# IDENTIFICATION OF THE FACTORS CONDITIONING THE SUSCEPTIBILITY OF NATURAL AND MAN-MADE HAZARDS IN AN URBAN CONTEXT

Alberto VAVASSORI[1], Angelly DE JESÚS PUGLIESE VILORIA[1], Maria Antonia BROVELLI[1]

[1]Department of Civil and Environmental Engineering, Politecnico di Milano, P.zza Leonardo da Vinci 32, 20133 Milano, Italy

*Correspondence to*: Alberto VAVASSORI[1] (alberto.vavassori@polimi.it)

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**Abstract**

The problem of multi-hazard mapping in urban areas is relevant for preventing and mitigating the impact of natural and human-induced disasters and it is a very complex one because different expertises have to be put together. Single-hazard maps may be produced by taking advantage of Machine and Deep Learning techniques, once the factors conditioning the susceptibility of the hazard are defined and relevant data inventory is collected. From a proper combination of single-hazard maps, a multi-hazard map may be derived. The objective of this study is the identification of the conditioning factors for the most relevant natural and human-induced hazards in an urban context through an exhaustive literature review. All factors found in the literature were methodically listed in tables and order of importance was assigned to each factor depending on the number of citations of each paper and on the number of publications in which such a factor was taken into account. The resulting list will be then validated with domain experts. The obtained results can be used for the production of single and multi-hazard susceptibility maps in urban areas.

**Keywords:** conditioning factors, multi-hazard mapping, urban context, Machine and Deep Learning

## INTRODUCTION

Natural and human-induced hazards are extreme phenomena that may have severe impacts on both the natural and man-made environment. Overpopulation and urban development in areas that are susceptible to this kind of disaster lead to an increased impact on the environment and communities (Skilodimou and Bathrellos, 2021). Therefore, proper urban planning is of paramount importance to prevent the negative consequences of natural and man-made disasters as well as to mitigate the associated risk. Despite the majority of the published studies being focused on the analysis of single hazards, urban areas are typically susceptible to numerous disasters that may occur simultaneously or consecutively (Skilodimou, 2019). For this reason, the development of a state-of-the-art method for an effective multi-hazard assessment is crucial. This is especially true for the urban centers, where the amount of exposed and vulnerable elements, such as people, settlements, and infrastructures, is particularly significant. As multi-hazard maps are ultimately derived from a proper combination of single-hazard maps (Skilodimou et al., 2019; Nachappa et al., 2020), a thorough understanding of the factors driving the susceptibility of the single hazards in a certain urban area is key to an exhaustive multi-hazard assessment. To that end, this work investigates through an in-depth literature review the conditioning factors that play a role in the most typical hazards that may threaten the urban environment. The obtained list of conditioning factors is promising to support the production of single and multi-hazard susceptibility maps at the urban level by means of Machine and Deep Learning techniques. This work is developed in the framework of the HARMONIA project, which aims at providing stakeholders and urban planners with a decision support system to improve urban resilience and mitigate the effects of climate change in four European cities (Milan, Sofia, Ixelles, and Piraeus).

## METHODS

The following natural and man-induced hazards were considered in this study: earthquakes, ground subsidence, landslides, fires, floods, droughts, extreme precipitations, heat islands, air pollution, and danger of explosion. The conditioning factors playing a role in the occurrence of each hazard were identified based on an extensive scientific literature review. The research was limited to the most recent publications (from 2017 to 2022): taking advantage of the results obtained by previous research works, they may be considered best exhaustive and state-of-the-art. The method employed for the production of susceptibility maps, summarized through a diagram in Fig. 1, is common in most of the publications: a list of conditioning factors for one or a few hazards is defined; data about conditioning factors and past events occurrences is collected either from national inventories or exploiting modern surveying techniques; data regarding events occurrences is split into a training and a validation dataset in the modeling process; Machine and Deep Learning techniques are adopted to produce susceptibility maps and results are finally validated. Despite most of the studies sharing a common list of conditioning factors for each hazard, some differences were found in the different publications. To be as exhaustive as possible, all conditioning factors reported in the literature were taken into consideration. They were methodically reported in tables listing the type of conditioning factor (e.g. hydrological, meteorological, topographical), the corresponding physical variable (e.g. groundwater level, maximum daily temperature, slope angle), its unit of measurement (e.g. meters, Celsius degrees), and the papers where a reference to such a factor was present. A method for selecting the most relevant conditioning factors was conceived and applied. As a first step, an order of importance was assigned to each factor depending on the number of publications in which it appeared: a higher number of publications, a higher degree of relevance; secondly, the number of citations of the single papers was taken into account; therefore, the conditioning factors appearing in highly-cited publications were considered as most relevant.

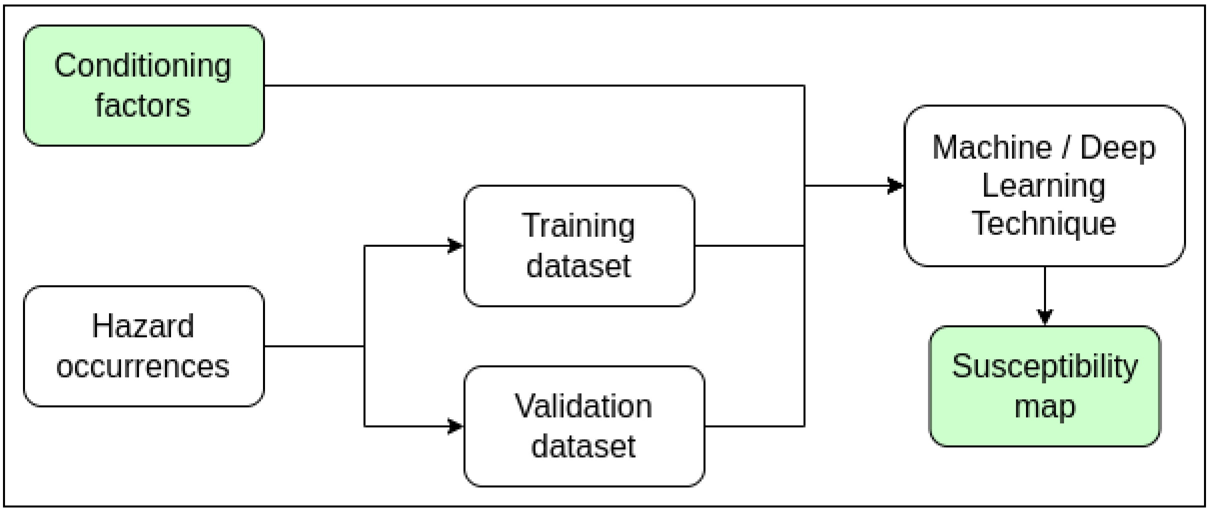


**Fig. 1.** Methodology workflow for the susceptibility mapping of individual hazards.

## RESULTS AND DISCUSSION

A consistent number of conditioning factors was found in the literature. In order to better understand which type of variables affects the susceptibility for the different hazards, conditioning factors were grouped into categories (e.g. geological, hydrological, meteorological factors). This raw subdivision allowed pointing out similarities and differences among the various hazards. For instance, the susceptibility to droughts and extreme precipitations is mostly affected by meteorological variables (e.g. temperature). Hydrological, geological, topological, and land cover variables are common conditioning factors to the main hydro-geological hazards (floods, ground subsidence, landslides, and fires). Susceptibility to earthquakes is conditioned by similar types of variables, namely topological (e.g. slope), geological (e.g. distance to faults), and seismic (e.g. epicenters density) factors. More singular variables affect the susceptibility to air pollution and heat islands. Despite many meteorological factors being common to both hazards, heat islands are strongly conditioned by the characteristics of the city in terms of structure, anthropogenic heat, and city canyons, whereas air pollution is strictly related to the type and amount of emissions along with different socio-economic variables (e.g. industrial activity). The analysis brought to light the relevance of land cover in conditioning the majority of the above-cited hazards; therefore, the type of surfaces constituting the urban environment is pivotal in determining the city's predisposition to a series of natural and human-induced disasters. A singular case is constituted by the danger of explosions; the main conditioning factor for such a technological hazard is the presence of companies and industries dealing with potentially explosive chemical substances; national or local cadasters of high-risk industries are fundamental for proper hazard mapping. For the sake of clarity, Fig. 2 reports a brief and non-exhaustive summary of the conditioning factors per hazard. Complete tables with references to the papers found in the literature will be provided and illustrated in the paper. As discussed in the previous section, a selection of the most relevant conditioning factors was performed based on the number of publications in which each factor appeared and the number of citations of each publication. Nevertheless, the proposed list will be discussed with domain experts that are partners of the HARMONIA project. Furthermore, a nonnegligible limitation to the choice of conditioning factors is given by the problem of data availability. Only factors for which data is available may be included in the analysis; this is strictly linked to the case study under consideration and the type of variable. As a future development of this work, data about conditioning factors and historical hazard occurrences will be collected, and the most suitable Machine and Deep Learning techniques will be selected and applied for the production of single and multi-hazard maps for the four target European cities (Milan, Ixelles, Sofia, and Piraeus).

| CONDITIONING FACTORS | | | HAZARDS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Type of factor** | **Physical variable** | **Unit** | **Air Pollution** | **Drought** | **Earthquake** | **Extreme precipitation** | **Flooding** | **Ground subsidence** | **Heat island** | **Landslide** | **Wildfire** |
| Hydrological | Distance to rivers/streams | km | | | | | • | • | | • | • |
| | Groundwater drawdown/level | m | | | | | | • | | | |
| | Stream power index | kg $m^2/s^3$ | | | | | • | | | | |
| | Topographic wetness index | - | | | | | • | • | | • | |
| Land cover | Distance to road network | km | | | | | • | • | | • | • |
| | Highway/road density | m/km2 | • | | | | | | | | |
| | Distance to villages/urban areas | km | | | | | | | | | • |
| | Land cover albedo | albedo | | | | | | | • | | |
| | Land cover greenery | % greenery | | | | | | | • | | |
| | Land use/land cover | - | | | | | • | • | | • | |
| | NDVI | | | | | | | | | | • |
| Topolographical | Aspect | - | | | | | | • | | • | • |
| | Elevation/DEM | km | • | | • | | • | • | | • | • |
| | Slope | degrees | | | • | | • | • | | • | • |
| Geological/seismic | Amplification factor | - | | | • | | | | | | |
| | Epicenter density | no./$km^2$ | | | • | | | | | | |
| | Fault density | no./$km^2$ | | | • | | | | | | |
| | Hypocenter depth density | no./$km^2$ | | | • | | | | | | |
| | Lithology | - | | | | | • | • | | • | |
| | Magnitude density | Mw/$km^2$ | | | • | | | | | | |
| | Proximity to epicenters | km | | | • | | | | | | |
| | Proximity to fault | km | | | • | | | | | • | |
| Meteorological | Humidity | - | • | | | • | | | | | |
| | Potential evapotranspiration | mm/year | | • | | | | | | | |
| | Precipitation | mm/year | • | • | | • | • | • | | | • |
| | Temperature (min, max, mean) | °C | | • | | • | | | • | | • |
| | Wind exposition index | - | | | | | | | | | • |
| | Wind speed | m/s | • | | | • | | | | | |
| Air quality | Annual pollutants concentration | µg/m3 | • | | | | | | | | |
| Socio-economic | Socio-economic factors | - | • | | | | | | • | | |
| Anthropogenic | City Canyons | - | | | | | | | • | | |
| | Population Density | ab/$km^2$ | | | | | | | • | | |
| Geomorphological | Plan curvature | - | | | | | | • | | | |
| | Profile curvature | - | | | | | | • | | | |

**Fig. 2.** Summary of conditioning factors for each hazard.

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