Flood Forecasting with Sentinel-2 Images Using Machine Learning

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Abstract

This paper proposes a methodology for detecting flooded areas using Sentinel-2 images, followed by flood forecasting based on a combination of the deep neural network U-Net and a support vector machine (SVM). The U-Net architecture classifies a given Sentinel image into the two classes "water" and "no water", the SVM subsequently performs a near-future prediction of flooded areas based on the U-Net results and additional information (DEM, land use information, precipitation data etc.). Experimental results demonstrate that for a test site in Ukraine the U-Net/SVM model achieves the highest overall accuracy (98.8%), slightly outperforming other models, including Random Forest and SVM. The resulting flood maps provide valuable information for planning rescue operations and territory management, allowing for rapidly identifying areas of flooding. It can thus contribute to a significant reduction in economic losses and an increase in emergency preparedness.

1. Introduction

Flooding is one of the most dangerous and widespread natural hazards in the world, causing damage to people, infrastructure, and the economy. According to the United Nations, water-related disasters such as floods have dominated the list of disasters over the past 50 years and account for 70 % of all deaths related to natural disasters (UN 2025). Effective and quick response to flooding emergencies requires, among others, flood maps which contain information about geographical features such as transportation networks, place names, landscape conditions, and areas of possible flooding. These maps are widely used in political, social, and environmental studies. However, generating them is a labour-intensive process, which creates the need to develop automated methods for producing such maps.

In recent years, there has been a growing interest in producing flood maps in photogrammetry and remote sensing. These maps are based on topographic maps and show such additional information as flooded areas and water depth as a result of flooding[1].

The goal of this paper is to create such flood maps, which do not only show the present state, but can also forecast the flooding situation for the near future. The current state is derived from Sentinel-2 imagery via semantic segmentation, while the following scenario is generated using additional information (e.g., land cover, digital terrain models, precipitation data) in a separate step, using a support vector machine in a type of multi-criteria decision-making in order to produce the desired flood map.

2. Literature review

An older review of flood risk assessment can be found in Ologunorisa, Abawua (2005). More recently, to assess flood risks in the Mulde River area in Saxony, Germany, Meyer et al. (2009) used the multi-attribute utility theory (MAUT, von Winterfeld, Fischer, 1975). The flood hazard was evaluated using a quasi-dimensional (2D) hydrodynamic model. Dang et al. (2010) studied the Red River Delta in Vietnam using the Analytic Hierarchy Process (AHP) method (Saaty 1990). Like MAUT, AHP is widely used in multi-criteria decision-making (MCDM), however, in AHP many of the parameters needed for decision-making are determined automatically, unlike in MAUT, where those parameters need to be set interactively (Velasquez et al., 2013). The criteria selected by Dang et al. (2010) for assessing the flood risk (economic, social, and environmental losses) are more detailed than those of previous studies. However, obtaining the above criteria is a difficult task. Parameters such as water depth, duration, and speed of water flow are proposed to assess flooding territories. To this end, the positions and extents of residential buildings, unique purpose buildings, public infrastructure and agricultural land were considered. Social losses were estimated based on population density and income. Environmental damages were estimated based on pollution (industrial emissions, waste, and stagnation of flood waters), erosion, and the availability of open spaces. Thus, flood assessment for large areas or regions with limited information detail may be complicated due to the need to use the above criteria, which requires significant resources and may complicate the implementation of the proposed methodology.

In another flood risk assessment study, conducted by Yeganeh et al. (2014) for the Iskandar region in Malaysia, fuzzy logic, multi-criteria ranking and weighted linear combination were employed. The criteria for creating the map of flooded areas were distance to the mainstream river, elevation, slope, land use, land cover type, distance to the drainage channel, and population density. One of the limitations of this approach is the lack of a theoretical

[1]Note, that flooded areas and water depth at a particular position can only roughly be derived from a digital elevation model alone, as the amount of flooding is also a function of land cover, individual building locations, water flow etc.

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basis for the method, which makes it difficult to justify the assigned weighting factors.

In recent years, machine learning methods such as support vector machines (SVMs, Opella et al., 2019; Islam et al., 2021) and artificial neural networks (Andaryani et al., 2021; Avand et al., 2021; Islam et al., 2021) have been increasingly used to detect potential flood zones. Both methods have advantages and limitations that affect their effectiveness in this area. For example, SVM is rather robust with respect to noise and has demonstrated high classification accuracy, also when relatively little training data are available. On the other hand, artificial neural networks need significantly more training data and higher computing resources, but are generally more accurate than traditional machine learning (see, e.g., Heipke, Rottensteiner, 2020 for an overview with selected examples).

In any case, besides height data, land cover estimation is critical for accurate flood mapping and forecasting, as different land cover types affect the outflow and accumulation of water. For example, water bodies, urban areas with low permeability, and vegetation have different effects on flooding. Land cover classification using satellite image time series (SITS) and deep neural networks, as proposed e.g., by Honcharov et al. (2024) and Voelsen et al. (2024), allows spatial and temporal data characteristics to be combined accurately to deliver the necessary information.

This work aims to develop a methodology that combines the U-Net deep learning architecture (Ronneberger et al, 2015) for semantic segmentation of satellite images and the SVM method for digital mapping of flood zones. The aim is to provide a flood map with improved accuracy for analysing potentially flooded areas, particularly in urban landscapes.

3. Flood forecasting method

In this chapter we introduce our new method for flood forecasting (we call it our flooding model). Fig. 1 shows the block diagram, integrating the U-Net architecture for semantic segmentation of satellite images and the SVM method for predicting and mapping flood zones. This approach allows the creation of maps of flooded areas that show the spatial distribution of flooding and its intensity shortly after the satellite image was taken, thus allowing prompt response to be taken.

3.1 Overview

The proposed method consists of the following steps:

1. The first step is to select the affected area incl. the necessary data: (a) the most recent suitable Sentinel-2 image; (b) a digital landscape model, which contains the topographic objects in vector form, (c) the height information in form of a digital elevation model (DEM)[2]; (d) precipitation data (we obtained them from meteorological stations, satellite observation, and the web site (Ukrainian Hydrometeorological Center, 2025).
2. U-Net is employed for segmentation of the Sentinel-2 image with the two classes "water" and "no water" for each pixel. The model was trained on satellite images acquired previously.
3. An SVM further processes the U-Net results. First, the U-Net results are superimposed with the vector data of the polygons of the digital landscape model (see K1 in Fig.1). These polygons are then classified together with additional information to extract final water and non-water areas. Besides the U-Net result and the date of image acquisition, we use for each polygon as input: statistical textural image features (entropy, contrast, homogeneity), the Modified Normalized Difference Water Index (MNDWI, Xu 2006), the DEM, more precisely the max. volume of each polygon, and the precipitation data, denoted as K 2 to K5 in Fig. 1, respectively. The SVM was also trained previously using data available to us.

The result is a flood map forecasting the flooding situation, where each polygon is marked with the appropriate class: flooded or not. It provides a precise classification of the flooded areas, their extent, and the surrounding environment, allowing the quick identification for further action.

3.2 U-Net architecture

The U-Net consists of an encoder and a decoder, which allows for detailed recognition of the boundaries of different zones. The input is a 321x321 satellite image tile. The encoder consists of several levels, each of which applies two-layer convolutional operations to highlight key features of the image. Each convolutional layer is followed by a max pooling operation. The bottleneck is a middle layer between the encoder and decoder, providing the most compact representation of the extracted features. This layer contains two convolutional operations with five filters. The decoder is designed to gradually restore the spatial resolution of the image. It consists of upsampling layers that increase the size of the feature map and convolutional layers that allow for detail recovery. At each decoder level, concatenation with the corresponding encoder level occurs. The final layer uses a convolution with a single filter and a softmax classification function. The output of U-Net is a segmentation mask labelled "water" or "non water" for each image pixel that allows to separate potentially flooded areas.

3.3 SVM details

A multi-class SVM takes the final decision on flooded areas. A polynomial kernel is used to ensure accurate differentiation of classes in a high-dimensional feature space, improving the quality of flood zone detection. As mentioned, the process involves superimposition of the U-Net results with the polygons of the digital landscape model. This allows flooded and non-flooded areas to be represented as spatial objects with clearly defined boundaries (highway line, water line, water line polygon, railway, buildings, water, 5 flooding classes (+5m, +4m, +3m, +2m, +1m)), facilitating their integration with other geodata for further analysis.

[2]In our case, the DEM was interpolated from the drainage network and the height contours taken from the military topographic maps of scale 1:25.000 with a 10 m contour interval; it has a spatial resolution of 5 m.

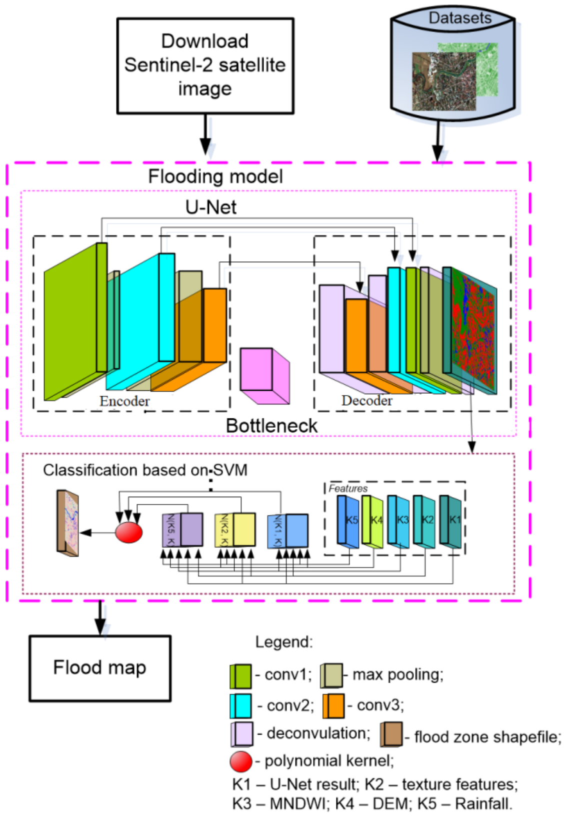

Figure 1. Block diagram of the methodology for digital mapping of flooded areas.

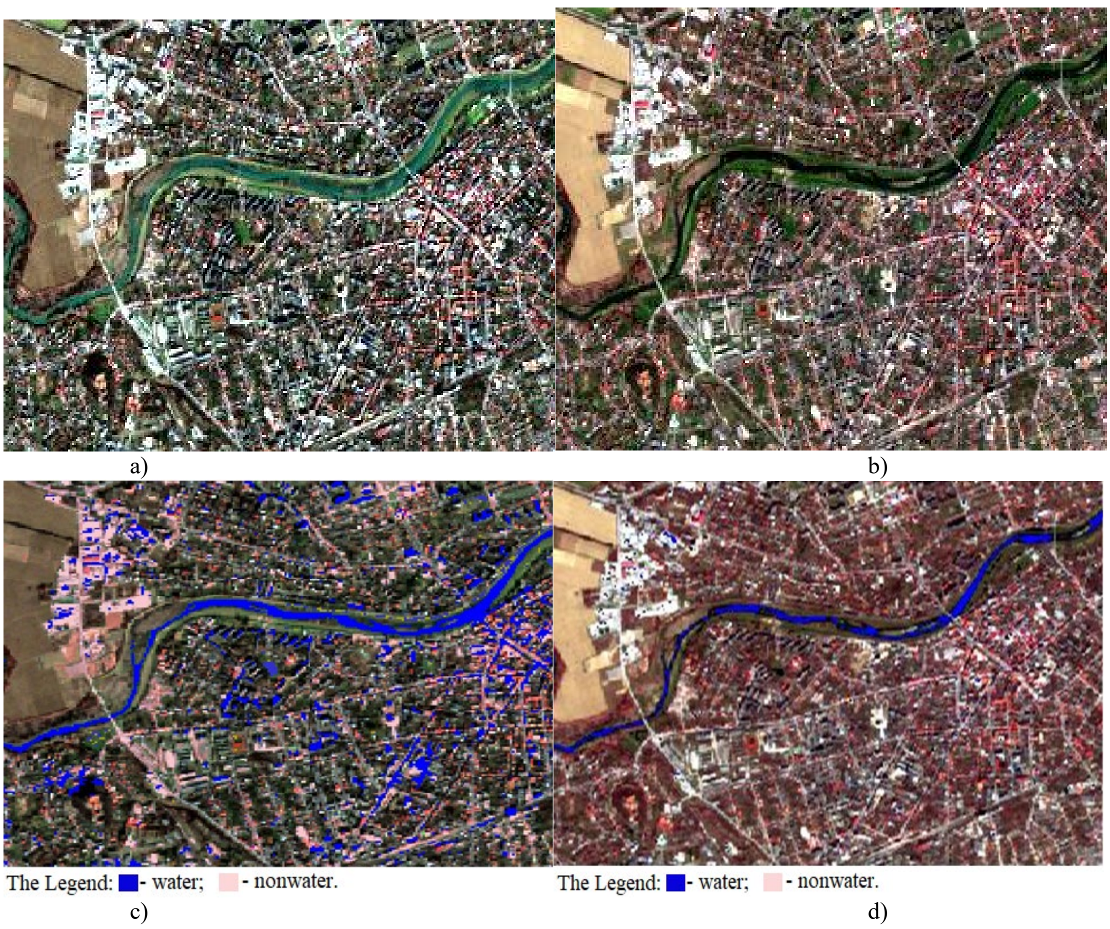

Figure 2. Results for the city of Mukachevo: a) and b) two Sentinel-2 satellite images; c) and d) results of U-Net classification.

4. Results

The research uses imagery depicting Mukachevo, a city in Western Ukraine, taken in winter and spring 2024 during the flooding season. Mukachevo is located in an area with a high risk of flooding due to its proximity to nearby river systems.

Experimental tests were conducted based on the analysis of multi-temporal Sentinel-2 satellite images (Fig. 2a, Fig. 2b). Each image was pre-processed to correct for atmospheric and spectral characteristics according to the methodology proposed in Hnatushenko, Kashtan et al. (2021).

The results of U-Net are shown in Figure 2c for the winter image, and in Figure 2d for the spring image, where colour coding for different types of surfaces is used. Blue indicates water bodies, and red indicates buildings, vegetation, and other land areas. Flooding is clearly visible on the winter mage. Areas marked in blue indicate the largest threat to infrastructure and residential areas that require immediate response.

Fig. 3 shows the result of the U-Net/SVM classification for flood forecasting based on the winter image (Fig. 2a), marked with colours corresponding to different levels of water rise: red (112-113 m, +5 m), green (111-112 m, +4 m), dark green (110-111 m, +3 m), pink (109-110 m, +2 m), yellow (108-109 m, +1 m). The analysis considers different levels of terrain elevation, indicated by the colour scale. The map shows the areas that could be flooded if the water level changed between 1 to 5 meters. Not surprisingly, the main areas at risk of flooding are concentrated along the river. The red and pink zones indicate the largest extent of flooding (+4 to +5 meters of water rise). It includes certain residential and commercial areas and infrastructure that could be severely damaged at high flood levels. Infrastructure elements such as roads, railroads, and buildings are also marked on the map. In particular, it shows that significant transportation routes, such as railways and some roads, can be damaged at high flood levels. This can cause considerable inconvenience to residents and complicate logistics, which emphasizes the importance of considering these areas when planning infrastructure projects.

When evaluating the overall accuracy of the models (Fig. 4), U-Net/SVM achieves the highest overall accuracy of 98.8%, while using only SVM has an overall accuracy of 97%, and a Random Forest classifier reached an overall accuracy of 98%. Although these differences are small, it can thus be concluded that the U-Net/SVM model provides the highest overall accuracy among the three models considered.

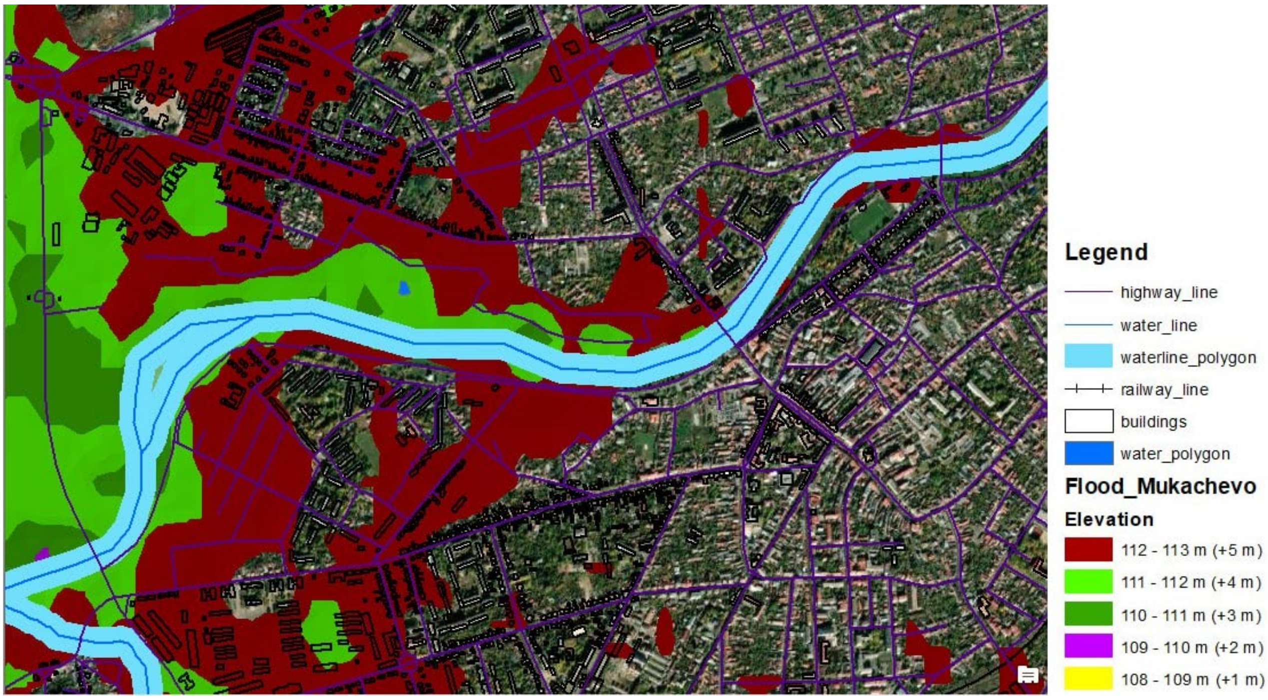

Figure 3. Digital map of predicted flooding for the city of Mukachevo based on the winter image (Fig. 2a) as a result of our study.

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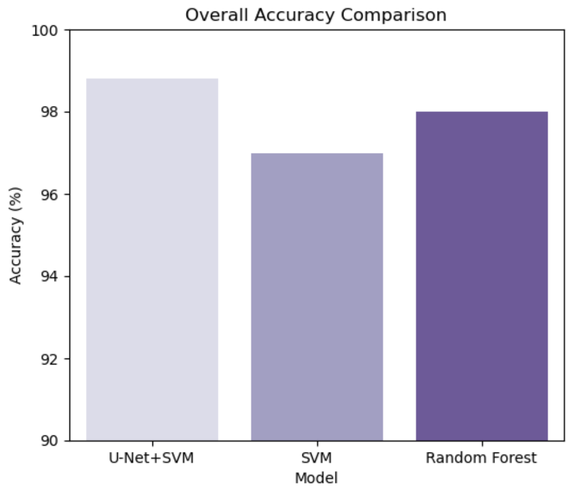

Figure 4. Graph of overall accuracy comparison of the three tested methods.

5. Conclusion

The paper proposes a methodology for digital mapping of flood forecasting that combines the U-Net architecture for semantic segmentation of satellite images into the classes "water" and "no water" and a multi-class version of the SVM method for classification using, among others, a digital landscape model, a digital elevation model, texture, water indices and precipitation data as additional information. The proposed approach allows for obtaining detailed flood maps with high accuracy, which is especially relevant for urban areas, such as our test site, the city of Mukachevo, which is at risk of flooding due to its geographical location near various river systems.

The use of U-Net ensures accurate semantic segmentation of flooded and non-flooded areas. At the same time, SVM can classify these areas based on the additional information. Experimental results show that the U-Net/SVM model has the highest overall accuracy (98.8%) compared to other models, such as Random Forest and SVM. The resulting flood maps provide valuable information for planning rescue operations and area management, allowing for quick identification of the areas. It, in turn, can significantly reduce economic losses and improve emergency preparedness.

In future work, we will further experiment with the combination of U-Net and SVM as well as try to develop a fully trainable end-to-end neural network solution. Further, particularly in areas containing rivers, upstream gauge information will be considered as additional information in concert with those we integrate already. In this context we will also conduct an ablation study, investigating the role and relevance of each of these sets of information as well as the required accuracy in order to have a useful impact on the final result.

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