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Double thresholding GeoAI prediction to fill gaps in extracted watercourse network

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Abstract:

Neural networks can be powerful tools in automatically detecting topographical features like watercourses (Stanislawski et al. 2021) but their results may be flawed causing errors in vectorizing results like distorted geometries or missing features. In our case, we have been working with a trained convolutional neural network (CNN) model that detects watercourses from digital elevation models (DEMs) (see Koski et al. 2023). In Jussila et al. (2024) we presented a post-processing workflow that vectorizes CNN results into vector lines and corrects distorted geometries at junctions. In this abstract, we present a new addition to the earlier workflow, which is filling gaps of the watercourse network. This is work in progress.

The post-processing workflow takes as input the neural network predictions in raster format, where the values were decimal numbers from zero to one. The cell values were reclassified to binary values zero and one based on whether the cell value was above or below a threshold value. In this case, we created two reclassified raster images. The first was reclassified using a threshold value of 0.5, which was used as a base dataset. The second raster was reclassified using a threshold value of 0.1, which was used as a second dataset to aid in finding gaps in the watercourse network. Both datasets were vectorized into polygons, which were then pre-processed and simplified. Then, centrelines were calculated from the polygons. The gaps between watercourses were detected by calculating difference between base dataset polygons and second dataset centrelines. The remaining centrelines were the potential gaps between watercourses. The remaining watercourses were then filtered according to a two-meter distance to the endpoints of the base dataset centrelines. Consequently, the filtered watercourses were buffered to match the width of the watercourses in the base dataset. The buffered watercourses were rasterized to the base dataset, which was again vectorized into centrelines. The final step was to correct the distorted geometries at junctions, which were caused by the vectorization of raster cell values. This was done by categorizing the junctions into two types. Each junction type had their own correction method. For more detailed description of the vectorization, simplification, calculation of centrelines and geometrical corrections, see Jussila et al. (2024).

Overall, the results show that the vectorization improves with this gap filling method (Figure 1). The vectorization of the raster to centrelines produces proper vector lines, which are mostly created at the centre of the polygons. Filling gaps in the watercourse network works to a moderate degree. The process does fill gaps between watercourses, but it also adds false features. There are also situations where the process doesn't add watercourses when it should. The process seems to work best at simple cases where there is a gap between watercourses. Problems occur if the watercourse gap should connect to a junction or if the gap area is of complex structure. In addition, the process extends the watercourses from the endpoints. The correction of the junctions also works mainly well. Currently the process detects only two types of junctions, which might cause problems in the future. There are also outliers where corrections are not applied properly. Currently, the process has also been tested on a single site.

In the future the plan is to improve the post-processing workflow further. The process is to be tested in different kinds of regions to see how well it works and what kind of new problems arise. We also plan to improve the process that fills the gaps between watercourses since it is essential for creating completed watercourse network. In addition, the inclusion of ponds and lakes in the network should be considered. This way the watercourses could be connected to the lakes and the lakes could also be used to filter watercourses. The main target is to create a continuous watercourse network to be used in topographic maps.

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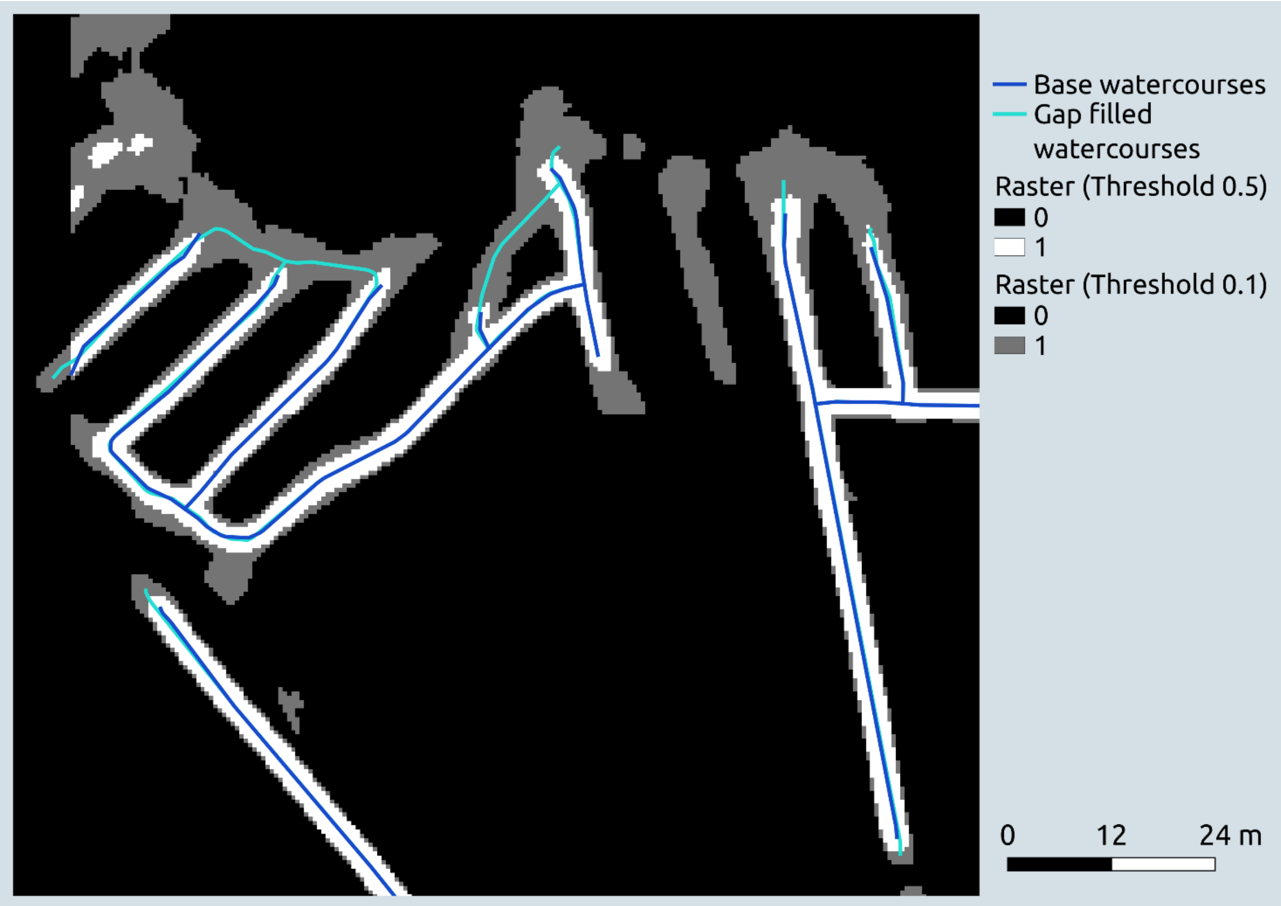

Figure 1. Vectorized watercourses with and without gap filling method. The raster with threshold value of 0.5, is the base dataset. The raster with threshold value of 0.1 was used to find gaps between watercourses.

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