Using GeoNet 2.0 for feature identification in an urban environment

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Introduction

Urban flow paths are a critical means of mass and energy transport within the cityscape. Flow paths in the urban landscape are often highly complex and involve natural features, engineered canals, and ditches; furthermore, streets and walkways can become flow paths during intense precipitation events. Recent advances in high resolution topography data have improved the resolution of terrain mapping such that the complexity of these features can be visualized down to the millimeter scale. This improvement in resolution created a need for feature extraction tools which can obtain flow path information from terrain data. One such framework is GeoNet (https://sites.google.com/site/geonethome/), which automatically extracts channel features from lidar-derived digital elevation models (DEMs). The goal of this project is to assess the performance of GeoNet in the task of extracting flow paths in an urban landscape, and make recommendations for its use in support of the NFIE goals. The ability to quickly and reliably identify potential urban flow paths has numerous potential applications for support flood prediction and risk mitigation.

GeoNet has been shown to successfully extract channel network features in natural landscapes and agricultural regions with anthropogenic features [*Passalacqua et al.,* 2010a; *Passalacqua et al.,* 2012]. This project focuses on an area within the city of Austin, which presents a variety of surface feature complexity. The output results from GeoNet include shapefiles of channel centerlines and channel heads (the most upstream point on a channel), as well as various raster files including: the channel skeleton, slope, flow accumulation area, and curvature. The raster file of the channel skeleton is used in this project to estimate of urban flow paths, and is used as a means to compare different settings and methods within the GeoNet framework.

Data

The CAPCOG lidar data was used to examine a 1565 m by 1798 m region within the City of Austin. This area, which lies northwest of downtown Austin, is relatively flat and exhibits significant complexity of surface features, including: residential areas, open fields, densely vegetative areas, buildings, roads, irrigation canals, as well as a natural channel-- Walnut Creek. The lidar scan was collected at a foot-scale resolution, DEMs were created using the ESRI lidar tools at ~0.3 m (1 foot) resolution and at 1 meter resolution. The following figure shows satellite imagery of the site and a hillshade of the ground surface.

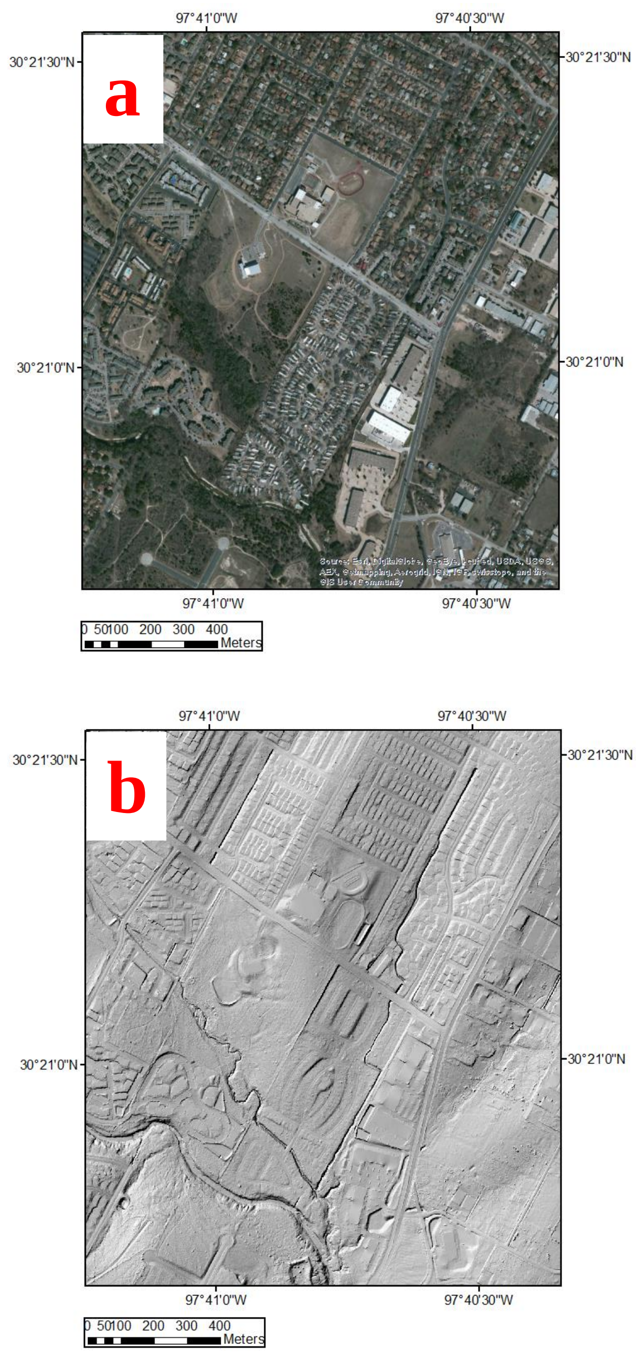

Figure 1. Image *a* shows satellite imagery of the study site; *b* is the hillshade of the same extent.

Methods

Background: Overview of the GeoNet algorithm

The GeoNet feature extraction algorithm can be summarized by the three primary steps in the framework. The first step of the algorithm is a filtering procedure which removes small-scale topographic noise from the DEM. The recommended filtering method in GeoNet is a nonlinear Perona-Malik filter which removes small scale noise while preserving important edge features such as channel banks. The next major step in GeoNet algorithm is a statistical analysis of curvature which identifies likely channelized pixels from a quantile-quantile plot of curvature versus the standard normal variate. An example of this plot is shown below.

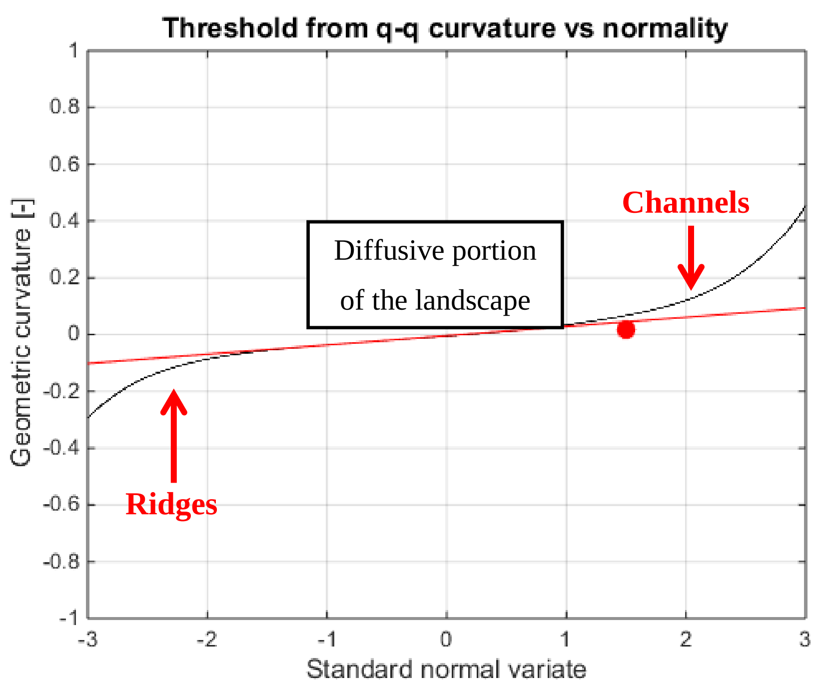

Figure 2. Quantile-quantile plot of curvature versus the standard normal variate. The inflection point (red dot) indicates where the curvature values deviate in the positive direction from the standard normal. The pixels with curvature values above this threshold form the first estimate of the channels in GeoNet.

There are currently two options for computing curvature in GeoNet: the Laplacian and geometric methods. Each is recommended for different landscape types based on previous work by *Passalacqua et al.* (2010a, 2010b, 2012). Laplacian curvature, γ, is defined as the second derivative of the elevation h, and is expressed simply as:

$$\gamma = \nabla^2 h$$

Geometric curvature, κ, is normalized by the absolute value of the slope $|\nabla h|$, as shown in the following equation,

$$\kappa = \nabla \cdot \left({}^{\nabla h}/_{|\nabla h|} \right)$$

Geometric curvature method more accurately identifies channel convergence in high relief, complex mountainous landscapes, as the normalization of the curvature by the slope allows for pixels with small positive curvature and large positive curvature to be equally detectable [*Passalacqua et al.,* 2010a]. The Laplacian method performs better in low relief landscapes with the presence of engineered features [*Passalacqua et al.,* 2012].

The final major step in GeoNet is the extraction of the channel network and end point locations based on a global geodesic analysis of the landscape. Flow routing is performed across the landscape to estimate flow accumulation area. Next, geodesic minimization is used to trace the pathways of least cost, in terms of energy, across the landscape. Finally, a search box traces the channel structure to identify channel upstream end points or heads. The results of GeoNet are written out as raster files (.tif), and include: slope, flow accumulation area, curvature, geodesic distance, and the channel skeleton. Vector files (.shp) are also written out of the channel network and end point locations.

The following sections describe how this original framework has been adapted to extract channel features in urban landscapes. This was done via MatLab-based and Python-based verisons of GeoNet. The majority of the framework is the same between these two versions, but there were some differences which are also outlined in the following text. For both MatLab-based and Python-based GeoNet, the flow accumulation area threshold was set to 1300 m^2. This value was determined through trial and error of various area values and by visual inspection of those results.

MatLab-based GeoNet

The MatLab-based version used a mask of building footprints to set the pixels which correspond to buildings to certain values during processing. This was done to make sure flow routing passed around the buildings and to ensure that no extracted channels crossed over buildings. The building pixels were set to NaNs during slope and curvature computations, and therefore building pixels were not erroneously identified as convergent or channelized features. However, during the flow routing procedure the elevation values for the building pixels were set to the highest elevation value in the dataset. Flow routing was then performed across the entire landscape but it circumvented the buildings. The building mask used in this analysis was derived from a shapefile of building footprints made available for Travis County by the City of Austin GIS portal (ftp://ftp.ci.austin.tx.us/GIS-Data/Regional/coa_gis.html).

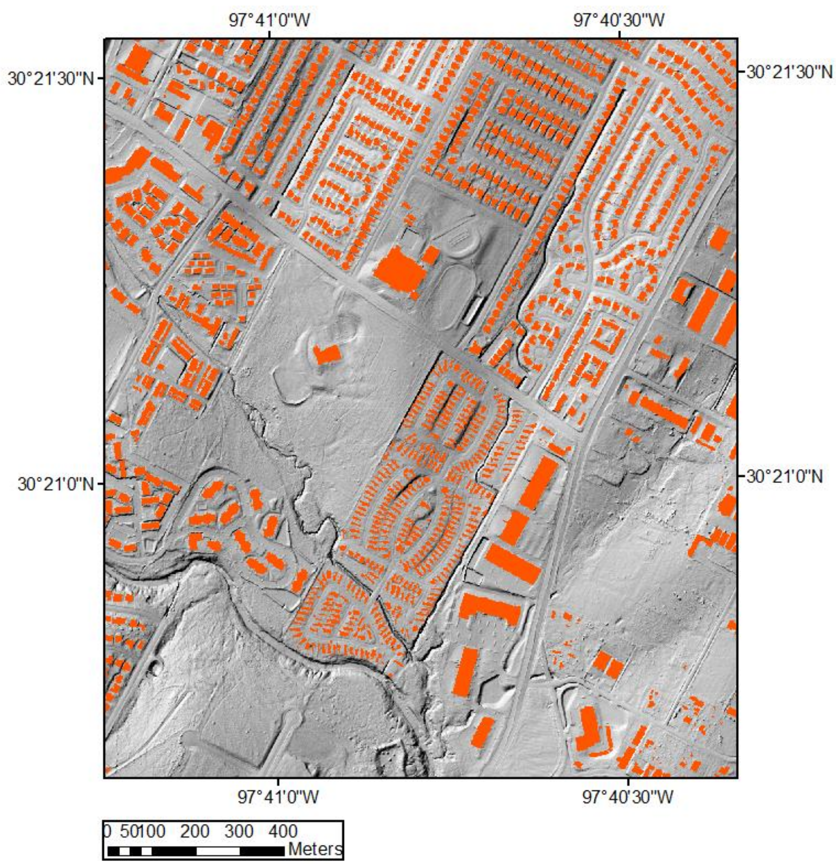

Figure 3. Building mask used in the MatLab-based GeoNet analysis.

A recent addition to the MatLab-based version of GeoNet is the use of a low pass median filter prior to the Perona-Malik filter. This was added to further filter landscapes with a significant amount of engineered features as found in an urban landscape [*Sangireddy et al.*, in review]. A low pass median filter further attenuates small-scale impulsive noise such as engineered features. The filter works via a kernel which moves across the image and sets the elevation value of the centroid pixel in the kernel to the median elevation value within the kernel. A simplified depiction of this process is shown in the following figure.

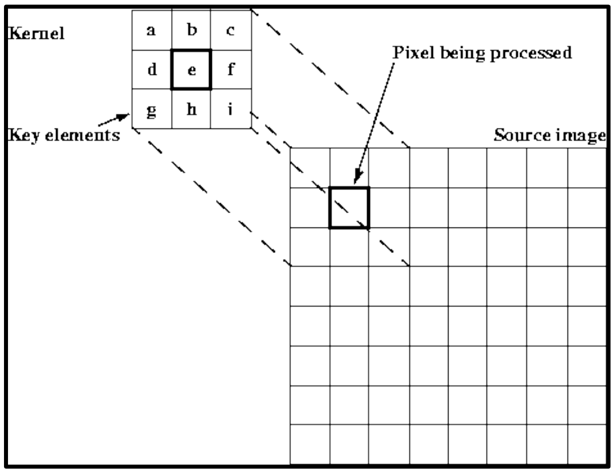

Figure 4. The median filter works via a kernel passing across the landscape and setting the centroid pixel, *e* in this example to the median of the values *a-i* within the kernel. Image source: http://www2.hs-fulda.de/caelabor/inhalte/java/j3d/j3d_seminar/19/JAI%20Guide%20von%20Sun/Image-enhance.doc.anc5.gif

The size of kernel impacts the filtering process, as too large of a kernel may smooth out important features whereas two small of a kernel may not filter out the small-scale noise to the desired degree. *Hughes et al.* (2004) suggested setting the kernel edge size to the average road width in the study area; for the urban landscape analyzed here, the average road width is approximately 16 meters. In this study, kernel edge sizes 16, 32, and 48 meters were used.

The geometric curvature computation method was used in the MatLab-based analysis instead of the Laplacian which is typically recommended for GeoNet users if the landscape of interest is relatively flat and presents engineered features [*Passalacqua et al.*, 2012]. *Sangireddy et al.*, (in review) proposed using the geometric curvature coupled with the median filter procedure, as the combination of the median and Perona-Malik filter effectively strips the landscape of anthropogenic features, and leave essentially a "natural" landscape—which the geometric curvature has been shown to perform well on.

Python-based GeoNet

The Python-based GeoNet version was used with the only the Perona-Malik filtering procedure, and both Laplacian and geometric curvature methods were tested. The Python-based GeoNet does not yet include the building mask process as described for the MatLab-based version. The 0.3 meter resolution and the 1 meter resolution DEMs of the study were run in the Python-based GeoNet. This framework uses a multi-directional flow routing algorithm available through GRASS GIS, which is more robust for analyzing large datasets (the D-infinity algorithm is used in the MatLab-based GeoNet version).

Field Work

Field work was conducted on April 16th and 17th of 2015 to observe urban flow paths within the study site during non-storm conditions and during an intense precipitation event. The two sites examined are shown in the following figure.

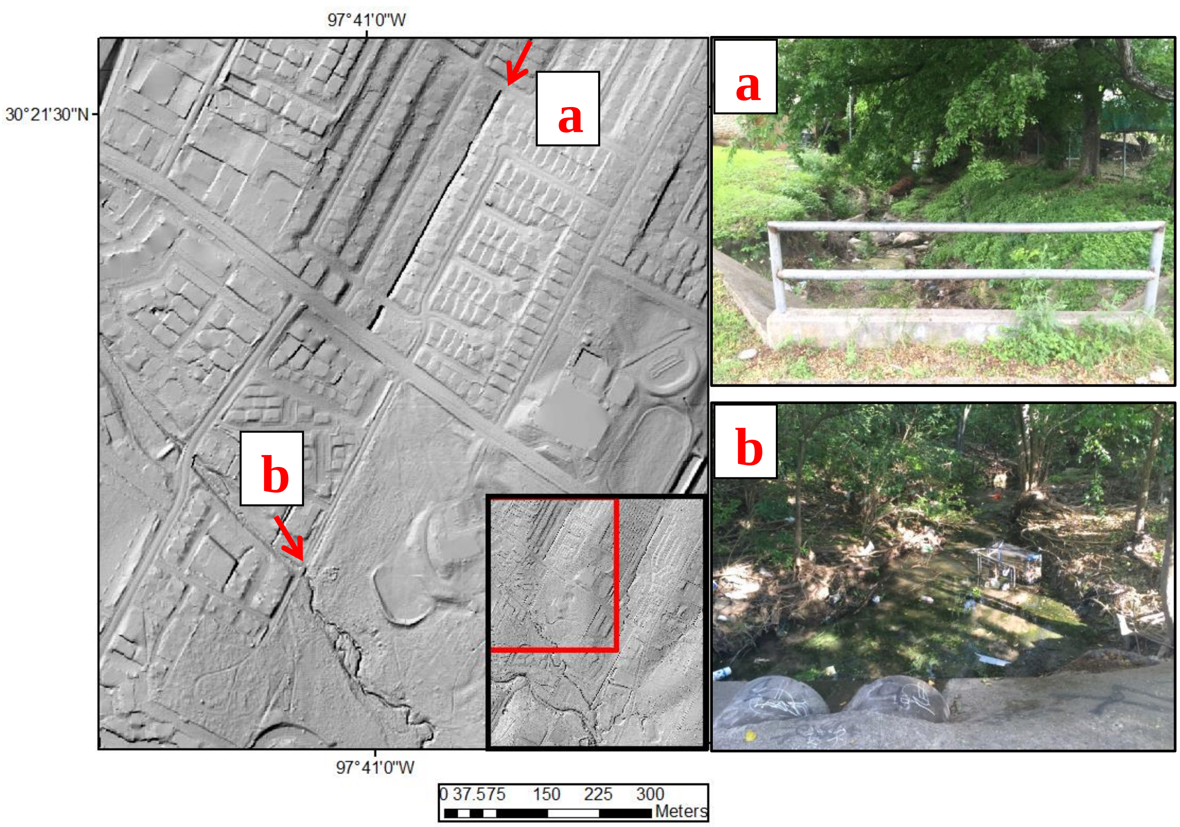

Figure 5. The locations of field sites *a* and *b* are shown in the map and the arrows indicate the view shown in the photos on the right.

Site *a* is located at the upstream extent of an engineered canal that runs between two rows of houses. Site *b* is more complex and is located at a culvert where a road crosses Walnut Creek. The following figure describes site *b* in more detail.

Figure 6. The red star is located at the road culvert over Walnut Creek and the photo is shot looking downstream. The orange moon is located upstream of the culvert where the channel narrows, and the photo is again taken looking downstream. The yellow triangle is located further upstream where the channel widens and meanders.

Results

MatLab-based results

The channel skeleton results for all three median filter kernels sizes used are shown below.

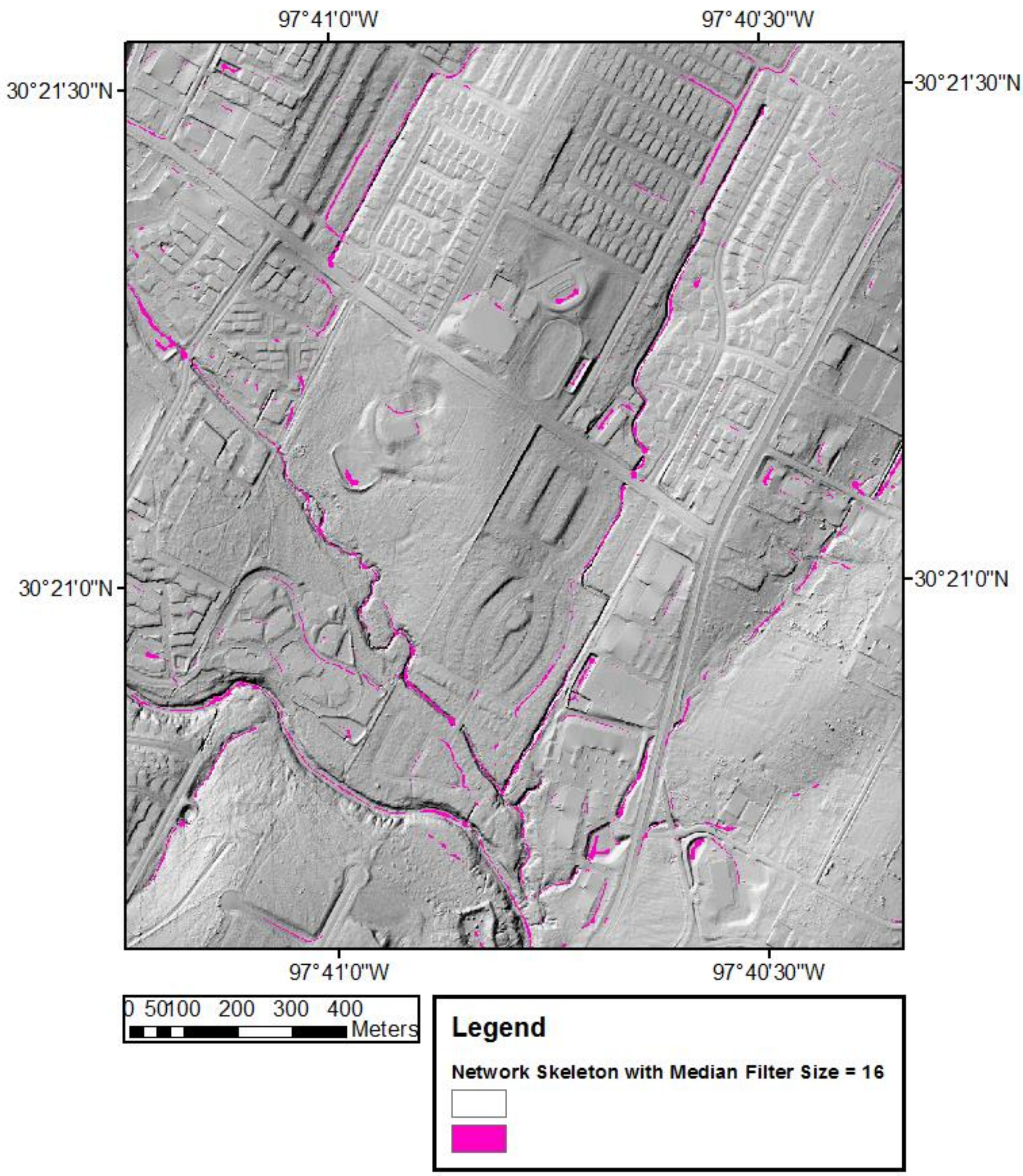

Figure 7. Channel skeleton results for median filter kernel size of 16 m (~1 road width).

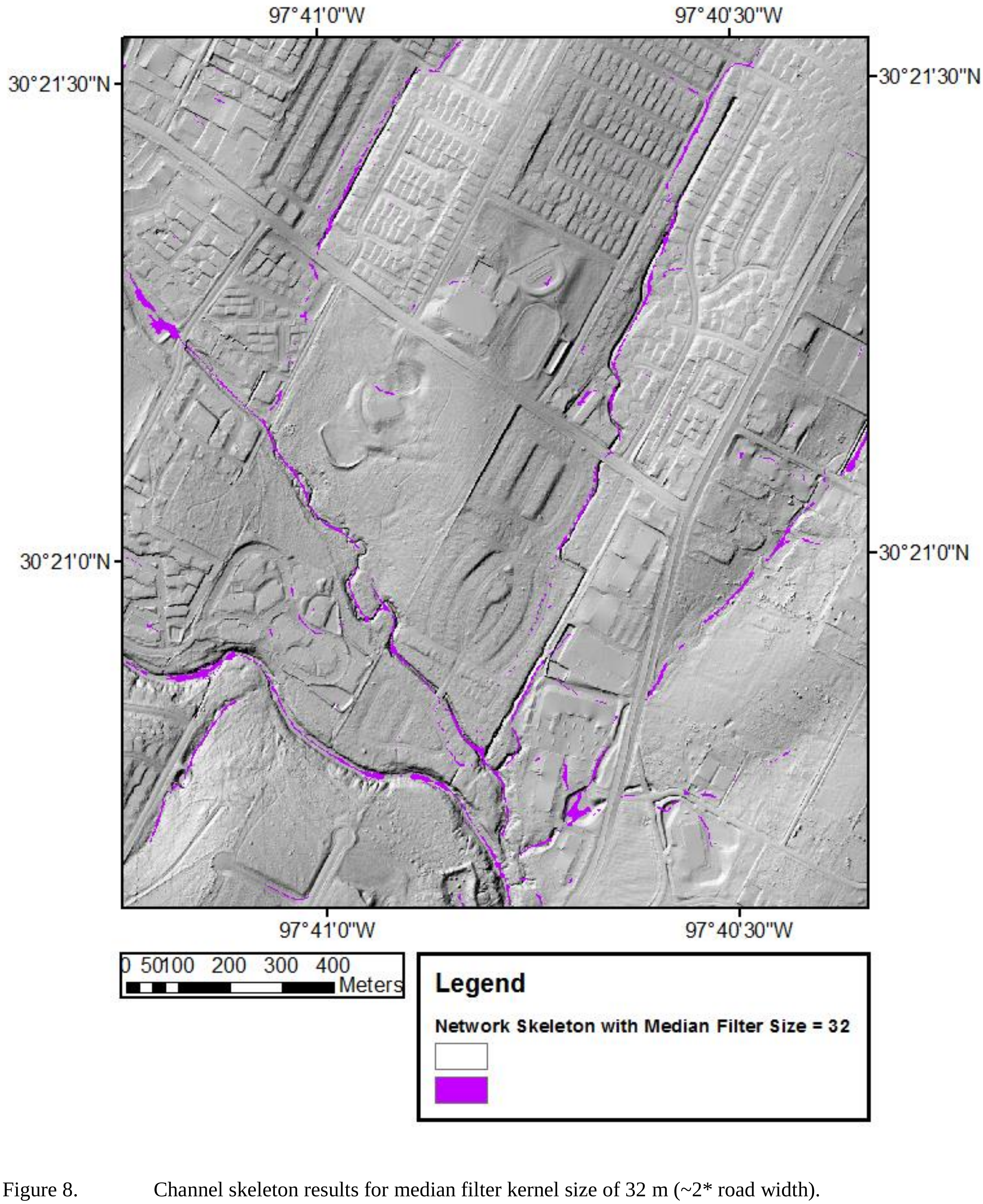

Figure 8. Channel skeleton results for median filter kernel size of 32 m (~2* road width).

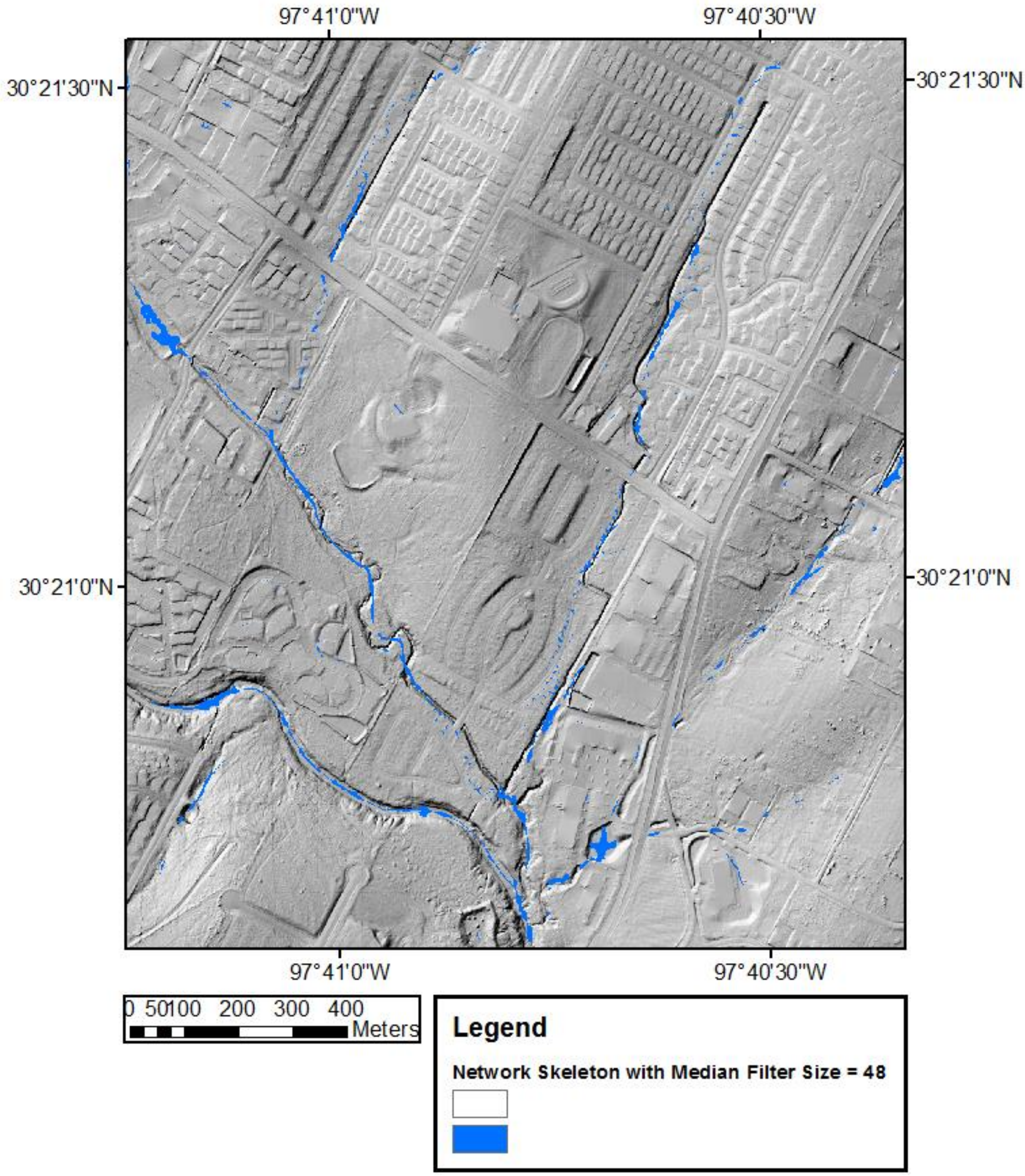

Figure 9. Channel skeleton results for median filter kernel size of 48 m (~3* road width).

As shown in the progression of Figures 7-9, the results with the largest filter kernel size of 48 m identifies most of the channel features without having many disconnected convergent pixels throughout the landscape.

Python-based results

1. 1 meter resolution DEM

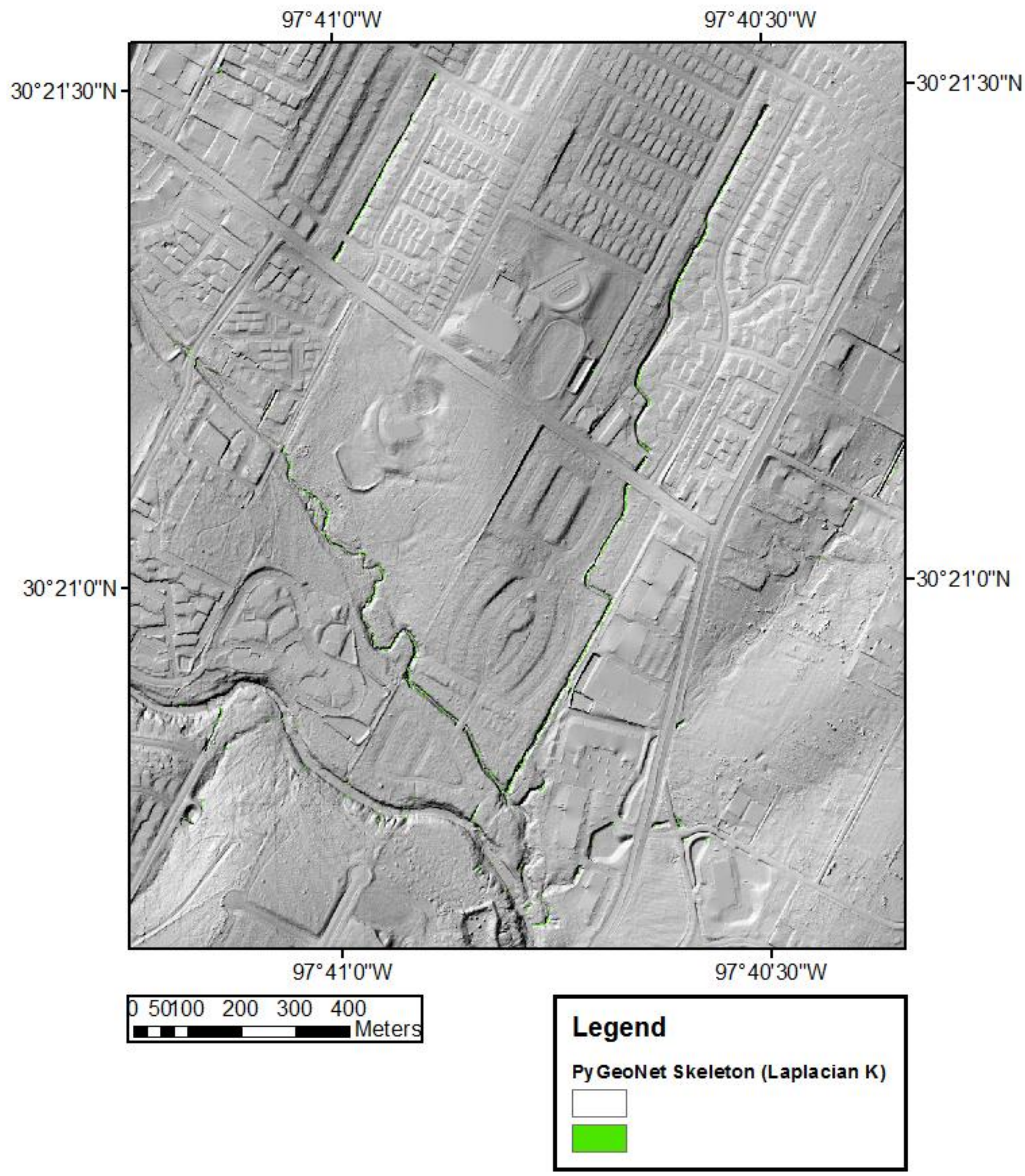

Figure 10. Python-based channel skeleton results for Laplacian curvature computation method.

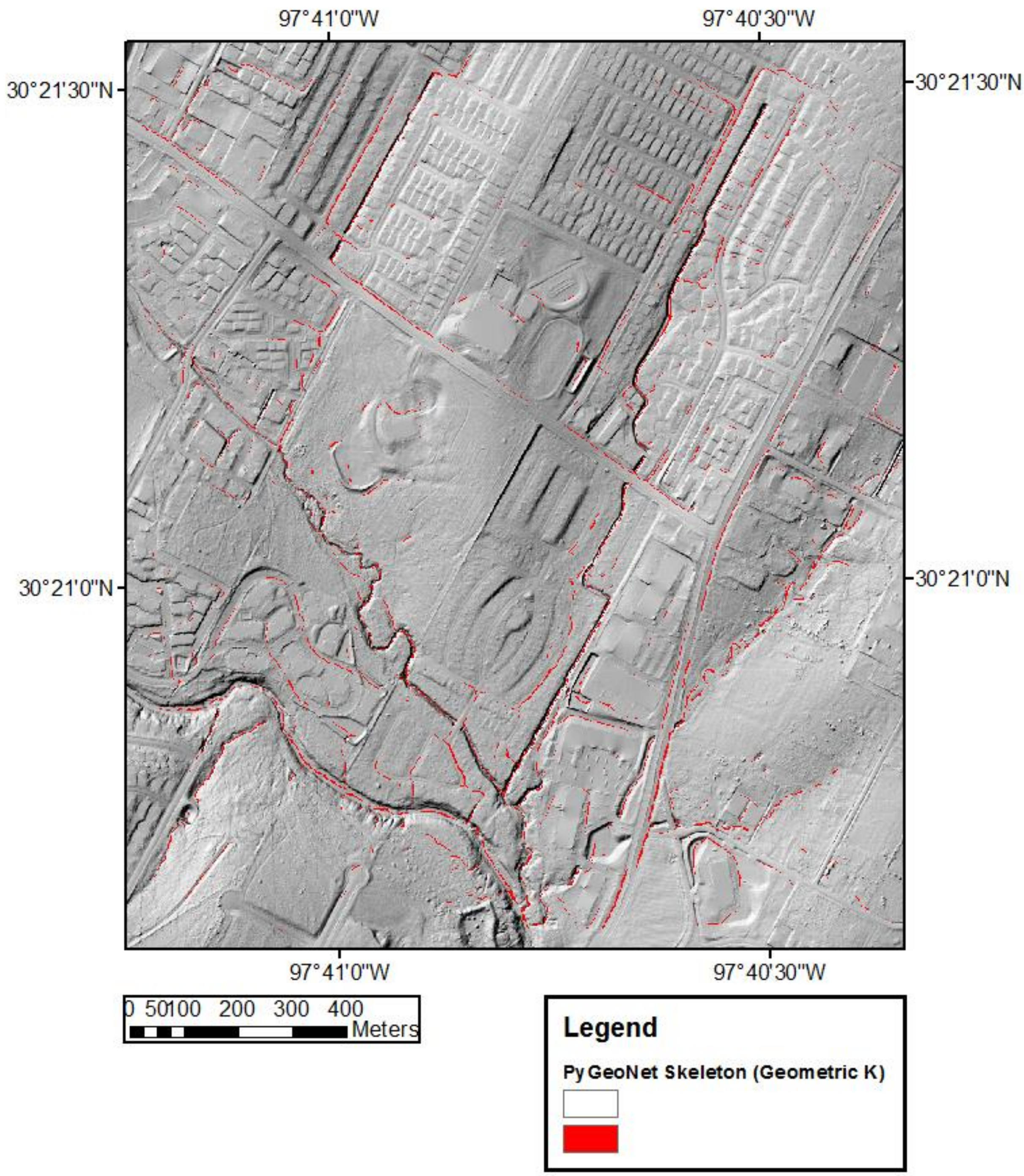

Figure 11. Python-based channel skeleton results for geometric curvature computation method.

Note that the skeleton found using the Laplacian curvature (Figure 10) is in better agreement with the majority of the channel features in comparison with the results using the geometric curvature (Figure 11).

2. 0.3 meter resolution DEM

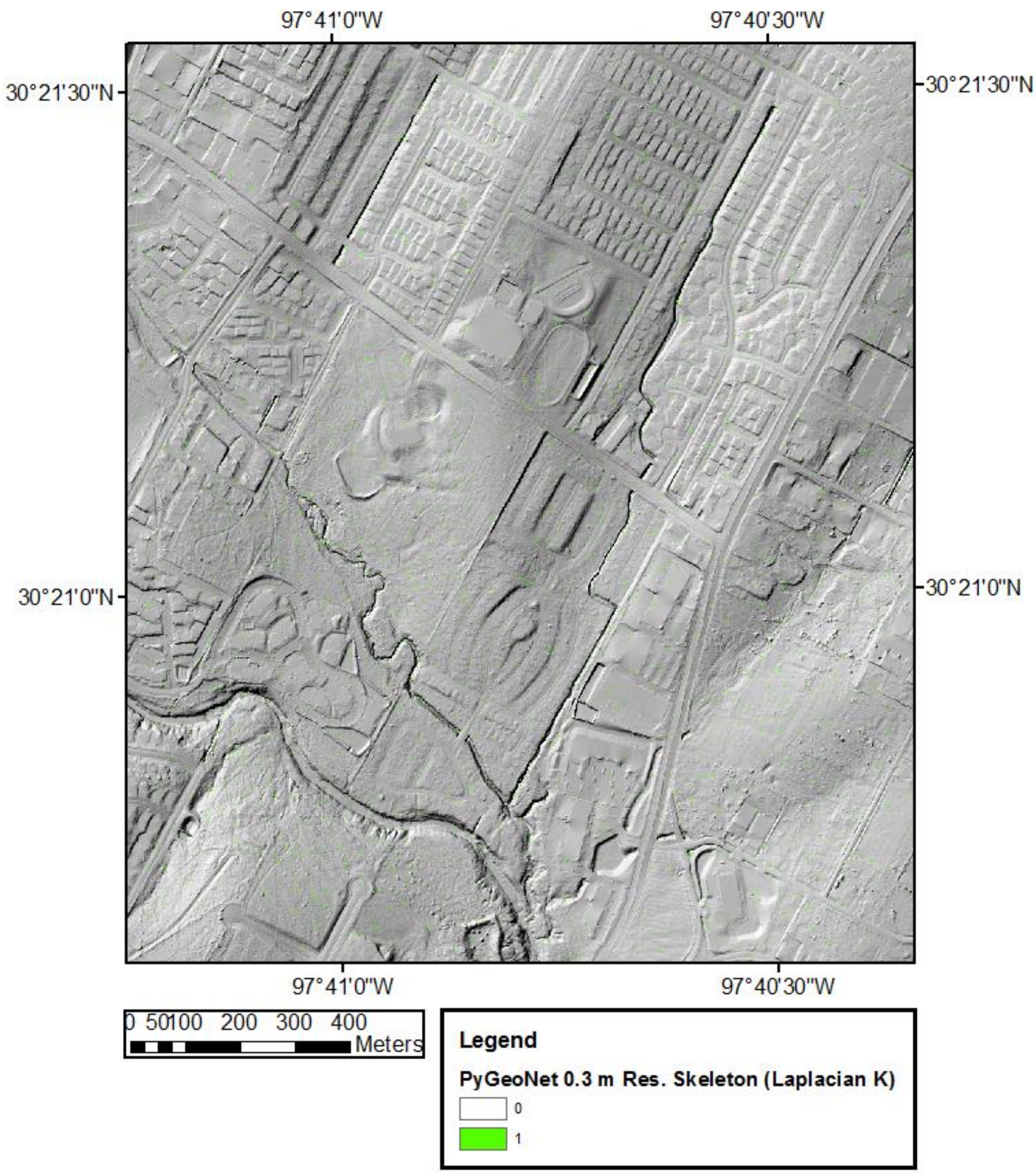

Figure 12. Python-based channel skeleton results for Laplacian curvature computation method with 0.3 m resolution DEM.

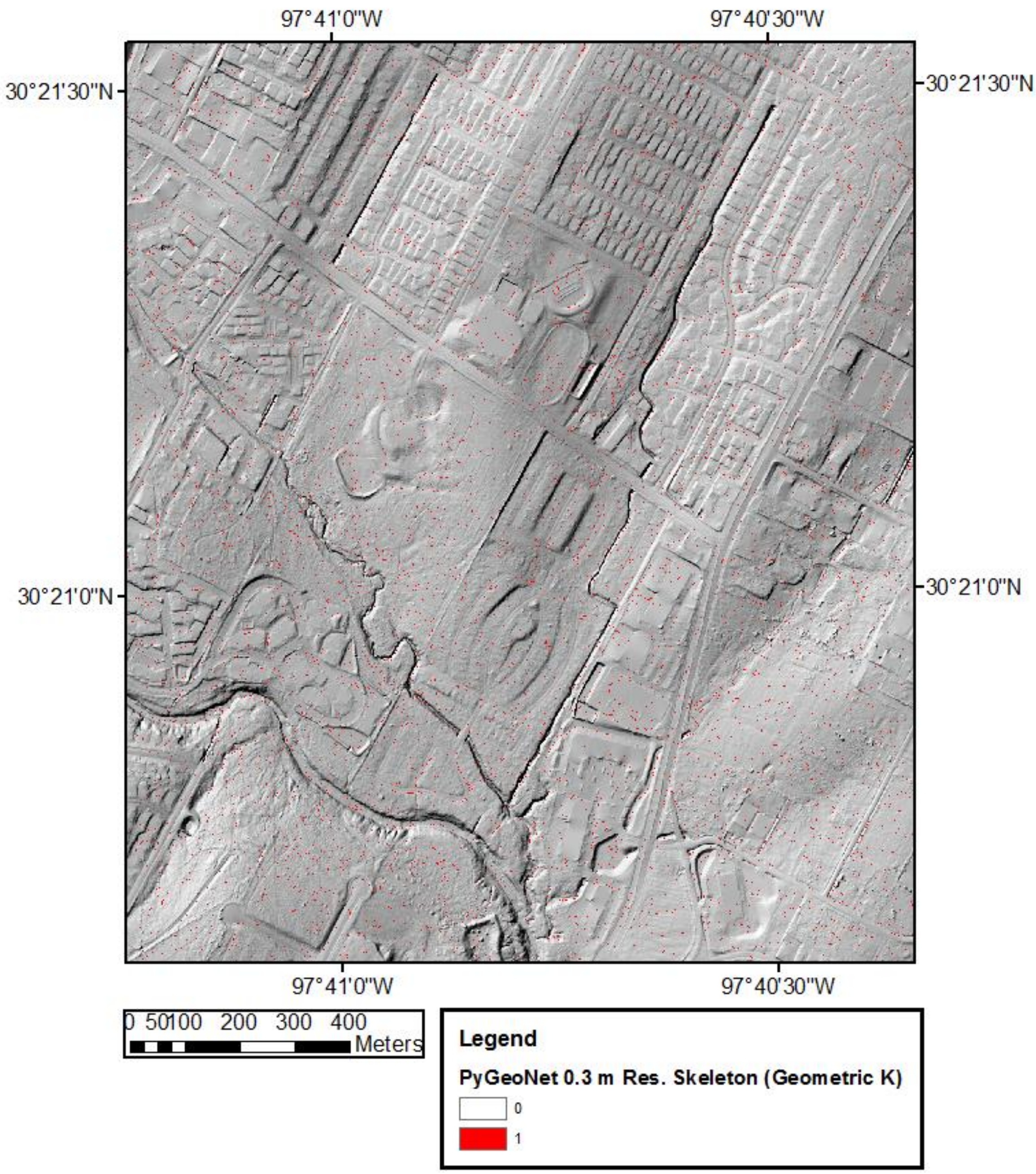

Figure 13. Python-based channel skeleton results for geomtric curvature computation method with 0.3 m resolution DEM.

The channel skeleton results from the 0.3 resolution data look very disconnected when looking at the entire data extent (Figures 12 and 13). The following figure shows a zoomed in portion of the landscape, centered at the culvert that crosses Walnut Creek for both the geometric and Laplacian curvature results.

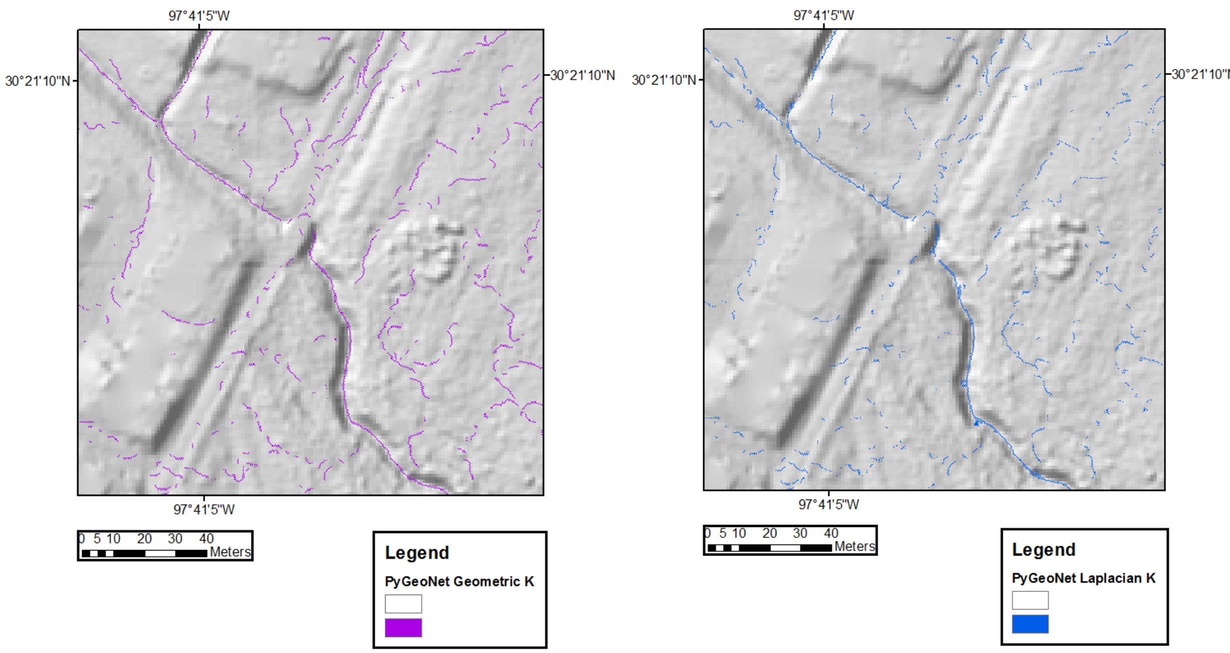

Figure 14. Channel skeleton results for 0.3 m resolution data for both curvature computation methods. This is a detailed view centered at the culvert that crosses Walnut Creek.

Discussion of Results

The results from the MatLab-based version of GeoNet indicate a kernel edge size of 3 times the road width is superior to using the road width or twice the road width. The channel skeleton in Figure 9 exhibits fewer road features integrated into the flow paths, and the channel skeleton is in good agreement with both natural and engineered channel features.

The results for the 1 meter DEM, using the Python-based GeoNet show the Laplacian curvature computation method is preferable to the geometric. The channel results for the Laplacian curvature computation method do not cross through any buildings within the dataset, even without the use of a building mask. However, there is some crossover of the channel network through the buildings using the geometric curvature computation method. This is easier to see in a more detailed view of the channel network; an example of this is show in the following figure.

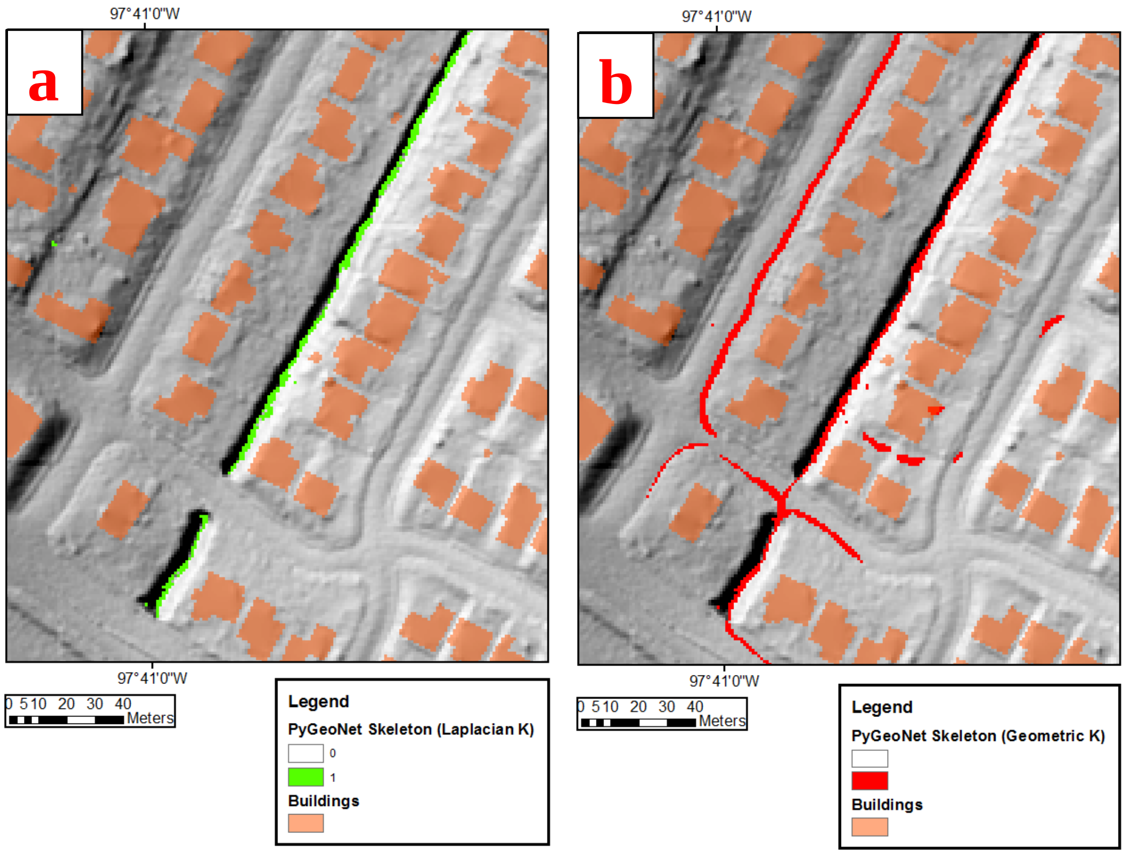

Figure 15. Python-based GeoNet channel skeletons for the 0.3 m resolution data using the Laplacian (*a*) and geometric (*b*) curvature computation methods. Note in *b* there are some locations where the channel network crosses through the buildings.

The results for the 0.3 m and 1 m DEMs indicate the Laplacian curvature computation method is preferable for the analysis of this urban landscape, due to the overall better agreement of the channel network, and the extracted channels do not cross through buildings. The Laplacian can be described as more selective in terms of which convergent features are identified as channels because it is not normalized by the slope as the geometric curvature method is. This leads to a more robust identification of channel features in the urban landscape.

Field Work Response

As mentioned previously, field work was performed during a storm event on April 17th, 2015. During this period, a flow path formed in which flow converged from the along Fiskville Cemetery Rd. with flow contributions from the cemetery south of Walnut Creek and the road between the residential area south of Walnut Creek. This storm flow path came to a confluence at the culvert over Walnut Creek, and flow from the road, Fiskville Cemetery Rd. north of the creek, and the upstream portion of Walnut Creek all converged in the downstream portion of the creek. This is further described in the figure below.

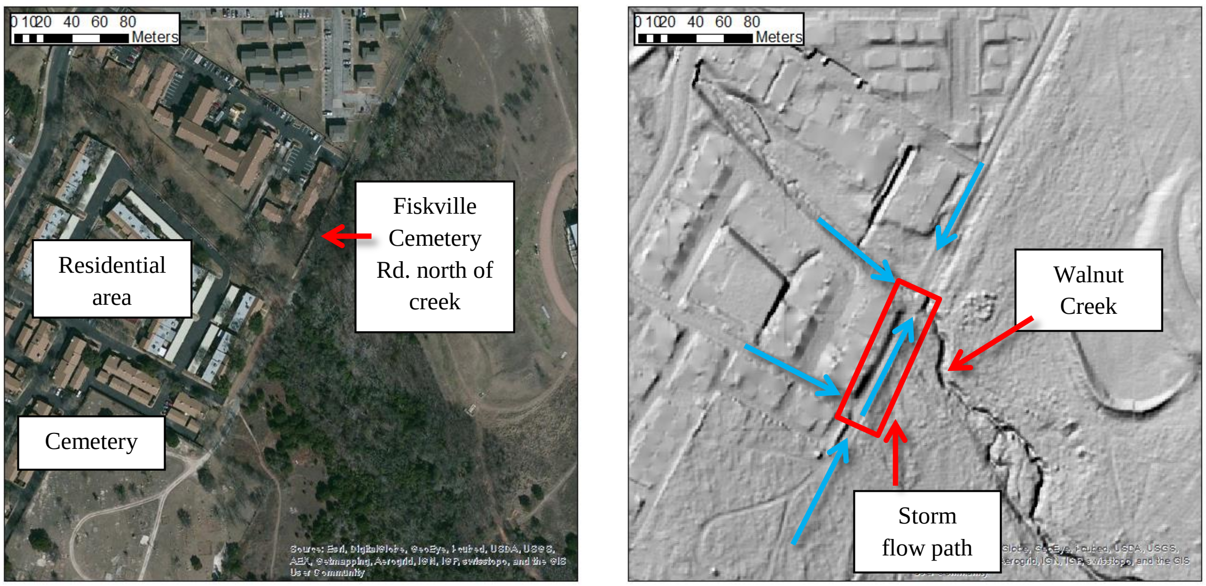

Figure 16. The red box in the hillshade on the right is where the urban flow path emerged along during the Fiskville Cemetery Rd. during the storm event. The blue arrows indicate flow contributions from the cemetery and street within the residential area which formed the flow path along the road in the red box.

The following photo shows the storm flow path taken looking NE from the intersection of the residential street and Fiskville Cemetery Rd.

Figure 17. Photo of the storm flow path with contributing flow from the cemetery (note suspended sediment in right portion) and from the residential street.

After this flow path was observed, I was interested to see if by lowering the threshold of the flow accumulation area, GeoNet would pick up the road as a flow path. Both curvature computation types were tested and the Python-based version.

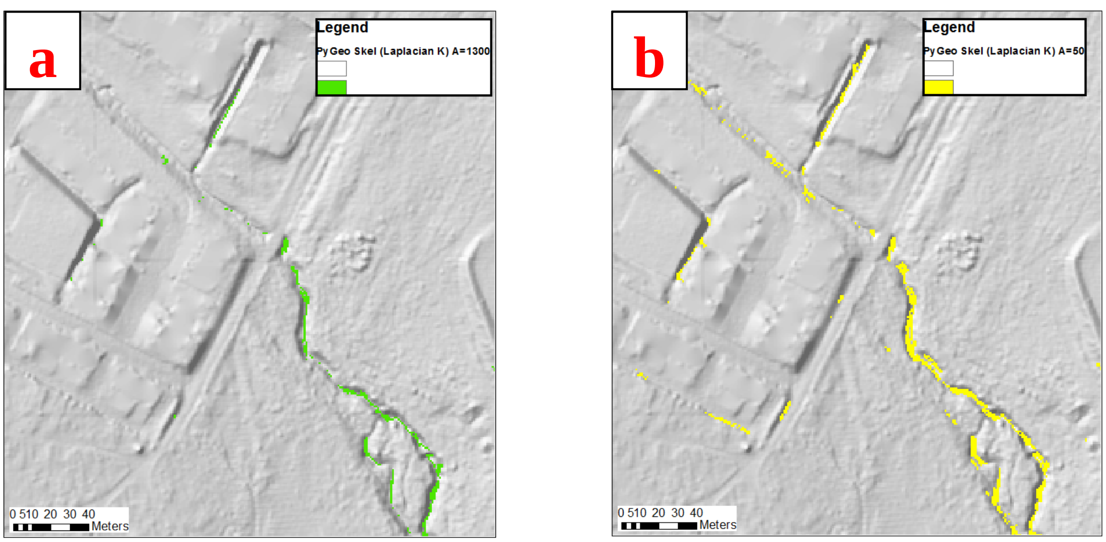

Figure 18. Python-based GeoNet channel skeletons for the 1 m resolution data using the Laplacian curvature. In (*a*) the results with the original flow accumulation area threshold of 1300 m^2 are shown, in (*b*) the results with a threshold of 50 m^2 is shown.

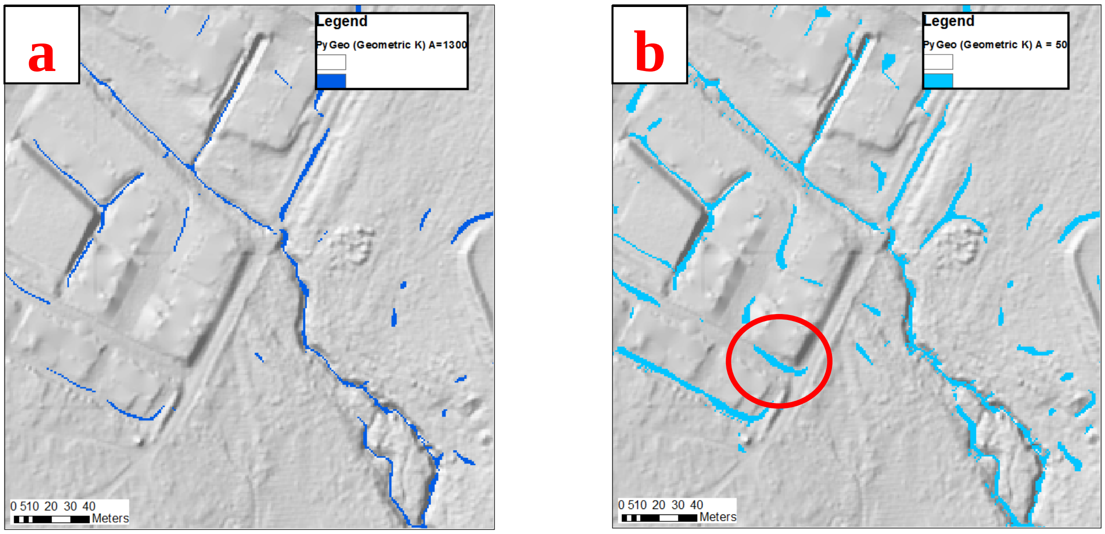

Figure 19. Python-based GeoNet channel skeletons for the 1 m resolution data using the geometric curvature. In (*a*) the results with the original flow accumulation area threshold of 1300 m^2 are shown, in (*b*) the results with a threshold of 50 m^2 is shown. The red circle highlights the flow contribution from the street in the residential area that is partially visible in the photo in Figure 17.

Although the flow path along Fiskville Cemetery Rd. is not picked up in any of these results, the image in Figure 19 showing the channel skeleton results using geometric curvature and a flow accumulation threshold of 50 m^2 does identify the flow path coming out from the residential street, as shown in the red circle.

Conclusions

The MatLab-based and the Python-based GeoNet successfully extracted urban flow paths for this landscape, though differences in the results were present. For the MatLab verison, the median filter kernel size of 48 m identified the channel features most clearly. The results from the Python-based version indicate the Laplacian curvature method performs better than the geometric, which is consistent with previous research on flat landscapes with engineered features [*Passalacqua et al.*, 2012]. The success of the MatLab-based version which uses the geometric curvature, can be attributed to the addition of the median filter which when coupled with the

Perona-Malik filter, essentially attenuates the anthropogenic noise in the landscape. Further studies should be undertaken to validate these results in other urban study sites.

The results for the 0.3 m resolution dataset do not provide a better estimate of the channel network in comparison with the results from the 1 m resolution data. Data of this resolution may be better suited in an analysis of smaller-scale urban flow paths along urban roadways, culverts, and drains. The ability for the algorithm to identify very small convergent features in the urban landscape may enable new opportunities for detailed analysis in urban flooding applications.

Another promising direction for further research using GeoNet is to adjust certain parameters in the algorithm in order to detect ephemeral storm flow paths that appear during flood events. The adjustment of the flow accumulation area threshold in this study was not entirely successful in detecting the flow path that was observed in the field, but this parameter would be a good starting point for further research.

GeoNet is capable of supporting the NFIE framework by identifying flow paths in urban landscapes from high resolution topography data. Both natural and engineered channel features can be extracted from DEMs of 1 meter resolution. More work is necessary to fully utilize data of higher resolution, and future work should also focus on adjusting parameters within the algorithm in order to identify storm-induced flow paths.

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