Automated Post-Disaster Vessel and HAZMAT Debris Mapping

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During the 2017 through 2019 hurricane seasons, multiple hurricanes inflicted severe damage to communities and coastal resources over large areas of the U.S. Southeast and Gulf Coast, depositing large amounts of debris in coastal waters and along shorelines and causing numerous spills. Prior to this, in 2012, Hurricane Sandy caused similar impacts in the Northeast. Beginning with Hurricane Sandy and evolving under later responses, NOAA conducted mapping of debris accumulations and specific items of interest that may pose an oil spill concern, such as vessels and tanks. This mapping has been traditionally accomplished via manual digitization of debris items and targets, a method still widely employed (e.g., Moy et al., 2018) for both operational and scientific debris mapping.

To improve timely and accurate mapping of vessels and debris in coastal shallow subtidal, intertidal, and supratidal regions following tropical storm, tsunami, or other debris-generating events in coastal areas, NOAA is developing a rapid and operational pipeline for automated processing of high-resolution remotely sensed imagery such as generated by NOAA's National Geodetic Survey (NGS). Once operationalized, the goal is to enable these automated pipelines to operate on volumes of imagery typically acquired in post-disaster scenarios on timescales of hours to generate initial operational products.

As a first step, training data and the accompanying imagery from previous tropical storm responses were used to develop and train models and post-processing steps for both 1.) synoptic image processing for mapping of overall generic debris density; and 2.) mapping of specific debris item types of HAZMAT concern. For mapping of overall debris density, we used the corpus of training data collected after Hurricane Sandy and Hurricane Rita, as well as limited data from Hurricane Laura in 2020.

These data were used to train, calibrate, and evaluate a convolutional neural network (CNN) model for mapping areas with generic intertidal debris items present in natural areas. The final generic debris CNN-based model utilized an image segmentation and classification U-net CNN architecture (Ronneberger et al., 2015) trained with a Resnet34 backbone via transfer learning. The model was implemented in Python using the Pytorch deep-learning libraries (Paszke et al., 2019), as well as the deep-learning library available from ESRI for ArcGIS Pro (ESRI, 2020).

For mapping vessels specifically, we used the corpus of training data collected after Hurricanes Irma and Maria to train, calibrate, and evaluate a CNN model for identifying vessels. A training dataset was prepared of image chips representing most vessels mapped as part of the Emergency Support Function 10 response (ESF-10; a legal framework for Federal support in response to an actual or potential hazardous materials discharge) during Hurricanes Irma and Maria and supplemented with additional non-ESF-10 vessel location from Hurricane Irma. The final vessel-detection model uses region-based convolutional neural network (R-CNN) for object-detection using the Faster R-CNN architecture (Ren et al., 2015) as implemented via Pytorch deep-learning library combined with the deep-learning library available from ESRI for ArcGIS Pro.

These models were then tested using independent imagery and manually identified debris items from other independent responses. These tests were conducted for areas impacted by landfall of Hurricane Sally in the north central Gulf of Mexico in 2020, and Hurricane Ida in western Louisiana in 2021. To evaluate model performance, we computed the percentage of manually identified target data within the mapped areas for each storm that were within 50 meters (m) of a vessel detection bounding box or debris item location. Figures 1 and 2 below depict model results with post-storm imagery.

The vessel model component was found to reliably identify most vessels identified as of concern via manual mapping by analysts. Further, the performance of this model is generally insensitive to off-nadir angle, image exposure, and limited cloud cover present in the post-storm imagery. For a broad range of vessel sizes, the vessel detection model is relatively insensitive to vessel location (on land, docked, at anchor or underway), orientation (upright, listing, capsized), condition (aground, afloat), or type (recreational, commercial, sailboat). Vessel model performance is better in developed, residential, and wetland areas and worse in upland and beach areas.

The debris model component output clearly represents patterns in distribution storm-generated debris in natural intertidal areas. Large debris accumulations along levees and swash lines are easily visible in the point data output. There was only a weak relationship between the distribution of non-vessel debris items of concern (tanks, drums, containers), and those mapped by the debris model. While the model reproduces the spatial distribution of accumulation of storm generated debris in natural areas well, the distribution of manually identified targets of particular concern for either incident was not very closely related to the spatial distribution of debris in general. Further there are simply far fewer non-vessel items of concern, as compared with vessels, so it is difficult to draw conclusions about the utility of this model component for post-disaster oil spill risk assessments.

Primary findings and lessons-learned:

- Debris model performance well suited for identifying large aggregations of general debris in natural intertidal areas, and adjacent subtidal and upland areas
- Vessel model performance adequate for improving speed and accuracy of vessel target identification by manual analysts
- Processing time on suitable commodity computing hardware is adequate for overnight/daily processing of typical image volumes
- Recommended routine deployment of these models following collection of post-storm imagery
- The best use of the model output at present is to improve efficiency and accuracy of manual review by mapping analysts; inspection by analysts remains critical for identifying false positives and classifying vessel condition
- Recommend masking areas for model processing to only include intertidal or nearshore areas and avoid processing extensive open-water or upland areas within imagery extents
- Improvements to accuracy of both model components are possible though the inclusion of additional training data including from both Hurricanes Ida and Sally

- Post-detection vessel status classification model component to identify capsized, sunken, or grounded status after vessel detection may improve utility of modeling pipeline
- Additional object-specific model components are likely to improve overall utility of model output, including barges, large commercial vessels, tanks, and on-water sheen.

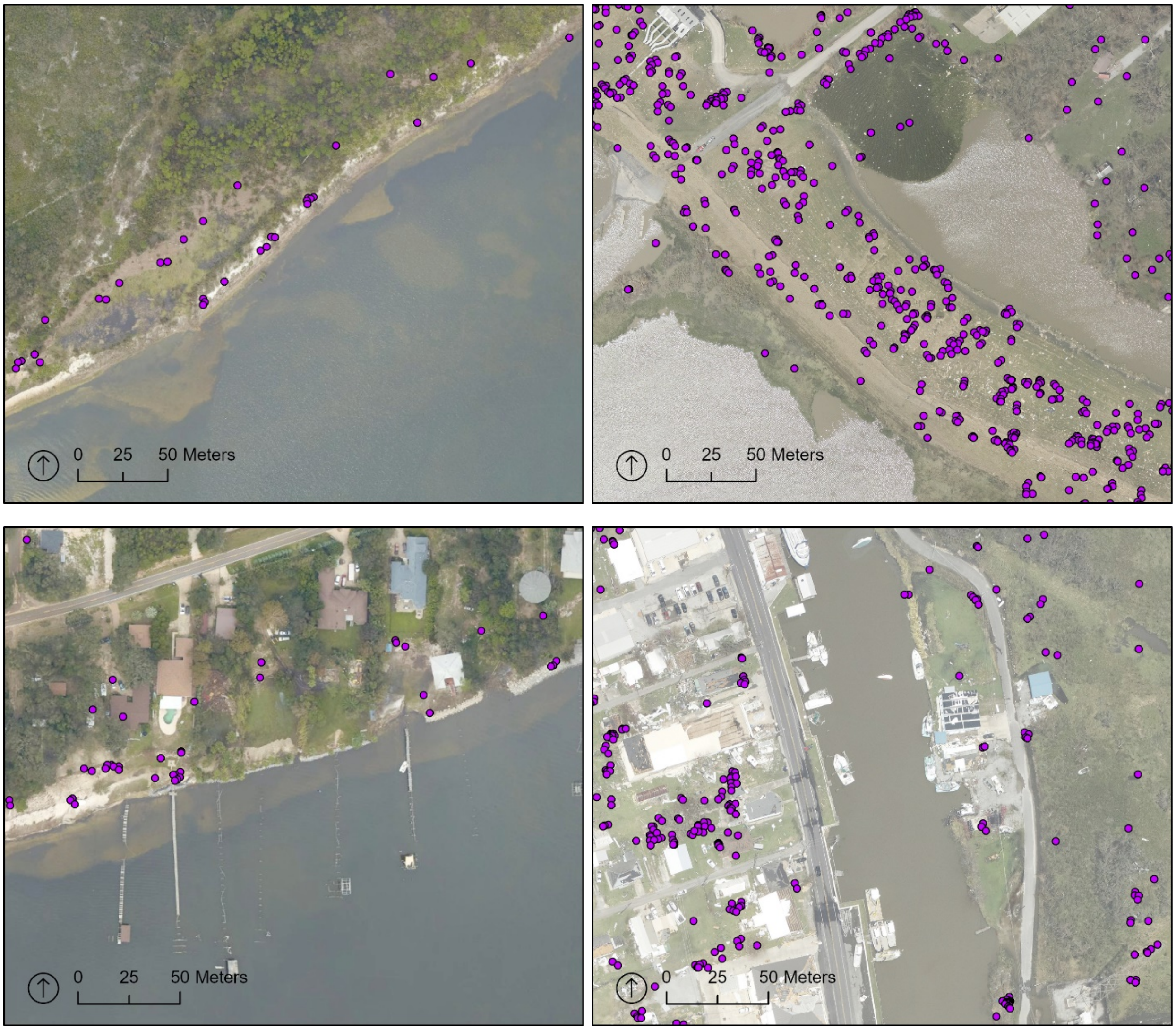

Figure 1. Typical examples of automated debris item mapping model output from Hurricane Sally (left) and Hurricane Ida (right) in both natural and developed areas.

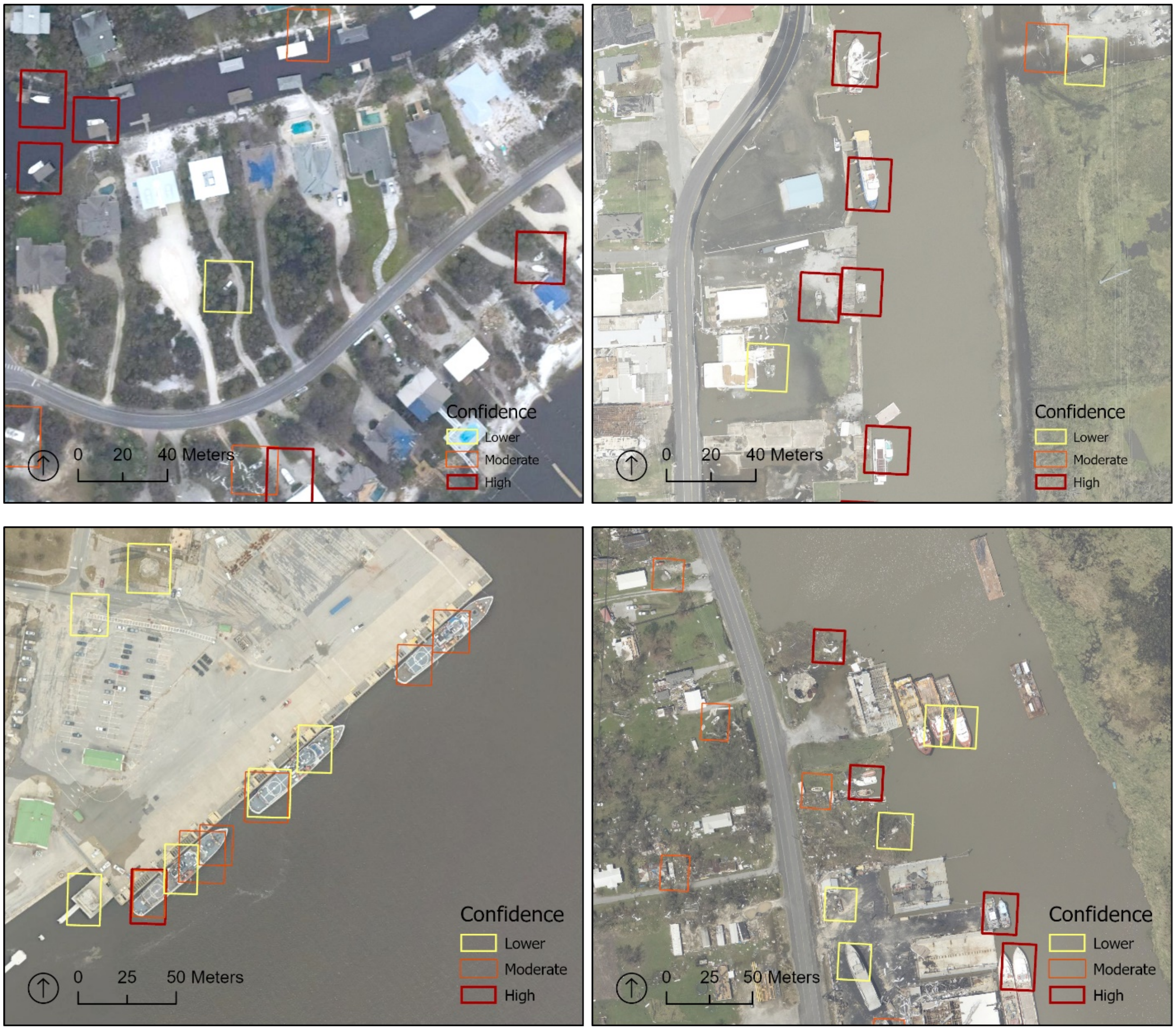

Figure 2. Top: Typical examples of automated vessel mapping model output from Hurricane Sally (left) and Hurricane Ida (right) for both inland and coastal areas and large and small vessel sizes.

References

ESRI. 2020. ArcGIS Pro v2.7. https://www.esri.com

Jiang, S. and Friedland, C.J., 2016. Automatic urban debris zone extraction from post-hurricane very high-resolution satellite and aerial imagery. Geomatics, Natural Hazards and Risk, 7(3), pp. 933-952.

Moy, K., Neilson, B., Chung, A., Meadows, A., Castrence, M., Ambagis, S. and Davidson, K., 2018. Mapping coastal marine debris using aerial imagery and spatial analysis. Marine Pollution Bulletin, 132, pp. 52-59.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L. and Desmaison, A., 2019. Pytorch: An imperative style, high-performance deep learning library. arXiv preprint arXiv:1912.01703.

Ren, S., He, K., Girshick, R. and Sun, J., 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems (pp. 91-99).

Ronneberger, O., Fischer, P. and Brox, T., 2015. October. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-assisted Intervention (pp. 234-241). Springer, Cham.