Automating extraction of broad-scale topographical and spatial information for urban streams

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Funding provided by Melbourne Water under the Melbourne Waterway Research Practice Partnership (mwrpp.org)

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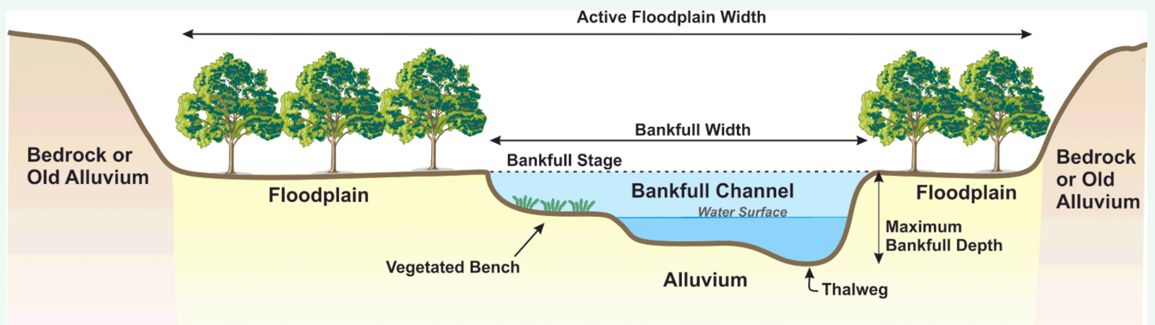
Summary

Motivation: We needed channel dimension data across the Greater Melbourne region to better understand drivers of physical form and channel enlargement, and to provide input data to other analyses of water quality and ecosystem condition. We have lidar data across the region which is a rich source of channel morphology information, but we needed efficient workflows to extract that information on a regional scale.

Our approach: We developed, tested and compared three automated methods for delineating bankfull channel boundaries based on lidar digital elevation models (DEMs).

Main findings: All methods performed well in comparison to an expert geomorphologist, but different methods had different strengths. Methods which used cross-sectional data were more accurate overall, but the method which used AI to directly classify the channel from a lidar tile was more accurate in complex channels with inset floodplains.

Implications: We can now efficiently extract information about channel size and shape such as width, depth and bank slope. We can also overlay bankfull channels with other layers to derive important channel information (e.g., riparian vegetation, channel boundary materials, land uses). This advance opens the door to larger-scale spatial analyses of rivers than before.



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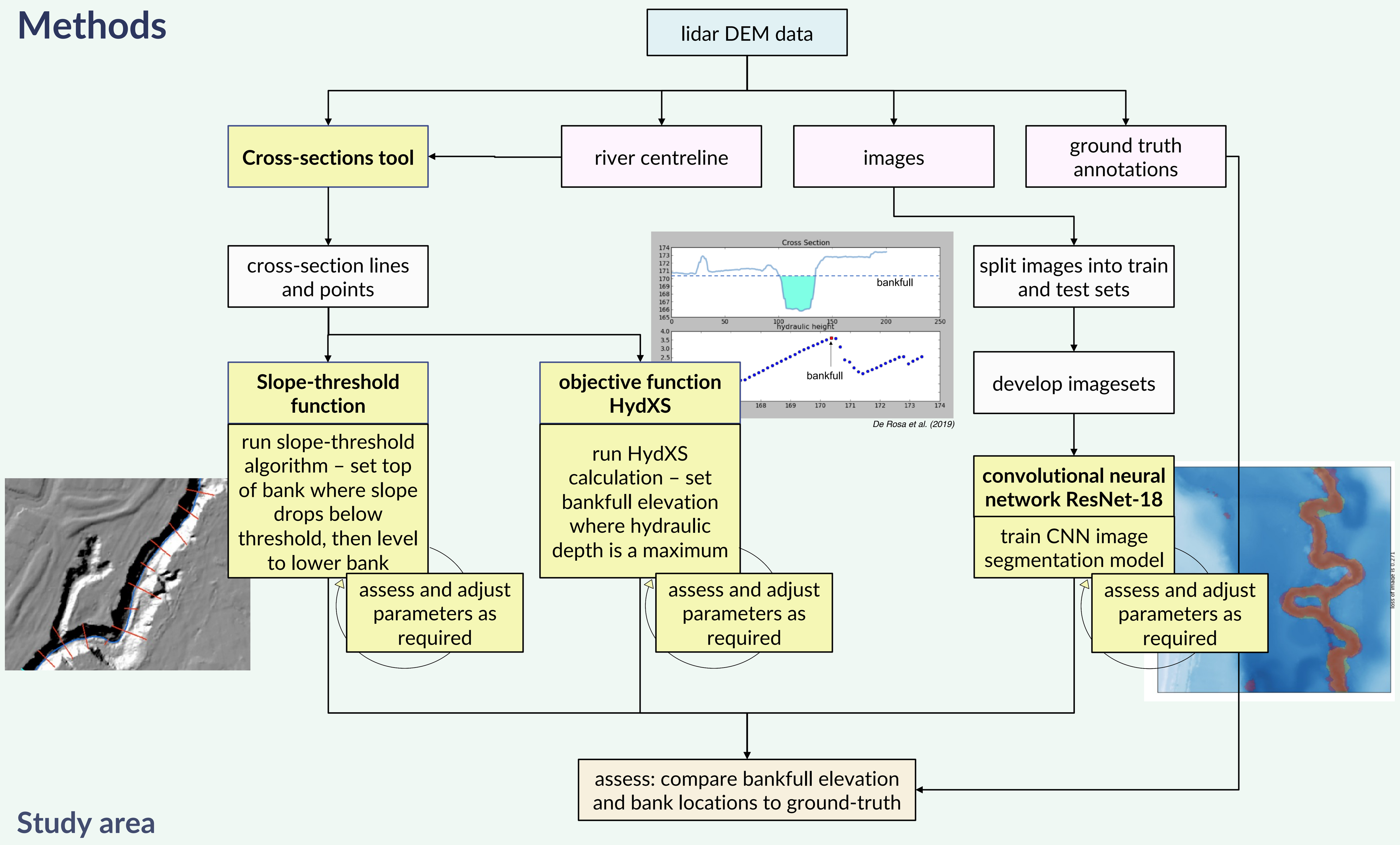
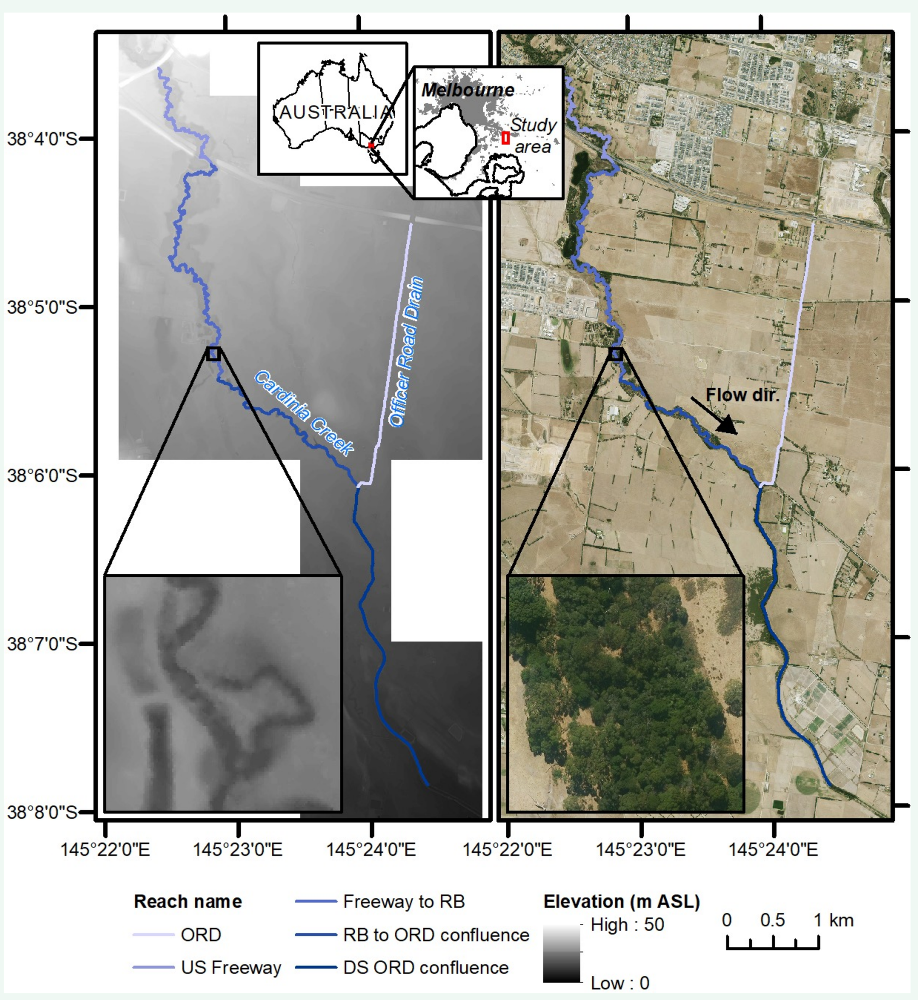
Methods

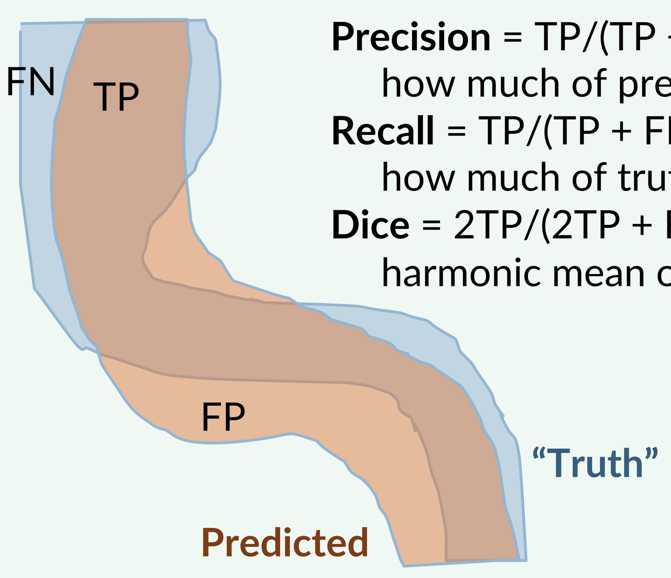


Study area



Performance metrics

We compared the results to bankfull delineation undertaken manually by a geomorphologist.



Precision = TP/(TP + FP)
how much of prediction is correct?

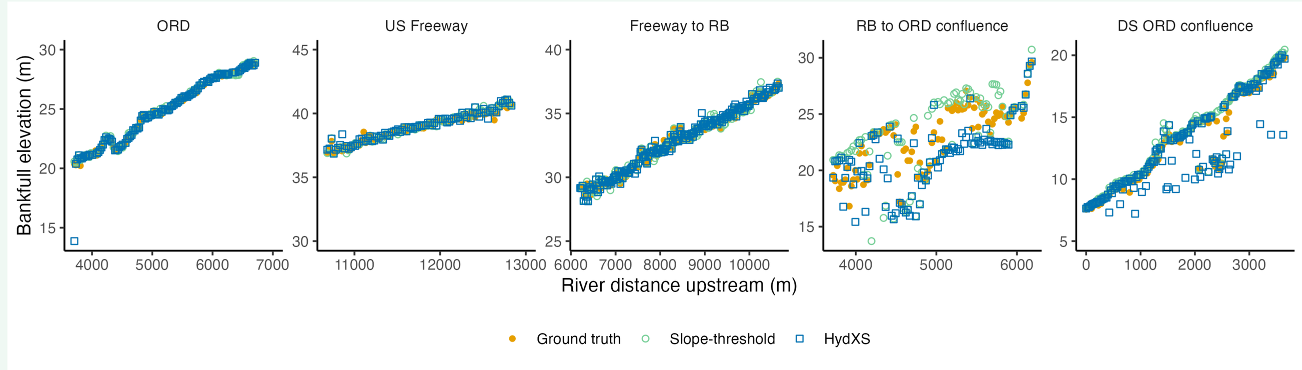
Recall = TP/(TP + FN)
how much of truth is correctly predicted?

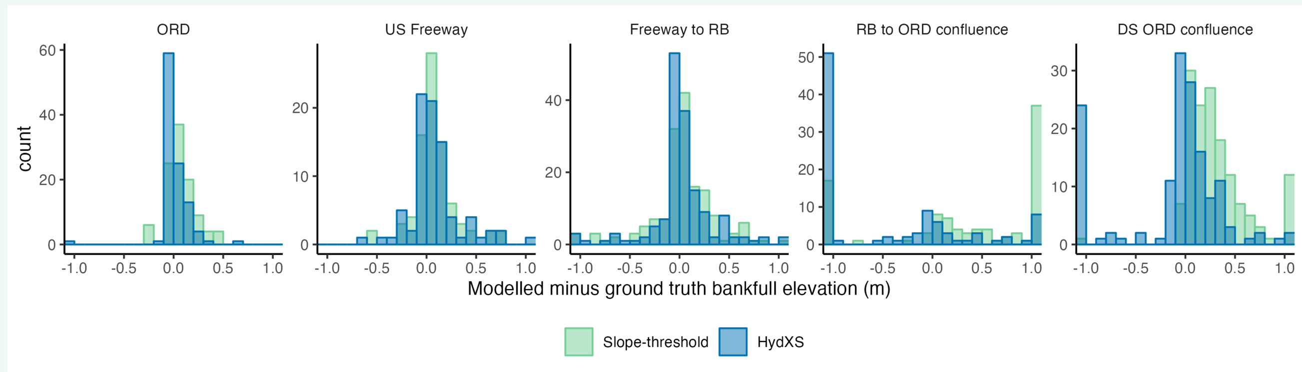
Dice = 2TP/(2TP + FP + FN)
harmonic mean of precision and recall

Results

Slope-threshold function and HydXS

Slope-threshold method had a tendency to overpredict.
HydXS was more balanced and performed slightly better overall.

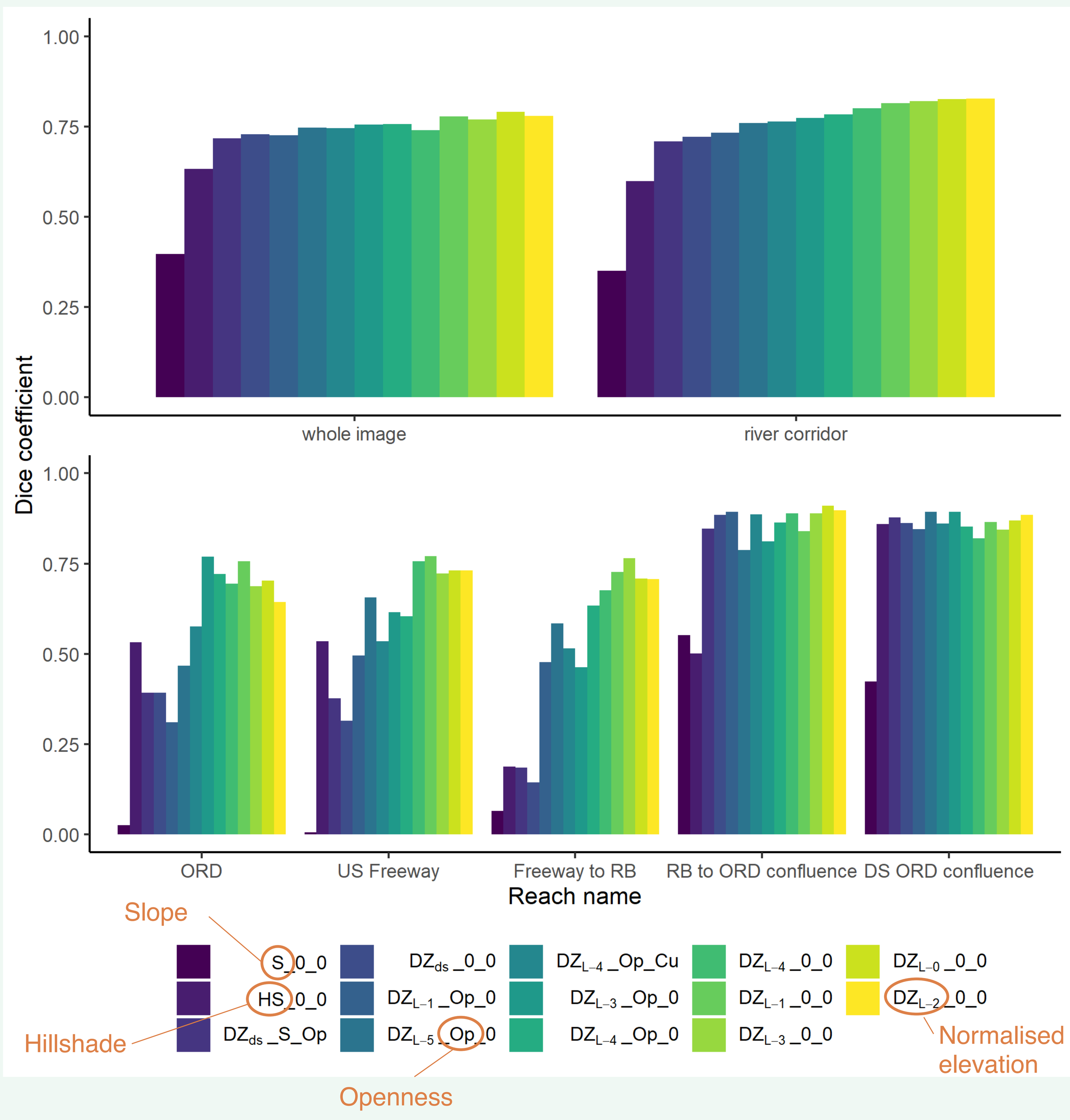




	Slope-threshold	HydXS
Precision	0.75	0.87
Recall	0.88	0.80
Dice	0.81	0.83

Convolutional Neural Network (CNN)

Variable performance with different input layers (e.g. slope, hillshade, elevation, openness)
Best performance with elevation layer only (Dice > 0.8)



Comparison – HydXS vs CNN

HydXS performed better in smaller channels.
CNN performed better in larger, incised and inset channels.