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Enhancing U-net extraction of hydrographic features from IfSAR data in Alaska using shallow water channel depth models

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Abstract:

High-resolution elevation data and accurate detailed delineations of surface water features are crucial for many scientific investigation and resource management purposes, such as flood mapping, drought mitigation, and environmental and habitat monitoring. The U.S. Geological Survey (USGS) 3D Elevation Program (3DEP) coordinates the collection and distribution of high-resolution elevation data within the United States. USGS data can be used free of charge and without restrictions (U.S. Geological Survey, 2023a). The National Hydrography Dataset (NHD) is a comprehensive vector database of surface water features for the United States (U.S. Geological Survey, 2023b) that can be freely used for scientific and resource management purposes. However, because of the different time frames and technologies applied for data collection, the NHD and 3DEP data are not well integrated. The useability of these datasets and associated benefits can be greatly enhanced by improving the integration of these datasets (Terziotti et al., 2018). Therefore, the goal of this work is to advance machine learning methods to automate the extraction of detailed hydrographic features from the high-resolution 3DEP data. Resulting predictions can inform updates to existing NHD features or aid validation or collection of new data thereby providing hydrographic features that are well integrated with the elevation data.

Recent advances in machine learning research have shown promising results for extraction of hydrographic features from lidar point cloud and other remotely sensed data. Specifically, Xu et al. (2021) used a 1-m resolution digital elevation model (DEM) layer and seven other surface-water related layers derived from 3DEP high-precision Geiger-mode lidar data to extract hydrographic features for a small watershed in North Carolina using a U-net neural network model with square sample windows having 224 pixels per side. Training on about half of the watershed provided F1-scores for test areas that range between 79 and 91 percent, and average 84.3 percent (Xu et al. 2021). In another study, 3DEP interferometric synthetic aperture radar (IfSAR) 5-m resolution data for a 50-watershed study area in Alaska was used in a similar U-net model with 224-pixel square samples and 14 IfSAR-derived surface-water related input layers to predict hydrographic features (Stanislawski et al., 2021). Training with 15 to 35 percent of the 50-watershed study area provided predictions with F1-scores for test watersheds between 66 and 68 percent.

In addition, Stanislawski et al. (2021) noted that the most influential input layer for U-net models predicting hydrography is a 2-D shallow water (2DSW) depth model, which is derived from a DEM layer using r.sim.water module (Mitasova et al., 2004) from Geographic Resources Analysis Support System (GRASS) Geographic Information System (GRASS Development Team, 2023). Subsequent research indicates that a small percent (less than 1 percent) of reference hydrography pixels can be filtered using 2DSW channel depth estimates to improve U-net hydrography prediction accuracies by up to 10 percent (Stanislawski et al., 2022). Given the importance of the 2DSW model inputs, this paper evaluates the effect of different 2DSW channel depth models on hydrography predictions from U-net models. In addition to several DEM-derived input layers as described by Stanislawski et al. (2021), U-net input layers derived by 2DSW channel depth models are tested. The GRASS 2DSW model is derived by the r.sim.water module from a raster-based DEM. For comparison, a 2DSW model proposed by Costabile and Constanzo (2021), which uses a triangulated irregular network (TIN) elevation model, is also tested in U-net hydrography prediction models.

Methods are demonstrated using IfSAR-derived data layers for 22 watersheds in Alaska that cover about 2500 square kilometers. Various combinations of the hydrologic input layers derived from the IfSAR data, along with channel depth

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and/or discharge layer generated from one of the 2DSW models will be tested in U-net models using multiple sampling designs to train the models. Different sampling designs will test effects of different sample distributions on model training time and prediction accuracy. The most accurate set of available hydrographic features are used as reference data for training and testing the U-net models. The reference data were recently (2019) derived from the IfSAR elevation data with traditional flow-routing techniques and manual editing procedures that were performed by USGS contractors. Therefore, the reference NHD data used in this study is integrated with the 3DEP IfSAR elevation data and has since been included in the NHD. Aside from assessing the quality of U-net predictions, the topologic connectivity of vectorized flow networks constrained to U-net model predictions will be evaluated for each watershed. Workflows are implemented through Python programming with open-source tools, including Tensorflow™ (Abadi et al., 2015) and Keras (Chollet et al., 2015), using high-performance computing environments.

This research is expected to reveal possible enhancements in automated extraction of hydrographic features from high-resolution 3DEP elevation data that may improve the integration of USGS hydrographic and elevation databases. Enhancements may be based largely on adjustments to 2DSW channel depth model layers. Improved integration of high-resolution elevation and hydrography data would better support water and land resource management procedures.

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