Multi-Hazard Susceptibility Mapping in Europe Using Deep Learning

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ABSTRACT

This research aims to create Europe's first high-resolution, continent-wide multi-hazard susceptibility map using deep learning, addressing a critical gap in existing methodologies that often focus on single hazards or smaller geographic areas. By integrating hazard-specific models and adapting knowledge from a Japan-focused framework, the study will boost predictions for data-scarce hazards such as earthquakes. The large-scale MYRIAD-HES dataset and an extensive set of pre-engineered features form the basis for training and validation, with model performance evaluated via ROC-AUC and F1 metrics and interpretability measured through SHAP values. Potential risks, including limited computational resources on the Snellius cluster and data availability issues, will be mitigated through resource reallocation, open-data sourcing, and continuous expert guidance. Ultimately, this work seeks to advance European disaster preparedness and policymaking by offering a robust, unified hazard map capable of capturing complex hazard interactions at the continental scale.

1 INTRODUCTION

Natural hazards such as floods, droughts, landslides, and earthquakes present significant risks across Europe [7]. Understanding the susceptibility of regions to these hazards is essential for effective disaster risk management and planning. Multi-hazard susceptibility mapping is a tool for identifying areas at risk, but existing methods often focus on single hazards or lack a standardized approach for integrating multiple hazards.

This research builds on the methodology in development by Tiggeloven et al., which applied deep learning techniques to map multi-hazard susceptibility in Japan. This study adapts the same approach for Europe, addressing regional differences in hazard characteristics and data availability. Unlike the Japan study, where feature engineering was a central focus, this work uses pre-engineered features prepared by the supervisor, allowing the study to focus on deep learning modeling and validation.

Supervised learning techniques, including Convolutional Neural Networks (CNNs) and Transformers, will be used to model hazard susceptibility. The Hazard Event Sets (MYRIAD-HES) will serve as ground truth for validation, providing labeled data for evaluating model performance. This dataset contains global multi-hazard events, spanning from 2004 to 2017, which includes eleven hazards (coldwaves, heatwaves, droughts, earthquakes, extreme wind events, floods, landslides, tropical cyclones, tsunamis, volcanic eruptions, and wildfires) [6]. Transfer learning will also be explored to improve predictions for hazards, such as earthquakes, where data is less comprehensive.

Current approaches to multi-hazard susceptibility mapping are often limited in scope, focusing on single hazards or small geographic areas. [12] While statistical methods and machine learning techniques have been applied in some contexts, their ability to model interactions between hazards remains underexplored in Europe. The unpublished study by Tiggeloven et al. demonstrated the effectiveness of deep learning in integrating multiple hazards for Japan. However, the applicability of this framework to other regions, such as Europe, has not been validated [14].

1.1 Research Question

To what extent can deep learning approaches produce high-resolution, continental-scale multi-hazard susceptibility maps across Europe's diverse geophysical and climatic regions?

1.2 Sub-Questions

- *Which deep learning architectures (CNNs, Transformers) are most effective for modeling multi-hazard susceptibility at a continental scale?*
- *How can knowledge transfer from prior studies (Japan) be leveraged to improve performance for data-scarce hazards in Europe?*
- *How do susceptibility patterns vary across Europe's diverse regions, and what implications do these variations have for disaster preparedness and policy-making?*
- *What methodologies or metrics can be used to evaluate and validate the accuracy of high-resolution, continent-wide susceptibility maps?*

2 RELATED WORK

2.1 Multi-Hazards: Definitions and Context

Natural disasters have significant negative impacts on economic, human, and environmental systems. They can cause severe short-term economic disruptions and hinder long-term growth, development, and poverty reduction [2]. A recent shift from considering the effects and consequences of hazards individually has led to a holistic framework for identifying and studying multi-hazards. Defined by the UNDRR as "the specific contexts where hazardous events may occur simultaneously, cascadingly or cumulatively over time, and taking into account the potential interrelated effects" [16], multi-hazard account for 59 % of worldwide economic losses attributable to natural hazards from 1900-2023 [10]. Therefore, understanding and mapping multi-hazard risk is a key element of modern disaster preparedness.

2.2 Susceptibility Mapping: Concepts and Methods

Hazard susceptibility mapping integrates various datasets and methods to create risk assessment maps, aiding in disaster preparedness and land management [9]. However, considering the interrelated effects of hazards, interest in multi-hazard susceptibility mapping has grown. These maps assess multiple natural hazards and their interactions, providing a comprehensive view of risk compared to single-hazard approaches [11, 15]. This method combines individual hazard susceptibility maps to create an integrated multi-hazard map, offering decision-makers visual information for effective disaster management and land use planning [11]. Advanced techniques like Convolutional Neural Networks have shown superior performance in predicting multiple hazards compared to conventional machine learning algorithms [15].

Multi-hazard susceptibility mapping in Europe is gaining importance due to the increasing vulnerability of society to environmental risks. Studies have assessed multiple climate-related hazards across Europe, projecting a progressive increase in overall climate hazard, particularly in southwestern regions, driven by heat waves, droughts, and wildfires [8]. Research has also focused on specific infrastructure, such as power plants, evaluating their susceptibility to earthquakes, floods, tornadoes, and lightning [13]. Methodological approaches for creating multi-risk maps at regional levels have been developed, integrating stakeholder perceptions with classical risk assessment frameworks [4] . These studies underscore the current localized focus of each study, tailored to the unique hazard profiles and socio-economic contexts of different European regions, but also the varying methodologies employed, ranging from purely statistical models to hybrid frameworks that use qualitative inputs. This disjointed landscape of methods emphasizes the need for a unified, deep learning framework that can integrate these diverse approaches to produce a consistent and comparable multi-hazard susceptibility map for Europe.

2.3 Deep Learning in Susceptibility Mapping

Deep learning techniques are increasingly applied to single-hazard susceptibility mapping, offering improved accuracy and efficiency over traditional methods [15]. Convolutional Neural Networks (CNNs) have shown excellent performance in landslide susceptibility mapping, outperforming other machine learning algorithms [1**?**]. For flood mapping, deep learning models based on convolutional layers generally provide more accurate results by leveraging spatial characteristics of flooding events [3]. Furthermore, the capacity for modeling non-linear behaviors through non-linear activation functions is crucial for handling the complex interaction effects between hazards.

2.4 The MYRIAD Hazard Event Set

The MYRIAD Hazard Event Dataset is a global multi-hazard event set database developed using the MYRIAD-Hazard Event Sets Algorithm (MYRIAD-HESA) [5]. This open-access method compiles historically-based multi-hazard event sets from 2004 to 2017, incorporating eleven hazards across various classes. The dataset aims to provide insights into multi-hazard event frequencies and hotspots, considering temporal dimensions like time-lags between hazard occurrences. It supports the MYRIAD-EU project's vision of "catalyz[ing] this paradigm shift required to move towards a multi-risk, multi-sector, systemic approach to risk management" [17].

2.5 Research Gap and Opportunity

As pointed out by Ward and the MYRIAD-EU team, there is an ongoing paradigm shift from considering single hazard risk to multi-hazard risk to address real-world challenges [17]. While multi-hazard susceptibility has been mapped on the regional scale in Europe, a continent-wide cohesive map is still lacking. It is with this scientific gap in mind that this research will use a deep learning framework, alongside traditional numerical methods, to create a unified European multi-hazard susceptibility map. The purpose of this map is to facilitate the European non-expert stakeholder with policy- and decision-making surrounding disaster preparedness and prevention.

3 METHODOLOGY

The overarching goal of this research is to create a multi-hazard susceptibility maps of the European continent. To achieve this goal, single-hazard susceptibility maps are first generated using statistical and deep learning methods, on which a comprehensive multi-hazard map can be trained. These models will be trained on pre-engineered features and optimized using state-of-the-art hyper-parameter tuning. The MYRIAD-HES will be used a ground truth for the final map and will be validated using performance metrics such as ROC-AUC and F1 scores. Interpretability techniques like SHAP values will be used to analyze feature importance and identify key susceptibility patterns across Europe, supporting disaster preparedness efforts.

The secondary objective focuses on applying transfer learning to address data gaps, particularly for earthquakes. Pre-trained models from Japan will be fine-tuned with European data to improve predictions in regions with limited hazard data.

3.1 Data and Resources

The single-hazard maps will be generated from feature engineered raw data. The feature engineering will follow the methodology from Tiggeloven et al. nd and will be generated from topological and environmental data including Digital Elevation Maps (DEM), roads, rivers, coastlines, faultlines, soil, lithology, landcover, Normalized Difference Vegetation Index (NDVI), wind, temperature and precipitation maps. The feature engineered data, as well as the hand-labeled ground truths for the deep learning approaches will be provided by the project supervisor and the IVM.

The multi-hazard map will use the single-hazard maps for training and validate against the primary ground truth provided by the MYRIAD dataset, which covers eleven different hazards (e.g., floods, droughts, landslides, earthquakes) for the period 2004–2017.

3.2 Data Pre-processing and Exploratory Data Analysis (EDA)

Although feature engineering has been done, the datasets will be verified for consistency and completeness. Features will be normalized and resampled to a common resolution of 10 arc-seconds (3̃00m a the equator). Additionally, a thorough EDA will be conducted to identify residual inconsistencies or outliers, and to examine the distribution and inter-correlations of the pre-engineered features.

3.3 Individual Hazard Modeling

Single-hazard susceptibility maps will be generated using statistical methods and deep learning. Following the methodology from the Japan study, statistical methods will be used for extreme wind, droughts, heatwaves and wildfire hazard susceptibility maps, while deep learning is used for floods, landslides, and tsunamis. Earthquake and volcanoes are dealt with based on occurrence and distance metrics.

3.3.1 Extreme Wind. Extreme wind can be statistically mapped by choosing a threshold (Beaufort scale 6, 10.8m/s) and summing the days with a wind speed above said threshold. A normalization can be applied to obtain a usable range.

3.3.2 Droughts. Droughts can be modeled using the Standardized Precipitation Evaporation Index (SPEI, Vicente-Serrano et al., 2010), and normalizing for consistency.

3.3.3 Heatwaves. A heatwave signal can be generated from consecutive periods of high temperatures. Given a threshold (95%), periods above this can be flagged as heatwaves. Similarly to the extreme wind signal, heatwave periods can be statically summed and normalized for each cell.

3.3.4 Wildfires. Although the Japan study used simple statistical modeling for forest fires, because of the general lack of hazard on the island, in Europe wildfires are more common. Therefore a deep learning modeling can create a susceptibility map from predictors such as, temperatures, landcover, distance to rivers, accumulated water flux to model historical data.

3.3.5 Floods. Susceptibility maps for floods can be generated from the feature engineered data slope, curvature, aspect, accumulated water flux, landcover, NDVI, precipitation, soil type, and distance to rivers using CNNs.

3.3.6 Landslides. Similarly to floods, landslides can be mapped using CNNs, with slope, curvature, aspect, accumulated water flux, landcover, NDVI, soil type, distance to roads, and distance to fault lines as predictors.

3.3.7 Tsunamis. The tsunami signal can be created using the same deep learning framework, using elevation, distance to coastlines, and distance to fault lines as predictors.

3.3.8 Earthquake. Though earthquakes are uncommon in Europe, the east of the region is susceptible. The susceptibility can be generated from distance to fault lines, and based on historical data.

3.3.9 Volcanoes. Volcanic susceptibility can be modeled by identifying historical volcanically active sites and estimating the affect area scaled by the Volcanic Explosivity Index (VEI) following Shi Kasperson (2015)

3.4 Deep Learning Framework

Convolutional Neural Network (CNNs) architectures will be used to capture spatial patterns within the hazard features. The design includes multiple convolutional layers with ReLU activations, followed by max pooling and batch normalization layers. The single-hazard susceptibility maps will be trained per hazard, while the overall multi-hazard susceptibility map will use a meta-model, or ensemble, approach to combine the outputs of all single-hazards and accounts for the interaction effects between various models.

For each model, the input tensor will be split into training, validation and testing tensors. The training will be done using the PyTorch library and performed on the Snellius cluster, using Binary Cross Entropy (BCE) for classification or Mean Absolute Error (MAE) for regression tasks as loss functions. Standard metrics such as ROC-AUC, F1 scores, and MAE will be used to quantify accuracy and robustness. To further enhance transparency, interpretability techniques like SHapley Additive exPlanations (SHAP) can be applied to understand the influence of each input feature on the model's predictions. Hyperparameters tuning will be done using the weights and biases API, also on Snellius.

3.5 Transfer Learning

To improve predictions for hazards with limited European data, pre-trained models from the Japan study will be fine-tuned, if time permits. Using the deep learning models used for single-hazard mapping in Japan as foundational models, further fine tuning on the available European data can be used and compared against the previously established methods.

4 RISK ASSESSMENT

A number of risks have been identified that may impact the project's timeline and outcomes. First, while European land data such as elevation and land cover maps are provided by the supervisor, any gaps can be addressed using publicly available datasets from sources like Copernicus, Sentinel, and ERA5-Land.

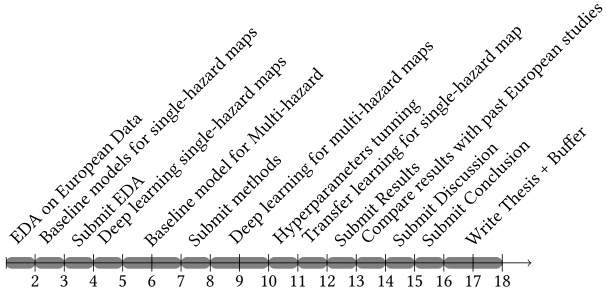
Second, the compute budget poses a significant challenge; the current allocation on the Snellius cluster is limited to 150k SBUs, which may be insufficient given the volume of data. To mitigate this, steps have already been initiated to secure a larger budget on behalf of the supervisor.

Additionally, if computational resources remain constrained, transfer learning from the Japan study offers a viable alternative, as fine-tuning pre-trained models requires significantly fewer resources. However, this approach may come at the cost of reduced generalization and is dependent on the timeline. If the generation of individual hazard maps and the subsequent multi-hazard map takes longer than anticipated, there may be insufficient time to implement transfer learning effectively.

Finally, given the niche domain of multi-hazard susceptibility mapping and the specialized physical concepts involved, there is a risk that certain domain-specific nuances might be initially overlooked. This risk will be mitigated through consistent, daily feedback from the supervisor, ensuring that any knowledge gaps are promptly addressed and the scientific rigor of the research is maintained.

5 PROJECT PLAN

The first phase of the research is to study the European spatial data provided by the supervisor for any relevant correlations, missing data and distributions to help determine the best architecture for the map generation. At this stage, single-hazard maps will be developed using baseline models and statistical modeling. After writing up the exploratory data analysis (EDA), a baseline for the multi-hazard susceptibility map will be developed for future comparison. Deep learning methods for the relevant single-hazards will be put in place here, and the methodology will be fleshed out for the rest of the project. Once the methods are submitted, the deep learning architecture will be developed for the multi-hazard maps based on the already generated single-hazard maps. Hyperparameter optimization will be performed using the weights and bias API for all deep learning models. These models will then be validated and their results visualized and compared against past research. Transfer learning will also take place at this point, using the single-hazard maps to fine-tune the models from the Japan case-study. Then, the result section will highlight the findings of this research and will be submitted for feedback. Lastly, the final weeks will be spent writing the manuscript, with two weeks for buffer.



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