A MACHINE LEARNING APPROACH TO FLOOD DEPTH AND EXTENT DETECTION USING SENTINEL 1A/B SYNTHETIC APERTURE RADAR

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ABSTRACT

The rising number of flooding events combined with increased urbanization is contributing to significant economic losses due to damages to structures and infrastructures. Here we present a method for producing all weather maps of flood inundation using a combination of synthetic aperture radar (SAR) remote sensing data and machine learning methods that can be used to provide information on the evolution of flood hazards to DisasterAware©, a global alerting system, that is used to disseminate flood risk information to stakeholders across the globe. While these efforts are still in development, a case study is presented for the major flood event associated with Hurricane Harvey and associated floods that impacted Houston, TX in August of 2017.

Index Terms— Synthetic Aperture Radar, Flood Characterization, Flood Inundation, Machine Learning, Geospatial Data Fusion

1. INTRODUCTION

Flooding is one of the most frequent hydro-meteorological hazards, resulting approximately $10 billion (USD) in financial losses annually [1]. Without adaptation, those average losses are projected to increase to more than $1 trillion per year by 2050 [2]. Similarly, estimates in 2004 suggested that more than half a billion people were impacted worldwide every year worldwide and that number could double by 2050 [3]. It is likely that climate change, growing populations and regional subsidence will exacerbate the issue, especially for large coastal cities [4]. As a result, it is critical that we better assess the risk of flooding and quantify the dynamics of water bodies worldwide through improved remote sensing instrumentation and analysis and incorporate those into improved flood risk mapping, impact assessments, forecasting, alerting and emergency response systems.

Effective risk communication provides accurate information about impending and ongoing hazards to aid in both preparatory and response actions to reduce their impacts [5,6,7]. Today, the growth in technology has enabled message dissemination via cell towers, commercial mobile providers, and social media and networking sites [8,9]. However, no platform currently exists that delivers rapid assessment and impact analysis for flood events. The DisasterAWARE® platform operated by the Pacific Disaster Centre (PDC) provides multi-hazard warning and situational awareness information for decision support through mobile apps and web-based platforms to millions of users worldwide for a variety of hazards. DisasterAWARE® is developing an integrated remote sensing and model component for flood forecasting and impact assessment. That module will incorporate high-resolution SAR images of flood extent and inundation into integrated hydrological models for flood forecasting and risk assessment. Here we present research aimed at improving the resolution and accuracy of those SAR images of flood extent.

In this research, we first apply advanced methods for characterizing water versus land pixels at spatial resolutions of 15 m, using freely available C-band satellite SAR data. We demonstrate this technique for flooding associated with Hurricane Harvey, which struck the Houston, TX, region on August 26, 2017 as a slow-moving Category 4 event. Aerial optical imagery of the region was acquired by the National Oceanic and Atmospheric Administration (NOAA) to support emergency response activities. That data will be used to identify flooded polygons for both ground truthing of the initial results and as training data for machine learning algorithms (MLA) to increase image quality and improve identification of water pixels.

2. DATA

2.1. Sentinel-1A/B SAR

In this study, imagery from the European Space Agency's (ESA) Sentinel-1A/B satellite (C-band SAR, IW mode) with a 6-12 day repeat period is used, providing high temporal and spatial resolution imagery over large regions for flood mapping. Images are freely available from the National Aeronautics and Space Administration's (NASA) Alaska Satellite Facility Distributed Active Archive Center (ASFDAAC) in both single-look complex (SLC) and high-resolution ground range detected (GRD) data (https://search.asf.alaska.edu/). Here we downloaded images for August 5, 29 and September 10, 2017.

2.2. Airborne optical images

The NOAA Remote Sensing Division acquired airborne digital optical imagery of the Houston area between August 27 and September 3, 2017 in response to Hurricane Harvey. The images were acquired from an altitude between 2500 to 5000 feet using a Trimble Digital Sensor System (DSS). Individual images were combined into a mosaic and tiled for distribution (Figure 1). Approximate ground sample distance (GSD) for each pixel is between 35 and 50 cm (https://storms.ngs.noaa.gov/storms/harvey/download/metadata.html).

3. METHODOLOGY

3.1. Flood extent and depth modelling using SAR imagery

Flood mapping offers particular challenges for many types of remote sensing due to the extensive cloud cover during large rainfall events. However, SAR is an all-weather collection system at Earth's surface, making it extremely useful for real-time, or near real-time, flood mapping.

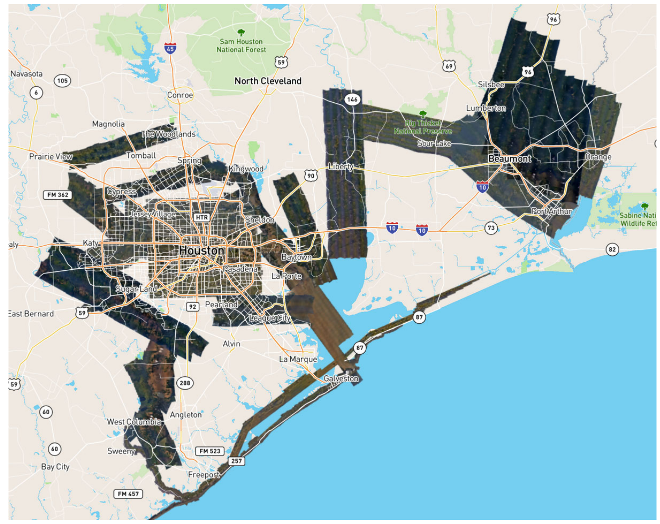

Figure 1. Available NOAA digital aerial imagery of Hurricane Harvey flooding, August – September 2017 (https://storms.ngs.noaa.gov/storms/harvey/index.html#9/29.6176/-94.8381).

Methods applied to detection of inundation have included simple and automatic histogram thresholding-based methods [10,11], multitemporal change detection-based methods [12,13] and machine learning and neural network methods [14,15,16]. In this work, a threshold method was employed to map inundated regions based on the low backscatter coefficient of the GRD SAR data. From [10], SAR data with the appropriate power transform displays a bimodal Gaussian distribution that separates water and non-water pixels. We exploit this characteristic to automatically determine a threshold for the image to classify those regions. The image is divided into tiles for different sections of the SAR scene that behave differently due to the wide SAR swath. Those pixels within each tile that have a bimodal distribution are identified using the maximum normalized between-class variance (BCV) [10,17]. From simulations, a maximum value of BCV greater than 0.65 can be assumed bimodal. Each tile is further split into an array of s x s pixels. Bimodal pixels were identified and the threshold estimated for that tile. The value of s is varied to determine an optimal threshold for that tile. An automatic threshold is selected using either the mode of the distribution or the local minimum separating the peaks in the bimodal distribution. The mean of the thresholds for each set of s x s pixels is used as the threshold for the entire tile. This process is repeated for each tile to generate a binary output displaying the classified water regions. Because this method also classifies permanent water bodies a well as transient flooded pixels, an earlier set of images is used to remove the common classifications in all images, assuming sufficient temporal coverage. This method can be applied to VV (vertical-vertical) and VH (vertical-horizontal) polarizations, separately or jointly, to improve accuracy. These outputs will serve as input to MLAs to improve flood change detection.

3.2. Machine learning

The goal of this phase of the project is to train a machine learning model to detect differences between pixels in our SAR scenes and attribute these changes to inundation, which is captured in the machine learning model through the relevant input parameters. We will develop a training data set that identifies water and land pixels, both from before the inundation and during flooding, as in the case of the NOAA data (Figure 1). This can require several months or more of data. Synthetic data sets will be developed from these original images to provide additional training data sets [18,19]. We are currently investigating employing a deep convolutional network for semantic image segmentation, which historically have worked well on these types of image segmentation problems [20].

4. INITIAL RESULTS

Results for the thresholding method alone are shown in Figure 2. For comparison we show images from before the hurricane, August 5, at the height of flooding, August 29, and after flooding had receded significantly on September 10, 2017. We also identified several locations in the aerial images from August 29 to use for ground truth results and as training data for the image segmentation algorithms in the next stage.

5. DISCUSSION

While the initial results are promising, additional testing is required to estimate the identification accuracy at these resolutions and the improvement associated with the image segmentation MLA. In the next stages, we will incorporate higher resolution DEMs (5-10m) to distinguish smaller flood features. Finally, we will incorporate that high-resolution topographic information into the MLAs to improve flood characterization and provide better estimates of inundation depth.

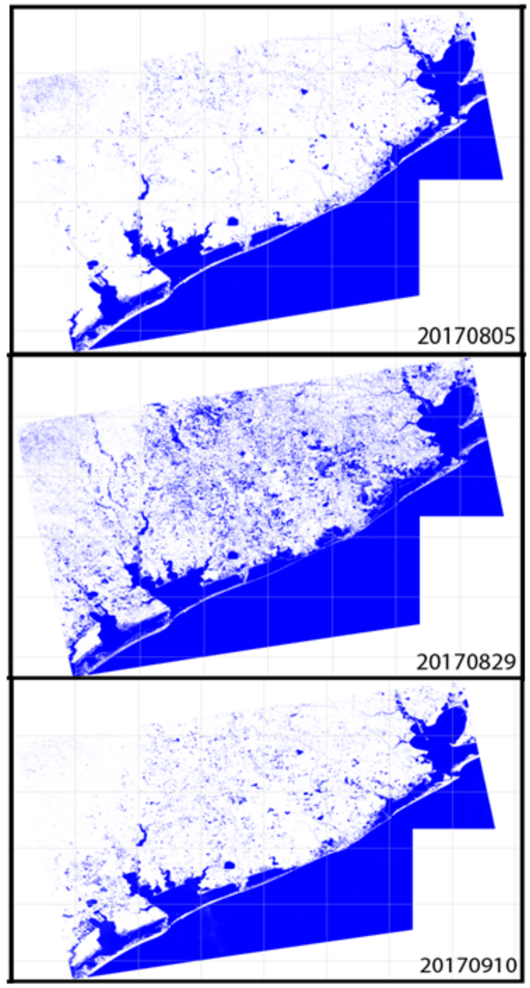

Figure 2: Results for the SAR threshold method for identification of flood extent caused by Hurricane Harvey. Blue denotes pixels identified as water at 15 m resolution. The upper image is from before the rainfall began, the middle is during the storm and the bottom image was after the waters had receded significantly.

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REFERENCES

[1] *EM-DAT: The International Disaster Database, Université catholique de Louvain,* https://www.emdat.be/, retrieved 2 July 2020.

[2] S. Hallegatte, C. Green, R.J. Nicholls, J. Corfee-Morlot, "Future flood losses in major coastal cities," *Nature Climate Change*, 3, 802-806, 2013.

[3] United Nations University, "Two billion vulnerable to floods by 2050; Number expected to double or more in two generations," *Science Daily*, sciencedaily.com/releases/2004/06/040614081820.htm

[4] *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Edenhofer et al. (eds.)]. Cambridge University Press, Cambridge, U.K.

[5] B. Reynolds, M.W. Seeger, "Crisis and emergency risk communication as an integrative model," *Journal of Health Communication*, 10, 43–55, 2005.

[6] H. Gladwin, J.K. Lazo, B.H. Morrow, W.G. Peacock, H.E. Willoughby, "Social science research needs for the hurricane forecast and warning system," *Natural Hazards Review*, 8(3), 87-95, 2007.

[7] S. Krimsky, "Risk communication in the internet age: The rise of disorganized skepticism," *Environmental Hazards*, 7, 157-64, 2007.

[8] L. Palen, S. Vieweg, S.B. Liu, A.L. Hughes, "Crisis in a networked world features of computer-mediated communication in the April 16, 2007, Virginia Tech event," *Soc. Sci. Comp. Rev.*, 27, 1-14, 2009.

[9] Federal Emergency Management Agency, Integrated alert and warning system (IPAWS). www.fema.gov/emergency/ipaws/index.shtm, 2012.

[10] A. Refice, A. D'Addabbo, D. Capolongo, *Flood monitoring through remote sensing*, Cham: Springer. doi:10.1007/978-3-319-63959-8, 2018.

[11] H. Cao, H. Zhang, C. Wang, F. Zhang, "Operational flood detection using Sentinel-1 SAR data over large areas," *Water*, 11(4), 786, 2019.

[12] O.A. Ajadi, F.J. Meyer, P.W. Webley, "Change detection in synthetic aperture radar images using a multiscale-driven approach," *Rem. Sens.*, 8, 482, 2016.

[13] A. D'Addabbo, A. Refice, G. Pasquariello, F.P. Lovergine, D. Capolongo, S. Manfreda, "A Bayesian network for flood detection combining SAR imagery and ancillary data," *IEEE Trans. Geosci. Remote Sens.*, doi:10.1109/TGRS.2016.2520487, 2016.

[14] M. Gong, J. Zhao, J. Liu, Q. Miao, L. Jiao, "Change detection in synthetic aperture radar images based on deep neural networks," *IEEE Trans. on Neural Networks and Learning Syst.*, doi:10.1109/TNNLS.2015.2435783, 2016.

[15] C. Bayik, S. Abdikan, G. Ozbulak, T. Alasag, S. Aydemir, S.F Balik, "Exploiting multi-temporal Sentinel-1 SAR data for flood extent mapping," *Int. Arch. Photogr. Rem. Sens. Spatial Inf. Sci.*, doi:10.5194/isprs-archives-XLII-3-W4-109-2018, 2018.

[16] Y. Li, S. Martinis, M. Wieland, "Urban flood mapping with an active self-learning convolutional neural network based on TerraSAR-X intensity and interferometric coherence," *ISPRS J of Photogr. and Rem. Sens.*, doi:10/1016/j.isprsjprs.2019.04.014, 2019.

[17] O. Demirkaya, M.H. Asyali, "Determination of image bimodality thresholds for different intensity distributions," *Signal Processing: Image Communication*, doi:10.1016/j.image.2004.04.002, 2004.

[18] L. Huang, L. Liu, L. Jiang, T. Zhang, "Automatic Mapping of Thermokarst Landforms from Remote Sensing Images Using Deep Learning: A Case Study in the Northeastern Tibetan Plateau," *Remote Sensing*, doi:10.3390/rs10122067, 2018.

[19] L. Huang, J. Lu, Z. Lin, F. Niu, L. Liu, "Using deep learning to map retrogressive thaw slumps in the Beiluhe region (Tibetan Plateau) from CubeSat images," *Remote Sensing of the Environment*, doi:10.1016/j.rse.2019.111534, 2019.

[20] L.-C. Chen, G. Papandreou, L. Kokkinos, K. Murphy, A.L. Yuille, "Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs," *International Conference on Learning Representations (ICLR)*, 2015.