QUANTIFICATION OF CHRONIC COASTAL FLOODING USING MACHINE LEARNING

Ryan McCune, North Carolina State University, rmccune@ncsu.edu
Katherine Anarde, North Carolina State University, kanarde@ncsu.edu
Evan B. Goldstein, Sediment, LLC, evan@sediment.science
Emma Rudy Srebnik, University of North Carolina at Chapel Hill, emmarudy@unc.edu
Thomas Thelen, North Carolina State University, ththelen@ncsu.edu
Miyuki Hino, University of North Carolina at Chapel Hill, mhino@unc.edu

INTRODUCTION

Coastal communities are experiencing more frequent flooding outside of extreme events due to sea-level rise (SLR) (Hague et al., 2022; Sweet et al., 2021; Taherkhani et al., 2020). By 2100, 360 million people globally will occupy land at risk of flooding due to SLR (Kulp & Strauss, 2019). Although typically shallow in depth, these floods generate a chronic, cumulative impact on coastal communities by corroding infrastructure with saltwater (e.g., stormwater networks, roadways), reducing business revenues, and disrupting daily activities (Hino et al., 2019). These floods are difficult to measure with in situ sensor networks (e.g., pressure sensors and ultrasonic distance meters) because they are hyper-local and often short-lived: floods vary from small puddles to entire roadway widths, and last for minutes to several hours. In contrast to in situ sensors, subaerial cameras can capture the extent of flooding over larger areas (multiple residential blocks) at relatively low cost and therefore may provide a new mechanism for characterizing flood risk in areas with limited in situ flood measurements.

OBJECTIVE

Here, we supplement in situ flood sensors at flood hotspots with cameras to assess the utility of imagery for automated flood detection, quantifying the spatial extent of floods, and validating numerical models. This is done in three steps: (1) develop a trained machine learning model for semantic image segmentation of flood imagery, (2) extract the spatial extent of flood waters from the segmented imagery, and (3) compare the spatial extent maps to numerical model outputs. The combination of machine learning and image rectification will provide an automated workflow to quantify the area inundated by flood waters. Observed spatial extent maps of flood events will then be used to validate numerical models of chronic coastal flooding – here, defined as shallow, frequent floods driven by SLR, with contributions from marine (tides, wind) and land-based sources (rainfall, groundwater).

MACHINE LEARNING MODEL DEVELOPMENT

We use images collected with an existing network of open-source, low-cost sensors - the Sunny Day Flood Sensors ("SuDS") - deployed in four communities in coastal North Carolina, USA. The SuDS consist of a pressure logger and communications gateway equipped with a camera. The pressure logger is deployed at roadway flooding hotspots, within storm drains or other stormwater infrastructure (drainage ditches or catchments). The communications gateway, built with a Raspberry Pi, is also connected to a camera and is installed in close proximity to the pressure logger (Gold et al., 2022).

We train separate machine learning models for several camera locations in three coastal communities in North Carolina: Beaufort, Carolina Beach, and Down East. There is one camera in Beaufort, four in Carolina Beach, and four in Down East. We use Doodler (Buscombe et al., 2022) to label a training dataset of images for each camera location. The labels consist of nine classes: water, roadway, sidewalk, building, person, vehicle, vegetation, sky, and other. The labeled images are then used to train location-specific deep learning models using Segmentation Gym (Buscombe & Goldstein, 2022). Figure 1 is an example model prediction on an image from Beaufort, NC, USA.

Figure 1 – (A) Image of roadway flooding during inundation of stormwater network in Beaufort, North Carolina, USA; (B) predicted segmentation from ML algorithm showing water (dark blue), roadway (red), sidewalk (orange), vehicle (green) and building (light blue).

SPATIAL EXTENT OF FLOODING

These predicted segmentations are then used to quantify spatial extent. We rectify each labeled image to real world coordinates using identified control points in the field of view. The rectified image is then used to quantify the real-world flooded area.

The process of image rectification to world coordinates is challenging in the varied environments of these three communities. The urban environments of Carolina Beach and Beaufort provide a larger quantity of static control points, whereas rural environments do not have as many. Additionally, the rural community of Down East is more open and has a larger field of view. This greater view allows for quantification across a larger spatial scale than the more limited views in the urban communities.

NUMERICAL MODELING - ONGOING WORK

Ongoing work is focused on the comparison of spatial extent observations to numerical models of chronic flooding. Spatial extent maps for flood events recorded in Carolina Beach will be compared to a coupled hydrodynamic (ADCIRC) and stormwater model (3Di) (Casulli & Stelling, 2013; Luettich et al., 1992; Volp et al., 2013). A similar hydrodynamic model (high resolution ADCIRC) for the Down East community is in development for comparison. Spatial extents in Beaufort will be compared to flooding predictions from a simplified stormwater pipe flow model.

Validation of numerical model time series with measured time series of spatial extents will aid in model development to better resolve the source of data-model mismatch for hindcast and forecast scenarios.

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