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Flood susceptibility assessment using deep neural networks and open-source spatial datasets in transboundary river basin

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ABSTRACT

The Mekong Basin is the most critical transboundary river basin in Asia. This basin provides an abundant source of fresh water essential for the development of agriculture, domestic consumption, and industry, as well as for the production of hydroelectricity, and it also contributes to ensuring food security worldwide. This region is often subject to floods that cause significant damage to human life, society, and the economy. However, flood risk management challenges in this region are increasingly substantial due to conflicting objectives between several countries and data sharing. This study integrates deep learning with optimization algorithms, namely Grasshopper Optimisation Algorithm (GOA), Adam and Stochastic Gradient Descent (SGD), and open-source datasets to identify the region of probably occurring floods in the Mekong basin, covering Vietnam and Cambodia. Various statistical indices, namely Area Under the Curve (AUC), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2), were used to evaluate flood susceptibility models. The results show that the proposed models performed well with AUC values above 0.8, specifying that the DNN-Adam model achieved an AUC of 0.98, outperforming DNN-GOA (AUC = 0.89), DNN-SGD (AUC = 0.87), and XGB (AUC = 0.82. Regions with very high flood susceptibility are concentrated in the Mekong Delta of Vietnam and along the Mekong River in Cambodia. The findings of this study are significant in supporting decision-makers or planners in proposing appropriate flood mitigation strategies, planning policies, and strategies, particularly in the Mekong River watershed.

Keywords: Flood susceptibility, Mekong basin, deep learning, machine learning, AUC validation, climate change, hydrological modeling.

1. Introduction

Flooding is considered one of the most dangerous natural hazards, causing significant damage to infrastructure and people's livelihoods and hampering economic development in regions around the world (Costache et al., 2024; Mangkhaseum, Bhattarai, Duwal, & Hanazawa, 2024). In 2021, there were approximately 206 flood

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events worldwide, causing 4,393 deaths and affecting approximately 29.3 million people (Maharjan et al., 2024). These flood events caused damages of USD 74.6 billion, or 30% of the total economic losses related to natural disasters. The impacts of flooding on human life, society, and the economy have increased by more than 40% in the past two decades and will tend to increase in the future due to climate change and urban growth (Maharjan et al., 2024). In addition, the probability of flood occurrence is increased mainly in Asia, Europe, and North America (Wahba, Sharaan, Elsadek, Kanae, & Hassan, 2024). Among these regions, Asia is the most affected by flooding. In 2015, approximately 62.7% of the total natural disasters were recorded in Asia. Among natural disasters, floods appear to account for up to 30%. China, Thailand, Vietnam, the Philippines, and Indonesia are the countries most affected by floods (Saleem Ashraf, Iftikhar, Ashraf, & Hassan, 2017). Floods significantly impact the society, economy, human life, ecosystems, and natural resources. However, it should be noted that floods also have possible impacts; for example, they help replenish water sources, improve soil quality, and supplement aquatic resources. Therefore, identifying the region with a high probability of flood occurrence is an important task and can support the decision-makers or planners in proposing appropriate strategies for the sustainable development of the territory.

Several studies have highlighted that runoff in the Mekong River basin could increase 2.5 times during the peak rainy season, with increased interannual variability due to climate change (P. Van et al., 2012). With growing flood risk and low economic capacity for adaptation, Cambodia and Vietnam are most exposed to climate change (Q. Dinh, Balica, Popescu, & Jonoski, 2012).

Flood susceptibility is defined as the probability that a flood will occur in a region. The assessment of flood susceptibility generally involves two factors: the first consists of flood drivers (precipitation, storm, etc.), and the second is the environment generating the flood. Therefore, flood susceptibility maps play an important and effective role in reducing the negative impacts of floods and providing information on the characteristics of the corresponding region. There are four methods to identify flood susceptibility: (i) hydrodynamic modeling, (ii) remote sensing and GIS, (iii) multicriteria decision analysis (MCDA), and (iv) machine learning.

Hydrodynamic modeling allows simulating flood events with high precision (Hicks & Peacock, 2005; Patro, Chatterjee, Mohanty, Singh, & Raghuwanshi, 2009; Tansar, Babur, & Karnchanapaiboon, 2020). However, this model requires much detailed data, such as meteorology, topography, and land use data. So, its application is limited to a wide range of areas. In recent years, with the development of remote sensing data, particularly the data-sharing policy of large companies, e.g., NOAA, NASA, etc., remote sensing has been widely applied by researchers to pinpoint regions at flood risk (Hoque, Nakayama, Matsuyama, & Matsumoto, 2011; Samanta, Pal, & Palsamanta, 2018). Although this method has proven effective, its use depends on the availability and quality of the data. In recent years, remote sensing has been integrated with multicriteria decision analysis (MCDA) to assess flood susceptibility (Tang, Zhang, Yi, & Xiao, 2018; Tella & Balogun, 2020). Although MCDA is simple to compute and understand, it is based heavily on expert opinions, leading to data redundancy issues. In recent years, with the development of computer science and remote sensing data, statistical models and remote sensing have been integrated into flood research (Khosravi, Pourghasemi, Chapi, & Bahri, 2016; Tehrany, Pradhan, & Jebur, 2013; Youssef, Pradhan, & Sefry, 2016). statistical models evaluate correlations between flood events and their causes. However, the effectiveness of these models may be limited by the quality of the data and the complex characteristics of flood events. Machine learning models have been widely used by researchers (Band et al., 2020; Dodangeh et al., 2020; Madhuri, Sistla, & Srinivasa Raju, 2021; Zhao, Pang, Xu, Peng, & Xu, 2019) To solve these problems. Such models present advantages for resolving nonlinear relationships of flood events, particularly in the context of climate change and increasing urbanization. Although machine learning models have significant potential in constructing flood susceptibility maps, they also have limitations (Dodangeh et al., 2020). A model may not fully understand input data characteristics in different areas, leading to limited accuracy in flood assessment. Additionally, the accuracy of a machine learning model depends on the quality and quantity of data. Accurately identifying flooding patterns is difficult, particularly in areas with complex topography and coverage (Nguyen, Nguyen, & Bui, 2024). Ultimately, overfitting is a significant issue for machine learning. (Zhu, Guo, & Huang, 2024) were used XGBoost, Support Vector Machine, Multilayer Perceptron, and Multimodal Deep Learning to evaluate flood susceptibility in Tianjin in China. (Kurugama, Kazama, Hiraga, & Samarasuriya, 2024) Applied five machine learning, namely gradient boost machine (GBM), extreme gradient boosting, categorical boosting, logit boost, and light gradient boosting machine (LGBM), to assess flood susceptibility in Rathnapura, Sri Lanka. (Costache et al., 2024) used hybrid models, i.e., Deep Learning Neural Network-Harris Hawk Optimisation Index of Entropy (DLNN-HHO-IOE), Multilayer Perceptron-Harris Hawk Optimisation Index of Entropy (MLP-HHO-IOE), and Stacking ensemble-Harris Hawk Optimization-Index of Entropy (Stacking-HHO-IOE) to build the flood susceptibility map of southeast Romania. (Mangkhaseum et al., 2024) Evaluated flood susceptibility in the Nam Ngum River Basin in Lao PDF using machine learning and remote sensing (Random Forest, Support Vector Machine, Artificial Neural Networks, and Long Short-Term Memory. (Wahba et al., 2024) integrated the ANN and MLP model to evaluate flood susceptibility in the Kanto region of Japan. Their performance was compared with three other machine learning methods, i.e., support vector machine, gradient boosting, least absolute shrinkage, and selection operator (LASSO). The literature shows that although several studies have applied machine learning to construct flood susceptibility maps, issues. However, the construction of flood susceptibility maps varies from one case to another and depends on the characteristics of each region (Bhattarai, Duwal, Sharma, & Talchabhadel, 2024; Kazemi, Mohammadi, Nafooti, Behvar, & Kariminejad, 2024). Therefore, the exploration of a highly stochastic environment motivates our study.

The lack of data and the capacity to generalize models are significant challenges when using machine learning. This study integrates deep learning with optimization algorithms, namely GOA, Adam, and SGD, and open-source datasets to identify the region where floods are probably occurring in the Mekong basin, covering Vietnam and Cambodia. Our optimization occurs in the. Although there are some machine learning optimization algorithms, this study selects three optimization algorithms, namely GOA, Adam, and SGD, to improve the performance of DNN model. In addition, GOA is considered an efficient algorithm for solving nonlinear problems and fast convergence (Al-Qadhi, Latip, Chiong, Athauda, & Hussin, 2025; Alirezapour, Mansouri, & Mohammad Hasani Zade, 2024). Adam is considered a computationally efficient and fast optimization algorithm. This is particularly important for improving the performance of deep learning models where complex models train data. In deep learning applications, gradients may be sparse, meaning that not all parameters must be updated simultaneously. Adam handles sparse gradients well because it uses adaptive learning rates to adjust updates accordingly (Kang, Zhu, Shen, & Li, 2024; Sun et al., 2024). While SGD updates the model parameters using the cost function gradient for each training example. So, it performs frequent updates based on single or small batch training examples, which makes it much faster than other algorithms for large datasets (Dagal, Tanriöven, Nayir, & Akın, 2025; Hashem, Alaba, Jumare, Ibrahim, & Abulfaraj, 2024). This study is the first to evaluate floods in the Mekong watershed. Evaluating flood susceptibility in the Mekong River basin, which covers the regions of Vietnam and Cambodia, is very important because this region is characterised by dense river networks and intense agricultural activity, but is often affected by floods. Therefore, by assessing flood susceptibility, decision makers can better manage crops, irrigation systems, and biodiversity conservation. Ultimately, this study uses open source datasets; therefore, the models used in this study can be replicated in other regions of the world.

2. Study Area

The Mekong River, the largest in Southeast Asia, has a total basin area of 795,000 km² and spans approximately. 4,909 km. It boasts an average discharge of 14,500 m³/s and flows through six countries: Lao People's Democratic Republic (25%), Thailand (23%), China (21%), Cambodia (20%), Vietnam (8%) and Myanmar (3%) (Mrc, 2010). The Mekong River Basin is home to 70 million people, with more than 17 million concentrated in the Mekong Delta. Most people in the Mekong River Basin depend on agriculture, such as rice cultivation, because the region has a dense irrigation network. In addition to rice cultivation, fishing and aquaculture contribute significantly to the livelihoods of people in this region and ensure food security. In addition, industrial zones and urban areas have also developed strongly in recent decades, such as large cities such as Can Tho and Phnom Penh.

The Mekong River Basin (MRB) experiences diverse climates, from temperate to tropical monsoons. The Upper Basin, known as the Lancang River in China, originates from the glaciated Tibetan Plateau. The Lower Mekong basin begins downstream from Yunnan province, passing through the tripoint of the Golden Triangle to the South China Sea, exhibiting a tropical monsoon climate (known as the Lower Mekong basin) (Mrc, 2010).

The Mekong River basin is characterized by varied topography, with elevations ranging from more than 6,000 meters in the Tibetan Plateau to less than a meter (0.3–0.7 meters) above sea level in the downstream delta. (Fig. 1). the basin contains deep-cut valleys within high mountain regions (Mrc, 2010). Annual precipitation averages 1300 mm, with more than 70% occurring during the summer. The dry period extends from December to May, with high evapotranspiration rates.

River flow has a distinct seasonal pattern, with peak flows from June to November accounting for 80 to 90% of total annual discharge (K. D. Dinh, Anh, Nguyen, Bui, & Srinivasan, 2020). This yearly flood season significantly impacts the environment and the inhabitants of the Lower Mekong Basin.

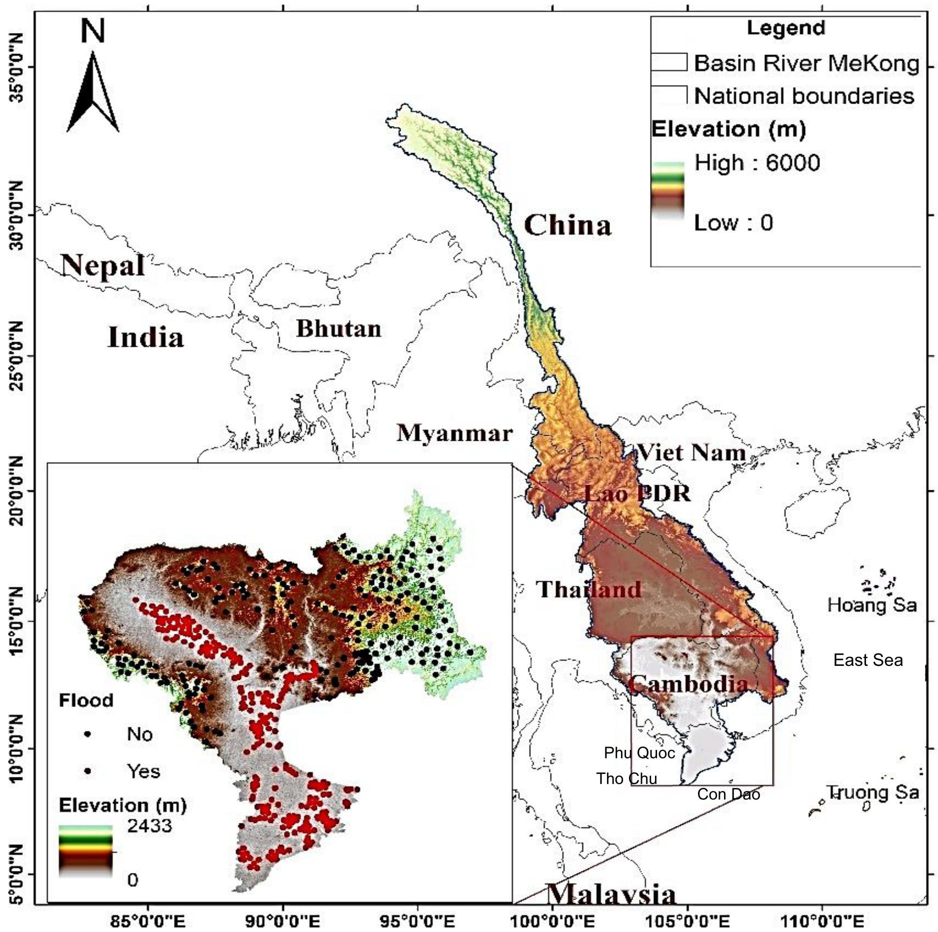


Figure 1. Mekong River Basin

The Mekong Delta is an intricate hydrological system experiencing significant environmental challenges, including annual flooding, drought, and salinity intrusion. These challenges are projected to intensify in the context of climate change and rising sea levels, with prolonged inundation and salinity intrusion becoming persistent under severe sea-level rise scenarios (Toan 2014). The increasing influence of sea-level rise has altered flood dynamics in the VMD, leading to heightened flood frequency and saltwater intrusion in coastal and low-lying areas. Tidal motion dominates water level variations, exacerbating flooding in urban and central deltaic regions (Nghia et al., 2022). The construction of large-scale hydraulic infrastructure, including extensive irrigation networks, Dams, and high dyke systems, has significantly transformed the Mekong Delta's flood regime (Manh et al., 2015). The high dyke system, in particular, has disrupted natural flood retention mechanisms, contributing to a reduction in upstream floodwater storage and an increase in peak water levels in downstream areas (Duc Tran et al. 2017). Consequently, urban flooding has intensified due to constrained drainage capacity and increasing tidal influence (Nghia et al., 2022)

Floods offer substantial benefits to the Lower Mekong Basin (LMB). They sustain the annual fish catch, particularly in the Great Lake, support 5.24 million hectares of flooded wetlands, provide water for irrigation in the dry season, and fertilize the floodplains with an annual silt deposit (Im, 2018). The case study area is located on the lower Mekong River, in the territory of Vietnam and Cambodia. The Central Highlands of Vietnam have the Sesan River in the north and the Srepok River in the south, which flows into the Mekong mainstream in Cambodia. The Phnom Kravanh and Damrei Mountains in the Southwest and the Dangrek Mountains in the North surround Cambodia's vast basins and plains. The higher lands in the northeast and East of Cambodia border the central Highlands of Vietnam.

The Tonle Sap Lake regulates the downstream water by connecting with the Tonle Sap River, whose flow direction changes seasonally. During the flood season, water flows from the Tonle Sap River into the lake, and during the dry season, water flows from the lake into the Tonle Sap River. The Mekong River flows into Vietnam through two main streams, The Tien River and the Hau River, which flow into the East Sea through 9 estuaries. The Mekong River system in South Vietnam is often called the Cuu Long River.

3. Materials and methodology

3.1. Flood Inventory Map

Flood inventory is essential when using machine learning to assess flood susceptibility. It provides information on past floods, such as frequency and spatial distribution. It also presents the relationships with flood causes (Amiri, Soltani, Ebtehaj, & Bonakdari, 2024; Widya et al., 2024). The location of previous floods was used to predict the flood susceptibility potential because the region has the same characteristics as regions affected by previous floods (Islam & Chowdhury, 2024). The flood inventory included areas affected by floods in the past and those that will potentially be affected in the future. In this study, the flood inventory was collected from previous studies. Additionally, to improve data quality, this study used the Sentinel 1A image to detect the flood event in 2010, 2020 in Cambodia and Vietnam country of Mekong bassin. 291 flood points covering Vietnam and Cambodia were collected to build the flood susceptibility model along the Mekong River.

In machine learning, flood points were assigned a value of 1, and nonflood points were assigned a value of 0. The flood and nonflood data set was divided into training (70%) and validation (30%). Evaluating model performance using unpublished validation data allowed us to obtain more unbiased results.

3.2. Flood Conditioning Factor

When evaluating flood susceptibility with high precision, it is necessary to consider flood conditioning factors. In this study, flood susceptibility factors were selected based on the availability of data because one of the main objectives of this study was the evaluation of flood susceptibility using free data so that it can be reproduced in other regions (Bhattarai et al., 2024; Elghouat et al., 2024). Additionally, the selection of factors also depends on characteristics of physical geography, hydrology, climate, and human activity in Vietnam and Cambodia. Finally, 12 flood conditioning factors were selected to assess flood susceptibility in the Mekong watershed, that is, elevation, curvature, aspect, slope, river density, road density, rainfall, Normalised Difference Vegetation Index (NDVI), Normalized Difference Build-up Index (NDBI), Normalized Difference Water Index (NDWI), Landcover/land use (LULC) and soil type (Fig. 2).

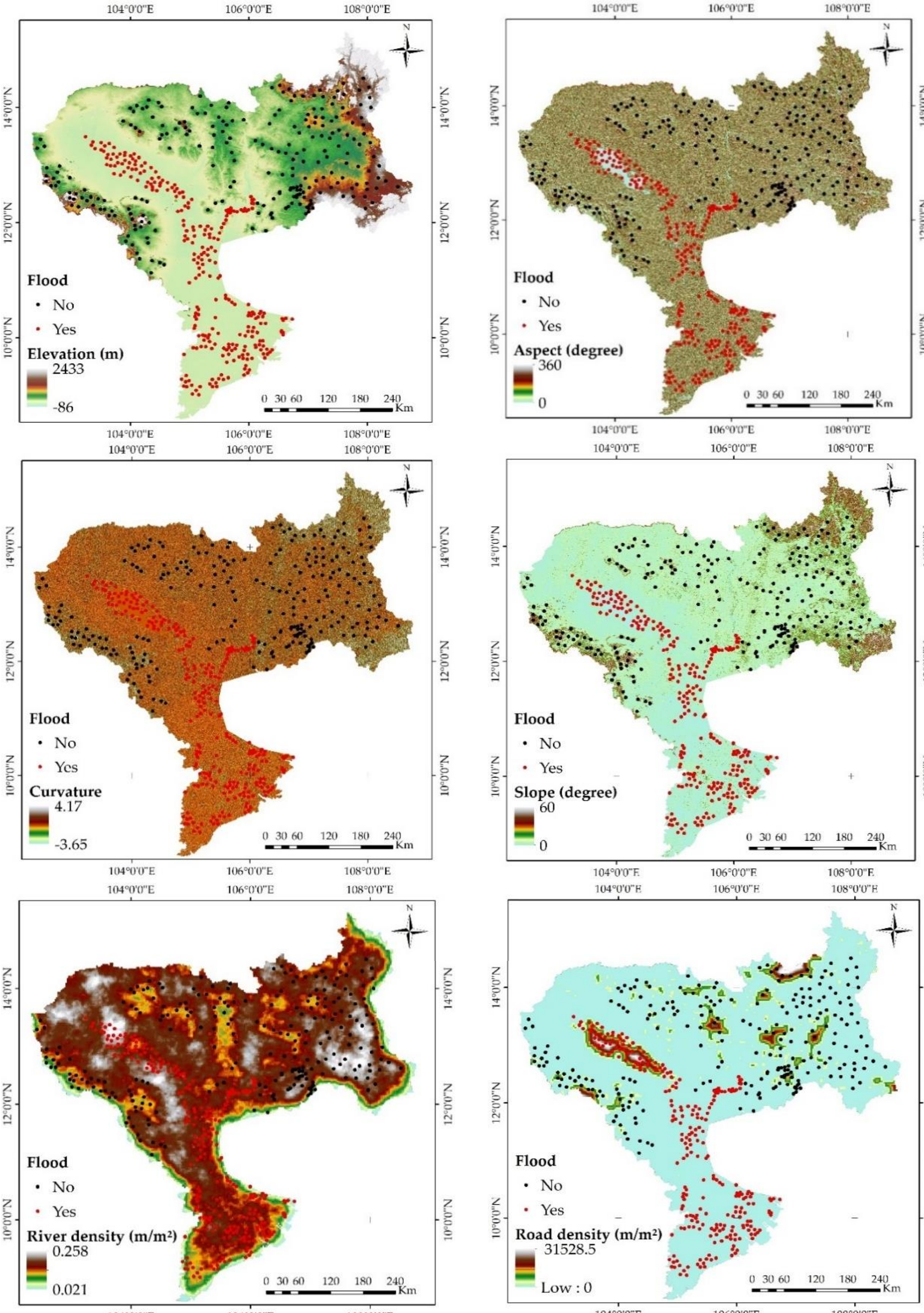


Figure 2. Flood conditioning factor used for the flood susceptibility model in the Mekong basin

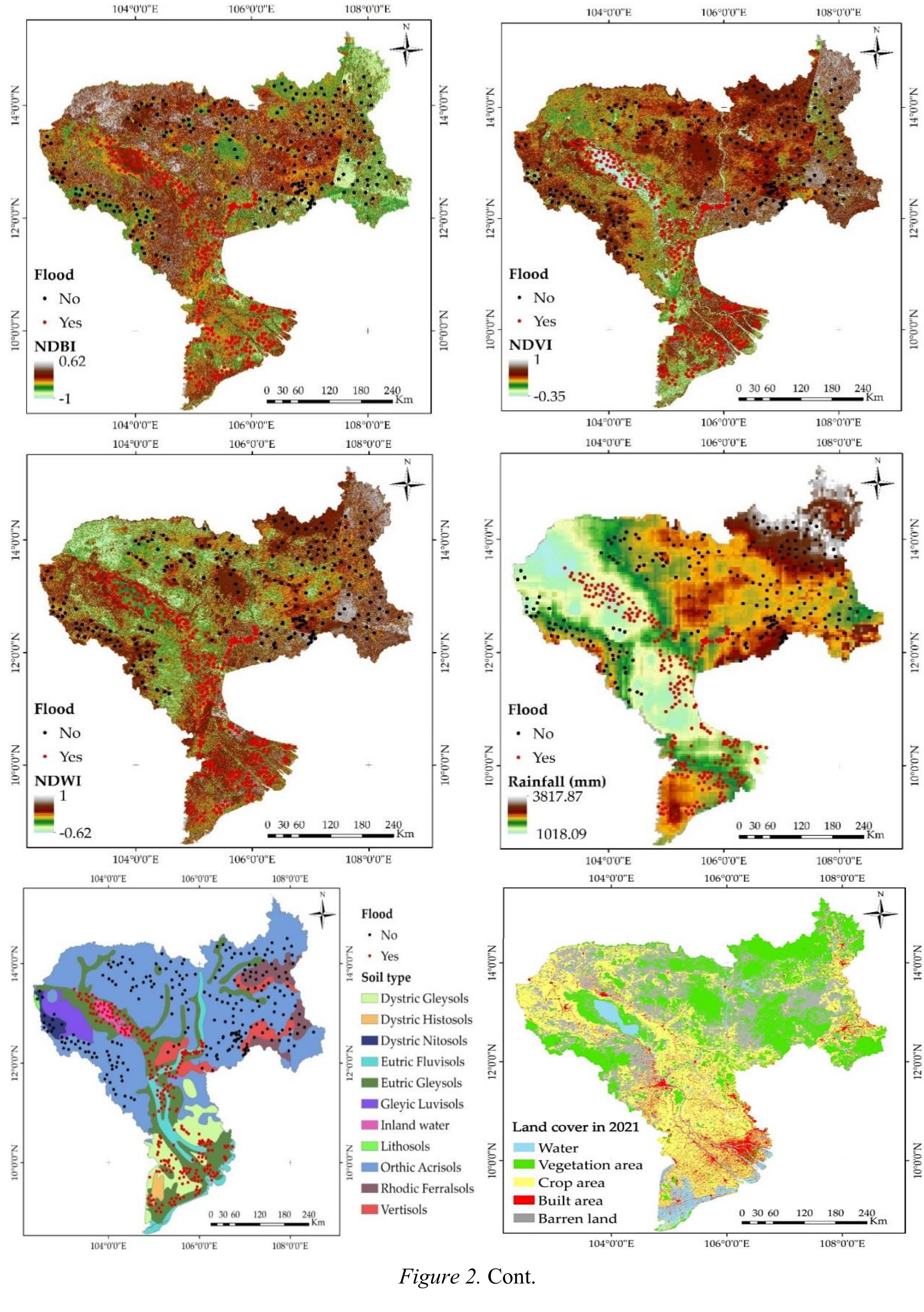


Figure 2. Cont.

Elevation, curvature, aspect, and slope were extracted from the DEM downloaded from https://search.asf.alaska.edu/. The river and road density were constructed using the river and road system collected from https://www.openstreetmap.org/. Annual rainfall in 2021 was collected from https://chrsdata.eng.uci.edu/. NDVI, NDBI, and NDWI were computed using the September 2021 Landsat OLI 08 image (available at https://earthexplorer.usgs.gov/). LULC in 2021 was downloaded from https://www.arcgis.com/apps/instant/media/index.html?appid=fc92d38533d440078f17678ebc20e8e2&fbclid=IwAR0V3ZEdUqhn79qN_JNPMtswxWfi2dE1_Gj-1ZD_XcN7oPyGMSn3-scE9KY. The soil type was collected from the Food and Agriculture Organisation of the United Nations (FAO) on their website https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/en/.

Elevation plays an essential role in assessing flood susceptibility in any region. A clear correlation exists between elevation and floods because floods occur in low-lying areas (Kurugama et al., 2024). In the study area, the altitude ranged from 0 to 2433. The low altitude is concentrated in the Mekong Delta of Vietnam and along the Mekong River in Cambodia.

The aspect also plays a key role in identifying the region where floods are likely to occur because it directly influences the flow direction. Furthermore, this factor significantly affects local climate and soil humidity (Al-Areeq, Saleh, Ghaleb, Abba, & Yaseen, 2024). The aspect values ranged from 0 to 360 degrees.

The slope significantly impacts the probability of flooding because it is directly related to the surface flow speed. Floods often occur in flat areas because floods last long periods, resulting in water stagnation (X. Zhu et al., 2024).

The curvature reflects the shape of the ground surface; therefore, assessing the susceptibility to floods is crucial. Water often concentrates in areas with concave surfaces, so these areas are susceptible to floods (K. Zhu et al., 2024).

River density is a vital hydrology factor in identifying the regional probability of flood occurrence. It is directly related to the speed of flow accumulation and surface exposure to overflowing water. Because the type of flood is riverine, floods tend to occur in the region with high river density (Maharjan et al., 2024).

Distance to the road is a vital flood conditioning factor for identifying flood regions because it directly affects the surface infiltration capacity (Islam & Chowdhury, 2024; Narendra et al., 2024). The study region, the Mekong Delta of Vietnam, and the river in Cambodia present a high road density.

Land use plays an essential role in identifying water flow and modifies the sedimentation capacity, directly affecting the probability of flood occurrence. Construction regions are more susceptible to floods than forest regions due to their infiltration capacity (Hitouri et al., 2024; Narendra et al., 2024).

The type is selected to analyze or evaluate the flood occurrence in a region because it influences the infiltration capacity, which significantly affects the capacity to generate precipitation and runoff (Jahanbani, Vahidnia, Aghamohammadi, & Azizi, 2024; Rashidiyan & Rahimzadegan, 2024).

NDVI indicates the density of vegetation in a region. This factor influences the water infiltration capacity and volume of surface water. Generally, an area with high vegetation density reduces the probability of flood occurrence by improving water retention and infiltration (Yaseen, 2024). In contrast, the NDBI is the construction density. Increase impermeable surfaces and surface water volume. Therefore, the built area increases the probability of flooding in a region (Hoang & Liou, 2024).

NDWI is the water content of the soils. A high NDWI value indicates a high water content in the soil, identifying water-saturated regions where flooding is more likely (Widya et al., 2024).

In the study area, the elevation changes significantly, increasing towards the north and East of Cambodia and the west of Central Highlands. Terrain elevation directly affects the curvature of the terrain. Plains and coastal plains have a smaller curvature than mountainous areas, especially the area around Tonle Lake, mountainous areas of western Cambodia, and the upper reaches of the Sesan and Srepok river basins of Vietnam. The change in elevation of the terrain directly affects the distribution of areas likely to be flooded.

Rainfall is one of the factors that directly affect floods. In the Mekong River basin, heavy rain is concentrated quickly, rapidly increasing river water levels and creating flood conditions. Heavy rainfall in a short period combined with deforestation and urbanization increases the flood likelihood (Minh et al., 2024; Wood et al., 2024). In the study area, vegetation cover is often concentrated in mountainous regions and upstream of river tributaries such as the Tonle Lake area. Therefore, the NDVI index in these areas is high. Meanwhile, urban areas often develop in plains and plateaus, increasing the NDBI index (Do, Nguyen, & Do, 2024; Park, 2024).

3.3. Flood susceptibility modeling

The identification of regions where floods probably occur in the Mekong watershed had four steps: (i) preparation of data, including flood inventory, and preparation of flood conditioning factor preparation; (ii) construction of deep learning and machine learning models; (iii) validation of proposed models; and (iv) analysis of flood susceptibility in the Mekong basin, covering Vietnam and Cambodia (Fig. 3).

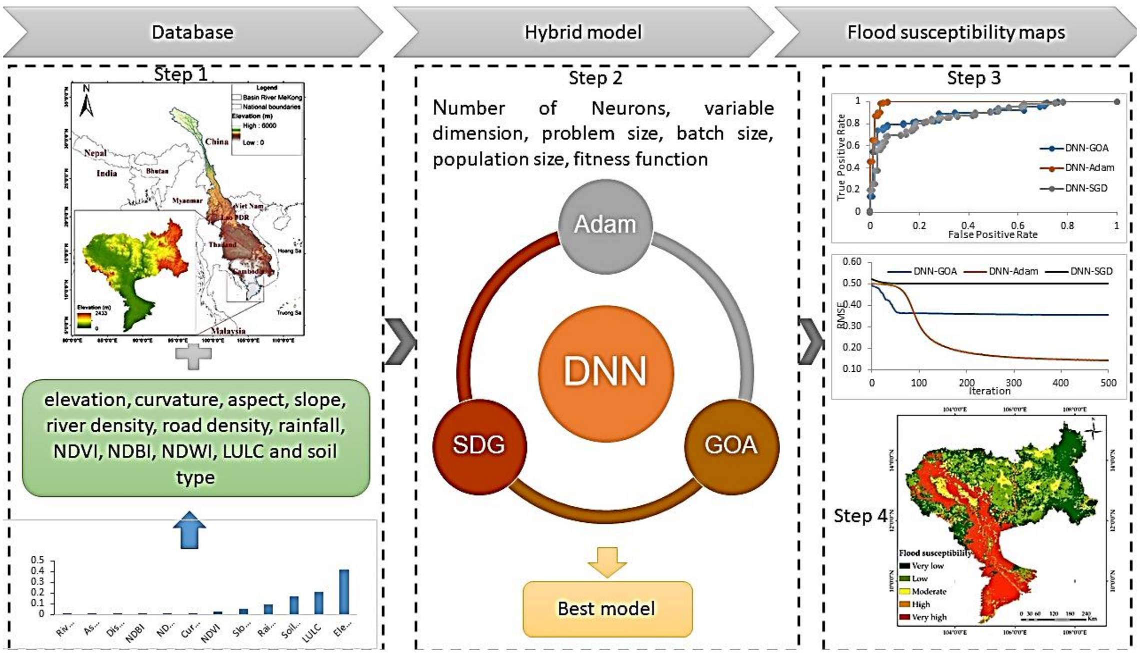


Figure 3. Methodology of the study

(i) Data preparation: the data used in this study includes flood inventory and flood conditioning factors because one of the objectives was to build a flood susceptibility model with free data to reproduce in other regions. Therefore, the flood inventory in this study was collected from previous studies and satellite images. Ultimately, 291 flood points and 241 nonflood points were collected and used in the machine-learning model as input data. The conditioning factors include 12 factors, i.e., elevation, curvature, aspect, slope, river density, road density, NDBI, NDVI, NDWI, land use/land cover, and soil type. The data sources cover all of these factors.

In the end, 532 flood and nonflood points were assigned to 12 conditioning factors to form the data set, divided into two parts: 70% to train the models and 30% to validate them.

(ii) Construction of deep learning and machine learning models: in this study, a deep learning model optimized by three algorithms (Adam, SGD, and GOA) was built to map flood susceptibility, and their performance was compared to that of the XGB model. The accuracy of DNN-Adam, DNN-SGD, and DNN-GOA models depends on adjusting parameters (number of neurons, variable dimension, hidden layer, population size, and number of iterations). During the model training process, the weights of neurons in the network were computed and adjusted so that the neural network output matches reality as closely as possible when input data is provided. Because the training process was repeated 500 times, it was necessary to use a loss function to evaluate the accuracy of the neural network. The network accuracy was improved by adjusting the parameters. The process of changing these parameters took place in two stages: the first consisted of modifying the parameters using the trial and error method, and the second involved using optimization algorithms Adam, SGD, and GOA. More precisely, the parameters of DNN are described as follows.

The DNN model consists of three layers: an input layer, three hidden layers, and an output layer. The input layer collects information from 532 flood and nonflood points and 12 influencing factors. This information passes through hidden layers before reaching the output layer. Each hidden layer has 11 neurons and a sigmoid activation function. The Adam, SGD, and GOA optimization algorithms are used to optimize the parameters of the DNN model. The training process is repeated for 500 iterations, and the batch size is 100. The DNN model is optimal when the RMSE value is minimal.iii) Validation of proposed models: in this study, we used various statistical indices, i.e., RMSE, MAE, ROC, AUC, and R^2, utilized by previous studies to evaluate the accuracy of proposed models.

(iii) Analysis of flood susceptibility map: after validating proposed models, they were used to construct the flood susceptibility map. Flood susceptibility in the study area was divided into five classes: very low, low, moderate, high, and very high, serving as a basis for sustainable territorial planning.

Deep neural networks

DNNs are algorithms applied in a wide range of fields. They are considered the standard in modeling the nonlinear relationship between target and explanatory variables (Nguyen, Nguyen et al., 2022; Wang, Fang, Hong, & Peng, 2020). The structure of a DNN consists of input, hidden, and output layers. Each layer is made up of neurons that analyze and process information. The input layer allows the model to receive information from the input data and pass it to the subsequent (hidden) layer. The hidden layer in a DNN can consist of multiple layers, transforming complex features into abstractions with a high classification capability. The output layer results from the layer classification process described above (Nguyen, Nguyen, et al., 2022; Pham, Luu, Van Dao et al., 2021).

The framework was used to train the neural network by backpropagating output errors and optimizing connection weights between classes to reduce the difference between predicted results and outcomes; this difference was evaluated using the cost function (RMSE) (Ahmed et al., 2022). Adjusting the parameters of a deep learning model is very important in determining the accuracy of the model. In this study, the model parameters were optimized using three optimization algorithms: Adam, SGD, and GOA.

Adam

The Adam optimization algorithm is used to train deep learning models. This algorithm extends stochastic gradient descent (D. T. Bui et al., 2020). It uses an adaptive learning rate for each parameter, adjusting the rate during learning based on past gradients and partial derivatives, improving learning convergence. Adam has several advantages: it can perform optimizations quickly and efficiently (Nhu, Hoang, Nguyen, Ngo, Bui, et al., 2020) and handles sparse gradients well because it uses adaptive learning rates to adjust updates accordingly (Vincent, Parthasarathy, & Jidesh, 2023). In this study, Adam was used to optimize the DNN algorithm to build the Mekong Basin flood susceptibility model.

SGD

SGD is the optimization algorithm used to minimize a function, usually related to reducing the model error. SGD updates the model parameters using gradient functions for each dataset (Nguyen, Van, & Do, 2023). This algorithm frequently updates parameters based on single data examples or mini-batches, making it much faster than gradient descent for large datasets (Nhu, Hoang, Nguyen, Ngo, Thanh Bui, et al., 2020). However, due to frequent parameter updates with noisy data, SGD exhibits more fluctuations and does not necessarily converge to the global minimum. SGD also has the advantage of solving the local optimization problem because update noise can help escape shallow local minima. Finally, SGD is often used to train neural networks in high-dimensional spaces (Huang, Ling, Wu, & Deng, 2022).

GOA

GOA is one of the most popular optimization algorithms proposed by (Saremi, Mirjalili, & Lewis, 2017). GOA is inspired by the collective behavior of locusts in nature and uses swarm mechanics to solve complex problems in the real world. GOA operates in two main stages: exploration and exploitation (Q.-T. Bui et al., 2020). The exploration process identifies regions that are likely to have resources. Each locust is a set of optimization parameters. Locusts move in swarms to search for resources and interact with the environment to adjust their position toward potential resource regions, while exploitation allows them to identify resource-rich regions. Each locust is a potential solution. Solutions are constantly updated based on the forces of attraction and repulsion, allowing the swarm to converge on the best possible overall solutions (Nguyen, 2022; Nguyen et al., 2022).

XGB

XGB is a popular machine-learning model that can solve classification and regression problems. This algorithm uses gradient enhancement based on sequential ensemble learning and decision trees (Linh et al., 2022). XGB takes model errors into account and, to improve performance, trains a new model that successfully predicts errors made by the original model (Aydin & Iban, 2023). This process is repeated an arbitrary number of times to improve model accuracy, based on the principle that the error will continuously converge to 0 as the process repeats. XGB has two essential aspects: (i) regularisation is used in the process of computing similarity scores to reduce sensitivity for overfitting problems; (ii) pruning is selected to compare the gains to avoid the overfitting problem (Abedi, Costache, Shafizadeh-Moghadam, & Pham, 2022; Ghosh, Saha, & Bera, 2022).

4. Results

4.1. Flood Conditioning Factor Analysis

The selection of the appropriate flood conditioning factor plays a vital role in building flood susceptibility models because these factors determine the accuracy and reliability of the prediction models. Poor selection can lead to inadequate and inaccurate results, increasing the complexity of prediction models, which influences the prediction results (Dodangeh et al., 2020). Judiciously choosing these factors can improve the model's prediction ability, identifying regions where floods are likely to occur in the study area. This study used random forest (RF) to select conditioning factors. RF assigns weights for each factor, and the higher the weight, the greater the importance. In the study area, elevation, LULC, soil type, and rainfall were the most critical factors determining the probability of flood occurrence. In fact, in the Mekong basin, topography varies greatly, with mountains upstream and plains downstream. Mountains have high altitudes, contributing to rapid runoff downstream during heavy precipitation. In addition, the plains have very low altitudes (below sea level) and often lack drainage, leading to water stagnation during heavy rainfall. LULC is considered the second most important driver of the probability of flood occurrence because land use/land cover strongly influences floods in the Mekong watershed. Urban growth increases the waterproofing capacity of the soil.

Furthermore, the exploitation of groundwater resources serves agricultural and domestic development but leads to subsidence and increases floods. The soil type was third in importance in the flood susceptibility model because it significantly influences its infiltration and retention capacity. In the Mekong watershed, a large part is covered by clay soils with low infiltration capacity, possibly increasing runoff volume. The rainfall was fourth. It should be noted that the flooding in the Mekong watershed is fluvial; therefore, rain triggers floods. The Mekong basin is strongly influenced by Southeast Asian monsoons, which provide more redundant precipitation than other regions. Heavy rainfall in a short time leads to floods. Ultimately, all factors selected in this study influence the probability of flooding occurrence. Therefore, these factors were used as input data for the deep-learning model. (Fig. 4).

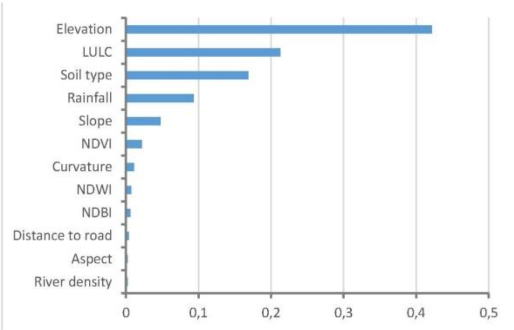
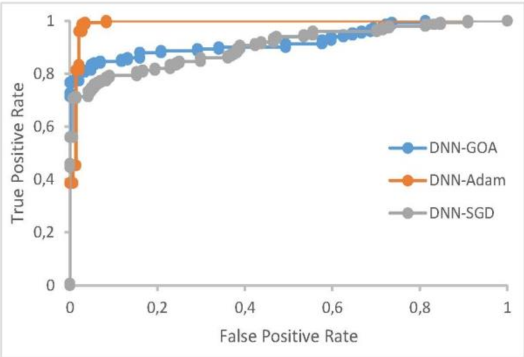


Figure 4. Flood Conditioning Factor Importance Analysis

4.2. Evaluating the Performance of the Deep Learning Model

The validation of the proposed models was evaluated using ROC and AUC. The AUC value was used to designate the prediction capacity considered a validation and comparison. The hybrid model was more accurate for the training dataset than the baseline model (XGB). In particular, DNN-Adam was more precise than other models (DNN-SGD, DNN-GOA), with an AUC value of 0.98, followed by DNN-GOA (AUC = 0.92), DNN-SGD (AUC = 0.9) and XGB (AUC = 0.87). The DNN-Adam model was more accurate for the validation dataset than other models (DNN-SGD, DNN-GOA, and XGB), with an AUC value of 0.98. The AUC value of DNN-SGD and DNN-GOA was 0.87, and that of XGB was 0.82. All proposed models generally had high precision, with AUC values above 0.8. Therefore, these models can construct flood susceptibility maps in the Mekong Basin (Fig. 5).



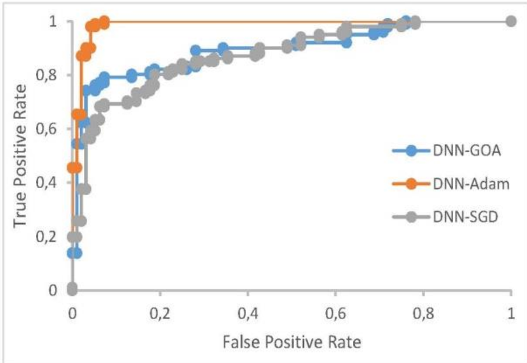


Figure 5. The prediction capacity of the proposed models (training data set (top) and validation dataset (bottom))

Figure 6 shows the shape of the hybrid DNN model after 500 iterations. The DNN-Adam model had the highest accuracy, with an RMSE value of around 0.5, dropping sharply to 0.2 after the first 150 iterations. From then on, the RMSE value slowly decreased and stabilized at 0.15 after 500 iterations. Next is the DNN-GOA model; it starts with an RMSE value of 0.5, which dropped sharply to 0.35 after the first 50 iterations. After that, the value slowly decreased and stabilized at 0.35. The DNN-SGD model had an initial RMSE value of approximately 0.52, which declined to 0.5 after the first 50 iterations and remained stable at 0.5 after 500 iterations. The DNN-Adam model had higher accuracy than others, demonstrating a more remarkable ability to predict flood susceptibility. The DNN-GOA model improved the initial RMSE value, but there was no further improvement through subsequent iterations. The DNN-SGD model performed the worst, with high RMSE values and no improvement after the first iterations. The DNN-Adam model had the highest and most stable performance, improved over iterations, and can be used to predict flood susceptibility. The DNN-GOA model, despite initial improvements, did not maintain similar performance. In contrast, the DNN-SGD model has less flood prediction ability than other models with high RMSE values.

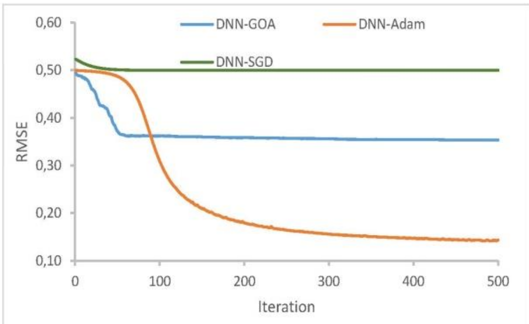


Figure 6. RMSE value after 500 iterations

In addition to the AUC and the RMSE index, this study also used the MAE and the R^2 index to evaluate the ability to predict the probability that a flood occurs in the study area. The results showed that the DNN-Adam model had a higher likelihood of occurrence for the training data set than other models, with the MAE value of 0.03 and R^2 of 0.91. This model was not only for the training data set but also for the validation one, with an MAE value of 0.048 and an R^2 of 0.88. The DNN-GOA model was second for training and validation data sets (MAE = 0.26, R^2 = 0.9, respectively, MAE = 0.28, R2 = 0.87). The DNN-SGD model was third for the training and validation datasets (MAE = 0.49, R^2 = 0.78, respectively MAE = 0.49, R^2 = 0.76). The XGB model performed less in the training and validation datasets (MAE = 0.5, R^2 = 0.75, respectively, MAE = 0.52, R^2 = 0.72) (Table 1).

Table 1. Performance of models using RMSE, MAE, AUC, and R^2

	Training dataset				Validation dataset			
	RMSE	MAE	AUC	R^2	RMSE	MAE	AUC	R^2
DNN-Adam	0.14	0.03	0.98	0.91	0.16	0.048	0.98	0.88
DNN-SGD	0.49	0.49	0.90	0.78	0.49	0.49	0.87	0.76
DNN-GOA	0.31	0.26	0.92	0.9	0.35	0.28	0.89	0.87
XGB	0.5	0.51	0.87	0.75	0.52	0.52	0.82	0.72

4.3. Flood susceptibility mapping in the Mekong basin

After validation and comparison of the proposed models, the DNN-Adam model was selected to predict flood susceptibility in the Mekong basin. Figure 7 shows the flood susceptibility map produced by the DNN-Adam model. The results showed that approximately 72,815 km² of the study area is located in the very low flood susceptibility zone, distributed in the upper Sesan and Srepok rivers in the Central Highlands of Vietnam and the coastal mountains of southwest Cambodia, 90,989 km² in the low probability zone of flood occurrence, located in the mountainous areas of Northern and Northeast Cambodia and the highlands and semi-plains of the lower Sesan and Srepok rivers of Vietnam, 14,167 km² in the moderate flood susceptibility zone, distributed in the lowlands between mountains or highlands of the plains, high sand dunes along the coast, 11934 km² in the high flood susceptibility zone, and 61777 km² in the very high flood susceptibility zone. The results also showed that regions with very high flood susceptibility concentrated in the Mekong Delta in Vietnam and along the river in Cambodia.

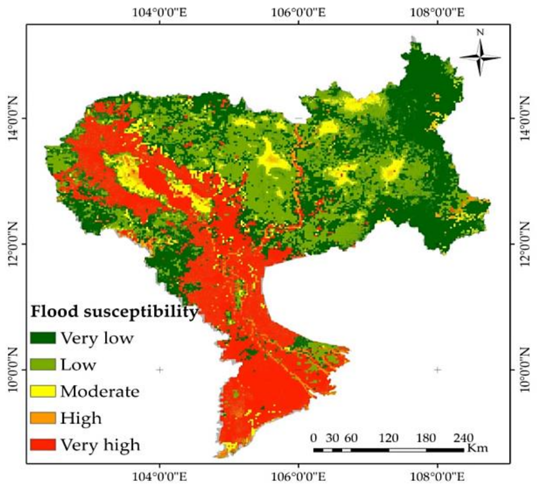


Figure 7. Flood susceptibility mapping produced by DNN-Adam

5. Discussions

This study used deep learning to assess flood susceptibility in the Mekong basin. Previous studies have found that deep learning solves nonlinear problems that traditional models cannot solve (D. T. Bui et al., 2020; Zhao, Pang, Xu, Peng, & Zuo, 2020). Additionally, these models can analyze multivariate data by integrating various sources, e.g., environmental data, hydrology, climate, and human activities. This allows susceptibility to be assessed with a better understanding (Pham et al., 2021). However, the overfitting problem is a major one when using deep learning. In addition, this model requires quality data. In the case of missing data, it is challenging to evaluate flood susceptibility with high precision (Luppichini, Barsanti, Giannecchini, & Bini, 2022). Therefore, it is necessary to integrate this model with optimization algorithms. Among the proposed models, the DNN-Adam model had better performance because it is one of the most popular algorithms for solving local optimization problems and was found to be effective in the case of noisy data (Cortiñas-Lorenzo & Pérez-González, 2020). Although Adam is a robust optimization algorithm and is effective in several previous studies. However, it should be noted that, unlike SGD, GOA, which uses a single learning rate for all parameters, Adam adapts the learning rate for each parameter individually. This makes the Adam model often converge faster and perform better than other models.

Furthermore, Adam uses momentum, which helps speed up the optimization process. Finally, Adam solves the problem of decreasing learning rates too aggressively by incorporating momentum and using an exponentially decaying average of past gradients, which provides a more balanced approach (Cortiñas-Lorenzo & Pérez-González, 2020; Fang, Xu, Li, Yang, & Gong, 2020; Reyad, Sarhan, & Arafa, 2023). The DNN-GOA model was second in terms of accuracy. The GOA algorithm presents the advantage of balancing exploration and exploitation, reducing the risk of local optimization situations. In addition, GOA can converge rapidly. Most importantly, GOA is robust to data disturbances (Askar et al., 2022; Nguyen Nguyen et al., 2022). The DNN-SGD model was less effective than others because it converged very slowly. Moreover, its algorithm cannot be easily generalized (Nhu, Hoang, Nguyen, Ngo, Bui, et al., 2020).

Compared with the flood susceptibility map produced by deep learning with optimization algorithms in this study, the flood map created by hydrodynamic modeling and remote sensing in previous studies has notable differences in terms of the flood area (Kuenzer et al., 2013; Triet et al., 2020; P. Van et al., 2012). This study's flood susceptibility in very high flood susceptibility areas was more significant than previous studies. These differences can be explained by our research using machine learning/deep learning to construct the flood susceptibility map, which can identify regions with a high probability of flooding. In contrast, previous studies simulated past flood events. Furthermore, our study aimed to develop a method using machine learning/deep learning and open-source data to construct the flood susceptibility map. Thus, this method could be applied to different world regions through open-source and low-cost data. However, the lack of detailed data, such as dike networks, influences the accuracy of flood susceptibility maps.

Although several studies have proven that the deep learning model is more effective than traditional machine learning models, there are still several debates around the extrapolation problem when using machine learning/deep learning in natural hazard research (Q.-T. Bui et al., 2020). Machine learning/deep learning models can predict natural hazards in general, floods in particular, climate change, and changes in socioeconomic conditions. Theoretically, this problem can be solved if we feed the machine learning/deep learning models with the data necessary for training the model. However, data collection is also complex due to the lack of funding, especially in developing countries like Vietnam. In addition, other studies have highlighted that integrating machine learning/deep learning models with optimization algorithms or traditional models, such as the hydrodynamic model, can effectively solve this problem (Nguyen et al., 2024). However, building this model requires a lot of time and effort. This study successfully built deep learning models with optimization algorithms and open-source data in the Mekong Basin. Our study's open-source models and data make it easy to replicate in other regions worldwide, such as the Red River watershed. In addition, the study area is considered one of the largest basins in the world and contains many essential resources and ecosystems. It is representative of other regions in Asia.

Floods are considered the most dangerous natural disaster, especially in the relationship between climate change and human activities. The sixth IPCC report highlighted the interactions and systematics related to different factors such as climate and human activities. Although the report indicated the systems, it lacks the approaches and methodologies to solve this problem. It is necessary to have models and methods with high accuracy that have the potential to solve complex and nonlinear problems (Hochrainer-Stigler et al., 2024) to reduce the effects of this natural disaster. In this study, we justified the development and application of machine learning to build the susceptibility map, which is the key to supporting decision-makers in creating the appropriate strategy and land use planning. Several studies have highlighted that effective flood risk management requires integrating land use planning into risk management strategies. Deforestation is a prime example of land use exacerbating flooding, with deforested areas considered the most vulnerable because proper planning can reduce the negative impacts of floods.

In contrast, poor planning can worsen flood risks. Planning policies are essential, but their enforcement requires strict regulations. In many countries worldwide, especially developing countries, planning for urban and industrial areas in flood-prone areas has ignored planning regulations (Nguyen, Dang, Nguyen, Bui, & Petrisor, 2022). The result is increased community exposure, leading to unsustainable development. Furthermore, in the context of climate change, which causes adverse impacts on people, planning becomes even more critical, and it needs to address its effects on the economy and society, especially in the Mekong Delta region, which is heavily affected by climate change. Therefore, planning needs to be sustainable and have a long-term vision to minimize the impact of floods, so limiting the planning of residential areas in areas prone to flooding is necessary.

Although this study successfully assessed flood susceptibility in the Mekong Basin, it also pre-assents general data limitations. First, flood points were collected from previous studies and Sentinel 1A images. However, the lack of data measured on the ground can influence the accuracy of the models. Furthermore, the selection of nonflooding points was based mainly on altitudes and slopes. Incorrect data selection also affects the predictive ability of proposed models. However, currently, there are no universal guidelines for data selection. Ultimately, floods in the study area were strongly influenced by climate change and dam construction upstream, so it is necessary to integrate these changes into future assessments of floods. Currently, flooding is influenced by climate change and urban growth, so evaluating this change in flooding is essential to support decision-makers in proposing effective strategies.

In future research, we will try to evaluate this change in flooding. Moreover, the extrapolation problem is considered one of the significant problems when using machine learning to solve environmental issues, for example, flooding because this model is the drive-model, so the statistical relationship between the flood locations in the past and the flood causes is significant to predict the flood in the future. The diversity of data in different places and cases plays an essential role in predicting the flood in various regions. In the future, we will try to collect data at other locations to solve this problem. Moreover, integration between individual models and optimization algorithms is a feasible solution to this problem. In general, the results of our study could be beneficial in water resource management strategies aimed at reducing flood damage and developing agriculture to combat climate change and drought. This goal could be achieved by declaring areas where new constructions are prohibited, significantly reducing damage to property and humans. Additionally, destabilizing the flood susceptibility zone can help restore its ecosystems.

6. Conclusions

This study proposes a framework for building flood susceptibility maps using deep learning and optimization algorithms with open-source data in the Mekong basin, which can be replicated in other regions worldwide. The results significantly support decision-makers or planners in proposing appropriate sustainable land-use planning strategies. The results indicate the following:

(i) Building a framework for flood susceptibility mapping in the Mekong River Basin highlighted the importance of machine learning and remote sensing in assessing flood susceptibility. This highlights that open-source data and machine learning algorithms can significantly contribute to building flood susceptibility models in other world regions.

(ii) Deep learning is a powerful method for building flood susceptibility maps. Among the proposed models, the DNN-Adam model had the best performance, with an AUC value of 0.98, followed by DNN-GOA, with an AUC value of 0.89, DNN-SGD, with an AUC value of 0.87, and XGB, with the AUC value of 0.82.

(iii) Approximately 72,815 km^2 of the study area is located in the very low flood susceptibility zone, 90,989 km^2 in the low probability zone of flood occurrence, 14,167 km^2 in the moderate flood susceptibility zone, 11934 km^2 in the high flood susceptibility zone and 61777 km^2 in the very high flood susceptibility zone.

Flood management strategies are essential for the Mekong basin, especially regarding climate change, because floods positively and negatively influence human life, society, and the economy in this region. This study applied open-source machine learning/deep learning and remote sensing data to construct a flood susceptibility map of the Mekong basin, which is very necessary and can support decision-makers or planners to propose appropriate strategies for sustainable territorial development, including the reduction of negative impacts on human life, society, economy, and a balanced distribution of surface water resources through floods to mitigate climate change effects.

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