AD-HOC SITUATIONAL AWARENESS DURING FLOODS USING REMOTE SENSING DATA AND MACHINE LEARNING METHODS

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ABSTRACT

Recent advances in machine learning and the rise of new large-scale remote sensing datasets have opened new possibilities for automation of remote sensing data analysis that make it possible to cope with the growing data volume and complexity and the inherent spatio-temporal dynamics of disaster situations. In this work, we provide insights into machine learning methods developed by the German Aerospace Center (DLR) for rapid mapping activities and used to support disaster response efforts during the 2021 flood in Western Germany. These include specifically methods related to systematic flood monitoring from Sentinel-1 as well as road-network extraction, object detection and damage assessment from very high-resolution optical satellite and aerial images. We discuss aspects of data acquisition and present results that were used by first responders during the flood disaster.

Index Terms— Disaster response, flood monitoring, road network extraction, object detection, damage assessment

1. INTRODUCTION

Rapid disaster response is critical for saving lives and minimizing the impact of natural disasters. Traditional methods of analyzing remote sensing data (satellite, aerial or drone imagery) for supporting an up-to-date situational awareness during disasters can be slow and labor-intensive, which might delay response efforts. Recent advances in machine learning and the rise of new large-scale remote sensing datasets have opened new possibilities for the automation of remote sensing data analysis to cope with the growing data volume and complexity and the inherent spatio-temporal dynamics of disaster situations.

In this work, we provide insights into machine learning methods developed by the German Aerospace Center (DLR) for rapid mapping activities and used to support disaster response efforts during the 2021 floods in Western Germany. We discuss several aspects of the data acquisition and present results that were used by first responders during the flood disaster. On the basis of the acquired data, we further show experimental results of research activities that have been conducted within the projects Drones4Good (safe, targeted and autonomous humanitarian transportation) [1], AIFER (artificial intelligence for analysis and fusion of earth observation and internet data to support situational awareness in emergency response) [2] and Data4Human (demand-driven data services for humanitarian aid) [3].

2. DATA AND STUDY AREA

The German districts of North Rhine-Westphalia and Rhineland-Palatinate were severely affected by rainfall-triggered floods on 14.07.2021 and 15.07.2021. The Center for Satellite based Crisis Information (ZKI) of the DLR supported the emergency and rescue teams with satellite data and aerial images that have been acquired, processed and analyzed within hours after notification. Flight campaigns were carried out on 15.07.2021, 16.07.2021 and 20.07.2021 using DLR's 3K [4], 4k [5] and MACS [6] camera systems from helicopters and aircraft platforms, obtaining data with a ground sampling distance between 10cm and 20cm. Continuous surface water monitoring with Sentinel-1 Synthetic Aperture Radar (SAR) images over Germany provided further information about flood extent on a daily basis between 14.07.2021 and 20.07.2021. In the aftermath of the disaster, several drone-based surveys were conducted in the most severely affected areas on 23.10.2021 and 29.10.2022.

3. FLOOD MONITORING

We deployed a modular processing chain for surface water monitoring that can autonomously handle satellite data search, preprocessing, analysis and dissemination over a predefined area of interest [7]. Sentinel-1 images are analyzed using a pre-trained water segmentation model to extract binary water masks. A pre-computed reference water mask is used to separate temporary flooded from permanent water bodies over a reference time period of two years [8]. To train the U-Net based water segmentation model, we developed an extensive globally sampled reference dataset with more than 150,000 256 x 256 pixels tiles. As input feature space we use VV and VH polarization as well as slope information derived from the Copernicus Digital Elevation Model. As reported in Helleis et al. (2022) [9] the model trained on data showing no distinct inundation performs well in mapping the water extent during flood events, reaching Intersection over Union (IoU) scores of >0.8. Moreover, we continuously improve the reference dataset and hence the model based on experiences gained during operational usage. Fig. 1 shows a flood inundation map of Euskirchen and surroundings derived from Sentinel-1 images on 15.07.2021.

Fig. 1: DLR-ZKI flood inundation map of Euskirchen and surroundings derived from Sentinel-1 on 15.07.2021. https://activations.zki.dlr.de/images/products/ACT152/P01/ZKI-004-P01-V02-low.jpg

4. ROAD NETWORK EXTRACTION

By accurately identifying flooded areas, emergency responders can plan support routes under consideration of up-to-date avoidance areas and focus on areas where help is needed most.

To create an up-to-date map that includes the portions of the road network which are still intact, we compare the pre-disaster and post-disaster road detections, where differences indicate potentially damaged sections of the roads. The first step towards this goal is to extract the road network from a pre-disaster image acquired at a date as close as possible to the event. The second step is to extract the road network from an image acquired as early as possible after the event, to minimize the impact of changes due to other reasons than the disaster in question. To extract the roads from the given images, we applied a modified U-Net [10] architecture, named Dense-U-Net-121 [11], and trained it on the large-scale DeepGlobe18 road dataset [12]. This dataset contains over 6000 images from Southeast Asia with roads annotated pixel-wise manually.

Fig. 2 shows the extracted road network in a pre- and post-disaster scene, as well as a change map highlighting the differences in the road map between the pre- and post-disaster image. In both scenes, the roads are clearly outlined, continuous, and well localized. This observation is reflected in the performance metrices where we obtain a completeness of about 70% (i.e. the ratio of non-omitted roads) and a correctness of 75% (i.e. the ratio of actual roads). Note that the ground truth used for evaluating the results was manually generated to contain as few inaccuracies as possible.

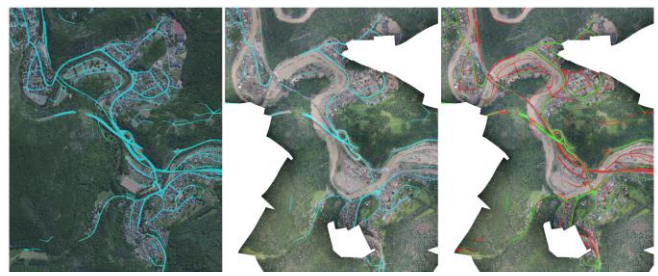

Fig. 2: Road extraction results on an area from the Ahr Valley, Germany. From left to right: pre-disaster image and extracted roads (left), post-disaster image and extracted roads (center), change map of the road network between the pre-and post-disaster images (right). Road color coding: cyan for all segmented roads in the pre- and post-disaster scene, green for intact roads and red for missing roads.

5. OBJECT DETECTION

Object detection in very high-resolution satellite, aerial or drone images is an important task that can provide important insights into where exposed assets and people are located during a disaster. In this work, we trained a YOLOv5 model on the xView dataset [13] for the detection of buildings and vehicles in multi-modal remote sensing images. The model achieves a mAP@0.5 of 0.57 on an independent test-split of the reference dataset. Emphasis was given to train a model capable of generalizing well across different imaging sensors and acquisition platforms. We successfully applied the method to images from a wide variety of sensors and platforms and further optimized it towards real-time image analysis. Fig. 3 shows an example of model predictions on four images of different sensors acquired by helicopter, plane and drone platforms at various dates around the disaster over the same area.

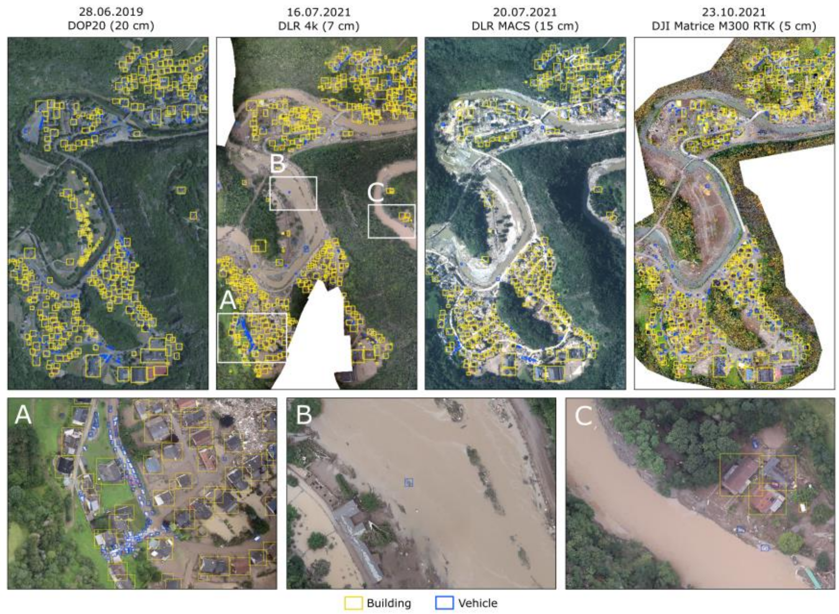

Fig. 3: Object detection from multi-source images depicting the evolution of buildings and vehicles throughout the disaster phases. Object color coding: houses have yellow boundaries, cars have blue boundaries.

The object detection allows to track the evolution of the building stock from the pre-event situation (28.06.2019) to co-event destruction (16.07.2021 and 20.07.2021) and post-event damage removal (23.10.2021). Furthermore, changes in the presence of vehicles become visible throughout the disaster phases. During the co-event situation for example, we can clearly observe clusters of vehicles along the borders of the most severely affected areas (zoom box A). Moreover, car wrecks are detected floating in the water (zoom box B) or covered by mud (zoom box C).

6. DAMAGE ASSESSMENT

To assess the extent of damage to buildings, we follow a two-step approach where we first identify existing buildings from the pre-disaster imagery and then classify the damage based on the predicted building masks and the corresponding pre-disaster and post-disaster satellite image pairs. The applied model is based on the solution proposed by the winning team [14] of the xView2 challenge [15] in combination with the HRNet [16] for the building segmentation step. For the network training, we use the xBD dataset [17], where the building damage from various disaster types are classified into four categories (no damage, minor damage, major damage, destroyed). Due to the lack of sufficient visual cues to clearly differentiate “minor damage” and “major damage” from a top-down view, we merge these two classes of the xBD dataset into a single class “damaged” for training and testing our model.

For building segmentation, we recorded an F1 score of 87%, an IoU of 76%, a precision of 86% and a recall of 87%. On the other hand, for the building damage assessment, we observed a lower performance with an average IoU of around 47%. This result is probably due to the differences between the training and test data. An illustration of the results for the building damage assessment is shown in Fig. 4. Note that the ground truth used for evaluating the results was manually generated as no public dataset covering this test area was available.

7. DISCUSSION AND CONCLUSIONS

Overall, the use of machine learning algorithms for satellite image analysis is a promising approach for improving rapid disaster response. Automated image processing routines together with pre-trained machine learning methods can reduce the time between image acquisition and final product generation from several hours/days to just a few minutes. It therefore allows not only for a faster product delivery but also for a higher analysis frequency and thus for a more continuous monitoring of the situation. A good generalization ability of the deployed machine learning models is however crucial to cope with the highly varying data availability in disaster situations like the 2021 floods in Germany.

8. ACKNOWLEDGEMENTS

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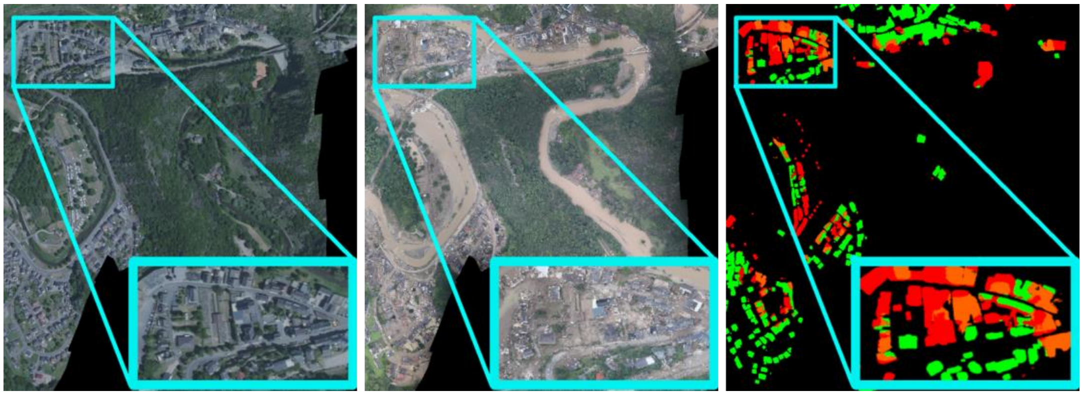

Fig. 4: Building extraction and damage assessment results on an area from the Ahr Valley, Germany. Building damage color coding: green no damage, orange damaged and red destroyed.

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