

Brecheisen, Z.S., Richter, D.D., Moon, S., and Halpin, P.N., 2021, Quantitative analysis of hillshed geomorphology and critical zone function: Raising the hillshed to watershed status: GSA Bulletin, <https://doi.org/10.1130/B35724.1>.

## Supplemental Material

We compare our interfluvial networks derived from our iterative flow-accumulation burn-in procedure and that produced using the drainage divide network tool in the MATLAB TopoToolbox (Scherler and Schwanghart, 2020a, 2020b) in Figures S1 and S2. We applied DIVIDEobj and divorder functions using 10 m DEM. We first extracted channel network based on a minimum drainage area of 500 ha, extracted drainage divide network, and assigned drainage divide order following the Strahler's method. Some of 1<sup>st</sup> order interfluvial networks delineated by TopoToolbox using this channel threshold form loops as part of their drainage-divide delineation due to the lack of connected channels. So, we set a 500 ha threshold for interfluvial as well, which resulted in 7 initial interfluvial orders. Then, we applied floodplain mask to only show the interfluvial network outside of floodplain. We also removed connected ridges and high-points around the perimeter of the DEM, which were erroneously identified as actual terrain features.

The resulting network from TopoToolbox appears qualitatively very similar with our interfluvial network, but there are some differences between them. In our approach at each iteration of inverted flow-accumulation analysis we use standard pit-filling algorithms in TauDEM and Whiteboxtools. Pit-filling is implemented such that the elevations of pit pixels are raised or backfilled to match the elevation of their outlet pixels. This results in small pit areas being filled but not to the extent that saddles are bridged. Resulting networks bridge small sinks but yield separate networks on either side of saddles, which produced different results compared to TopoToolbox.

We assess the general delineation classification agreement between the two techniques in Figure S2 by constructing a confusion matrix. We did this by tabulating agreement between the rasterized TopoToolbox divide order and our hillshed order raster for confusion matrix analyses (top right of Fig. S2). Cohen's Kappa and the Matthews Correlation Coefficient (MCC) (Delgado and Tibau, 2019; McHugh, 2012) along with total accuracy were determined in R with the caret and mltools packages (Gorman, 2018; Kuhn, 2020; R Core Team, 2020). Kappa and MCC values around 0.49 indicate moderate agreement between the two techniques, and total accuracy indicates a 2/3 agreement. Although those methods were not identical due to the procedural differences, we simply argue that our results are reasonably similar to the TopoToolbox results. Considering that both methods require user's choice of areal thresholds or post-processing (e.g., application of floodplain mask), we proceeded with our technique.

**Figure S1.** Comparison of the resulting ordered interfluvial networks derived from our iterative flow-accumulation burn-in procedure (left) and that produced using the ridge ordering tool in the MATLAB TopoToolbox (right)

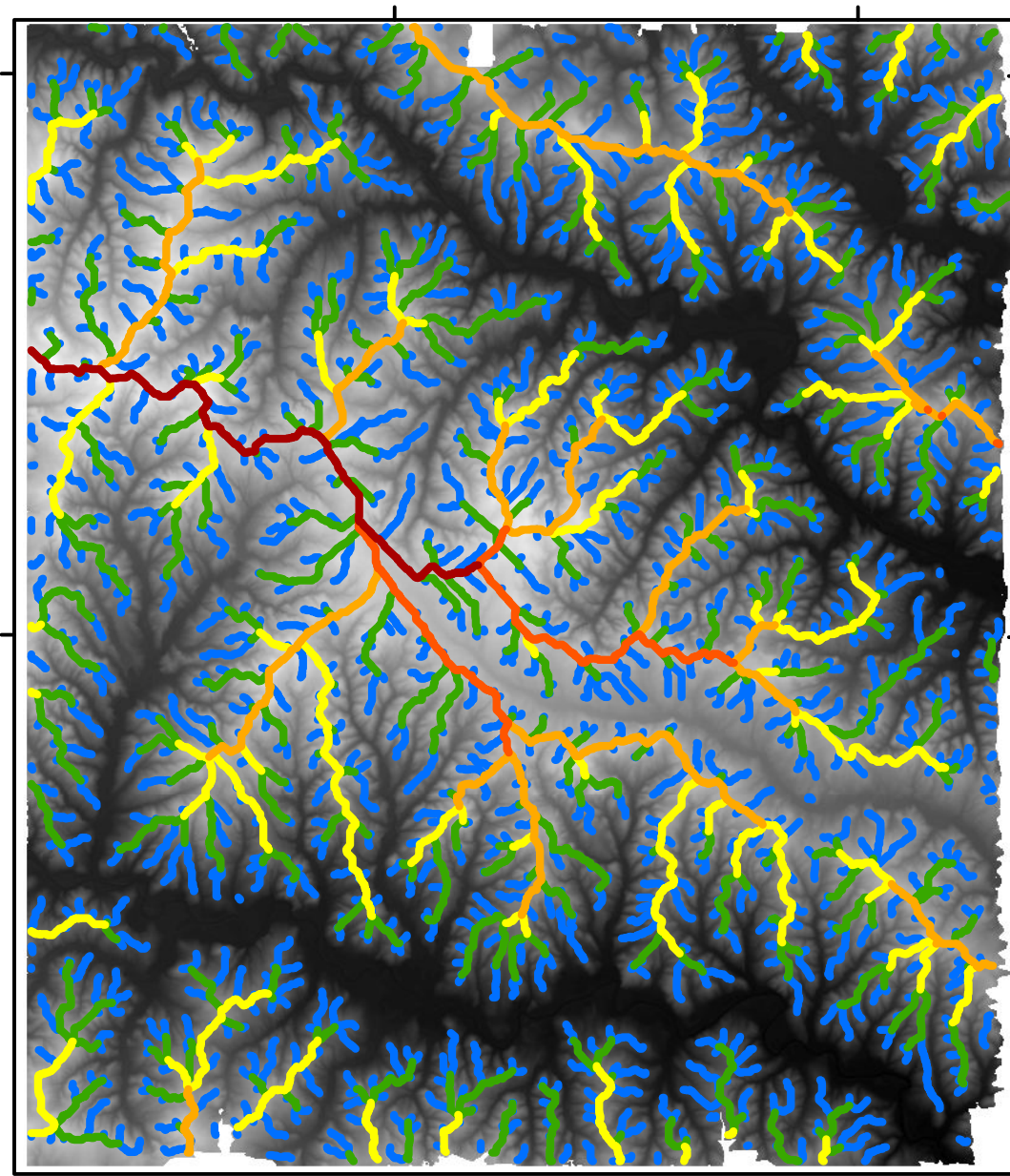
**Figure S2.** Comparison of the resulting ordered interfluvial networks derived from our iterative flow-accumulation burn-in procedure (left) and that produced using the ridge ordering tool in the MATLAB TopoToolbox (right) masked to isolate the primary interfluvial network tree at the Calhoun CZO with floodplains masked. The two bottom panels show most of Holcombe's Branch at the CCZO and serve to highlight the general similarity between the two results as well as some of their subtle differences.

**Figure S3.** boxplot and ANOVA analyses of the effect of DEM resolution on terrain curvature was explored via analyses of (top row) median hillshaded total curvature, (middle row) profile curvature, and (bottom row) plan curvature at 1 m (left column), 10 m (center column), and 50 m (right column) pixel resolutions. In all cases curvature values decrease as DEM pixel resolution is reduced. The general trend of total curvature decreasing as hillshaded order increases is consistent across DEM pixel resolutions with all differences observed via ANOVA analyses being statistically significant. Profile curvature differences among hillshaded orders are strongest and most clear at 1 m DEM pixel resolution with trends at 10 m and 50 m meter resolution either not having statistical significance or being difficult to interpret. Plan curvature ANOVA results are only statistically significant at 10 m DEM resolution generally having less curvature as hillshaded order increases at 10 m and 50 m resolutions.

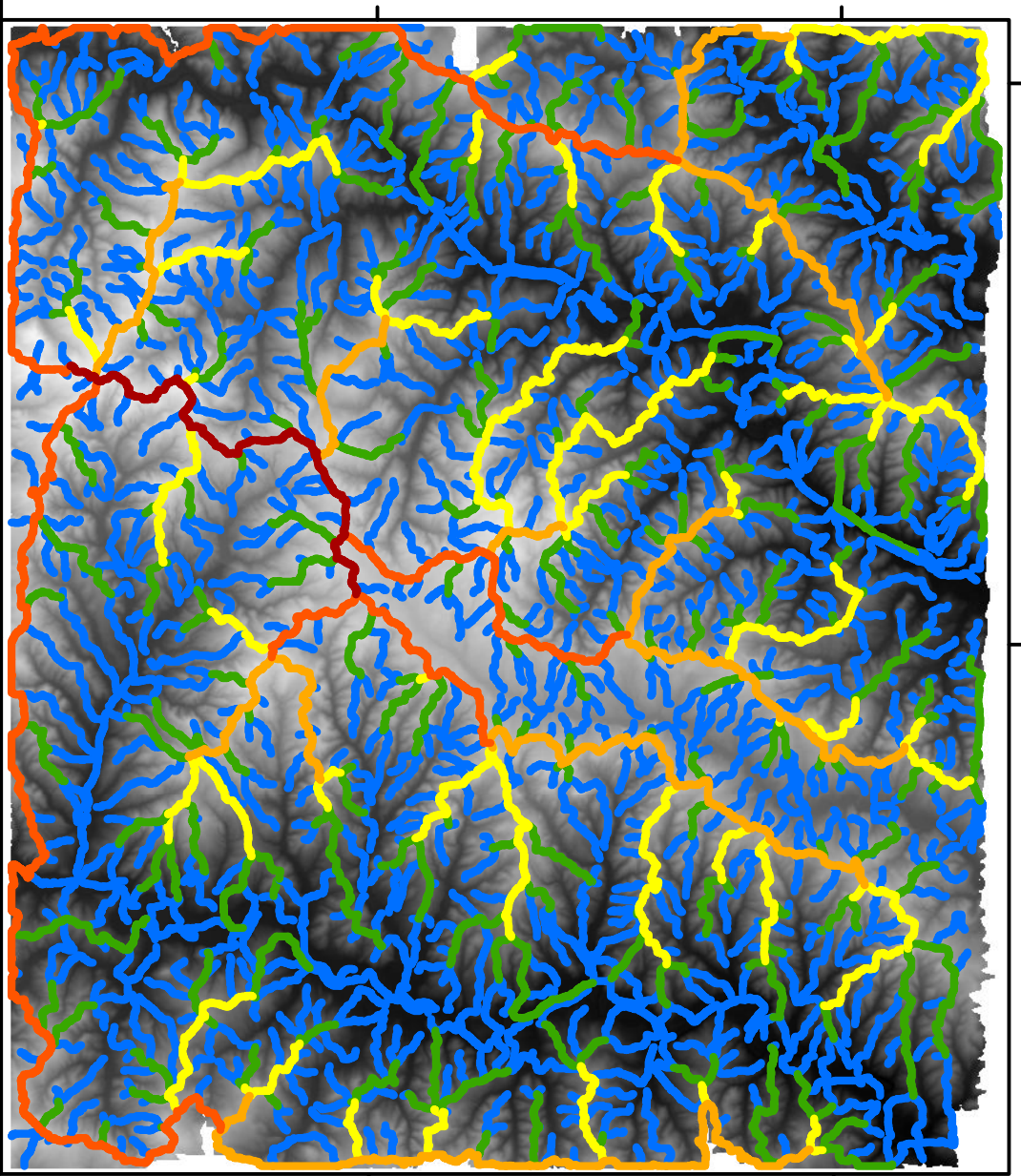
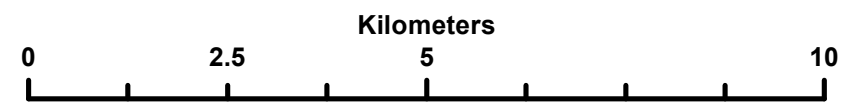
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# Inverted DEM Interfluve Ordering

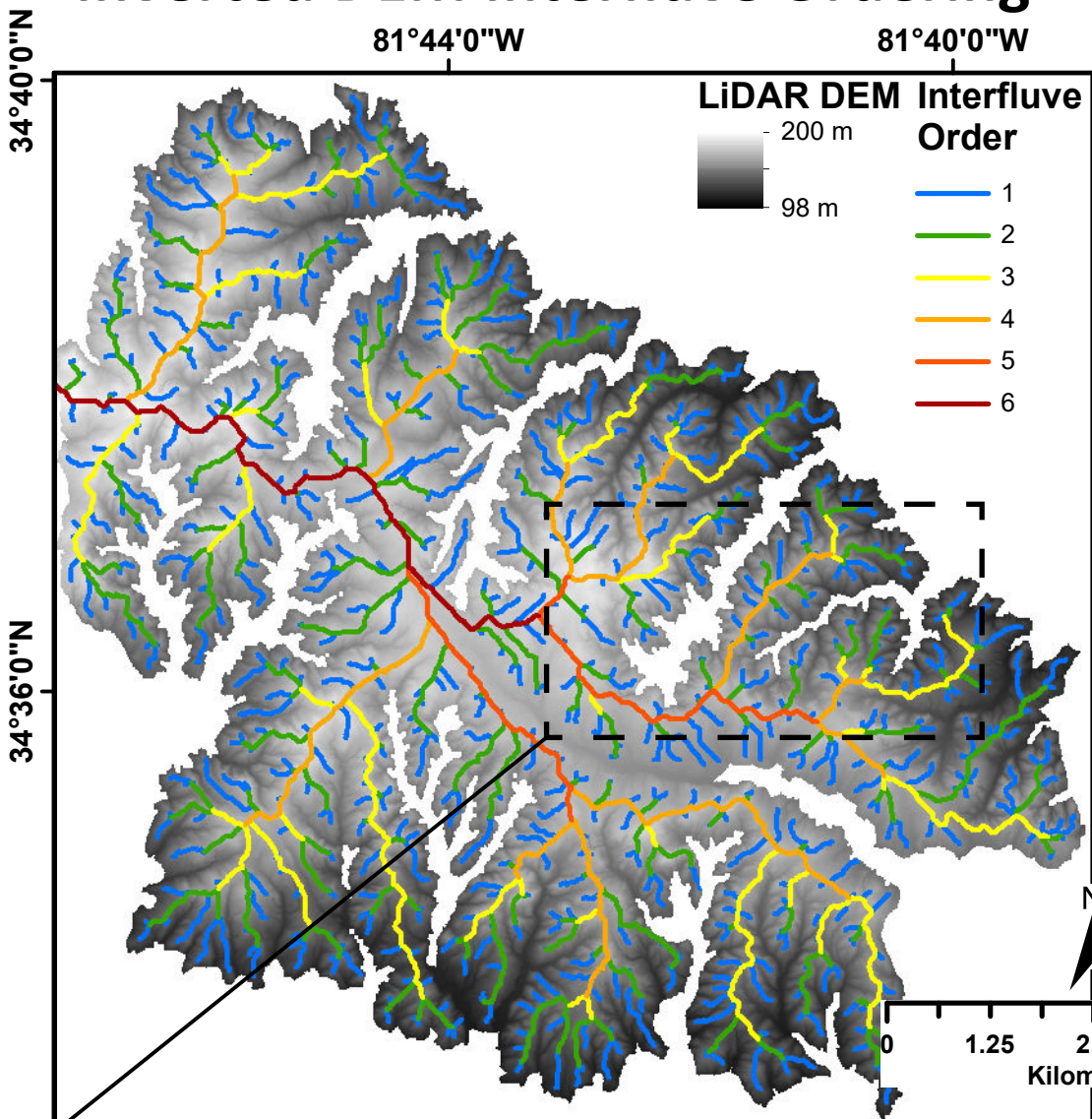


# TopoToolbox Interfluve Ordering

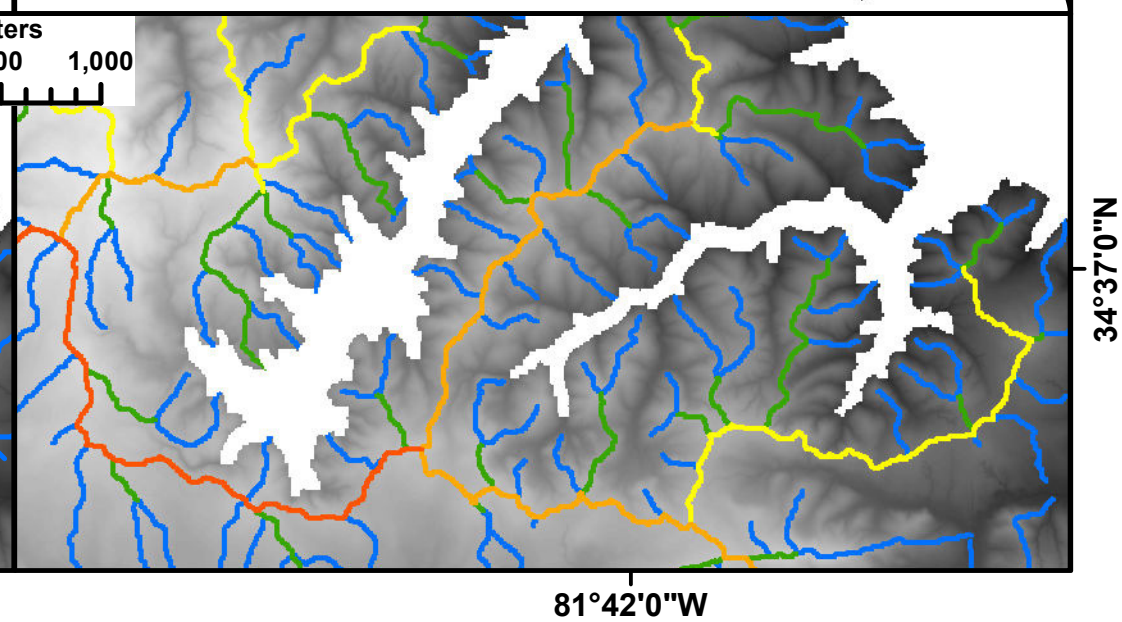
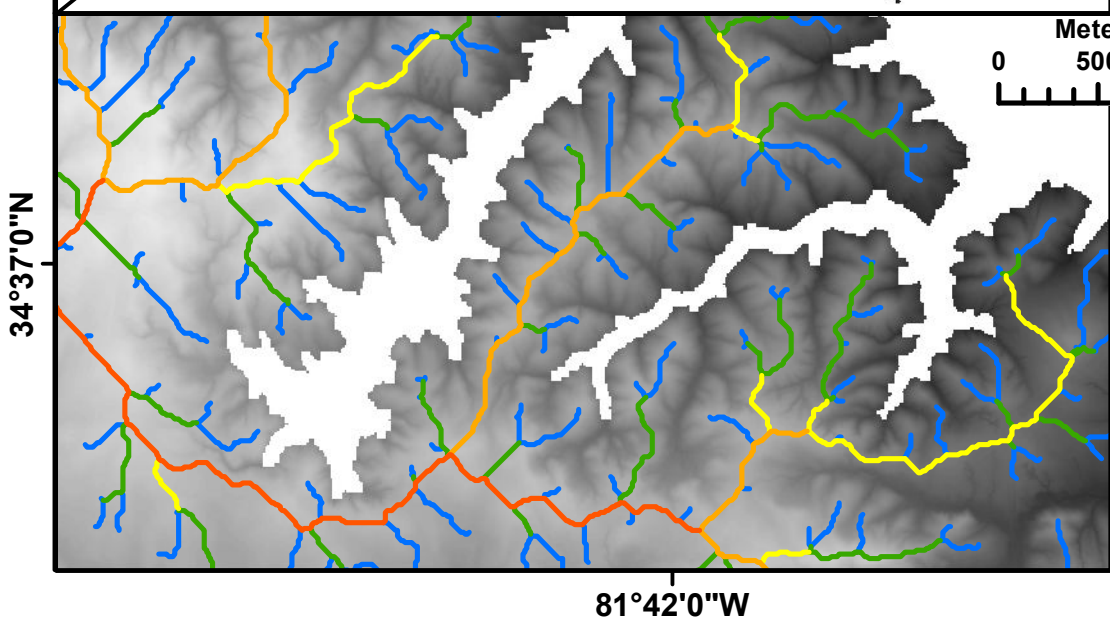
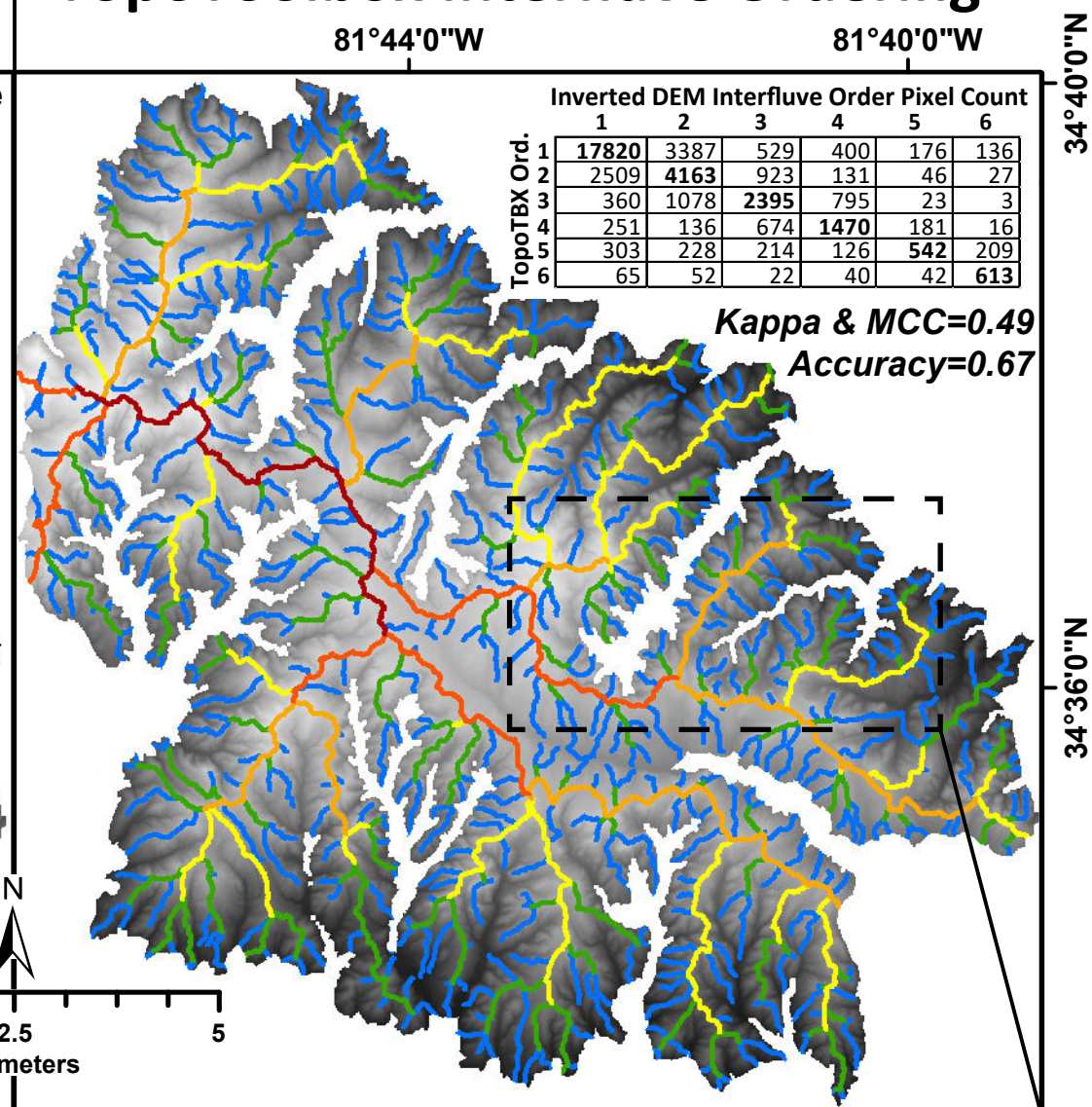




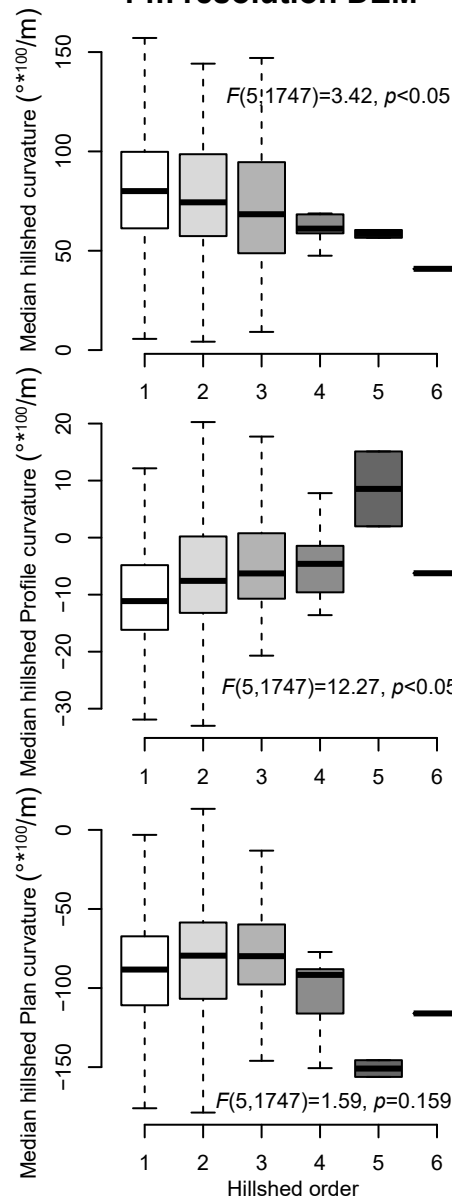
# Inverted DEM Interfluve Ordering



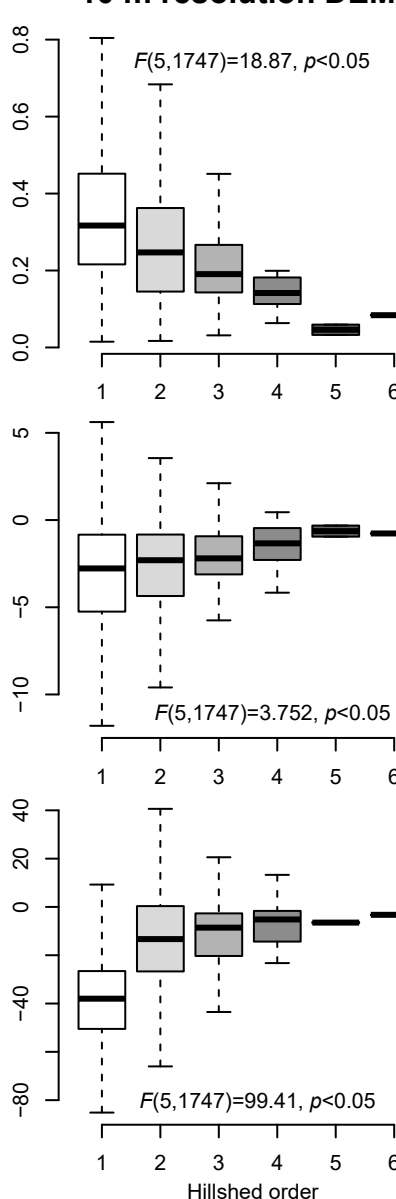
# TopoToolbox Interfluve Ordering



1 m resolution DEM



10 m resolution DEM



50 m resolution DEM

