Quanta Research
https://ijitis.org/index.php/QR
ISSN: 2806-3279
Volume 1, Issue 2
DOI: doi.org/10.15157/QR.2023.1.2.27-33
Received: 01.08.2023; Accepted: 05.10.2023

A Social-Based Decision Support System for Flood Damage Risk Reduction in European Smart Cities

Mohammad Gheibi[1,2*], Reza Moezzi[2,3,4]

[1]Institute for Nanomaterials, Advanced Technologies and Innovation, Technical University of Liberec, Czech Republic
[2]Faculty of Mechatronics, Informatics and Interdisciplinary Studies, Technical University of Liberec, Czech Republic
[3]Association of Talent under Liberty in Technology (TULTECH), Tallinn, Estonia
[4]Institute of Forestry and Engineering, Estonian University of Life Science, Tartu, Estonia

***Mohammad.Gheibi@tul.cz**

Abstract

Today, Decision Support Systems (DSS), which include monitoring, prediction, and control sections, are assumed to be tools for smart, sustainable management of disasters such as floods. On the platforms, first, a process is designed for receiving valid data before, during, and after a flood. Then, with the application of artificial intelligence (AI) models, the essential features can be predicted. Meanwhile, the main predicted factors should be determined according to the goals of each research project. In the present study, two-stage machine learning models will be used, including damage values in cities and rural regions and social impacts. In the first step, damages will be estimated by machine learning computations based on rainfall (mm), hourly flow of the river (m3/s), type of vegetation, density, etc. In a parallel way, after the determination of structural equation modeling (SEM) of social parameters in flood and their weights, in the second step of AI modeling, the social feedback factor will be forecasted based on effective achieved features. Finally, with the application of controlling systems such as the Decision Tree (DT) model, a fast reaction system is designed.

Keywords: Flood; Decision Support System; Smart City; Risk Reduction; Damage

INTRODUCTION

Based on the previous research as well as the available statistics, it has been proven that the flood has caused significant damage in different regions throughout the history of Europe [1]. This is despite the fact that this natural disaster has two different dimensions: financial losses and loss of life. As seen in Fig. 1, in 1967, Portugal also experienced significant damage from this phenomenon. Various factors influence the occurrence of floods, the most important of which are rainfall intensity, river discharge, density, type of vegetation, and topographic indicators [2]. With the application of the available data and the historical data analysis, a soft sensor can be designed for the prediction of damages [2]. With the model, the risk assessment can be done online and before the event. Therefore, based on the research background, it is an alarm management approach in flood disasters [3]. The current studies of flood machine learning computations are presented as per Table 1. With consideration to the declared table, it can be found that social-based DSS has not been considered by previous studies.

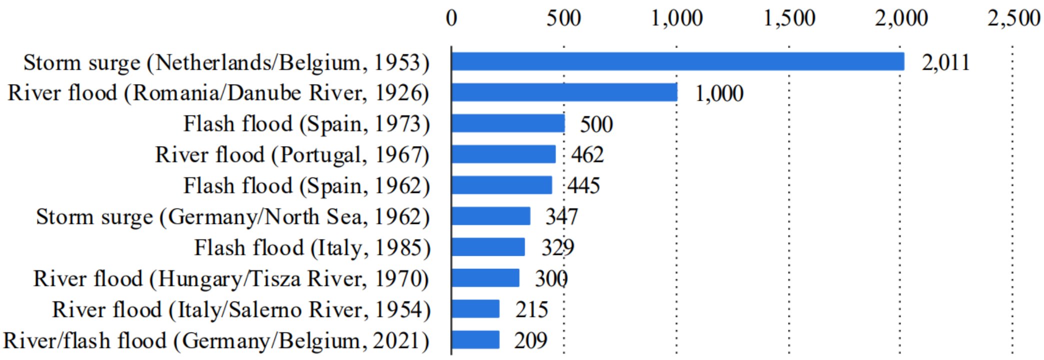

Figure 1. Deadliest floods in Europe 1921-2021, ID: Yale University; EM-DAT; ID 1295966.

Table 1. Research Review on tools and techniques

Researchers	Tools and techniques
Avand et al. (2022) [4]	Random Forest (RF), Artificial Neural Network (ANN), and Generalized Linear Model (GLM) Digital Elevation Model (DEM) Flood Probability Maps (FPMs)
Prasad et al. (2022) [5]	Rotation Forest (RF), Nearest Shrunken Centroids (NSC), KNearest Neighbor (KNN), Boosted Regression Tree (BRT), and Logit Boost (LB)
Chang et al. (2022) [6]	Integration of Self-Organizing Map (SOM), Principal Component Analysis (PCA), and Nonlinear Autoregressive with Exogenous Inputs (NARX)
Zhou et al. (2022) [1]	Quantile Regression Neural Network (MCQRNN) and Xinanjiang conceptual model (XAJ)
Nevo et al. (2022) [3]	Linear Model (LM) and Long Short-Term Memory (LSTM) networks
Elkhrachy et al. (2022) [7]	Sentinel-1, Sentinel-2, and Digital Surface Models (DSMs), Hydrologic Engineering Center's River Analysis System (HEC-RAS 2D), Gradient Boosting Regression (GBR), Random Forest Regression (RFR), Linear Regression (LR), Extreme Gradient Boosting Regression (EGBR), Multilayer Perceptron Neural Network Regression (MLPR), K-nearest Neighbors Regression (KNR), and Support Vector Regression (SVR)
Ha et al. (2022) [8]	Systematically Developed Forest of Multiple Decision Trees (SYS) and Decorate-SYS, Rotation Forest-SYS, and VoteSYS

Baig et al. (2022) [9]	Flood Probability Mapping (FPM), Gaussian Process Regression (GPR) and Support Vector Machine (SVM), and kernel functions
McGrath et al. (2022) [10]	Flood Susceptibility Mapping (FSM) and RF model
Antzoulatos et al. (2022) [11]	Satellite imagery, Geographical Information System (GIS), RF model

The present research contains three different main goals and eight sub-goals, as below:

- **designing a soft sensor based on available hydro-geographical data;**
  - Statistical data analysis and data mining of available data for the determination of the most significant features of flood occurrence
  - sensitive analysis of available data due to the determination of thresholds.
  - presentation of the optimum condition for reengineering nature with a concentration of managerial insights
- **Social-based DSS as per public transformational participation;**
  - Structural Equation Modelling (SEM) based on questionnaire practices as social monitoring system in flood.
  - Application of machine learning computations for prediction of social resilience factors during the flood event
  - The presentation of social risk management (SRM) platforms based on three categories includes catastrophic vs. non-catastrophic shocks, idiosyncratic shocks vs. covariant shocks, and single vs. repeated shocks with the application of the Decision Tree (DT) conceptual model.
- **Foresight study of SRM and flood events based on the System Dynamic (SD) model**
  - Designing a SD model for scenario-building social resilience enhancement during the flood
  - Sensitive analysis of the SD model and presentation of a Social Resilience Enhancement Model (SREM)

MATERIALS AND METHODS

According to the objectives of the present research, a research roadmap is presented as per Fig. 2. As per the mentioned scheme, it is clear that in the first step, all required data should be collected through a questionnaire and data gathering, and all the data will be archived in the Geographical Information System as a databank (Fig. 3). While focusing on the progress data, thresholds for creating desirable, allowable, and alarm conditions are justified. Then, by applying historical data analysis to response surface methodology (RSM), an optimum condition for minimizing flood damage is presented. Therefore, a conceptual model for nature-based facilities and complications modification is developed. After this part, the research roadmap is divided into three different branches: (I) machine learning computations, (II) social-based DSS, and (III) SD modeling.

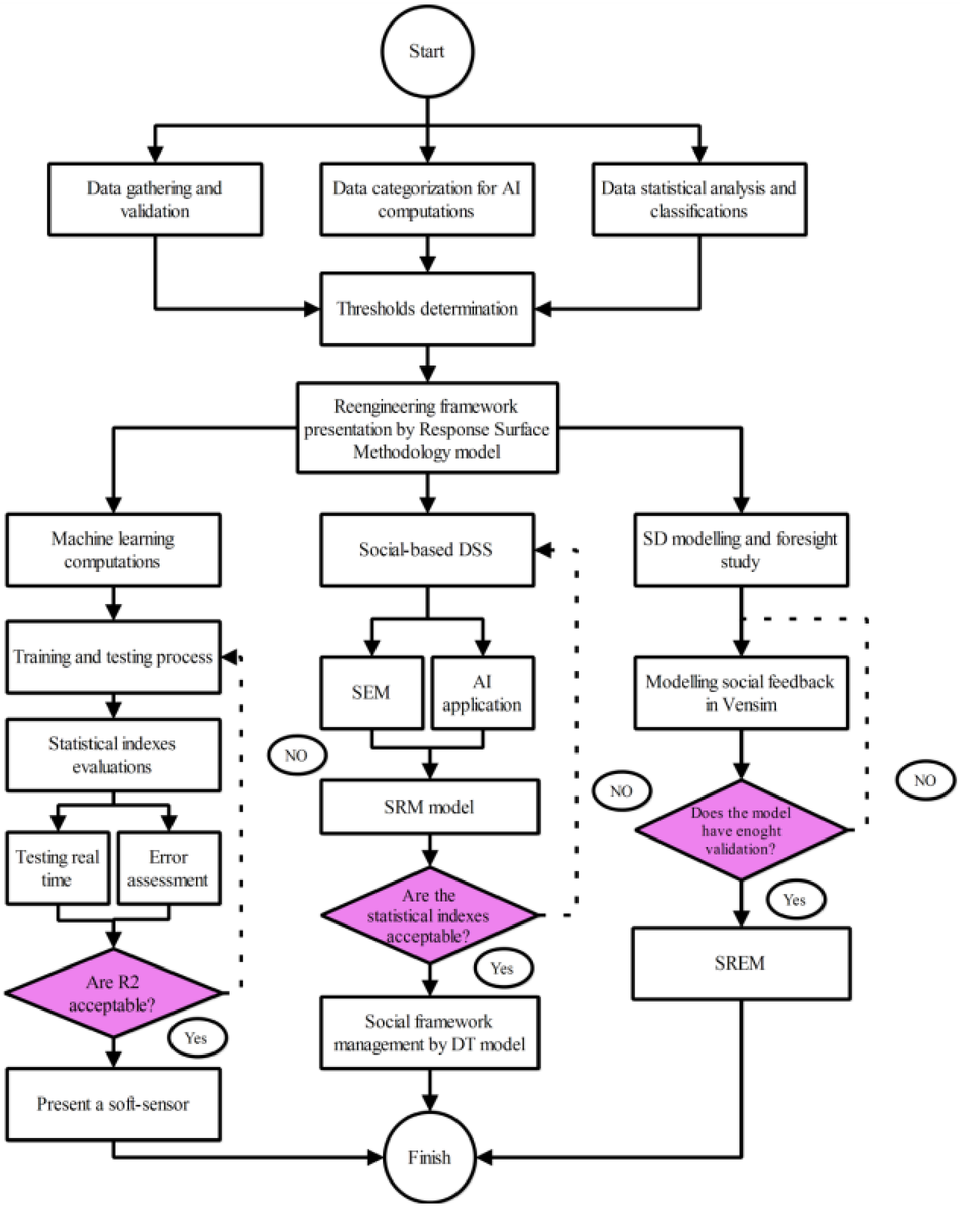

Figure 2. The research roadmap of the present study

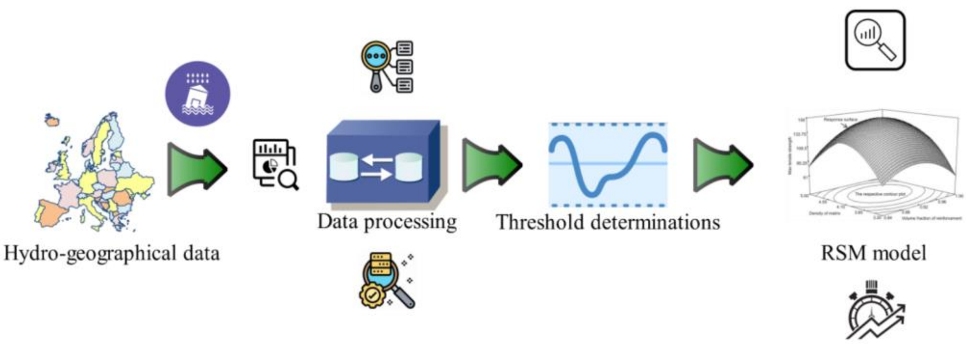

Figure 3. The structure of data processing and threshold assessment with consideration of complications and reengineering

With concentration on Fig. 4, it can be found that in the machine learning computations and creating the soft sensor, there is a milestone for checking the precision of the smart flood occurrence model. In this research, at least ten machine learning models are examined, and the best performances of them are introduced. In the process of machine learning practices, some computational parameters, such as number of folds, share of train percentage, etc., will be tuned by the Taguchi design technique.

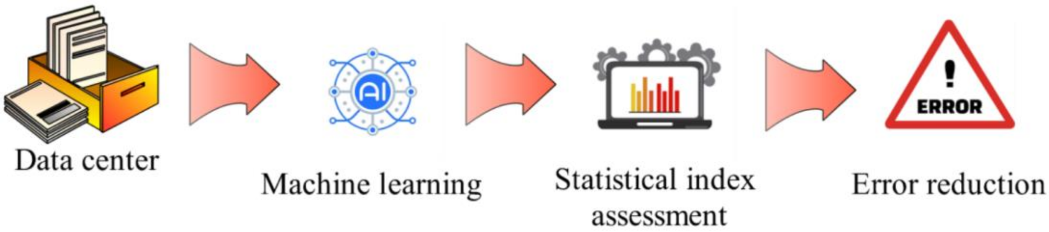

Figure 3. The machine learning computation steps in the research.

In the following, in the second step, for creating social-based DSS, in the first step, the questionnaire should be provided based on a literature review and knowledge management banks. Then, after surveying three groups, including citizens, principals, and experts, the statistical modeling is done to achieve a SEM, and with the mentioned approach, the importance of each social feature is determined. Then, an AI model is created for social resilience factor determination during the disaster. Finally, a SRM framework is presented as per the DT technique. In the milestone of this section, the statistical indexes of the model are examined. The summary of the model is illustrated according to Fig. 5.

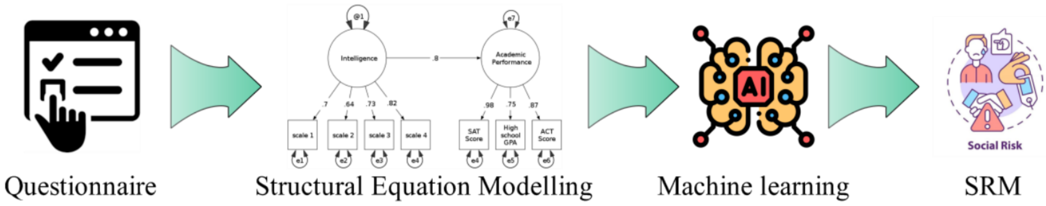

Figure 4. The structure of social-based DSS for flood SMR.

In the last part of this research (Fig. 6), a SD model is presented for the foresight study of social resilience feedback in different scenarios, which is simulated on the Vensim platform. In the last section, after sensitive analysis, a managerial insight is introduced.

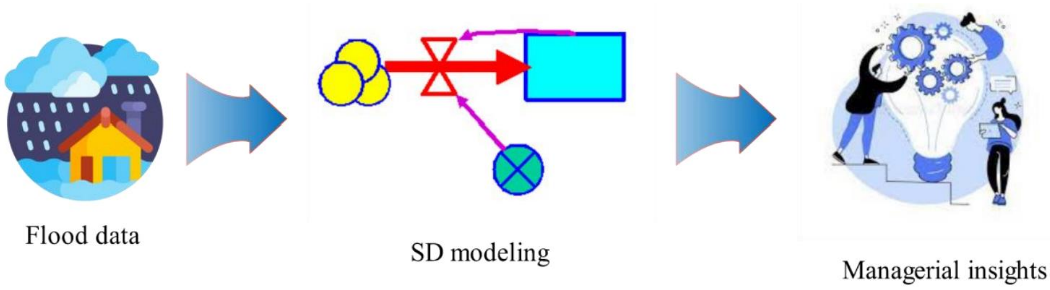

Figure 6. The stages of foresight study in different scenarios of flood

CONCLUSION

This paper proposes a social-based decision support system (DSS) for flood damage risk reduction in European smart cities. Acknowledging the importance of DSS in managing disasters like floods, the study introduced a comprehensive approach involving monitoring, prediction, and control mechanisms. The first stage of the proposed DSS focused on acquiring valid data before, during, and after a flood. Utilizing artificial intelligence (AI) models, the system predicts essential features crucial for effective decision-making. The study employed a two-stage machine learning approach, addressing both damage values in urban and rural areas and the social impacts of floods. In the initial step, damage estimation is carried out through machine learning computations, considering factors such as rainfall, hourly river flow, vegetation type, and density. Simultaneously, the social parameters and their weights are determined using structural equation modeling (SEM). In the second stage of AI modeling, the social feedback factor is forecasted based on identified influential features. To enhance the system's responsiveness, a controlling mechanism, specifically the Decision Tree (DT) model, is implemented. This fast reaction system contributes to timely decision-making and proactive measures in the face of flood-related challenges. Overall, the proposed social-based DSS integrates machine learning, AI, and SEM methodologies to provide a holistic approach to flood risk reduction. The study envisions the implementation of such intelligent systems in European smart cities to enhance resilience and minimize the social and structural impact of flooding events.

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest associated with this publication.

REFERENCES

[1]. Zhou, Y., Cui, Z., Lin, K., Sheng, S., Chen, H., Guo, S. and Xu, C.Y., 2022. Short-term flood probability density forecasting using a conceptual hydrological model with machine learning techniques. Journal of Hydrology, 604, p.127255.

[2]. Akbarian, H., Gheibi, M., Hajiaghaei-Keshteli, M. and Rahmani, M., 2022. A hybrid novel framework for flood disaster risk control in developing countries based on smart prediction systems and prioritized scenarios. Journal of environmental management, 312, p.114939.

[3]. Nevo, S., Morin, E., Gerzi Rosenthal, A., Metzger, A., Barshai, C., Weitzner, D., Voloshin, D., Kratzert, F., Elidan, G., Dror, G. and Begelman, G., 2022. Flood forecasting with machine learning models in an operational framework. Hydrology and Earth System Sciences, 26(15), pp.4013-4032.

[4]. Avand, M., Kuriqi, A., Khazaei, M. and Ghorbanzadeh, O., 2022. DEM resolution effects on machine learning performance for flood probability mapping. Journal of Hydroenvironment Research, 40, pp.1- 6.

[5]. Prasad, P., Loveson, V.J., Das, B. and Kotha, M., 2022. Novel ensemble machine learning models in flood susceptibility mapping. Geocarto International, 37(16), pp.4571-4593.

[6]. Chang, L.C., Liou, J.Y. and Chang, F.J., 2022. Spatial-temporal flood inundation nowcasts by fusing machine learning methods and principal component analysis. Journal of Hydrology, 612, p.128086.

[7]. Elkhrachy, I., 2022. Flash flood water depth estimation using SAR images, digital elevation models, and machine learning algorithms. Remote Sensing, 14(3), p.440.

[8]. Ha, H., Bui, Q.D., Khuc, T.D., Tran, D.T., Pham, B.T., Mai, S.H., Nguyen, L.P. and Luu, C., 2022. A machine learning approach in spatial predicting of landslides and flash flood susceptible zones for a road network. Modeling Earth Systems and Environment, pp.1-17.

[9]. Baig, M.A., Xiong, D., Rahman, M., Islam, M., Elbeltagi, A., Yigez, B., Rai, D.K., Tayab, M. and Dewan, A., 2022. How do multiple kernel functions in machine learning algorithms improve precision in flood probability mapping?. Natural Hazards, pp.1-20.

[10]. McGrath, H. and Gohl, P.N., 2022. Accessing the impact of meteorological variables on machine learning flood susceptibility mapping. Remote Sensing, 14(7), p.1656.

[11]. Antzoulatos, G., Kouloglou, I.O., Bakratsas, M., Moumtzidou, A., Gialampoukidis, I., Karakostas, A., Lombardo, F., Fiorin, R., Norbiato, D., Ferri, M. and Symeonidis, A., 2022. Flood Hazard and Risk Mapping by Applying an Explainable Machine Learning Framework Using Satellite Imagery and GIS Data. Sustainability, 14(6), p.3251.