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Multi-temporal surface water mapping with high-resolution elevation and image data through weakly supervised deep learning

Lawrence Stanislawski [a,*], Rongjun Qin [b], Jung Kuan Liu [a], Ethan Shavers [a], Shaowen Wang [c], Nattapon Jaroenchai [c], Philip Thiem [a]

[a] *U.S. Geological Survey, Center of Excellence for Geospatial Information Science, Rolla, Missouri, United States, lstan@usgs.gov, Ethan Shavers, eshavers@usgs.gov, Philip Thiem, pthiem@usgs.gov*

[b] *Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, Columbus, Ohio, United States, qin.324@osu.edu*

[c] *Department of Geography and Geographic Information Science, University of Illinois at Urbana-Champaign, Urbana, IL, United States, shaowen@illinois.edu, Nattapon Jaroenchai, nj7@illinois.edu*

* Corresponding author

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Abstract:

Monitoring the extent of surface water features (hydrography), accurately storing them in databases, and representing them on topographic maps are essential for various applications such as navigation and policy-making for legislative boundaries and permitting. In this context, hydrographic data includes features that generally have water present or image data showing signs that water is forming a terrain channel, and which would be included in 1:24,000 or larger scale topographic maps. In addition, reliable hydrographic data play a critical role to help manage environmental risks such as droughts, floods, fires, and landslides, as well as monitoring biological resources and pollutants. Inaccuracies in hydrography data can lead to modelling inaccuracies, resulting in economic, social, and environmental risks. However, generating sufficiently accurate high-resolution (HR) hydrography and terrain data for these purposes remains a substantial challenge primarily because of complex surface water dynamics and data handling limitations.

Traditional methods for deriving hydrographic drainage networks from elevation data involve flow-routing and raster cell aggregation methods to determine where water is likely to gather on the landscape (O'Callaghan and Mark, 1984; Tarboton, 1997). These methods require location-specific parametrization to extract a drainage network that sufficiently resembles the actual surface water extents. Also, deriving flow patterns from HR elevation models can present challenges, such as false flow obstructions caused by overpasses, bridges, and culverts, which obstruct remote sensing of underlying terrain or drainage channels. These obstructions must be manually or artificially corrected to ensure accurate flow models. After deriving the drainage channels from the elevation data, the extracted features are often manually refined to fit to HR image data.

While the traditional flow-routing approach combined with HR-image-guided manual editing has been widely trusted, it remains a time-consuming and costly solution with several drawbacks, such as removing flow obstructions in elevation data and setting thresholds to control extracted network density. The final product represents a single snapshot of hydrography tied to hydrologic conditions during data collection and relies on HR image data for quality assurance.

Recently, there has been a shift toward automated methods using machine learning (ML) and deep learning (DL) techniques. Despite requiring more data and computational intensity, DL has been shown to outperform traditional methods and simpler ML approaches (Xu et al., 2021). Stanislawski et al. (2021) used a U-Net model to predict hydrography for a 4,600 square kilometer study area in north-central Alaska, based on several hydrogeomorphic layers derived from 5-meter resolution interferometric synthetic aperture radar (IfSAR) data. The model was trained with hydrography extracted from IfSAR elevation data using traditional flow-routing methods and HR-image-guided editing. The model achieved average F1 scores of 66-68 percent when 15 percent or more of the study area was used for training. Subsequently, Stanislawski et al. (2024) improved the model using a filtering technique to remove likely errors from training data based on comparisons with channel depth estimates from a 2-D shallow water drainage model (Mitasova et al., 2004). Filtering training data boosted F1 scores to 80 percent.

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Other research has demonstrated that time-series hydrography can be extracted using DL from HR images in non-forested terrain where the features are not occluded (Bernhardt et al., 2020). However, these methods rely on manual image interpretation and feature editing to identify water pixels (for example, training labels) across multi-temporal imagery, which is an extensive limitation.

Figure 1. Sample of vector waterbodies and drainage lines (blue) in north-central Alaska predicted through deep learning and overlaid on high-resolution Maxar multispectral satellite image data.

This study proposes an integrated approach for multi-temporal hydrography mapping that uses DL to extract water features from elevation data. These initial features will serve as training labels to integrate HR image data from one or more collection dates with the elevation data and extract water features from the HR images using DL. Testing will be applied to a section of the Alaska study area (Stanislawski et al., 2024). Figure 1 shows an example of predicted waterbodies and drainage lines overlaying HR Maxar image data acquired near the time of the IfSAR collection. The approach will address misalignment between IfSAR-based labels and HR images, as well as label inconsistencies due to seasonal variations and occlusions, by using weak supervision and parameterized 2D transformations (Tang et al., 2025). Image-to-IfSAR registration can be performed using grid search or our previously developed mask-based minimization methods (Tang et al., 2025). The research will test the use of neural network-derived hydrography as noisy labels to extract water pixels from one or more dates of HR image data and develop and test a workflow—such as the Markov Random Field with a graph-cut approach—to prioritize labels from neural network predictions that can be used to train models for segmenting water pixels from HR images.

Our research aims to enhance hydrographic feature mapping and monitoring through the automated extraction of features from integrated HR elevation and image data. By automating surface water mapping tasks using DL, our research aims to reduce the labor- and time-intensive work, while enhancing multi-temporal water monitoring capabilities. The findings could support large-scale hydrologic mapping, improve disaster preparedness, and promote more sustainable water and land resource management.

Disclaimer: Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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