



One-dimensional deep learning driven geospatial analysis for flash flood susceptibility mapping: a case study in North Central Vietnam

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Abstract

Flash floods rank among the most catastrophic natural disasters worldwide, inflicting severe socio-economic, environmental, and human impacts. Consequently, accurately identifying areas at potential risk is of paramount importance. This study investigates the efficacy of Deep 1D-Convolutional Neural Networks (Deep 1D-CNN) in spatially predicting flash floods, with a specific focus on the frequent tropical cyclone-induced flash floods in Thanh Hoa province, North Central Vietnam. The Deep 1D-CNN was structured with four convolutional layers, two pooling layers, one flattened layer, and two fully connected layers, employing the ADAM algorithm for optimization and Mean Squared Error (MSE) for loss calculation. A geodatabase containing 2540 flash flood locations and 12 influencing factors was compiled using multi-source geospatial data. The database was used to train and check the model. The results indicate that the Deep 1D-CNN model achieved high predictive accuracy (90.2%), along with a Kappa value of 0.804 and an AUC (Area Under the Curve) of 0.969, surpassing the benchmark models such as SVM (Support Vector Machine) and LR (Logistic Regression). The study concludes that the Deep 1D-CNN model is a highly effective tool for modeling flash floods.

Keywords Flash flood · Susceptibility · 1D-CNN · Deep neural networks · Geospatial data · Tropical areas

Introduction

Flash floods continue to be recognized as a significant natural hazard (Kreibich et al. 2019), particularly in tropical regions (Hoyos et al. 2019), causing significant

infrastructure damage and detrimental environmental effects and consistently resulting in fatalities each year (Al-Aizari et al. 2022, 2024; Dayan et al. 2021; Hussain et al. 2021; Lorenzo-Lacruz et al. 2019). Unlike other types of floods, such as coastal, river, and ice-jam floods, flash floods are

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predominantly triggered by short-duration, high-intensity rainfall events (Borga et al. 2011), notably those associated with tropical storms and depressions. Flash floods typically occur in confined geographic areas and are marked by their rapid and sudden onset, strong flow velocities (Ngo et al. 2018), nonlinear dynamics, and complex interdependencies (Wu et al. 2019). Consequently, predicting flash flood hazards remains challenging and distinct from forecasting other types of floods.

Literature surveys indicate that research pertaining to flash floods, when viewed from a hazard perspective, encompasses a diversity of methodologies. The first segment of this research perceives flash floods as external processes. It considers flash floods as external processes, concentrating on the cataloging, geographical spread, scale, and distinct attributes of these phenomena (Borga et al. 2011; Marchi et al. 2010), as well as examining the geomorphic impacts of flash floods (Ozturk et al. 2018; Scorpio et al. 2018). The second segment, which is more prevalent, employs modeling methods to forecast, predict, and map the spatial likelihood of flash floods (Hussain et al. 2023; Saharia et al. 2017). This approach is critical for disaster management and preventive measures.

Over the past three decades, a variety of hydrological methods based on rainfall-runoff modeling have been developed to simulate and forecast flash floods (Douinot et al. 2016; Zhang et al. 2021). These hydrological models are categorized into three principal types based on their structural framework: empirical models, hydraulic models, and hydrologic models (Beven 2011; Devia et al. 2015). Initial research on flash flood forecasting primarily employed empirical models, such as the Soil Conservation Service Curve Number (SCS-CN) method (Reilly and Piechota 2005). This method presupposes a static relationship between rainfall and runoff, a simplification that may not adequately capture the intricate hydrological processes across various watershed conditions. The hydraulic models, i.e., 1D HEC-RAS (US Army Corps of Engineers), LISFLOOD-FP (University of Bristol), or MIKE FLOOD (Danish Hydraulic Institute – DHI), which simulate water flow based on channel topography, which simulate water flow based on channel topography, are extensively utilized for forecasting flash floods (Kourgialas and Karatzas 2014; Vozinaki et al. 2015). However, these models often rely on simplifications and assumptions about flow conditions, channel roughness, and sediment transport, which might not accurately represent real-world complexities in some areas.

In the case of the hydrologic models, such as TOP-MODEL (Vincendon et al. 2010), SWAT (Jodar-Abellan et al. 2019), HEC-HMS (Zema et al. 2017), HEC-RAS (Munna et al. 2021), HiResFlood-UCI (Nguyen et al. 2016), these models utilize a set of mathematical equations, ranging

from simple empirical formulas to complex differential equations, to estimate rainfall-runoff and to implement routing schemes. Herein, they usually consider factors such as soil type, land use, topography, and antecedent moisture conditions (Zhai et al. 2018) to convert rainfall data into an estimate of surface runoff. Then, the water movement is simulated through the river systems or over the land surface, incorporating channel characteristics and interactions between the channel and floodplain. Generally, the rainfall-runoff models are crucial tools for predicting flash floods in both spatial and temporal scales with reasonable accuracy (Bournas and Baltas 2022; Coustau et al. 2012; Trambly et al. 2010). Nevertheless, these rainfall-runoff models require a series of long-term monitoring data to achieve dependable predictions. Consequently, an alternative methodology, referred to as the “on-off” modeling (Tien Bui and Hoang 2017), has been considered. Therein, “On” signifies the presence or occurrence of a flash flood, while “Off” indicates its absence. This approach facilitates spatial prediction of flash floods by correlating historical flood events with conditioning factors.

With the development of Geographic Information Systems (GIS) and machine learning, various approaches employing “on-off” modeling have been explored for flash flood studies, i.e., logistic regression (Youssef et al. 2016), multilayer neural (Ngo et al. 2018), extreme learning (Bui et al. 2019), machine learning ensemble (Costache and Tien Bui 2020), CHAID tree ensemble (Nguyen et al. 2020b), Classification And Regression Tree (CART) (Liu et al. 2021), XGBoost and random forest (Abedi et al. 2022), support vector machine (Youssef et al. 2022), stacking ensemble (Yao et al. 2022). To construct precise flash flood prediction models, it is possible for these machine learning algorithms to assimilate a wide array of geospatial data sources, thereby identifying nuanced correlations and interactions among several influential factors. However, up to the present moment, there has not been a single methodology or technique for predicting flash floods that has achieved universal acknowledgment for its efficacy across diverse geographical regions. This underscores the critical need for ongoing research dedicated to developing and exploring innovative algorithmic models tailored explicitly for flash flood prediction.

In recent years, deep learning has emerged as a prominent approach in flood modeling (Trong et al. 2023), encompassing flash floods. The increasing interest in deep learning is attributed to its varied structures and groundbreaking successes in multiple fields (Dhillon and Verma 2020; Zhang et al. 2019). In this context, the amalgamation of exceptional performance capabilities of deep learning algorithms, the availability of extensive geospatial datasets (Hu et al. 2022), advancements in computational hardware (Rasch et

al. 2023), and the development of accessible frameworks (Nguyen et al. 2019) has elevated deep learning to a prominent position in contemporary artificial intelligence research and applications. This has particularly heightened its appeal and relevance in the past five years, including deep neural networks (Panahi et al. 2021), deep belief network (Shahabi et al. 2021), deep learning ensemble (Costache et al. 2020), long short-term memory (LSTM) (Zhao et al. 2022), and 1D Convolutional neural network (CNN) (Tsangaratos et al. 2023). While these deep learning models have the potential to markedly enhance the accuracy of flash flood predictions, conducting further research is essential to comprehend their applicability across diverse geographical contexts, aiming not only to broaden and deepen the existing knowledge base but also to harness the capabilities of these models fully.

This study aims to partially fill the above gap in the existing literature by investigating the potential application of 1D-CNN for spatial predictions of flash floods in a tropical area of the Thanh Hoa province. This province belongs to North Central Vietnam, which frequently experiences flash floods after heavy rainfall during tropical storms. The subsequent sections of this paper are organized as follows. Section 2 delineates the Materials and Methods employed. Section 3 describes the proposed methodology for the spatial prediction of flash floods using Deep 1D-CNN and

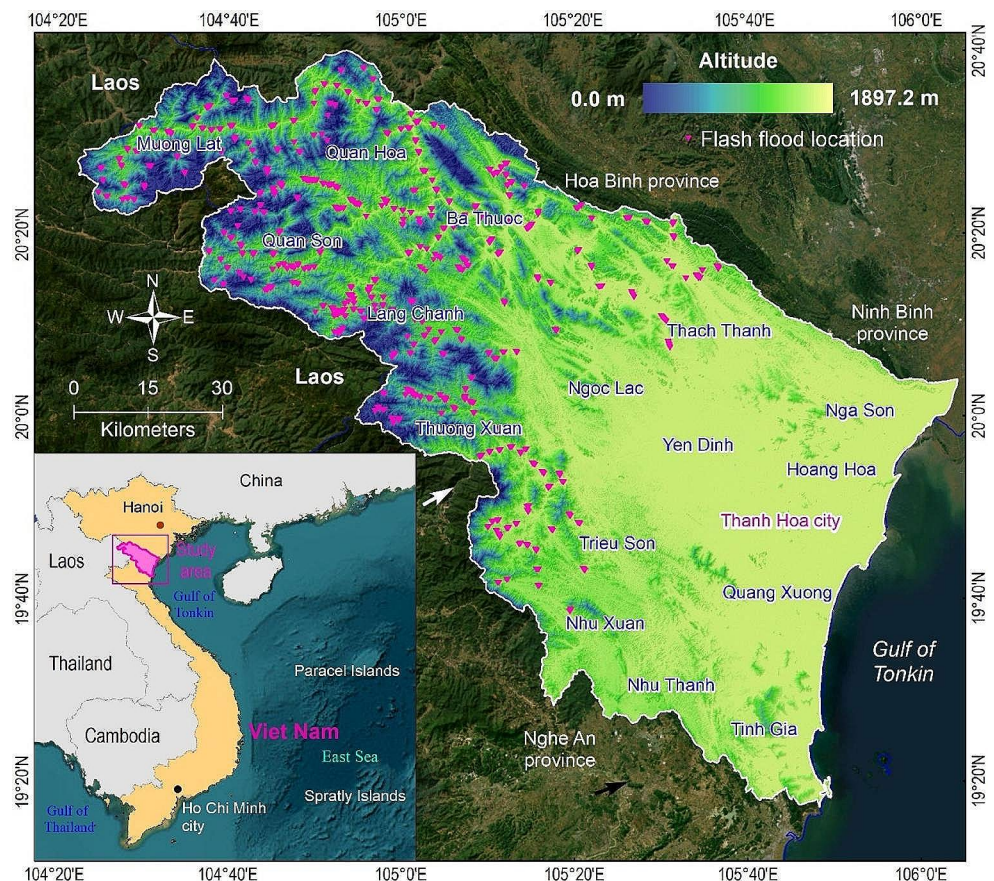
Multisourced Geospatial data. The Results and Analysis are presented in Sect. 4. Discussions are contained within Sect. 5, and the concluding remarks are provided in Sect. 6.

Materials and methods

Study area

The research is conducted in the Thanh Hoa province, situated in the north-central region of Vietnam. It is located approximately 110 km south of Hanoi and encompasses an area of approximately 11,080.8 km². Geographically, the coordinates of the study area span from 19°17'20" to 20°40' North latitude and from 104°22' to 106°04' East longitude (Fig. 1). The study area showcases a diverse topography characterized by various landforms such as mountains, hills, plains, and coastal areas. The elevation of the region ranges from 0.0 to 1897.1 meters above sea level (m a.s.l), further adding to its topographical heterogeneity. The western part is dominated by the Truong Son Mountain Range, which runs along the border with Laos. This mountainous terrain gradually transitions into hills and plateaus towards the east before reaching the flat plains along the coast (Fig. 1). The study area exhibits a slope variation ranging from 0.0 to

Fig. 1 Location of Thanh Hoa province and flash-flood locations



77.1° with a mean of 14.9° and a standard deviation of 12.4°. Approximately one-fourth (25%) of the study area consists of slopes less than 3°. Additionally, 13.3% of the study area comprises slopes between 3 and 7.5°, while another 13.3% features slopes ranging from 7.5 to 15°.

Concerning the soil type, the study area encompasses various soil types. The predominant one is the yellow-red soil found on clay, metamorphic, and acid-magmatic rocks, covering approximately 35.9% of the area. Following this, the yellowish-brown soil is present on basalt and limestone, accounting for approximately 12.5% of the study area. Additionally, the pale yellow soil on sandstone occupies about 11.7% of the region. Geologically, the province showcases a diverse range of more than 30 exposed formations and complexes. These geological formations exhibit distinct spatial distributions. Notably, three dominant formations, namely Dong Trau, Dong Son, and Song Ca, cover 42.7% of the study area. The main lithologies within these formations include sandstone, silty sandstone, quartz-mica sandstone, clay-sericite shale, yellow sand, silt, and motley lateritized clay.

As reported by the General Statistics Office of Vietnam (www.gso.gov.vn), the population of Thanh Hoa province in 2019 was recorded at 3,640,128 individuals, establishing it as the third most populous province in Vietnam, after Hanoi capital and Ho Chi Minh city. The population distribution within this province exhibits significant disparities between its plains and mountainous regions. The majority of the population is concentrated in urban centers, towns, coastal areas, and along riverbanks, while the mountainous areas remain sparsely populated. In particular, Thanh Hoa city stands out with a population density of more than 2,400 people per square kilometer. Similarly, Hau Loc, Hoang Hoa, and Quang Xuong districts (Fig. 1) also show relatively dense populations, exceeding 1,100 people per square kilometer. On the other hand, the mountainous districts, such as Muong Lat, Quan Son, and Quan Hoa (Fig. 1), experience significantly lower population densities, hovering around 40 people per square kilometer. This marked variation in population density underscores the contrasting settlement patterns between the plains and mountainous terrains in the province.

Thanh Hoa province is situated within the tropical monsoon climate zone, which is influenced by both the temperate climate of the Gulf of Tonkin and the North Central Coast (Nguyen et al. 2021). The region experiences two distinct seasons annually: summer and winter. The summer from May to October is characterized by hot, humid weather with frequent rainfall, influenced mainly by hot and dry southwesterly winds. Conversely, the winter from November to April brings cold conditions but little rain to the province. The temperature in the area exhibits a range between 20 and 28 °C throughout the year, whereas, as for

precipitation, the region receives an average annual rainfall of 1,800 mm (Nguyen et al. 2020a). The Thanh Hoa province is frequently impacted by tropical storms and depressions, resulting in the occurrence of numerous flash floods and associated landslides (Manh 2017; Thuy 2019). These natural events pose significant challenges to the region, necessitating careful monitoring and preparedness measures to mitigate potential risks and ensure the safety of its residents and infrastructure. For example, tropical storm Wipha occurred from the 2nd to the 4th of August 2019, bringing torrential rainfall that led to flash floods and inundation. Tragically, this event resulted in the loss of 16 lives, and the total estimated losses amounted to US\$43.1 million.

Data

Historical flash-flooded location

Flash-flooded locations occurred previously, and their influencing indicators are necessary for building prediction models. Therefore, in this research, we prepared the flash-flood inventory map (Fig. 1) using 2540 flash flood polygons deriving from the research project VAST05.01/21–22 funded by the Vietnam Academy of Science and Technology (VAST). These flash flood polygons that happened in the last five years were detected from the Sentinel-1 SAR imagery using change detection methods. The Sentinel-1 mission is a notable C-band Synthetic Aperture Radar (SAR) constellation composed of two polar-orbiting satellites. Each satellite is equipped with a C-band SAR sensor capable of capturing imagery at a spatial resolution of 10 m, offering a high revisit time and ensuring imagery availability every six days in constellation mode (Tarpanelli et al. 2022).

First, we focused on assessing tropical storms that occurred within the past five years, from 2018 to 2022, which have resulted in heavy rainfall and subsequent flash floods. We collected Sentinel-1 images for each storm before and after the flooding events. These images were then subjected to a rigorous processing procedure to identify and localize flash floods and inundations through change detections. Further regarding the change detection technique employed for multi-temporal SAR Sentinel-1 A image processing for flash flood detection can be found in (Trong et al. 2023), which provides in-depth details on the methodologies and algorithms utilized in this flash flood detection study. Finally, fieldwork was carried out to study and check flood locations.

Flash flood influencing factors

In the context of predicting flash flood inundation, a typical approach involves analyzing past flood events and their

associated influencing factors. The accurate prediction of future flash floods relies heavily on the careful selection of these influencing factors. To this end, based on a literature review (Abedi et al. 2022; Costache and Bui 2020; Ekmekcioğlu et al. 2022; Hapuarachchi et al. 2011; Ilia et al. 2022; Youssef et al. 2022) and our analyzing catchment characteristics to identify the most relevant influencing factors for our spatial prediction model. The selection of these factors is paramount in ensuring the precision and effectiveness of our flash flood prediction efforts. As a result, twelve flash flood influencing factors were considered: geology, soil type, Land use/land cover (LULC), stream density, NDVI, NDWI, elevation, TWI, slope, aspect, curvature, and rainfall.

Geology is crucial in predicting flash flood inundation, primarily due to its influence on key factors such as drainage characteristics, channel formation, and capacity (Mahala 2020; Montgomery and Buffington 1997). Different types of rocks and geological formations can either facilitate or hinder the movement of water. Moreover, the geological composition of riverbeds and channels plays a crucial role in determining their capacity to carry water (Matsuda 2004). In regions with narrow or obstructed channels due to geological features, flash floods can cause rapid water

accumulation and overflow, leading to destructive flooding downstream (Ba et al. 2022). In this research, the geology map (Fig. 2a) was constructed with 20 classes based on the Geological and Mineral Resources Maps at a scale of 1:200,000 provided by the Ministry of Natural Resources and Environment of Vietnam.

Soil type should be considered for spatial prediction of flash floods because it may influence infiltration patterns and runoff processes (Liu et al. 2019). Herein, different soil types have varying levels of permeability, affecting the rate at which water can infiltrate into the ground or runoff over the surface. Soils with high permeability allow water to infiltrate quickly, reducing surface runoff (Huat et al. 2006) and potentially mitigating flash flood risks. On the other hand, soils with low permeability lead to increased surface runoff (Naef et al. 2002), contributing to flash flood occurrences. In this analysis, the soil type map with 18 categories was compiled and shown in Fig. 2b. The soil type data was extracted from national pedology maps at the scale of 1:100,000 provided by the Ministry of Agriculture and Rural Development of Vietnam.

Land Use and Land Cover (LULC) is a critical component in flash flood modeling due to its significant impact on how rainfall interacts with the ground and the subsequent

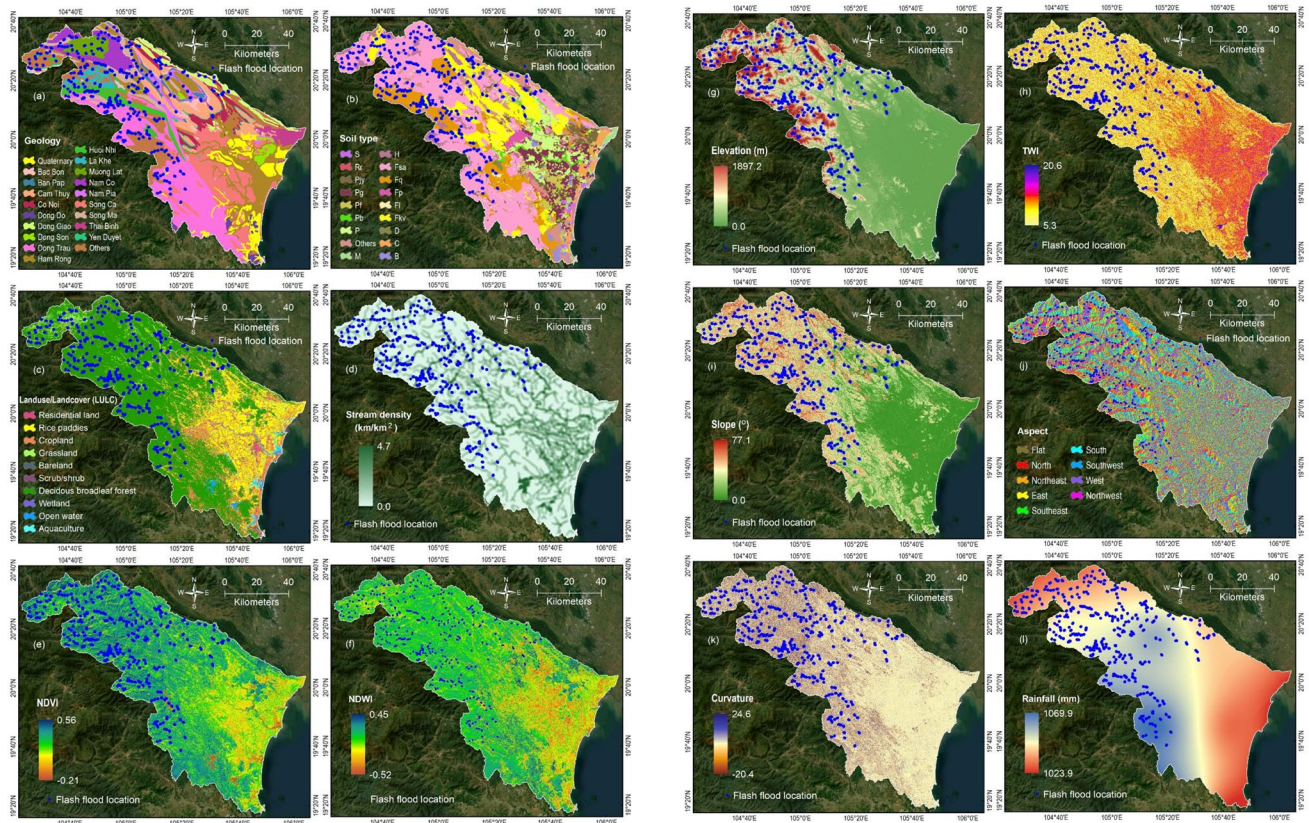


Fig. 2 Flash-flood influencing factors: (a) Geology; (b) Soil type; (c) LULC; (d) Stream density; (e) NDVI; (f) NDWI; (g) Elevation; (h) TWI; (i) Slope; (j) Aspect; (k) Curvature; and (l) Rainfall

movement of water (Rosso and Rulli 2002). Herein, different land cover types affect the amount of rainfall that infiltrates the soil versus that which becomes surface runoff. Therefore, incorporating LULC into flash flood modeling may provide a more comprehensive understanding of the potential flood dynamics, helping to predict flash floods better. In the conducted research, a LULC map featuring ten unique categories for the Thanh Hoa province was prepared, as illustrated in Fig. 2c. This map was constructed utilizing a LULC dataset from 2020 provided by the Japan Aerospace Exploration Agency (JAXA). The dataset, characterized by a 30-meter resolution, is accessible through JAXA's online portal at www.eorc.jaxa.jp, which was accessed on June 15, 2023.

For the stream density, this factor should be selected for flash flood modeling (Dutta et al. 2023) as it provides vital insights into an area's natural water flow patterns, drainage capacity, and overall hydrological characteristics, aiding in the accurate prediction of flash floods. In the present study, the stream density map for the Thanh Hoa province (Fig. 2d) was generated using the stream data obtained from Open Street Map (accessible at www.openstreetmap.org). The computation of stream density was performed utilizing the Line Density tool within ArcGIS Pro. The resulting stream density values varied, ranging from 0.0 to 4.7 km per square kilometer.

NDVI and NDWI are valuable indices that should be selected for spatial prediction of flash floods due to their significance in capturing crucial environmental information related to vegetation and water content. Herein, NDVI relates to the health and density of vegetation across the study area. Thus, areas with dense and healthy vegetation can slow down surface runoff by promoting water infiltration and reducing erosion (Rawat and Singh 2018). On the other hand, regions with sparse or degraded vegetation are more susceptible to rapid runoff (Miao et al. 2016), increasing the likelihood of flash floods during intense rainfall events. Regarding NDWI, this factor has a sensitivity to water content, and distribution allows (Tsangaratos et al. 2023) for more accurate and reliable flash flood predictions. In this research, the computation of the NDVI map (Fig. 2c) and the NDWI map (Fig. 2d) for the Thanh Hoa province was conducted using the reflectance values derived from bands 4, 5, and 6 of Landsat 8 OLI (Operational Land Imager) imagery, 30 m resolution. The calculation procedure followed Eq. 1 (Defries and Townshend 1994) for NDMI and Eq. 2 (Xu 2006) for NDWI, as presented below:

$$\text{NDVI} = (\text{Band5} - \text{Band4}) / (\text{Band5} + \text{Band4}) \quad (1)$$

$$\text{NDWI} = (\text{Band5} - \text{Band6}) / (\text{Band5} + \text{Band6}) \quad (2)$$

The Landsat 8 OLI imagery utilized in this study is accessible through the website www.earthexplorer.usgs.gov.

Topography and terrain characteristics play a significant role in determining the flow of water during rainfall events (Zevenbergen and Thorne 1987); therefore, they should be considered for flash flood modeling. In this research, the digital elevation model (DEM) for the study area was extracted from the ALOS DEM with 30 m resolution, which was provided by the Japan Aerospace Exploration Agency (JAXA) and can be accessed at www.eorc.jaxa.jp. Using the DEM, five morphometric factors were generated: elevation (Fig. 2e), TWI (Fig. 2f), slope (Fig. 2g), Aspect (Fig. 2h), and curvature (Fig. 2i).

Elevation refers to a location's height or vertical position above sea level. As elevation changes across the study area, there is a corresponding variation in gravitational force. This relationship between elevation and gravity fundamentally impacts shaping water flow patterns (Charlton 2007; Ullah and Zhang 2020) and influencing the occurrence of flash floods; therefore, the elevation was selected. For the case of the TWI, this factor was used in flash flood modeling because it provides essential information regarding areas that are susceptible to runoff accumulation (Zahura et al. 2020) during rainfall events. Regarding the slope, this factor is recognized as a crucial factor because it directly affects the rate of surface runoff during rainfall events. Steeper slopes facilitate faster water flow, leading to higher runoff volumes (Abuzied et al. 2016) and increased flash flood potential. Aspect indicates the direction a slope faces and was included in this analysis. This is because different aspects can lead to varying water flow patterns, affecting the pathways of surface runoff during rainfall events (Hinckley et al. 2014). Curvature was used for flash flood modeling in this research because it provides valuable information about the shape and form of the terrain, which influences water flow during rainfall events. Different curvatures can create depressions and concave areas where water accumulates (Mahmoud and Gan 2018). Thus, such areas are more prone to water pooling and potentially generating flash floods during heavy rainfall.

Rainfall plays a decisive role in the formation and movement of the water flow within a watershed, affecting the magnitudes, velocity, and dynamics of flash flood flows (Bryndal et al. 2017). In this study, we investigated the most severe rainfall events that led to flash floods in Thanh Hoa province over the past five years, from 2018 to 2022. Consequently, the period from July 7, 2021, to August 31, 2021, was identified due to its association with multiple flash floods. During this time, the study area experienced the impact of a tropical depression originating from the East Sea, which resulted in heavy to hefty rainfall. The highest recorded total rainfall was 1069.9 mm in the Trieu Son

district, with the lowest being 1023.9 mm in the Tinh Gia district. In this analysis, the rainfall data was extracted from the climate data POWER project, National Aeronautics and Space Administration (NASA) (www.firms.modaps.eosdis.nasa.gov, accessed on 15 February 2023). Then, the rainfall map (Fig. 2j) was generated using the Inverse Distance Weight interpolation method available in ArcGIS Pro software.

Deep 1D-convolution neural network

Deep learning is a modern machine learning field that employs structures with multiple processing layers to mine and represent data. In the last five years, deep learning that encompasses various types of neural networks, i.e., Deep neural networks (DNN), Convolutional Neural Networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, made a huge impact due to their groundbreaking success (Dhillon and Verma 2020) in various domains of our lives, i.e., energy forecasting (Wang et al. 2019); remote sensing and image classification (Paoletti et al. 2019), environmental modeling (López-Pérez et al. 2020), and flash flood prediction (Bui et al. 2020).

In this analysis, we selected CNNs for flash flood analysis, which has proven highly effective in various computer vision tasks, including image classification, object detection, and image segmentation (Feng et al. 2019; Yuan et al. 2023). Thus, CNNs have become a fundamental tool in the field of computer vision due to their ability to automatically learn hierarchical features from images, leading to impressive performance on various visual recognition challenges (Planche and Andres 2019). CNNs consist of various convolutional layers, where filters or kernels are applied to input images to detect diverse features, including edges, textures, and shapes. The subsequent layers aggregate these features to recognize higher-level patterns and objects.

The traditional CNNs were initially developed where the input data is typically in the form of 2D images (Kabir et al. 2020), and then, the CNNs' architecture was further developed to process other types of data beyond 2D images, including 1D data processing (Kiranyaz et al. 2015), i.e., time series anomaly analysis (Kim et al. 2023) and 3D data handling (Cawte and Bazylak 2022), i.e., video frames or volumetric medical images (Lin et al. 2022). Literature review shows that 1D-CNNs have experienced substantial popularity and demonstrated successful applications across diverse fields and, therefore, were selected for this analysis.

Considering a flash flood dataset $FFDS = (X, y)$, X is a vector of ten flash flood factors, whereas y is the flash flood

index with values belonging to $[0,1]$. A typical 1D Convolutional Neural Network (1D-CNN), shown in Fig. 1, comprises an input layer, a convolutional layer, a pooling layer, a flattened layer, a fully connected layer, and an output layer. The purpose of the 1D-CNN is to build an inference model that infers the ten flash flood factors into the flash flood indices. Then, these indices will be used to generate a flash flood susceptibility map.

To begin, the input layer receives the ten flash flood factors as an X matrix and represents it as a 1D tensor. The subsequent step involves the 1D Convolution layer, a fundamental building block of the 1D-CNN, which conducts convolution operations on the input data using filters (kernels). These filters slide over the input data, extracting local patterns and features. Each filter generates feature maps that emphasize specific patterns within the input sequence (Fig. 3). The output of the convolution layer is then directed to the Pooling layer, which reduces the spatial dimensions of the feature maps while preserving essential information. By selecting the maximum value from a pooling window and discarding the rest, the Pooling layer effectively down samples the feature maps (Ugli et al. 2023).

After convolutional and pooling layers, the output undergoes flattening to transform the 2D feature maps into a 1D vector. This flattened vector is then fed into fully connected layers (also known as dense layers) to learn high-level representations and make predictions. The final layer of the 1D CNN is the output layer, which produces the spatial predictions of flash floods based on the learned representations. The number of nodes in the output layer depends on the specific task being solved. In this research context, the spatial prediction of flash floods is considered to be a binary classification task; therefore, the output layer has one node. The Rectified Linear Unit (ReLU) (Eq. 3) is commonly selected as the activate function (Ullah et al. 2022), whereas the sigmoid (Eq. 4) is used as the transfer function.

$$ActF(x) = \max(0, x) \quad (3)$$

$$TranF(x) = \frac{1}{1 + \exp(-x)} \quad (4)$$

Dropout is recommended to mitigate the risk of overfitting (Lang, et al. 2020). Dropout randomly sets a fraction of the neurons' outputs to zero during training, encouraging the network to learn more resilient features. Additionally, incorporating batch normalization can enhance stability and accelerate the training process. Batch normalization normalizes the activations of each layer, ensuring consistent mean and variance throughout the training procedure.

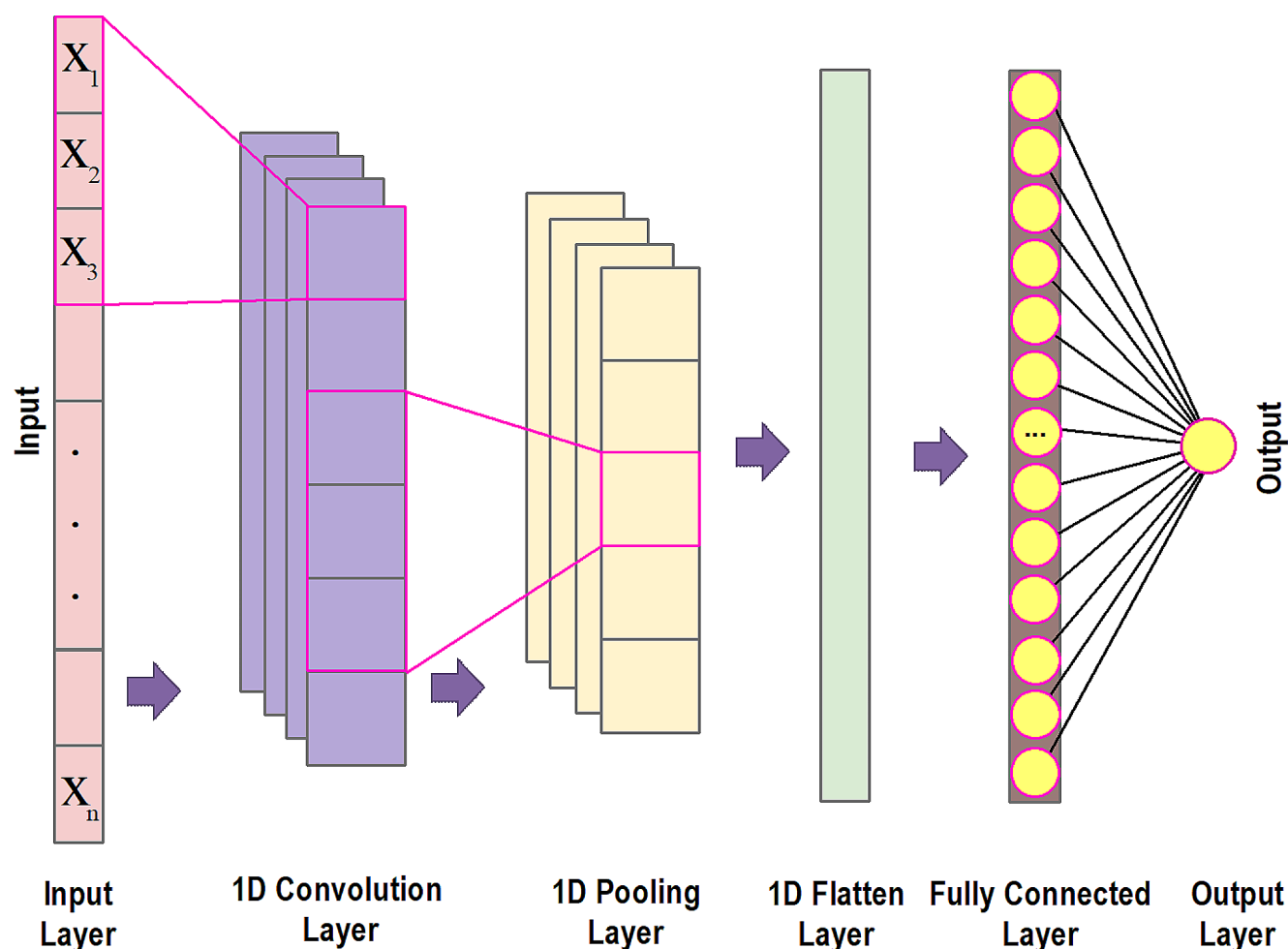


Fig. 3 Typical architecture of 1D Convolution Neural Networks (1D-CNN).

Proposed methodology for spatial prediction of Flash Flood using deep 1D-CNN and multi-source geospatial data

The description of the proposed methodology for spatial prediction of Flash Floods using 1D-CNN and GIS is presented in Fig. 4. In this research, the SNAP toolbox and ArcGIS Pro 3.0 were utilized for processing the Sentinel-1 SAR imagery and flash flood influencing factors, respectively. The statistics test was carried out using the IBM SPSS Statistics 29.0. The python code for the 1D-CNN algorithm codes can be found at www.tensorflow.org, whereas the authors wrote another python script to convert the twelve influencing factors to the input format of the 1D-CNN and convert the flash flood susceptibility indices to GIS format to open in the ArcGIS Pro. The modeling process was carried out using the Deep Learning toolset in ArcGIS Pro 3.2, which utilized the Tensorflow and Keras libraries, deep learning APIs Google developed. For the two benchmarked models, support vector machine (SVM) and logistic regression (LR), the API

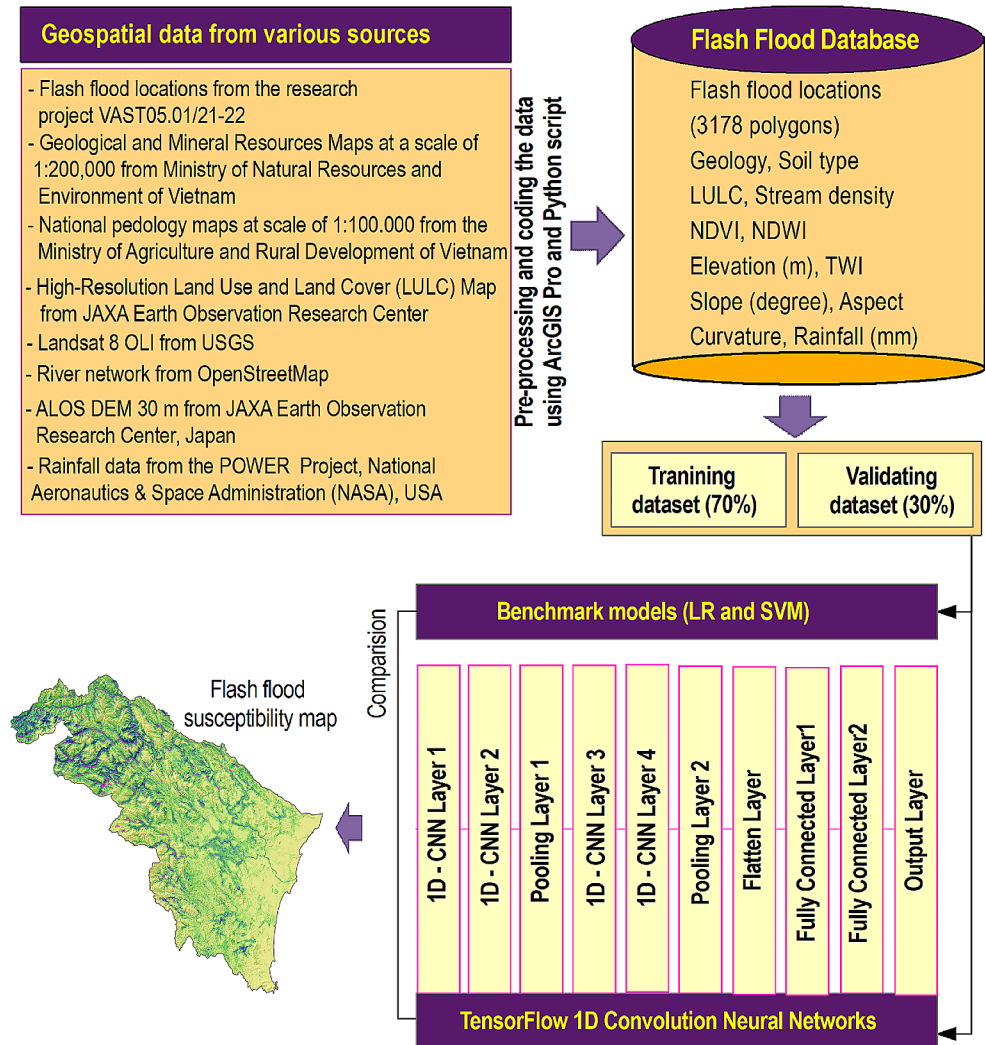
Weka Wrapper in Python (Reutermann 2020). It is noted that both Spyder and Microsoft Visual Studio Code Editor were used to edit and debug the Python code in this project.

Building flash flood database

This research utilized the ESRI-geodatabase format (Zeiler 1999) to construct the flash-flood database because it efficiently organizes geospatial data from diverse sources. We selected the WGS 1984 UTM Zone 48 N coordinate system for the study area. As a result, the flash-flood database in this research consists of 2540 flash-flood polygons and 12 influencing factors mentioned in Sect. 2.2. The next step involved converting all twelve influencing factors into a raster format with a spatial resolution of 30 m. Subsequently, these factors were normalized to a range of [0.01–0.99] using Eq. 5. This normalization process was performed using the Raster Calculator tool available in the ArcGIS Pro.

$$\text{NewFLF} = (\text{FLF} - \text{Min}(\text{FLF})) / (\text{Max}(\text{FLF}) - \text{Min}(\text{FLF})) * 0.99 - 0.01 \quad (5)$$

Fig. 4 The flowchart of the proposed methodology for flash flood susceptible mapping in this research



Here, NewFLF represents the new raster value of the flash flood influencing factor, while FLF denotes its original raster value. $\text{Max}(\text{FLF})$ and $\text{Min}(\text{FLF})$ correspond to the maximum and minimum values in the influencing factor, respectively.

This study's spatial prediction of flash floods is framed as a binary pattern recognition problem. The objective is to classify each pixel in the study area into one of two categories: "non-flash flood" or "flash flood" based on the patterns of 12 flash flood influencing factors. To achieve this, 2540 points representing non-flood areas were randomly generated in non-flash flood areas. As a result, a total of 5080 locations were obtained, combining flash flood and non-flash flood locations. Following this, the flash flood locations were labeled with a value of "1" while the non-flash flood locations were labeled with a value of "0". In the next step, a sampling process was conducted to extract the values of the ten influencing factors for these locations, employing the sample tool in the ArcGIS Pro. Finally, the data was randomly divided into a 70/30 ratio to create the training

dataset, which comprised 3556 samples, and the validation dataset, which comprised 1524 samples.

Multicollinearity and ranking of flash flood influencing factors

Multicollinearity checking of influencing factors is essential for flash flood modeling as it helps identify and address issues related to their intercorrelation. According to De Veaux and Ungar (1994), multicollinearity checking can help to enhance its predictive accuracy and preserve the model's interpretability. Thus, when multicollinearity exists between the influencing factors, it becomes challenging to isolate the individual effect of each factor on the flash floods. The presence of multicollinearity can lead to inflated coefficient estimates and standard errors, making it difficult to determine the true significance of each flash flood influencing factor. In order to address the multicollinearity, the Variance Inflation Factor (VIF) and Tolerance (TOL) (Mansfield and Helms 1982; Miles 2014) were employed

and computed for each influencing factor. Problematic multicollinearity is indicated by Variance Inflation Factor (VIF) values exceeding 10 and Tolerance (TOL) values below 0.1 (Menard 2002).

In addition to multicollinearity, the role of the influencing factors should be assessed to ensure all the factors are relevant before carrying out the flash flood modeling. The Random Forests-based Wrapper method (Cardenas-Martinez et al. 2021) with 5-fold cross-validation technique was employed for this task. We used 500 random trees in the Random Forests to search and rank each factor through various subset assessments, as suggested by Tuan et al. (2023). Herein, the Mean Absolute Error (MAE) in Eq. 6 was selected to measure the contribution of each factor.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |FFL_i - FLO_i| \quad (6)$$

where FFL_i is the flash flood value, while FLO_i denotes the flash flood output from the RFW; n is the total number of samples.

Designing Deep 1D-CNN model

The performance of the Deep 1D-CNN model significantly relies on its structure, activation function, transfer function, and parameter optimization, all of which require careful determination. This study proposes a specific structure for the Deep 1D-CNN model used in the spatial prediction of flash flood inundation, as depicted in Fig. 5. The model consists of an input layer, four 1D-CNN layers, two pooling layers, one flattened layer, two fully connected layers, and an output layer.

For the first 1D-CNN layer, we employed kernel sizes of 1 and 32 filters, while for the second 1D-CNN layer, kernel sizes of 3 and 64 filters were selected (Trong et al. 2023). The architecture incorporates pooling layers 1 and 2, each with a pool size of 2. Following these, the third 1D-CNN layer is configured with kernel sizes of 1, along with 64 filters, whereas the fourth 1D-CNN layer utilizes kernel sizes of 3 and is equipped with 128 filters. Upon integrating the flattened layer (as depicted in Fig. 5), two densely connected layers were systematically structured, featuring 200 neurons in the first dense layer and 50 neurons in the second dense layer.

Finally, the output layer was structured with two neurons, representing “non-flash flood” and “flash flood,” respectively. Herein, a threshold of 0.5 was adopted to separate output indices into the two classes, “non-flash flood” and “flash flood,” for the model performance assessment. To facilitate the model’s performance, we chose the ReLU as the activation function and employed the sigmoid function for

the transfer function. A summary of the proposed 1D-CNN model and its parameters is shown in Table 1.

Optimizer and loss function

As shown in Table 1, a total of 112,994 parameters of the proposed Deep 1D-CNN model were identified, and in this study, they were optimized using the Adaptive Moment Estimation (ADAM) algorithm (Kingma and Ba 2015). The ADAM algorithm calculates individual learning rates for each parameter of the Deep 1D-CNN model based on their historical gradients. This adaptiveness helps the optimizer converge faster and more efficiently compared to traditional optimizers with fixed learning rates (Goodfellow et al. 2016).

During the training phase, the 112994 parameters of the proposed Deep 1D-DNN model were adapted to identify the most appropriate functional mapping between the actual and the predicted values of the flash-flood and the non flash-flood. To measure the fitness of the parameters with the proposed Deep 1D-CNN model, we employed the Mean Squared Error (MSE) in Eq. 7 as the loss function in this study.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (FFL_i - FLO_i)^2 \quad (7)$$

where FFL_i represents the flash flood value in the inventory map, while FLO_i denotes the flash flood output obtained from the proposed Deep 1D-CNN model; the variable “ n ” corresponds to the total number of samples utilized in the analysis.

Performance assessment

A comprehensive set of performance measurement metrics was employed to evaluate the performance of the proposed Deep 1D-CNN model for spatial prediction of flash flood inundation. The evaluation included the use of TP (true positive), FP (false positive), FN (false negative), and TN (true negative), as described Nhu et al. (2020). Using these indices, additional metrics such as PPV (Positive Predictive Value), NPV (Negative Predictive Value), Sens (Sensitivity), Spec (Specificity), Accuracy, and F-Score were computed following the works of López et al. (2013). In addition to the above metrics, the widely adopted ROC curve and AUC (Area Under the Curve) were employed to assess the overall generalization capability of the 1D-CNN model, drawing insights from van Erkel and Pattynama (1998). Furthermore, the Kappa index, McHugh (2012) was also computed to quantify the predictive accuracy of the Deep 1D-CNN model.

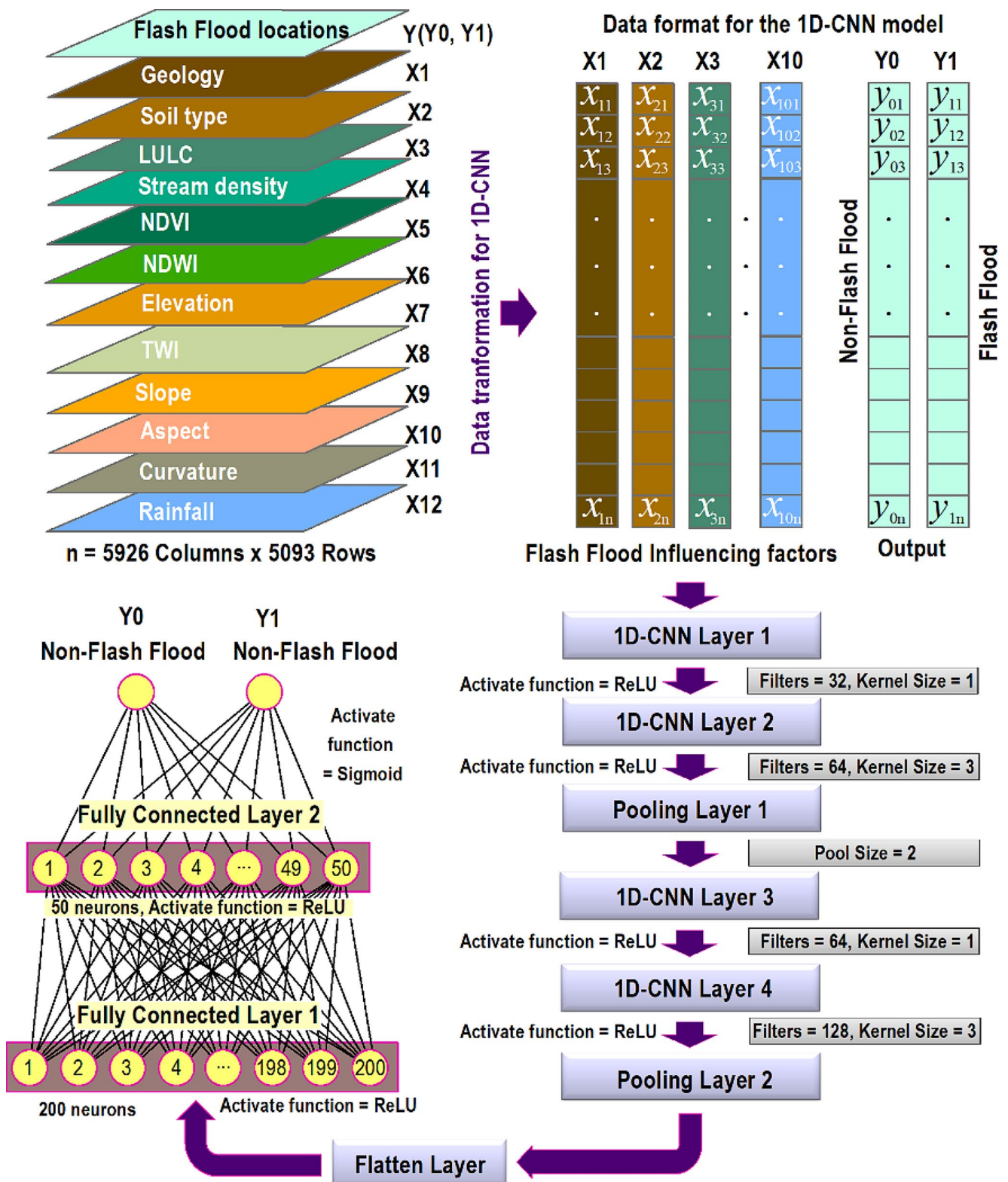


Fig. 5 Structure of the proposed Deep 1D-CNN model for spatial prediction of flash flood in this analysis

Table 1 Summary of the proposed Deep 1D-CNN model with 112,994 parameters for spatial prediction of flash flood in this research

No	Description	Number of parameters
1	The 1D-CNN Layer 1	128
2	The 1D-CNN Layer 2	12,352
3	The Pooling layer 1	0
4	The 1D-CNN Layer 3	4160
5	The 1D-CNN Layer 4	24,704
6	The Pooling layer 2	0
7	The flattening layer	0
8	The fully connected layer 1	51,600
9	The fully connected layer 2	20,050

Benchmark model comparison

In the present research, the effectiveness of the proposed Deep 1D-Convolutional Neural Network model is demonstrated through a comparative analysis with two established flash flood models: the Support Vector Machine (SVM) and Logistic Regression (LR). They were chosen as benchmark models for flash flood modeling (Ngo et al. 2021) owing to their demonstrated proficiency in predicting areas susceptible to flash floods across a variety of studies, including, i.e., (Costache 2019; El-Rawy et al. 2022; Pham et al. 2020; Youssef et al. 2016). The SVM analysis employed the Radial Basis Function (RBF) kernel, with the parameters C and gamma optimized through the grid search technique (Fayed and Atiya 2019). Meanwhile, for the Logistic Regression model, standard default parameters were utilized.

Compiling the flash flood susceptibility map

After successfully training and validating the Deep 1D-CNN model to meet the desired criteria, the model was utilized to calculate the flash flood susceptibility indices for the entire study area. The study area consists of a matrix with dimensions of 5926 columns $\times$ 5093 rows. In order to prepare the input data for the Deep 1D-CNN model, the twelve influencing factor maps were transformed into a study data matrix with a size of 30,181,118 rows $\times$ 12 columns (see Fig. 5), adhering to the model's input format. Subsequently, these indices were converted into a GIS format to generate the final flash flood susceptibility map.

Results and analysis

Multicollinearity and ranking result

The results of the multicollinearity analysis for the 12 influencing factors are presented in Table 2. It is evident that all 12 influencing factors have Variance Inflation Factor (VIF) values below 10 and Tolerance (TOL) values above 0.1,

Table 2 Multicollinearity of flash flood influencing factors in this research

Influencing factors	Multicollinearity statistics		Score value	Ranking
	Tolerance (TOL)	Variance Inflation Factor (VIF)		
Slope (°)	0.828	1.207	0.234	1
TWI	0.479	2.087	0.159	2
Geology	0.539	1.855	0.122	3
Elevation (m)	0.606	1.651	0.109	4
Rainfall (mm)	0.618	1.619	0.086	5
Stream density (km/km ²)	0.725	1.380	0.084	6
Curvature	0.845	1.184	0.062	7
Soil	0.949	1.054	0.057	8
LULC	0.852	1.174	0.041	9
NDVI	0.769	1.300	0.035	10
NDWI	0.629	1.590	0.020	11
Aspect	0.985	1.105	0.005	12

indicating the absence of problematic multicollinearity in the dataset. Notably, among these factors, TWI exhibits the highest VIF value (2.087) and the lowest TOL value (0.479), while soil demonstrates the lowest VIF value (1.054) and the highest TOL value (0.949) (Table 2).

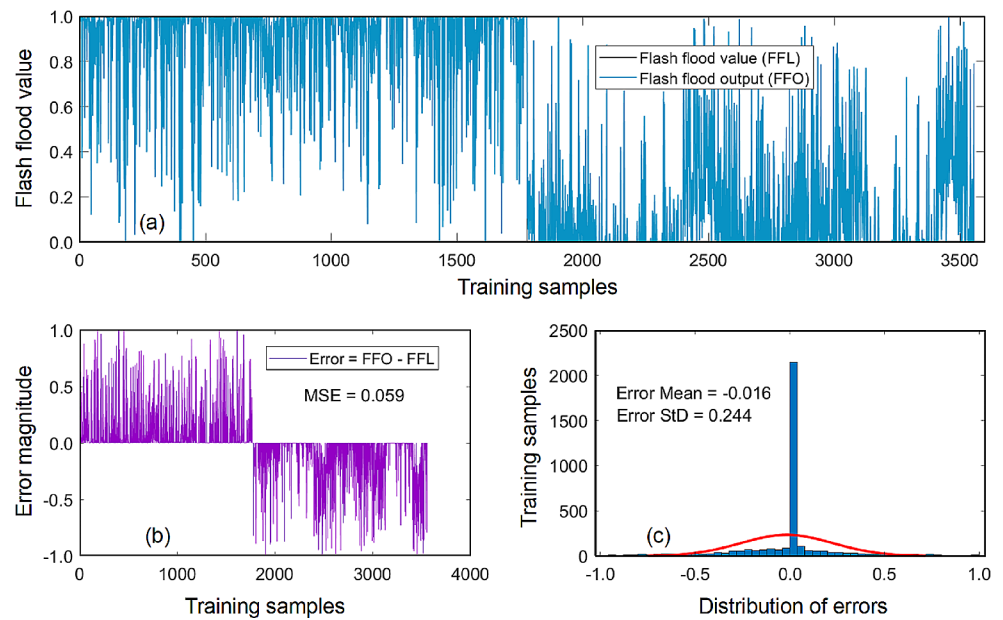
The 12 factors influencing flash floods in the study area have been assessed, and the findings are presented in Table 2. Notably, Slope, Topographic Wetness Index (TWI), geology, and rainfall emerged as the most influential factors. Their respective score values are 0.234, 0.159, 0.122, 0.109, and 0.086. They are followed by stream density (0.084), curvature (0.062), soil (0.057), LULC (0.041), and NDVI (0.035). Conversely, Aspect and NDWI exhibit the lowest impact on flash floods in this province, with scores of 0.005 and 0.020, respectively.

Model fitting and validation

Using the 3556 samples within the training dataset, the Deep 1D-CNN model underwent training in the training phase, employing the ADAM algorithm to optimize the 112,994 parameters. The outcomes are depicted in Fig. 6; Table 3, and Fig. 7. The results reveal a robust fitting of the proposed Deep 1D-CNN model with the training dataset, as evidenced by a Mean Squared Error (MSE) of 0.059, an Error Mean of -0.016, and a Standard Error (Error StD) of 0.244. In addition, the errors are distributed according to a normal distribution (Fig. 6).

The detailed metrics of the Deep 1D-CNN model are presented in Table 3. The model achieved an accuracy of 91.5%, a Kappa value of 0.830, an F-score of 0.916, and an AUC of 0.977, indicating a high fit for the proposed Deep 1D-CNN model. The Positive Predictive Value

Fig. 6 Performance of the Deep 1D-CNN model in the training dataset. **(a)** Distribution of flash flood values, **(b)** Magnitude of errors, and **(c)** Distribution of errors



(PPV) stands at 92.8%, signifying the likelihood that the model accurately classifies flash flood samples in 92.8% of cases. Conversely, the Negative Predictive Value (NPV) is 90.2%, indicating the model's correct classification of non-flash flood samples in 90.2% of cases. The sensitivity (Sens) is 90.4%, demonstrating the deep 1D-CNN model's ability to identify flash floods accurately in 90.4% of cases. Similarly, the Specificity (Spec) is 92.6%, indicating the model's correct identification of non-flash floods in 92.6% of cases.

The model is examined using the validation dataset to assess the Deep1D-CNN model's ability to generalize to new data and accurately predict flash flood occurrences in regions. The result is shown in Figs. 7 and 8; Table 4. Our observations reveal a remarkable accuracy of 90.2%, a Kappa value of 0.804, an F-score of 0.903, and an AUC of 0.969, underscoring the model's high predictive capability. Moreover, the model exhibits a low mean squared error (MSE) of 0.068, a mean error of -0.006, and a standard deviation of errors (Error STD) of 0.262, demonstrating a highly satisfactory outcome. Furthermore, the errors within the validation dataset follow a normal distribution pattern (Fig. 8). The model exhibits a PPV of 91.1%, implying a 91.1% accuracy in correctly classifying flash flood samples within the validation dataset. The NPV stands at 89.4%, indicating accurate classification of the non-flash flood samples in 89.4% of instances. The Sens of 89.5% underscores the Deep 1D-CNN model's capability to correctly identify flash floods in 89.5% of cases, while the Spec of 86.7% showcases its accurate recognition of non-flash flood instances in 86.7% of cases. The other metrics measured for the Deep 1D-CNN model in the validation dataset are presented in Table 4.

Comparative analysis and statistical evaluation

The efficacy of the proposed Deep 1D-CNN model was meticulously evaluated through a comparative analysis, pitting its performance and predictive capabilities against established benchmarks. As delineated in Sect. 3.6, this study chose support vector machine (SVM) and logistic regression (LR) as the benchmark models. In the case of the SVM model, the Radial Basis Function (RBF) kernel was applied, and a grid search approach was employed to explore the optimal parameters, specifically C (9.0) and Gamma (0.625), whereas, for the LR model, default parameters in the Weka API were used.

The fitting performance results are presented in Tables 3 and 4. It is evident that both the SVM model (accuracy=89.8.6%, Kappa value=0.797, F-score=0.899, and AUC of 0.960) and the LR model (accuracy=80.2%, Kappa value=0.603, F-score=0.800, and AUC of 0.880) demonstrate a good fit with the training data. However, the SVM model outperforms the LR model, as indicated in Table 3. Additional statistical metrics are detailed in Table 3. Overall, it is apparent that the performance of both the SVM model and the LR model is inferior to that of the proposed Deep 1D-CNN model.

The prediction capability of the benchmark models, as depicted in Table 4, demonstrates commendable results. Both the SVM model (accuracy=87.7%, Kappa value=0.755, F-score=0.876, and AUC=0.948) and the LR model (accuracy=80.7%, Kappa value=0.614, F-score=0.798, and AUC=0.873) show satisfactory performance. However, it is clear that the prediction performance of the SVM model is higher than that of the LR model. Nonetheless, the predictive performance of both the SVM model and the LR model

Table 3 Fitting performance of the flash flood models in the training phase

Flash flood model	Statistical metrics				CSI							
	TP	TN	FP	FN	PPV (%)	NPV (%)	Sens (%)	Spec (%)	Accuracy	F-score	Kappa	AUC
Deep ID-CNN	1650	1603	128	175	92.8	90.2	90.4	92.6	91.5	0.916	0.830	0.977
SVM	1610	1585	168	193	90.6	89.1	89.3	90.4	89.8	0.899	0.797	0.960
RF	1414	1437	364	341	79.5	80.8	80.6	79.8	80.2	0.800	0.603	0.880

is lower when compared to the predictive performance attained by the proposed Deep 1D-CNN model.

In order to ensure confident and reliable conclusions regarding the effectiveness of the proposed Deep 1D-CNN model compared to the two benchmarks in predicting flash floods, a rigorous statistical analysis using the Paired Samples T-Test was conducted. Herein, three pairs of the flash flood models, Deep 1D-CNN vs. SVM, Deep 1D-CNN vs. LR, and SVM vs. LR, were considered. The null hypothesis (H_0) posits that no significant difference in prediction capability exists among these model pairs within a 95% confidence interval around the difference in means. Subsequently, t-values and p-values are calculated for each pair. The null hypothesis is rejected if the t-value falls outside the range of -1.96 to + 1.96 and the p-value is less than or equal to 0.05. In this scenario, we deemed the prediction capability of these flash flood models to be statistically significant at the 5% level of significance.

The results of the Paired Samples t-Test for the flash flood models in this research are presented in Table 5. It is evident that the t-values for the two pairs, Deep 1D-CNN vs. SVM and Deep 1D-CNN vs. LR, fall outside the range of -1.96 to +1.96, and the corresponding p-values are less than 0.05 (Table 5). These findings signify that the prediction performance of the Deep 1D-CNN model surpasses that of both the SVM model and the LR model, establishing statistical significance.

Flash-flood susceptibility map

Based on the aforementioned analysis and result, the proposed Deep 1D-CNN mode has proved to be the best-suited model for flash-flood susceptibility assessment in this research; the model was used to compute the flash-flood susceptibility index for each pixel in the study area. As a result, the susceptibility index for 30,181,118 pixels of the study area (5926 columns $\times$ 5093 rows) was determined. These pixels, with index values from 0.0001 to 0.9999, were converted to the WGS 1984 UTM Zone 48 N coordinate system to generate the flash flood susceptibility map (Fig. 9).

An aerial interpretation of the susceptibility map indicates a high probability of flash floods in certain districts, namely Muong Lat, Quan Son, Ba Thuoc, and Lang Chanh. These districts frequently experience severe flash floods annually, attributed to the terrain's elevated altitude and steep slopes. Conversely, in the southeast districts, such as Quang Xuong and Hoang Hoa, the flash flood index is notably lower. This is due to the relatively flat terrain and proximity to the sea, which facilitates more efficient drainage (refer to Fig. 9).

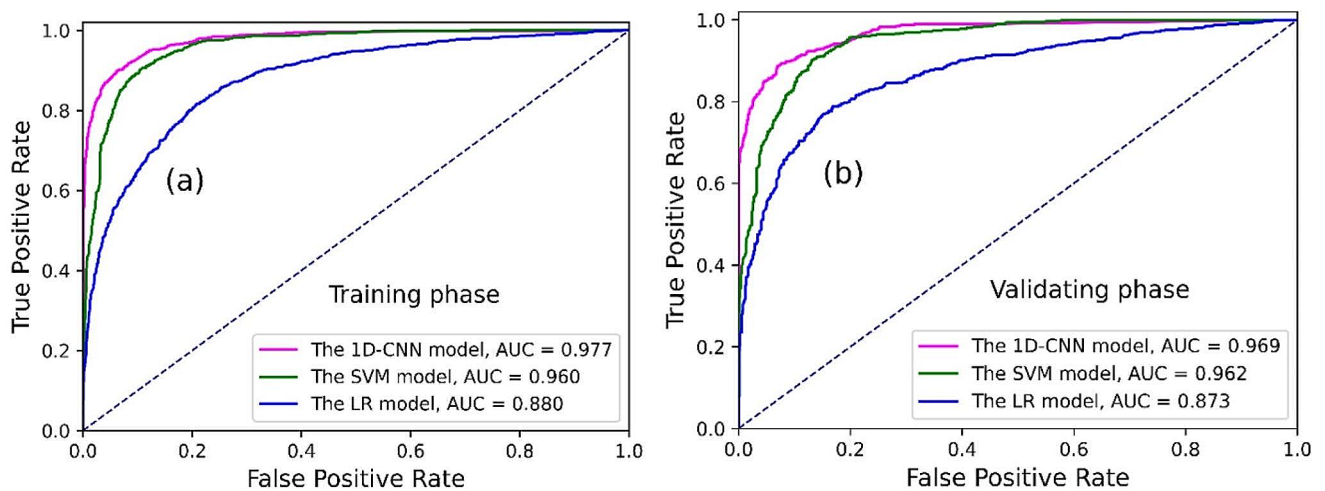
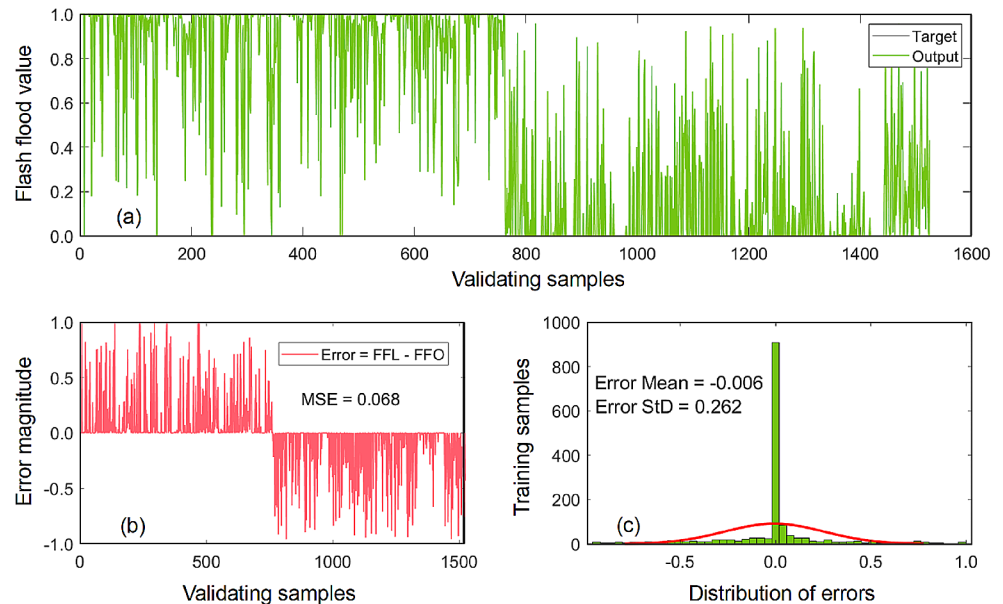


Fig. 7 ROC curve and AUC of three flash flood models, the Deep 1D-CNN, the SVM, and the LR: (a) Training phase and (b) the validating phase

Fig. 8 Performance of the Deep 1D-CNN model in the validating dataset. (a) Distribution of flash flood values, (b) Magnitude of errors, and (c) Distribution of errors



Discussion

Flash flooding persists as a perilous natural hazard, inflicting significant damage to infrastructure as well as natural and constructed environments, especially in tropical areas. Despite the challenges in forecasting flash floods, as highlighted in recent research (Brunner et al. 2021; Jay-Allemand et al. 2022; Maqtan et al. 2022; Mishra et al. 2022), identifying susceptibility in areas prone to flash floods in advance can be an effective strategy for reducing and mitigating flash flood risks. In this study, we propose a novel approach that combines 1D Deep Convolutional Neural Networks with multi-source geospatial data for modeling flash flood susceptibility, focusing on areas of the Thanh Hoa province in North Central Vietnam that have been heavily affected by flash floods in the last five years.

This study's findings highlight that the structural design of the Deep 1D-CNN significantly impacts its predictive effectiveness. Based on this insight, our research involved configuring the deep learning model with four convolutional layers, two pooling layers, one flattened layer, and two fully connected layers. This structure follows the recommendations of Trong et al. (2023). Within this modeling approach, we employed the ADAM algorithm as the optimizer and Mean Squared Error (MSE) as the loss function. The observed high performance of the Deep 1D-CNN under this configuration suggests that the ADAM algorithm effectively optimizes the 112994 parameters of the model, where MSE is preferable for the lost function. However, asserting that this specific structure is the most suitable for our research objectives remains premature. Consequently,

Flash Flood model	Statistical metrics
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Flash Flood model	Statistical metrics				FN	FP	TN	TP	NPV (%)	PPV (%)	Spec(%)	Sens(%)	Accuracy	F-score	Kappa	AUC
Deep 1D-CNN	694	681	68	81	89.4	91.1	89.5	90.9	90.2	0.903	0.804	0.969				
SVM	658	679	104	83	89.1	86.4	88.8	86.7	87.7	0.876	0.755	0.948				
R	580	650	182	112	85.3	76.1	83.8	78.1	80.7	0.798	0.614	0.873				

Table 5 Paired Samples T-Test for the flash flood models in this study

No.	Pairwise flash flood model	t-value	p-value	Significance
1	Deep 1D-CNN vs. SVM	3.587	<0.001	Yes
2	Deep 1D-CNN vs. LR	3.010	0.003	Yes

further investigations are necessary to identify the optimal structural design for autonomous flash flood modeling.

Comparing the proposed Deep 1D-CNN model with benchmarks, SVM, and LR, the proposed model performs better, as confirmed by the paired-sample sign test. This underscores the potential of 1D-CNN as a promising tool for spatial predictions of flash floods. The finding is inline with recent report results, i.e., (Bui et al. 2020; Shahabi et al. 2021; Tsangaratos et al. 2023). Therein, the better performance of the Deep 1D-CNN model over SVM (Support Vector Machines) and LR (Logistic Regression) in flash flood modeling can be attributed to its intrinsic ability to handle nonlinear relationships among influential factors. Logistic regression is less adept at capturing such complexities. Meanwhile, while capable of nonlinear modeling with appropriate kernels, SVM may not be as effective in delineating complex patterns in the given flash flood dataset. Moreover, the Deep 1D-CNN demonstrates robustness against noise and variability present in geospatial data pertinent to flash flood modeling. This robustness stems from its design focus on identifying and prioritizing the most relevant features, thereby diminishing the influence of extraneous or noisy data.

Another benefit of using the Deep 1D-CNN for flash flood modeling lies in its availability within the TensorFlow and Keras frameworks, as noted by Dürre et al. (2020). These frameworks, known for their open-source nature, offer significant advantages. TensorFlow and Keras, with their open-source licenses, facilitate extensive customization and benefit from community-driven improvements, enhancing their utility in complex modeling tasks like flash flood prediction. This accessibility ensures that Deep 1D-CNN architectures can be freely utilized, benefiting from the collaborative improvements and diverse applications contributed by the global open-source community. In this research, the Deep 1D-CNN modeling was conducted within the ArcGIS Pro 3.1.0 deep learning platform, which integrates both TensorFlow and Keras. This platform enables seamless integration with a variety of spatial analysis tools and the ArcGIS Pro model builder, thereby facilitating the autonomous processing of multi-sourced geospatial data. It aids in activities like data sampling, training, model validation, and the backend creation of the flash flood susceptibility map. As a result, there was a significant reduction in the time required for data processing, modeling, and creating the susceptibility map.

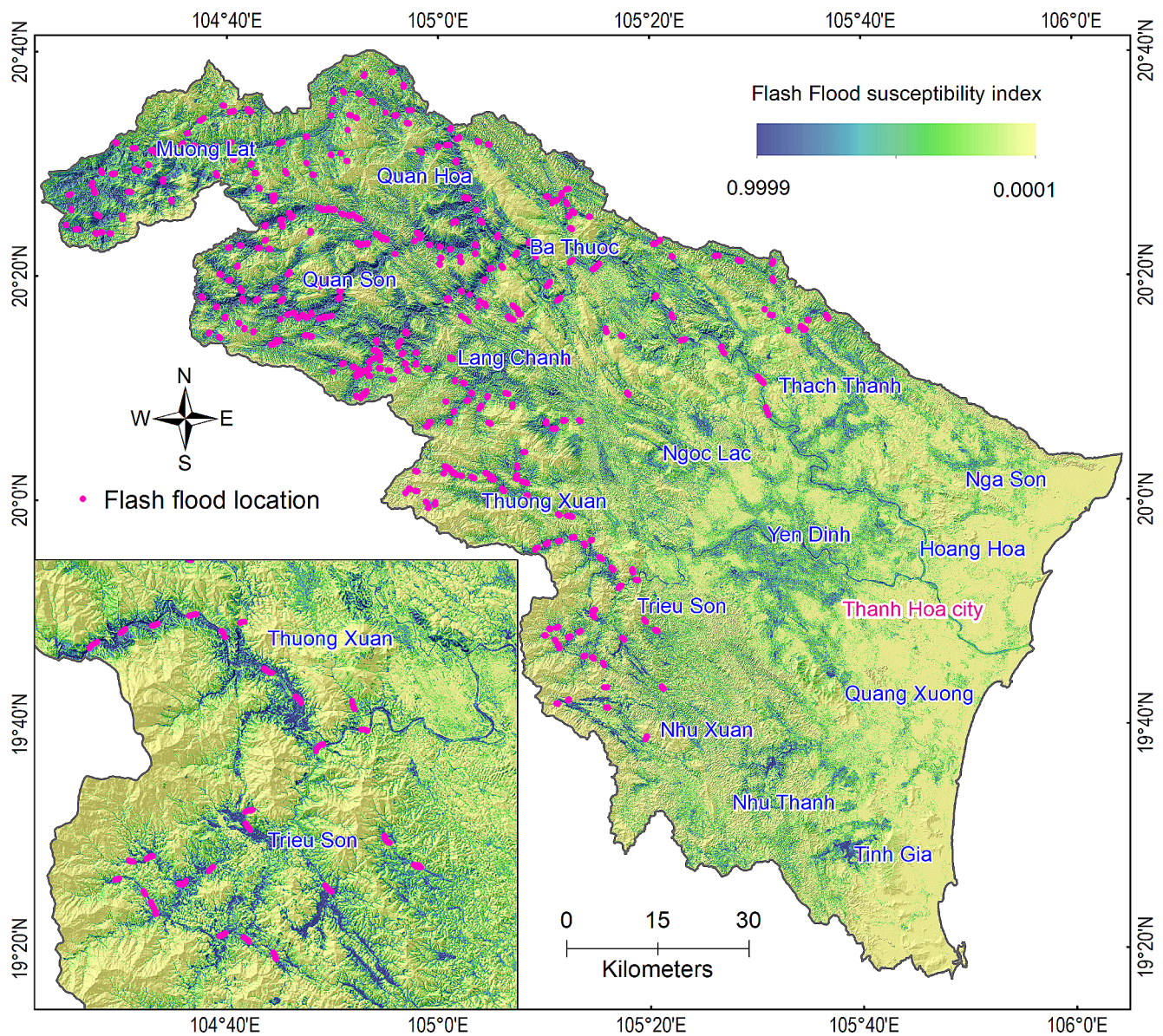


Fig. 9 Flash Flood susceptibility map for the Thanh Hoa province using the Deep 1D-CNN model

The modeling process necessitates the use of a Python Integrated Development Environment (IDE), which serves as an extensive coding tool. This environment facilitates the entire Deep 1D CNN modeling workflow for flash flood prediction, encompassing stages from data preprocessing to model deployment. While Spyder within Anaconda has been recognized as a powerful scientific environment in previous studies (Kadiyala and Kumar 2017), it is unsuitable for flash flood modeling in this project due to compatibility issues with libraries in the ArcGIS Pro 3.1.0 deep learning environment. Consequently, Visual Studio Code (bin Uzayr 2022) was employed. This choice, however, necessitates specific knowledge for effective utilization.

Regarding the input factors, in this work, twelve influencing factors were carefully considered, primarily based on an analysis of the characteristics of flash floods in the study area and the availability of geospatial data. The effective performance of the Deep 1D-CNN model suggests that the processes of selecting, processing, and integrating these influencing factors were successfully executed. Notably, slope and Topographic Wetness Index (TWI) emerged as the most critical factor for flash flood occurrences in this province. The prominence of slopes is justified because the province has diverse topography, where steep slopes are common, especially in Muong Lat, Quan Son, Lang Chanh, and Trieu Son (Fig. 9), significantly accelerating surface runoff, reducing infiltration, directing water flow rapidly

downhill, and increasing the risk of soil erosion and landslides, all of which contribute to the heightened potential for flash flooding. Regarding TWI, this factor is clearly shown where water is likely to accumulate, such as in the areas of Muong Lat, Quan Son, Lang Chanh. High TWI values correspond to areas with greater soil saturation (Fig. 2h), leading to flash floods during heavy rains.

The constraint in this research is related to the utilized data arising from varying resolutions across different sources. For instance, DEM and its derivatives, LULC, NDVI, and NDWI, possess a spatial resolution of 30 m. Conversely, the soil map is derived from the pedological maps at a scale of 1:100,000, while the geological data is sourced from Geological and Mineral Resources Maps at a scale of 1:200,000. This variation in scale and detail among the source maps may lead to content and precision diverging, thereby introducing potential uncertainties in flood modeling. In order to improve the prediction accuracy of flash floods, it is recommended to utilize geospatial data of higher resolutions. This approach can offer more detailed and precise information, which is crucial for effective flash flood modeling and risk assessment.

A notable limitation of this research lies in the omission of considerations regarding the impact of climate change on the predictive capabilities of the Deep 1D-CNN model, as well as the investigation into the variability of the model's performance. Consequently, future research will be undertaken to provide a more comprehensive evaluation and conclusions regarding the efficacy of this model in predicting flash floods, incorporating the potential effects of climate change and performance variability.

Nonetheless, on a regional scale, the flash flood susceptibility modeling conducted for Thanh Hoa province in this study carries substantial implications. The susceptibility map may help the authorities in creating strategic plans that reduce risks, improve disaster readiness, and establish policies that strengthen the resilience of both communities and infrastructure systems.

Concluding remarks

This study embodies a thorough research methodology for the spatial prediction of flash floods, incorporating Deep 1D-CNN and multi-sourced geospatial data to offer an innovative approach that improves predictive accuracy. Its contributions establish a result for future enhancements in flash flood management practices, underscoring the necessity for continued refinement of the model, an investigation into additional predictive variables, and the pragmatic application of these models. Moreover, this research not only progresses our comprehension of flash flood dynamics but

also accentuates the capacity of deep learning techniques to enhance disaster preparedness and mitigation strategies. From the findings of this study, several key conclusions can be drawn:

- The Deep 1D-CNN model, utilizing the ADAM optimizer and MSE (Mean Squared Error) loss function, has demonstrated its capability to generate accurate flash flood susceptibility maps.
- Comparatively, the performance of the proposed Deep 1D-CNN model exceeded that of the SVM (Support Vector Machine) and LR (Logistic Regression) models, which served as benchmarks in this study. This finding underscores the potential and effectiveness of 1D-CNN as an advanced tool in susceptibility mapping for flash floods.
- In the context of this study, Land Use and Land Cover (LULC), Slope, and Normalized Difference Vegetation Index (NDVI) have emerged as the most significant factors influencing flash flood occurrences.
- For future expansions of this research, the exploration of other advanced metaheuristic algorithms for training deep learning models is recommended. Additionally, innovative methods for autonomously determining the structure of deep learning models warrant further investigation.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

Conflict of interest The authors declare no conflict of interest.

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