AUTOMATED INDUNATION MAPPING: COMPARISON OF METHODS

Asmamaw Gebrehiwot, and Leila Hashemi-Beni

Geomatics Program, Department of Built Environment, North Carolina A&T State University, Greensboro, NC 27411, USA

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ABSTRACT

High-resolution imagery is increasingly used to detect flooded areas during a crisis situation. The article presents a comparison of four image classification methods for flood extent mapping. The methods include Random Forest (RF), support vector machine (SVM), fully convolutional network (FCN), and normalized difference water index (NDWI). High-resolution UAV imagery collected during Hurricane Matthew (2016) flood events were used to evaluate the classification methods for generating an accurate flood extent map. In this study, a fully convolutional network fine-tuned to segment the inundation areas. RF, SVM, and NDWI are implemented using the same dataset used for mapping flood extents. The results show that the FCN achieved an overall accuracy of 97.72%, followed by NDWI with 96.0%, SVM with 88.9%, and 87.8 % of RF. The results imply that FCN is more efficient than RF, SVM, and NDWI on generating real-time flood extent maps.

***Index Terms*—** Flood, Remote Sensing, Convolutional Neural Networks, Fine-tuning, UAV, Data Analytic

1. INTRODUCTION

Flooding is a severe hazard, which poses a great threat to human life and property. Generating flood extent maps during extreme flood events is vital for planning and efficient management of affected areas [1]. Detecting non-inundation areas are also equally important because these areas can serve as temporary shelters for the nearby affected areas. Several jurisdictions have begun considering the feasibility of relocating residential, commercial, and municipal structures, and the flood extent maps help to better understanding potential sites where relocation might be feasible.

The collection of geospatial information required to extract flooded areas is challenging and time-consuming using traditional survey techniques. Remote sensing technology in recent years has been regarded as an efficient means for generating flood extent maps and assess flood hazards over a large area at a given point of time.

Several manual, automatic or semiautomatic approaches have been introduced in the past decades for extracting flooded areas from remote sensing images including traditional photogrammetric techniques, spectral water indexes (e.g., NDWI), and machine learning classifiers. The traditional mapping techniques are based on satellite or aerial observation/stereoscopic methods or digitizing. However, when the flood covers large areas, these approaches are very time-consuming and does not satisfy the needs for real-time flood disaster responses [2]. The NDWI is another approach to delineate water content using the green and Near Infrared (NIR) bands of imagery. This method was proposed by McFeeters et al. [3] and is based on the concept that a water body has strong absorbability and low radiation in the range from visible to infrared wavelengths. Several studies are employing NDWI, to detect the flooded areas and delineate open water features effectively [4-5]. However, the main challenge of using NDWI for detecting inundation areas is that the water index is sensitive to built-up land and often results in over-estimating water bodies [3]. There are many different formulas for NDWIs considering different pairs of bands. For example, Gao et al. [6] evaluated NDWI computed from the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) channels for the detection of vegetation water liquids from satellite imagery. Their results show that NDWI is a good indicator of vegetation liquid water content and is less sensitive to atmospheric scattering effects than NDVI (Normalized Difference Vegetation Index). Machine learning classifiers are one of the other methods that have gained attention for extracting flooded areas from remote sensing images. In the past decades, the field of machine learning has made rapid progress for remote sensing mapping applications creating massive opportunities that were not possible before. The most commonly adopted approach of machine learning is Random Forest (RF) and Support Vector Machine (SVM). The RF approach has been used in many studies for generating inundation maps [7-8]. Several researches have also shown that RFs can be successfully used to detect the floods, and extract inundated areas using remote sensing data; however, the algorithm can be slow and ineffective for real-time mapping as more precise predictions need a large sample size which results in a slower classifier model [9]. SVMs are often claimed to be the best at dealing with complex classification problems such as flood detection for small datasets [10]. However, the complexity grows as the number of training samples increases. Recently, Deep learning is becoming an increasingly popular technique for remote sensing tasks due to their ability to handle large datasets for image analysis. However, a large amount of data is needed to build a deep learning model. With a small amount of data, the deep learning methods tend to overfit. Convolutional Neural Networks (CNNs) are the type of deep learning that has been successfully applied in several fields such as medical diagnosis [11], autonomous driving [12], and speech recognition [13]. The success of CNNs in these fields has motivated researchers in remote sensing community to investigate its potential in solving remote sensing problems. Unlike conventional machine learning approaches such as RF and SVM, CNNs can automatically extract features from images and successfully handle large training datasets. Although CNNs have been widely applied in several computer vision applications, its implementation in flood extent mapping needs further investigation, especially in terms of accuracy and processing time [14-15]. Gebrehiwot et al. [14] pretrained VGG-based fully convolutional network (FCN) to segment flooded areas from unmanned aerial vehicles (UAV) images and achieved more than 90% overall accuracy. Sarker, Chandrama, et al [15] proposed a fully convolutional neural network for mapping flood extents from Landsat satellite images and achieved a maximum precision rate of 76.7% compared to 45.27% for SVM classification.

Despite the research studies on the several inundation mapping methods for the classification of remote sensing data, studies that compare these methods are rare and have not been well documented. Based on that context, this research aims to evaluate and compare the performance of a fully convolutional network, RF, SVM, and NDWI approaches for flood extent mapping.

The paper is organized as follows. In **Section 2**, the study areas and the data used for the research are described. In **Section 3**, the methods to generate inundation maps and the experimental procedures are presented. The results and discussion are presented in **Section 4**. Finally, we conclude by summarizing our results in **Section 5**.

2. STUDY AREAS AND DATA

Three flood-prone areas in North Carolina, U.S., were selected as our study areas including Princeville, Lumberton, and Fair Bluff. The data used for the research include:

- UAV high-resolution imagery collected during hurricane Matthew (2016) over the study areas. These data were acquired by the North Carolina Emergency Management (NCEM). The size of each image is 4,000 x 4,000 with a resolution of 2.6 cm.
- Airborne multispectral imagery collected by the National Agricultural Imagery Program from the study areas. Each image contains 4-bands (red, blue, green, and infrared) with 6,574 x 7,698 pixels and 50 cm resolution.

3. METHODS AND DATA PROCESSING

3.1. Inundation mapping using FCN

The method used in the research is based on fine-tuning a pre-trained model to classify a new dataset. We fine-tuned the fully convolutional network with a stride of 8 (FCN-8s) proposed by Long et al. [16] to generate flood extent maps. The FCN-8s is the modified version of the VGG-16 CNN model, which is developed by Simonyan et al. [17]. The network is adjusted so that the convolutional layers replace the fully connected layers of the VGG-16 network. This enables the network to implement pixel-level classification rather than per-image class prediction, as VGG-16 originally was used for. The network is sketched in Figure 2.

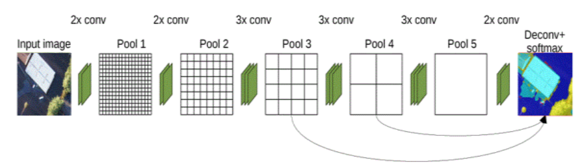


Figure 1. FCN-8s architecture [17]

To create a flood extent map, our research approach consisted of labeling, training, classification, and evaluation stages. In the labeling stage, 150 UAV images were labeled manually using a MATLAB labeler app. Each pixel in an image is assigned to a predefined class. In the training stage, we used 10-fold cross-validation technique to estimate the potential of FCN-8s. This approach involves randomly partitioned the set of observations into k equal-size folds. Of the K folds, the first fold is treated as a validation set, and the remaining k − 1 folds are used as training data. This procedure then repeated k times, with each of the k folds used exactly as a validation data. The purpose of this procedure is to give a less biased estimate of the model on unseen data. The network is trained using Stochastic Gradient Descent (SGD) for 6 epochs with a learning rate of 0.001, and a maximum batch size of 4. During training, 512-by-512 pixels size of 32 patches were randomly cropped and rotated in each batch size to increase the diversity of the training samples. The training stage ended after 230,000 iterations for all 10-fold experiments. In the classification stage, the performance of the network was tested using the unseen testing images. In this stage, the trained network is applied to the testing images to predict multiple classes. The network learned to associate image segments and labels during training and predicted the class labels for the test set, here, water and no water classes.

3.2. Inundation mapping using RF and SVM classifiers

An SVM classifier works by mapping the training sample data into a high dimensional feature space and finds the best hyperplane that separates all data points of one class from another class. It separates samples belonging to different classes by tracing maximum margin hyperplanes in the kernel space where samples are mapped. An RF classifier creates a set of decision trees from a randomly selected subset of the training set and aggregates the vote from different decision trees to decide the final output.

To evaluate the performance of the conventional machine learning approaches and comparison purposes, we trained the RF and SVM classifiers using the same set of training images used for the FCN-8s model. The classification learner in MATLAB is used to train the RF and SVM. 20% of pixels from each class were randomly selected as a training sample to train RF and SVM.

3.3. Inundation mapping using NDWI

The NDWI is an index for delineating and monitoring content changes in surface water. The NDWI is computed using the near-infrared and green band channels:

$$\mathrm{NDWI} = \frac{(Green - NIR)}{(Green + NIR)} \quad (1)$$

Where the Green and NIR refer to the reflection in the green and near-infrared spectra, respectively. The NDWI product is dimensionless and varies from -1 to +1, where water features have positive values, and soil and terrestrial vegetation features have zero or negative values, owing to their typically higher reflectance of Near-Infrared than green light [4]. In this study, the NDWI is calculated from the multispectral image using ArcGIS software.

4. RESULTS AND DISCUSSION

The sections below describe the results of flood extent maps in support of flood management.

4.1 Comparison of FCN-8s, RF, SVM, and NDWI Classification results

The pixels of each image were labeled using the MATLAB Labeler App, and the FCN-8s, RF, and SVM classifiers were implemented in the MATLAB 2019b software while the NDWI was computed in ArcGIS 10.7. The computer was configured with 32 GB memory, an Intel(R) Xeon(R) ES-2620 v3 @ 2.40GHz ×2 processors memory, and a single NVIDIA Quadro M4000 GPU.

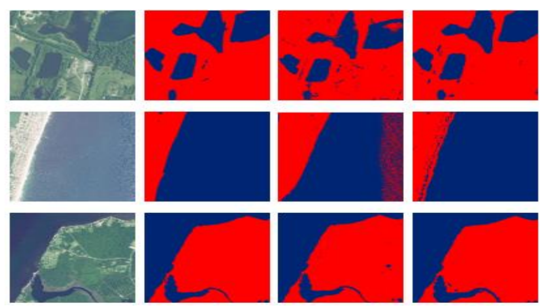
For this experiment, a confusion matrix was calculated to analyze the accuracy of the classification methods. The overall accuracy was calculated from the confusion matrix to assess the model's effectiveness by estimating the probability of the real value of the class label. Moreover, the kappa index was used to summarize the information provided by the confusion matrix. Kappa index measures how well the model performed as compared to how well it would have performed simply by chance.

The overall classification results and Kappa index of FCN-8S, RF, SVM, and NDWI on the test dataset are shown in **Table 1**.

Table 1. Overall accuracy and Kappa index for FCN-8s, RF, SVM, and NDWI classifiers to detect flood extent

	Overall Accuracy	**Kappa Index**
FCN-8s	97.2%	0.94
RF	87.8%	0.79
SVM	88.9%	0.82
NDWI	96.0%	0.93

The quantitative experimental results show the FCN-8s has a better classification performance than RF, SVM, and NDWI in generating flood extent maps using the high-resolution remote sensing data.



(a) **(b)** **(c)** **(d)**

Figure 2. Classification results of NDWI and FCN-8s approaches. (**a**) The original image; (**b**) Labeled image; (**c**) Classification results of NDWI; (**d**) Classification results of FCN-8s

As shown in **Figure 2**, the qualitative evaluation results show that as FCN-8s has better accuracy than NDWI to extract flooded areas. The NDWI has better classification results for only pure water or flood pixels. In addition to open water areas, the FCN-8s has better performance to extract flood extent in mixed pixels.

Finally, in terms of processing time, FCN-8s have more advantages compared to RF, SVM, and NDWI. Because FCN-8s can extract features automatically from the training images, while RF and SVM require to extract features manually from the input images using the traditional features extractor techniques. As a result, RF and SFM require more data preprocessing compared to the deep learning-based approaches. In this research, after training the FCN-8s, it took about three seconds to generate a flood extent map of a 4,000 x 4,000 pixels size image using a single GPU (NVIDIA Quadro M4000), similar to the processing time taken to generate a flood extent from the same image using NDWI in ArcGIS.

5. CONCLUSION

Flooding is a severe hazard, which poses a great threat to human life and property. Generating inundation maps during extreme flood events is vital for planning and efficient management of affected areas. The research attempts to investigate the potential of FCN for inundation mapping by comparing it with RF, SVM, and NDWI. Experimental results indicated that the FCN-8s classifier is a suitable method for real-time flood mapping with an overall accuracy of 97.2% compared to 87.8 % of RF, 88.9 % of SVM, and 96% of NDWI classification. Transfer learning and fine-tuning a network allows to overcome the problem of scarce and expensive data in flood applications instead of training from scratch, which requires a large amount of annotated training samples. The research results prove that the FCN-8s capable of extracting flooded areas in near real-time, even though only 150 images were used for training compared to RF, SVM, and NDWI.

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