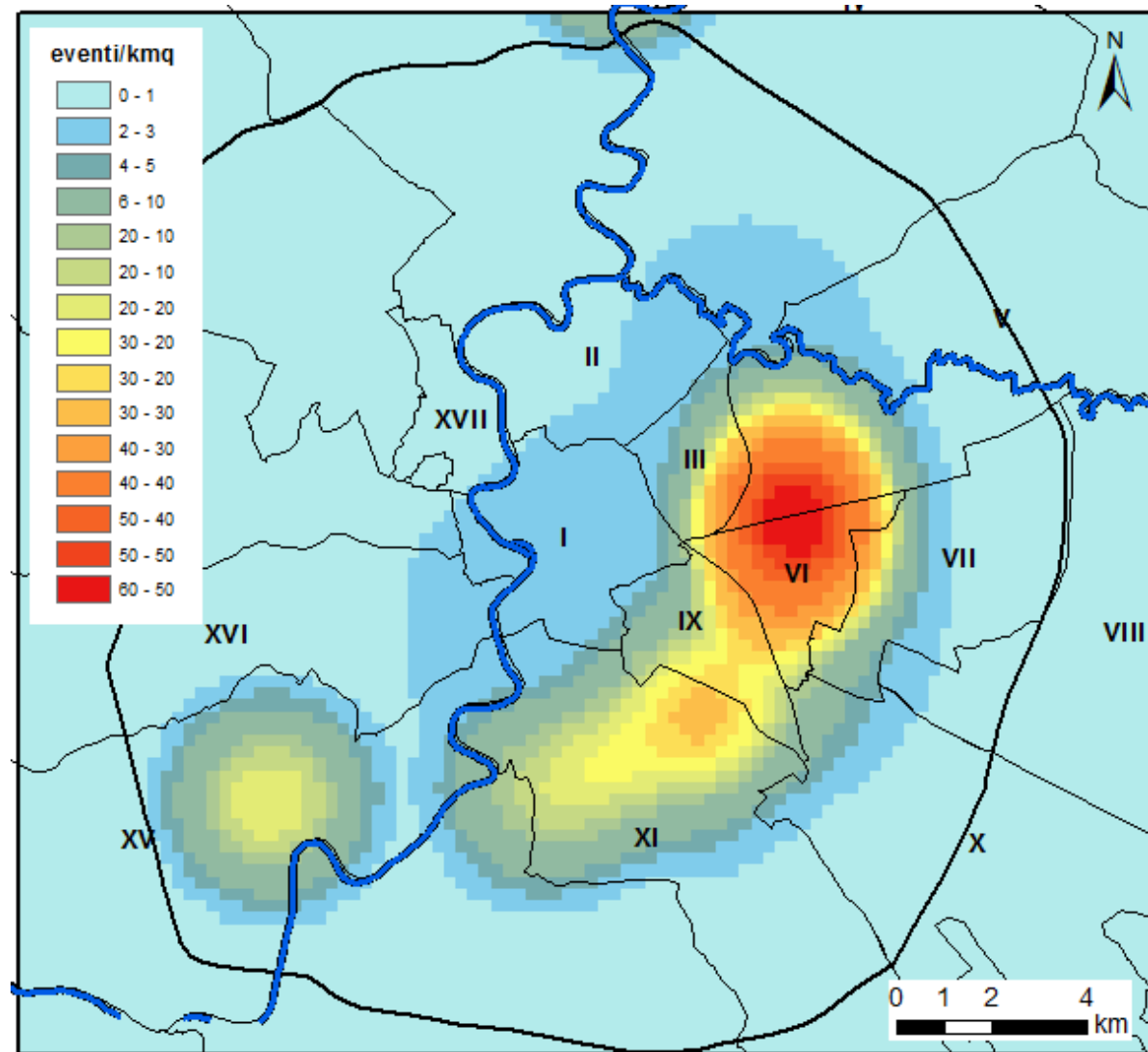
The Nearest Neighbor Distance, NND, map shows:

1. the degree of spatial clustering- dispersion of the collapses.
2. whether the new collapse tends to form in the vicinity of the existing ones.



First Level Modeling - Density Map

Highlights the number of collapses per sqkm. The density model is transformed into a map of susceptibility by assigning the highest susceptibility to areas with the highest density of events.

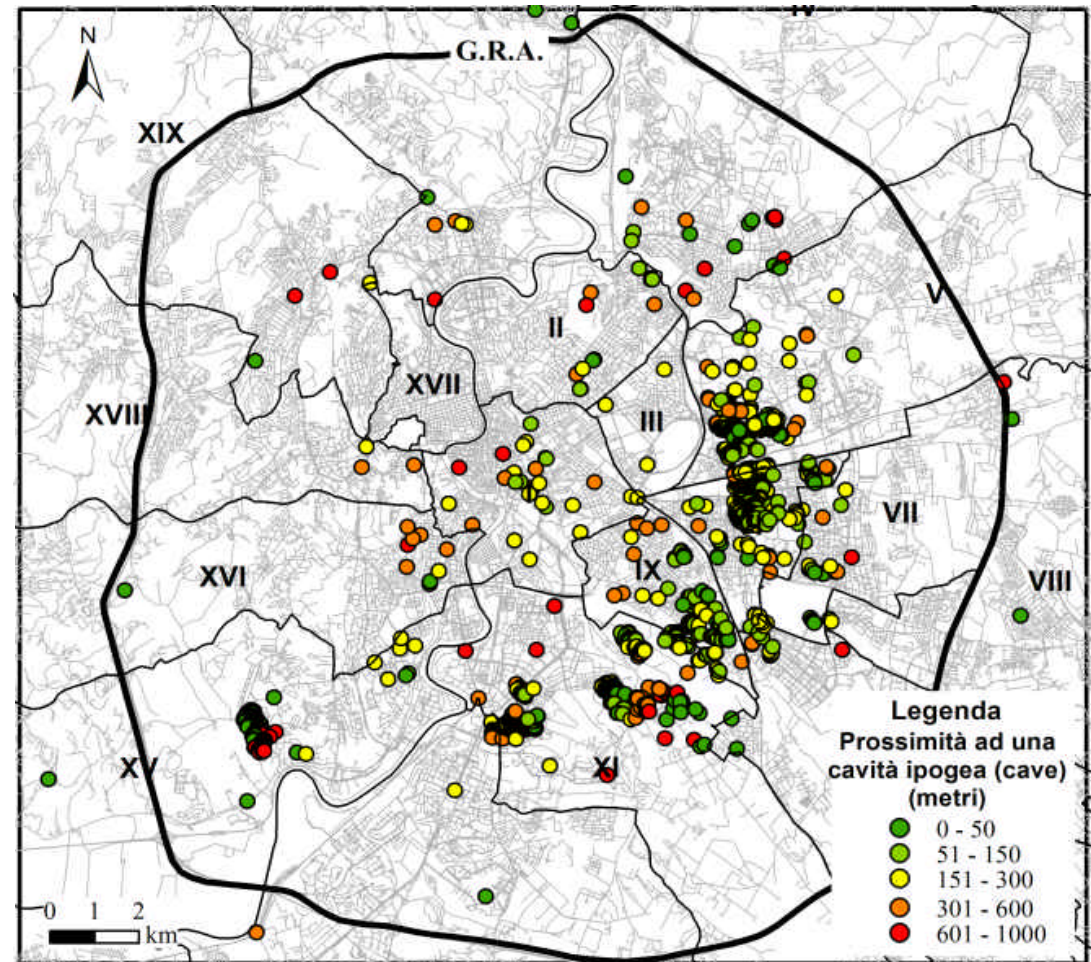
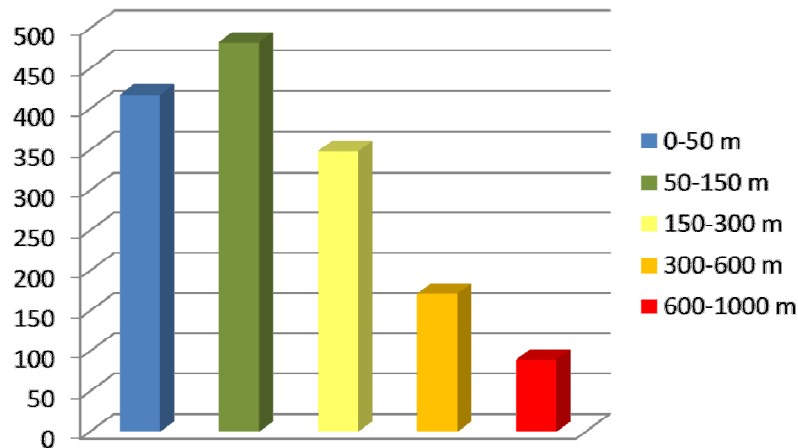


First Level Modeling - Proximity map

The proximity maps helps in the selection of the importance of specific conditioning factors, i.e., proximity to cavities.

About 65% of the collapses occur at about 150 m from the nearest cavity, and 85% about 300m.

Number of collapses for different distance classes from near cavities.



Second Level Modeling Probabilistic Model

The probabilistic model consists of a predictive approach that allows the elaboration of susceptibility maps by the analysis of statistical relationships between the presence of an events (i.e., collapse) and a series of conditioning factors.

A key objective is to assign weights to conditioning factors according to their importance in the phenomenon under investigation. Typically the weights are assigned subjectively based on the experience of the operator (heuristic model).

The Logistic Regression

- Logistic Regression Analysis (RL) has been applied as special case of linear regression analysis where the dependent variable is not quantitative, but dichotomous.
- The LR model allows the calculation of the regression coefficients which define the weight of each variable in the model.
- The exponential transformation of the coefficients is used to determine the weights in terms of probability that each variable has in the occurrence of the event.

$$\text{Pr} = \frac{e^y}{1 + e^y} \quad \text{where } y = \beta_{i0} + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon_i$$

Second Level Modeling – Probabilistic Model

The potential of a territory to this phenomenon can be defined by **natural conditioning factors**, to which **anthropic factors** are added in an urban areas.

Western district of Rome, April 2012



Lithology
quarried lithology

Hydrogeology
depth of the shallow
aquifer

Morphology
map of the surface
forms

Natural
Factors



Anthropic
Factors

**Underground
cavities**
(catacombs,
caves, etc.)

**Sewer
network**

**Backfill
thickness**

Second Level Modeling Logistic Regression Model

1. The LR correctly classifies 68% of the cells coded by 1 (presence of collapse)
2. The LR indicates the significance of the selected parameters.
3. The LR of type "forward" automatically eliminates variables not significant for the model, in particular backfill and sewer network are not included in the model.

Variables in the Logistic Model						
	B	St.Er	Wald	df	Sig.	Exp(B)
Aquifer depth	-.020	.01	9.87	1	.002	.980
Cavities	.112	.01	207.86	1	.000	1.118
Geology	.162	.06	6.31	1	.012	1.175
Costant	-3.163	.23	184.84	1	.000	.042

Second Level Modeling Logistic Regression Model

Model with 6
independent variables

β coefficients of the significant
variables in the model

$$Y = -3.173 + (0.162 \text{ Geology}) + (0.112 \text{ Cavities}) + (0.020 \text{ Aquifer Depth})$$

Weighted Sum of
Conditioning Factors

Geology

β_1

+

Aquifer
Depth
 β_2

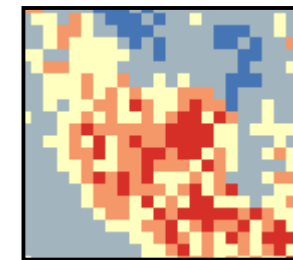
+

Cavities

β_3

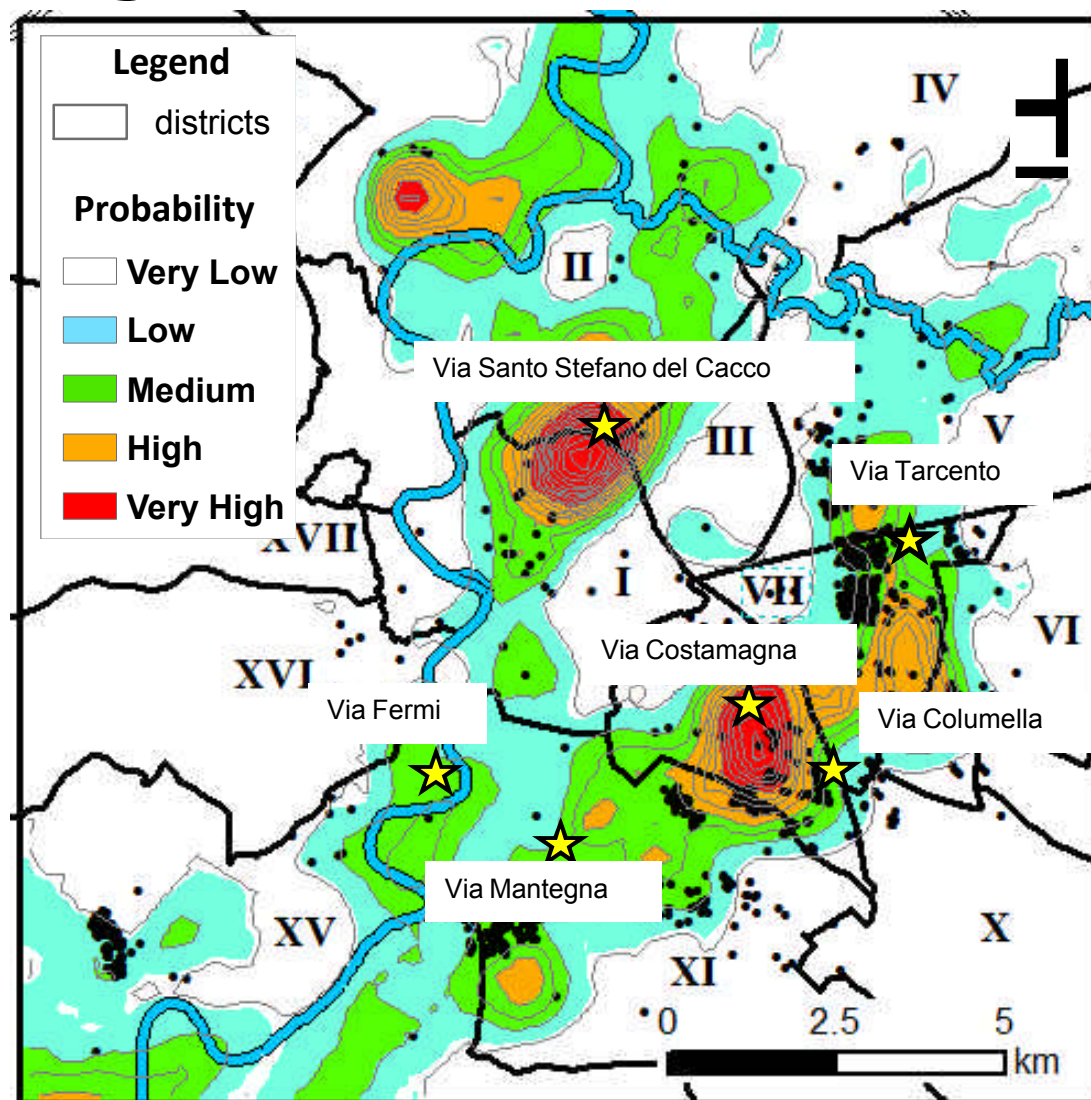
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Susceptibility
Map



Second Level Modeling Logistic Regression Model

Susceptibility map
elaborated by using
Binary Logistic Regression
(BLR).



Susceptibility Models – ROC Graph

Receiver Operating Characteristics

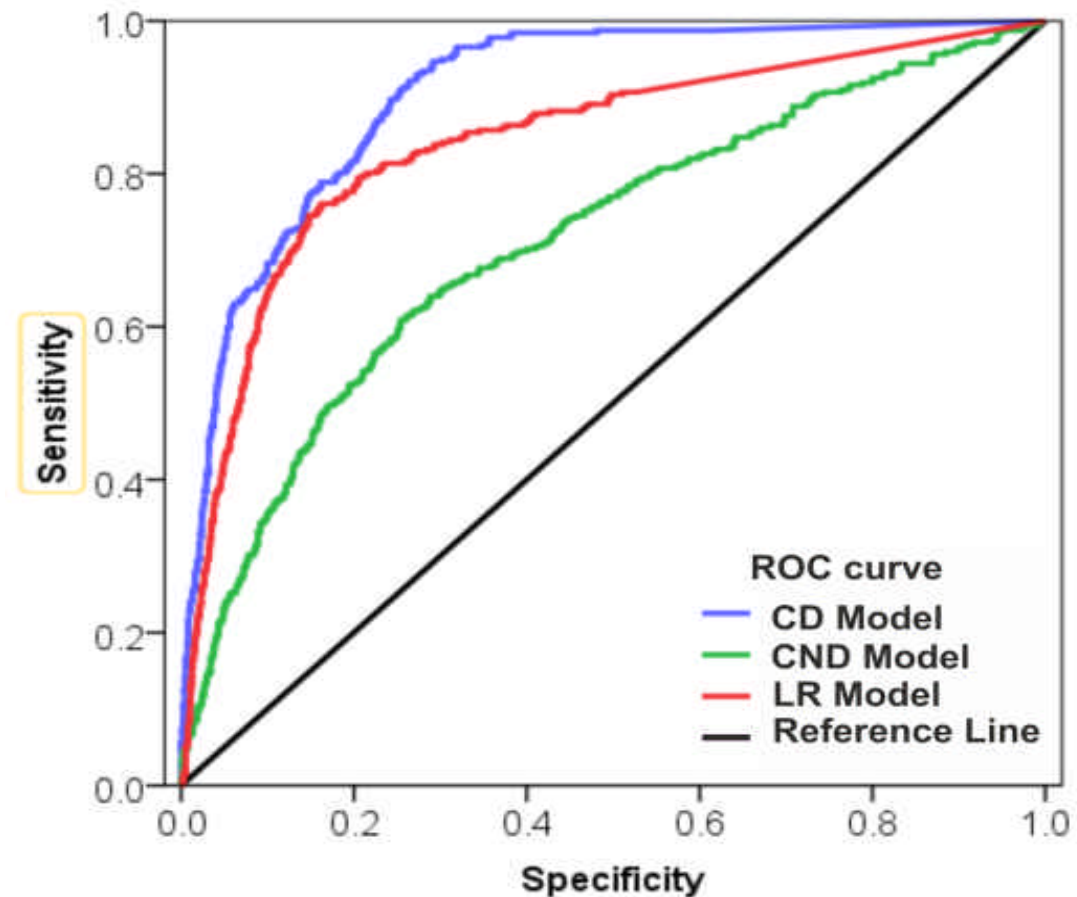
The reliability of the model was tested with the test graph ROC.

The ROC graph is a common procedure to evaluate the reliability of a diagnostic test in terms of sensitivity and specificity (Dorfman et al., 1969).

Area CD = 0.85

Area CND = 0.54

Area LR = 0.80



Conclusions

1. Geospatial analysis techniques provide useful tools of first level modeling to easily define collapse prone areas at large scale. In this case the density model results the most reliable model.
2. However the logistic model also shows high reliability. Furthermore, this model is able to provide objectives weights for the conditioning factors (i.e., β coefficients) by the analysis of their statistical relationships with the presence of the collapses.

Future Work

1. Application of the Geographically Weighted Regression (GWR) that allows to evaluate non stationary phenomena, i.e. when the measure of the relationships between the dependent and independent variables differ from place to place.
2. Implementation of predisposing factors by site-specific studies:
 - Collapse characteristics (geometry, depth, lithology, etc.).
 - Geometric characteristics of the underground cavities
 - Geomechanical properties of the cavity encasing lithology
 - Thickness of the cover above the cavity layers

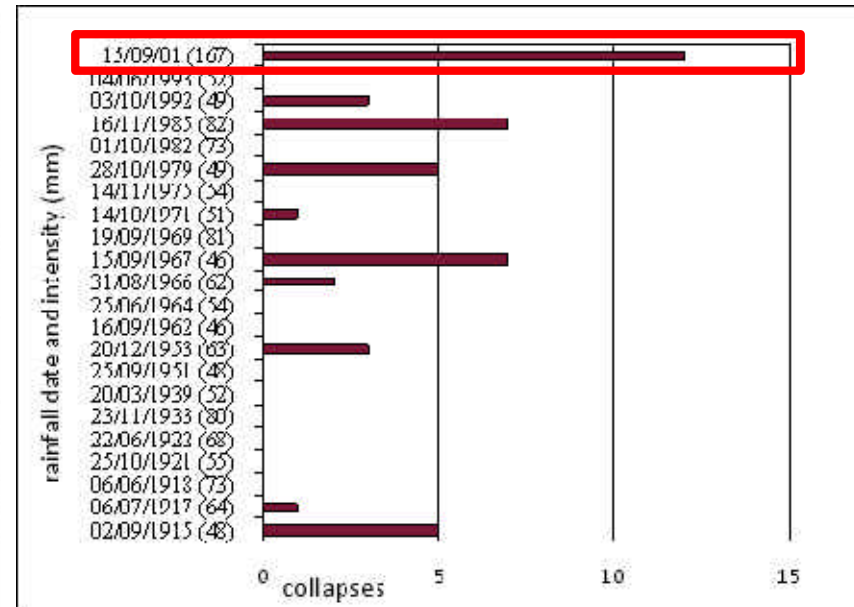
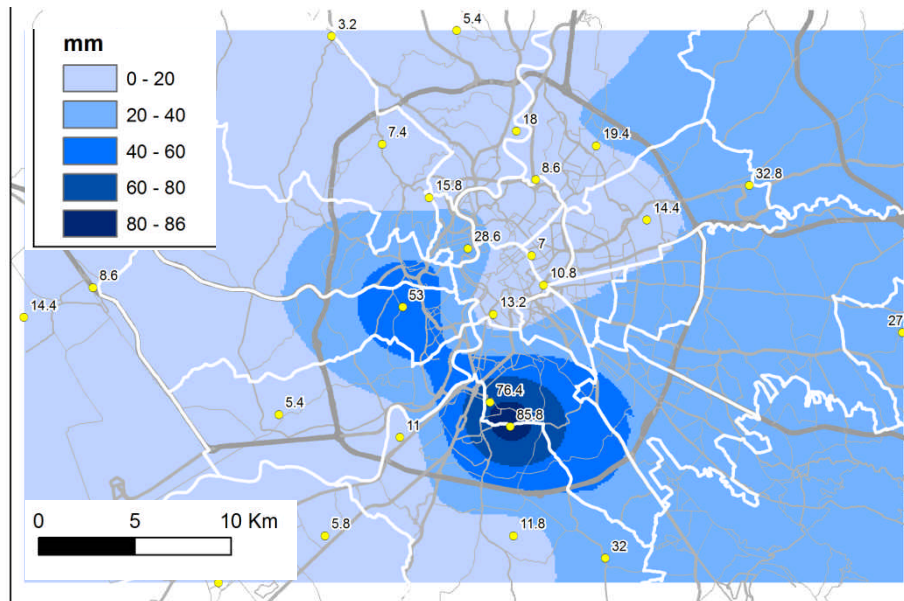
Thank you for the attention!

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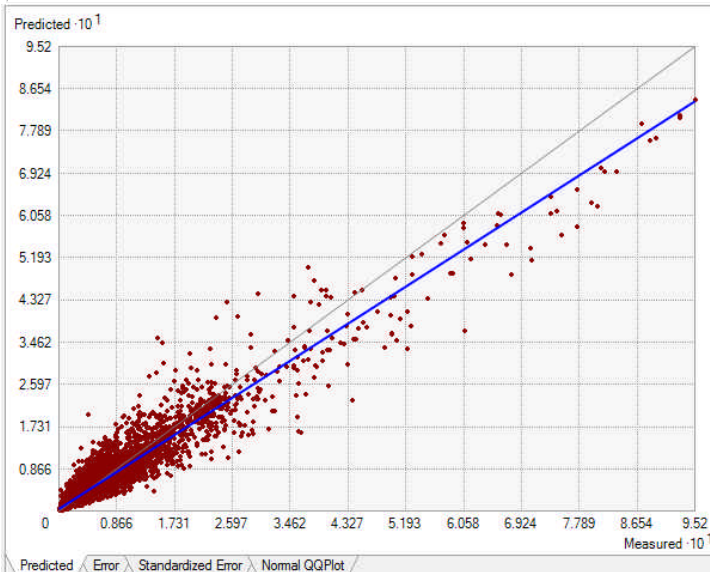
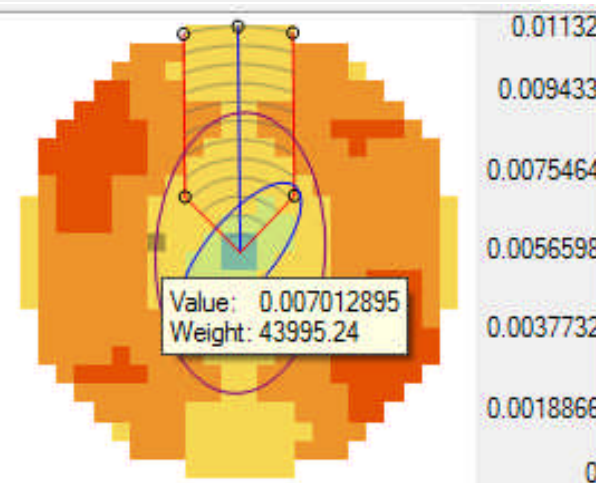
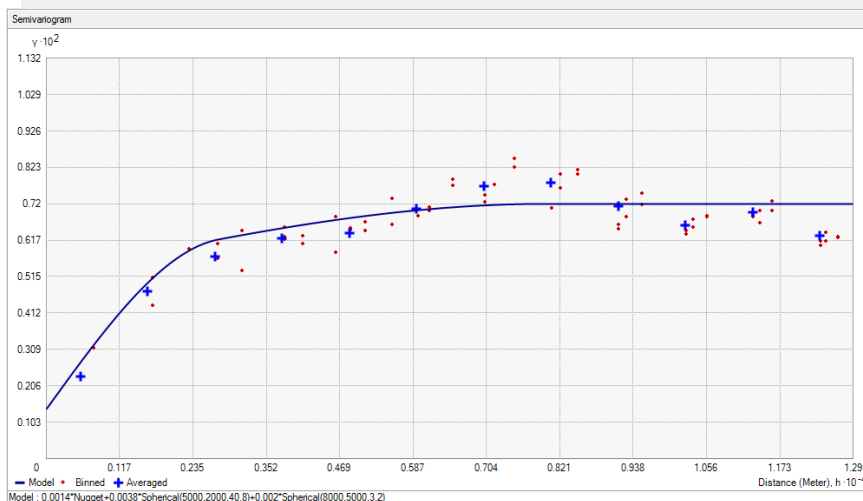
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Triggering of collapses in urban areas: intense rainfall of september 2001



Subordinate causes are associated to the loose of soil below the road surface linked to run-off phenomena concurrently with intense rainfall.

Model : $0.0014 \cdot \text{Nugget} + 0.0038 \cdot \text{Spherical}(5000, 2000, 40.8) + 0.002 \cdot \text{Spherical}(8000, 5000, 3.2)$



Regression function	0.8776778017640
Prediction Errors	
Samples	8258 of 8258
Mean	0.000004251556
Root-Mean-Square	0.0224891
Mean Standardized	0.00002559722
Root-Mean-Square Standardized	0.4943278
Average Standard Error	0.04554186
Export Result Table	