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Automated mapping of culverts, bridges, and dams

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Abstract:

Accurate maps of built structures around stream channels, such as dams, culverts, and bridges, are vital in monitoring infrastructure, risk management, and hydrologic modeling. Hydrologic modeling is essential for research and decision-making related to infrastructure and development planning, emergency management, ecology, and developing hydrographic data. Technological advances in remote sensing afford increasingly fine-scale elevation data, such as the U.S. Geological Survey 1-meter digital elevation models (DEMs), that can accurately model the Earth's surface characteristics and related hydrologic dynamics. A long-standing challenge in flow modeling is the presence of built structures in an elevation model that resist flow in a way that does not reflect actual dynamics, such as culverts, bridges, and dams (Figure 1a). This challenge is exacerbated in fine-scale elevation data as more built structures are resolved. Here we present a test of the extensibility of a culvert and dam detection workflow, culvert-net (CN). CN was developed using a large dataset of field-validated culverts, bridges, and dam locations for Alexander County, North Carolina, USA, supplemented by manual review and identification of additional features. In this workflow, the CN model is tested on a new study area in western Michigan, USA, where culverts and associated hydrography have recently been manually compiled.

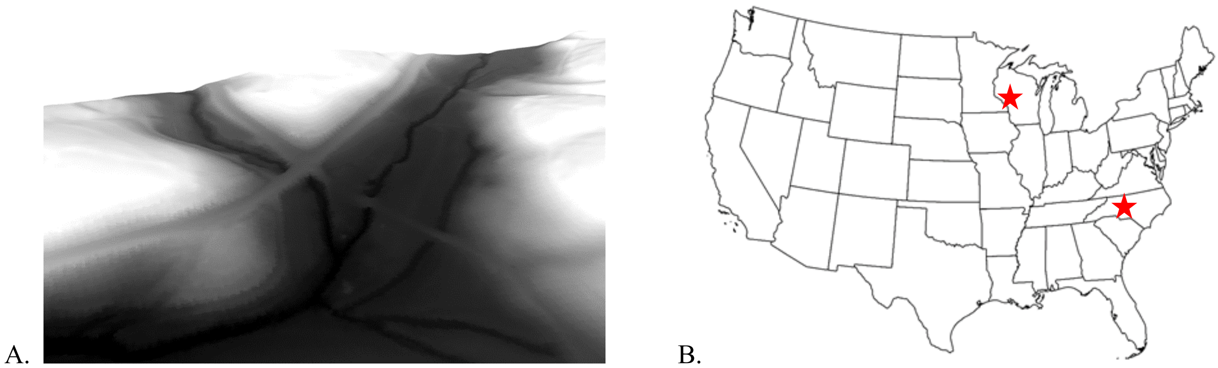

Figure 1. (A) An example un-breached DEM from the North Carolina study area with bridges obstructing channels. (B) The conterminous United States with the location of the two study areas identified.

The CN model was developed and trained on the Alexander County (AC) study area (200 km^2). The AC area is primarily forested, with some agriculture and suburban development located east of the Appalachian Mountains in the Piedmont region. The data for training and prediction in the model are a lidar-derived 1-m DEM and the associated elevation derivatives, curvature, and Sky View Factor (SVF). Curvature is the normalized sum of surface profile curvature in the x and y directions generated using GRASS GIS (GRASS GIS, 2023). The SVF is a model of diffuse hemispheric light centred on a specific cell. Relief Visualization software tools are used to generate the SVF with parameters of the number of sampling points at 250 and maximum shadow modeling distance at 100 pixels. These layers were found to be most effective for predicting the location of culverts over the course of the model development. The other layers tested are detailed in Stanislawski et al. (2021).

The above layers and identified culverts, dams, and bridges are used to train a RetinaNet deep-learning model (https://github.com/yhenon/pytorch-retinanet) using Python and Pytorch (Lin et al., 2017). The approach used for training and predicting the presence of culverts is to first find the pits in a DEM and then center prediction input images on these to reduce the amount of data the model sees and increase focus on clear obstructions in the DEM. The input images are 250 m^2. These images also undergo augmentation through rotation, flipping, and scaling to increase the

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amount of training data. Here, the model trained using the above data and parameters is tested on the 750-km^2 Michigan (MI) area. The 11 MI catchments are in the Hilly Moraines physiographic region of southwest Michigan and drain into Lake Michigan. The site is dominated by agriculture, with some forested areas and suburban development.

The test results are scored using the F1 score, which uses precision and recall to account for potential imbalances in classes (Kang et al., 2019); here, the two classes are channel obstruction and not channel obstruction. The preliminary F1 score for the MI predictions was substantially lower than training and predicting on the AC data; the average score was 0.35. The cause of the lower prediction scores is likely due to several factors. One factor is the difference in data sources and collection methods. The AC data were curated to train such models and exclude culverts that do not have an identifiable associated channel in the elevation data. In contrast, the MI channel structures vary from sparse in some regions to extremely dense in others, with many culverts having no indication of their presence in the elevation data. This is likely the result of the field validation limitations such as property access, and inclusion of small culverts not visible in the DEM. Another potential challenge for transferring the model from AC to MI is the response of the elevation derivative layers to the low-relief MI study area, as opposed to the higher-relief Piedmont AC region. This indicates that further input DEM-derivative layer testing could improve the predictions. Also, most small dams are not included in the MI validation data but are being predicted by the model. Adding additional training using data from the new study area would also likely improve scores.

The results of this work indicate that model adaptation and further collection and filtering of validation data would be useful to adequately implement the CN workflow in areas such as western MI. Yet, the results also show promise for the transferability of the CN workflow as many culverts and dams in the test area are accurately identified (Figure 2). The predictions of the workflow in its current state could be beneficial for mapping culverts, dams, and bridges with the addition of some manual review. Further testing is planned to investigate the use of different input layers and model tuning.

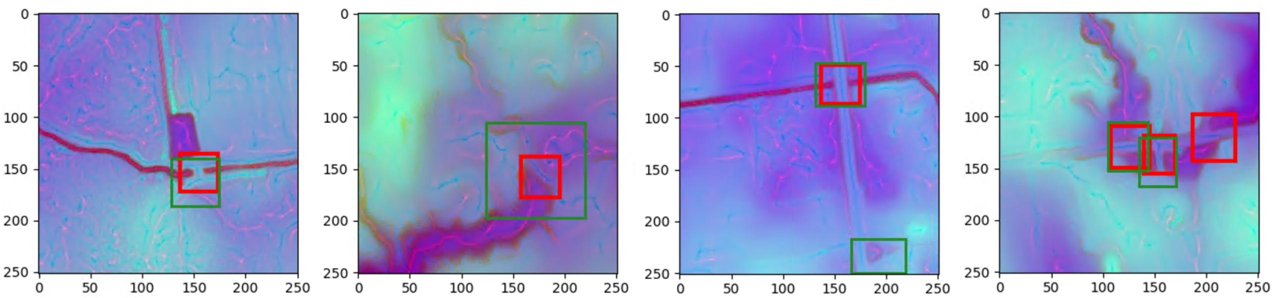

Figure 2. Examples of validation (red) and prediction (green) bounding boxes. The images are false-color composite images using the DEM, curvature, and Sky View Factor data. Lighter areas have a higher elevation while darker areas highlight channels. Axes are distance in meters.

Disclaimer

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