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Effects of point cloud density and DEM resolution to CNN recognition of small watercourses

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Introduction

The integration of machine learning (ML) in Geographic Information Systems (GIS) has opened new avenues for spatial analysis, enabling more efficient and accurate processing of geospatial data. The performance of ML models is often considered highly dependent on the granularity of input data, but the effects of different granularity levels have not been fully clear. Particularly in emergency applications, the granularity may cause significant effects in resulting actions. For example, better understanding of watercourse network is crucial in many applications and even lifesaving, e.g. flood modeling and preparedness (Petty, 2016). Currently, National Land Survey of Finland (NLS) is renewing its watercourse mapping from high resolution point clouds. In this study we present a comparative analysis of six distinct datasets, varying in both point cloud density and spatial resolution, to evaluate their effectiveness as input data for ML.

Methods

This study was conducted across two 36 km² study areas in central Finland, one located near Ristijärvi and the other near Heinävesi. We trained six ML models with different input datasets, varying in point cloud density and spatial resolution. The datasets consisted of elevation models generated from lidar point clouds with densities of 20 points per square meter (20p) and 5 points per square meter (5p), at three spatial resolutions: 0.25 meters, 0.50 meters, and 1.00 meter. The datasets were produced by the NLS.

The primary objective was to assess the performance of these datasets as input for ML models in research of watercourse networks. To achieve this, we implemented various ML training runs, systematically altering several key parameters. Specifically, we varied the tile side length, cropping strategies, and the number of training epochs to observe how these factors influenced model performance.

During the ML runs, we recorded multiple metrics to evaluate the models, including F1-score, precision, recall, and runtime. These metrics provided a comprehensive view of the effectiveness and efficiency of each dataset when used in ML tasks. We also calculated relaxed recall, precision, and F1-score, with a spatial toleration of 1 meter, to better assess the F1-scores in relation to feature detection. The results from each run were carefully documented and analyzed.

After completing the ML runs, the outcomes were further analyzed and discussed within our group of four researchers to interpret the results and identify the datasets that yielded the best performance with visual analysis. Hillshading, relative topographic position, NLS orthophotos and the NLS topographic map were used in the visual analysis. This discussion also focused on understanding trade-offs between data granularity, computational efficiency, and the accuracy of the models.

Point cloud	20p			5p		
Resolution	0.25 m	0.50 m	1.00 m	0.25 m	0.50 m	1.00 m
F1-score	0.900	0.902	0.897	0.879	0.882	0.975
Buffer F1-score	0.956	0.956	0.956	0.946	0.946	0.942
Runtime (h)	11.958	2.849	0.784	12.348	2.867	0.664

Table 1. Ristijärvi area results.

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Results

The F1-scores of the runs with different spatial resolutions had minor differences, while the input data with 20p showed consistently about 1-2 pps better F1-scores than input data with 5p, shown in Table 1. Runtimes increase up to four times with better resolution. With the buffer analysis, it was found that 4-5 pps of features were misidentified or left out from the calculation of the F1-score. The buffer analysis suggests that the edge pixels improve F1-scores equally independent of the raster granularity.

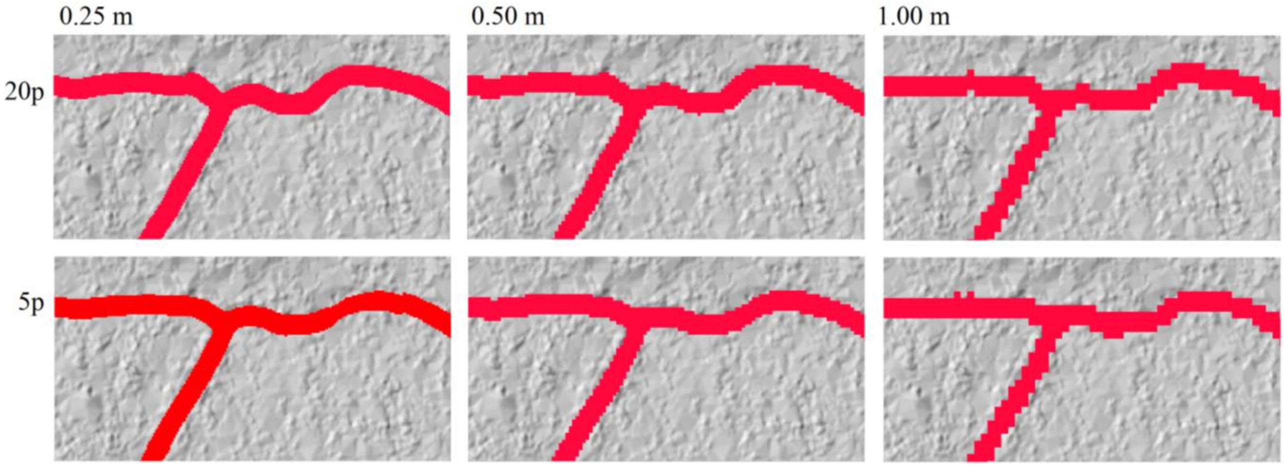

Figure 1. CNN predictions in Ristijärvi area. Horizontal watercourse is a natural stream, vertical is a ditch.

Summary and discussion

In summary, this research has found accuracy of CNN watercourse recognition to only slightly increase with granularity of the input data between 20 and 5 p lidar point clouds as well as 0,25 m, 0,5 m and 1,0 m DEMs from those point clouds, as shown in Figure 1. This enables using lower granularity data for achieving importantly faster calculations with almost the same recognition quality. Including buffer zones into the calculation of the F1 score enhances correctness of the measure from the viewpoint of watercourse existence and increases the accuracy of about 5 pps.

The spatial extent of this study is not sufficient for a comprehensive overview of the model. Still, the datasets used in this study are accurate enough to map watercourses at the decimetre level. This raises challenges on what to include, e.g. all depressions should not be included in the final output data. Also, defining individual watercourses can be difficult (Poutanen, 2023). More accurate watercourse networks can help e.g. in flow direction modelling, therefore improving flood models and related emergency planning and actions.

The quality of data necessary for modelling watercourse networks varies based on use-case. More research on the challenge of balancing runtimes and accuracy of data is required. Also, research in the future could focus on granularity and vectorization (Jussila, Koski, Kettunen, 2024).

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References

Petty, T.R., Noman, N., Ding, D. and Gongwer, J.B. (2016) Flood Forecasting GIS Water-Flow Visualization Enhancement (WaVE): A Case Study. Journal of Geographic Information System, 8, 692-728.

Poutanen, J., Koski, C., Oksanen, J., & Kettunen, P. (2023). Lessons learnt from digitizing a label dataset for AI-based feature extraction of watercourses. Abstracts of the ICA, 6, 205.

Jussila, A., Koski, C. and Kettunen, P., 2024. Vectorization of watercourse detection from neural network. Abstracts of the International Cartographic Association, in press.

