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Extraction of Previously Unmapped Headwater Streams from LiDAR in New Hampshire

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The New Hampshire Geological Survey proposed to develop a methodology to utilize high resolution topographic data to update existing mapped streams (hydrography) and map out additional streams to better reflect the number of streams actually present on the ground. High resolution digital elevation models (DEM) derived from airborne Light Detection and Ranging (LiDAR) data have recently been acquired for portions of New Hampshire. One dataset covers the Seacoast region of the state, which is characterized by high population growth (relative to the rest of the state) and low topographic relief. Additional data collection took place in the White Mountain National Forest, which is characterized by low population density, dense forest cover and high topographic relief (Figure 1). A number of potential methods were tested before the BotHat method of Cho et al 2011 was ultimately selected. The resulting stream networks were then field checked.

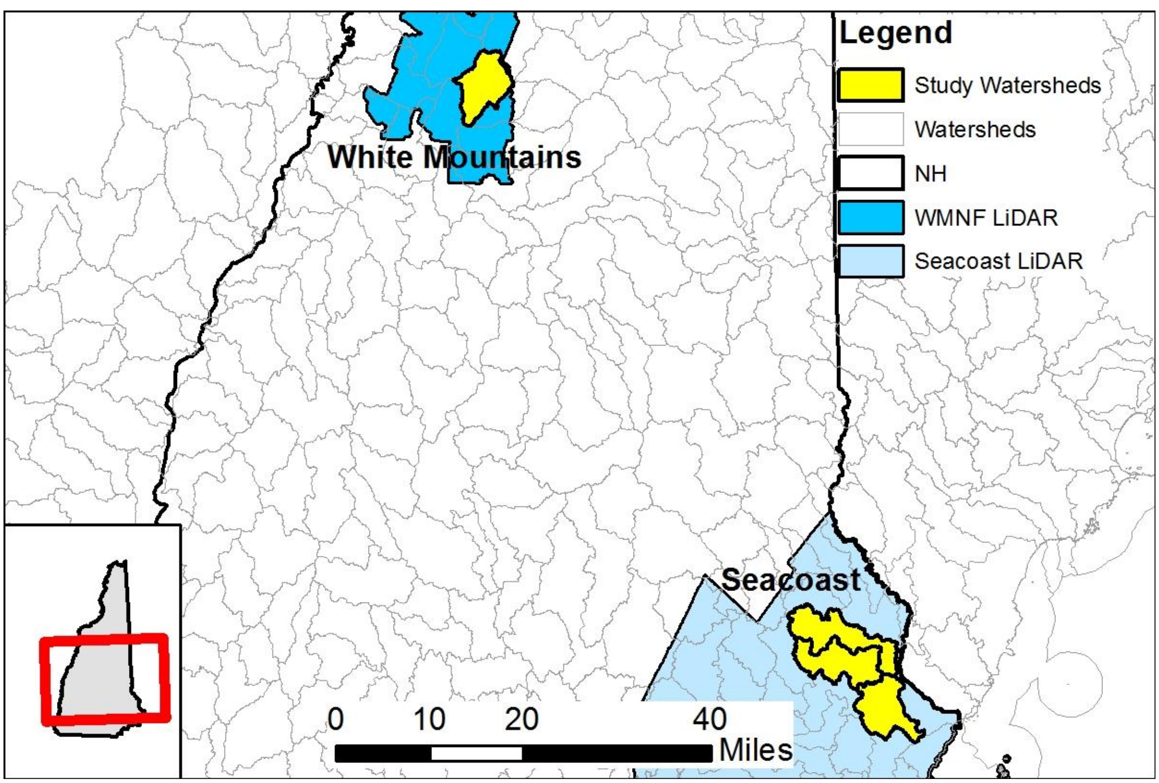

Figure 1. Study area

The National Hydrography Dataset (NHD) has been shown to under-represent the full extent of the stream network that is on the ground (Colson et al., 2008, Brooks and Colburn 2011). A number of motivations for accurately representing the ground condition of streams exist. Biological scientists are interested in potential habitat and nutrient cycling in these small headwater streams. Hydrologists are interested in these small headwater streams for the role that they play in flood routing. Road managers already know where these streams are located, because culverts are placed at existing crossings, but there has not been a systematic accounting of their occurrence or any determination on whether the culverts are appropriately sized for the associated streams.

In order to assess the need for LiDAR updating, a comparison was made with the existing NHD mapped streams. Based on the stated accuracy for the NHD, 95 percent of streams should fall within 40 feet of their true ground location. Following the methods of Poppenga et al 2013, a buffer of 40 feet was drawn on the NHD streams, and the headwater points of the NHD were used as initiation points that were traced downstream on the LiDAR DEM using standard D8 flow accumulation Geographic Information System (GIS) methods (Figure 2). In the seacoast area, 43 percent of NHD streams were found to be greater than 40ft from the corresponding LiDAR stream. In the White Mountain region, 23 percent of the NHD streams were outside of the specified range.

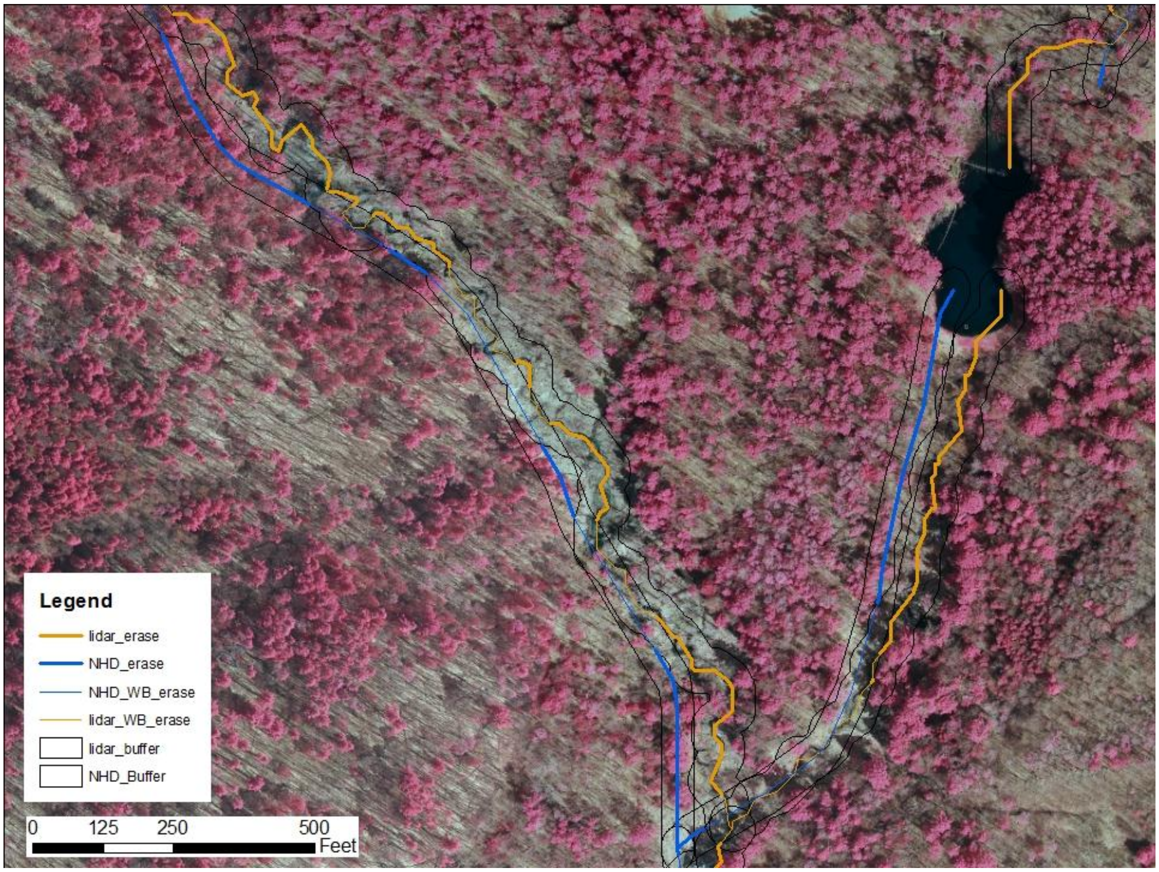

Figure 2. Results of buffer analysis. Orange lines show areas where the streams are outside of the 40ft buffer.

Other state stewards of the NHD have updated their hydrography using a number of methods. For a detailed review of the use of high resolution topographic data see, Lopez-Torrijos 2013. The most basic method for updating involves the use of LiDAR DEMs or hillshades, in combination with high resolution aerial imagery to manually draw streams on-screen. Because of the large commitment of time required and the variability of editor interpretations, we chose not to use this method. The traditional flow-accumulation method has also been implemented, based on the assumption of a relatively constant drainage area threshold for channel initiation. This method was dismissed due to the fact that it often under- or over-estimates the headward extent of streams. While it is true that flow accumulation (or drainage area) is a major driver in the formation of stream channels, many other factors such as land cover, subsurface materials, and slope all contribute to variations around a mean drainage area initiation point. Other methods for the identification of streams utilize the actual surface expression of the stream channel. Curvature (the second derivative of elevation) is one geomorphometric property that has been used to identify stream channels and represents the driving factor in the GeoNET program by Passalaqua et al (2010). The original proposal for the current project cited this method as a promising candidate to be fully explored. However, experimentation revealed shortcomings in its performance, ranging from the limited size of the area that could be processed at one time to difficulties in properly connecting areas of high curvature. Therefore, the method was deemed to be inappropriate for our application.

The method that was ultimately implemented for this project was the BotHat method of Cho et al. The BotHat is a type of morphological filter which is well established as an image processing technique to find local minima in an image (or in this case a DEM). A few initial test cases demonstrated that the method was able to accurately connect the features of interest. During the course of this project, the method outlined by Cho et al. was slightly modified, but the basic function of the BotHat remained the same. The original DEM is analyzed for the maximum value in a moving window of specified dimension (dilation). The minimum of this result then is taken (erosion). Lastly, the result of this operation is subtracted from the original DEM to yield the final BotHat image as given by equation 1:

$$h = ((I \circ e) \bullet e) - I \qquad \text{(Equation 1)}$$

where h is the BotHat filtered image, I is the original image, e is the structuring element or analysis window, dilation is ° and erosion is • . The basic operation is shown graphically in figure 3 with a simplified DEM.

7	6	5	6	7
6	5	4	5	6
5	4	3	4	5
4	3	2	3	4
3	2	1	2	3

A

7	7	6	7	7
7	7	6	7	7
6	6	5	6	6
5	5	4	5	5
4	4	3	4	4

B

7	6	6	6	7
6	5	5	5	6
5	4	4	4	5
4	3	3	3	4
4	3	3	3	4

C

0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
1	1	2	1	1

D

Figure 3. From left to right, the original DEM, dilation, closing and then BotHat image.

A multi-scale approach was adopted to support detection of features that differed in size and extent. This was accomplished by expanding the BotHat window (kernel) from 3x3 to 11x11.

The basic outline of the method is as follows: (Figure 4)

1. DEM was clipped by watershed (Hydrologic Unit Code [HUC] 12) and filtered using a low pass filter (Figure 4 A) to minimize noise in the elevation values

2. BotHat was performed on a 3x3 window.

3. Values exceeding a threshold equal to 1 standard deviation above the mean value for the BotHat image were identified and converted to 1's. All other values were converted to 0's to create a binary image. (Figure 4 B)

4. BotHat was performed on an 11x11 window.

5. Values exceeding a threshold equal to 1 standard deviation above the mean value for the BotHat image were identified and converted to 1's (as in Step 3). All other values were converted to 0's to create a binary layer (Figure 4 C)

6. The two binary images were intersected to identify all cells that exceeded the respective threshold for each kernel size and the results were converted to another binary image. (Figure 4 D)

7. Contiguous 1-valued cells were identified as discrete groups and a statistical analysis of the population of resulting groups was performed to determine the mean size (number of cells) and standard deviation of all groups. A threshold was set at 2 times the standard deviation above the mean and all groups below the threshold were eliminated. The results were converted to a binary image.(Figure 4 E)

8. Flow accumulation was performed and cells with values greater than 500 were converted to 1's while all other cells were converted to 0's.

9. The binary image from Step 8 (threshold flow accumulation) was intersected with the binary image from Step 6 (threshold BotHat) to create a set of seed points from which to generate flow paths.

10. Perform a weighted flow accumulation of this image to connect all of the seed points along individual flow paths, and then convert the results to a stream layer. (Figure 4 F)

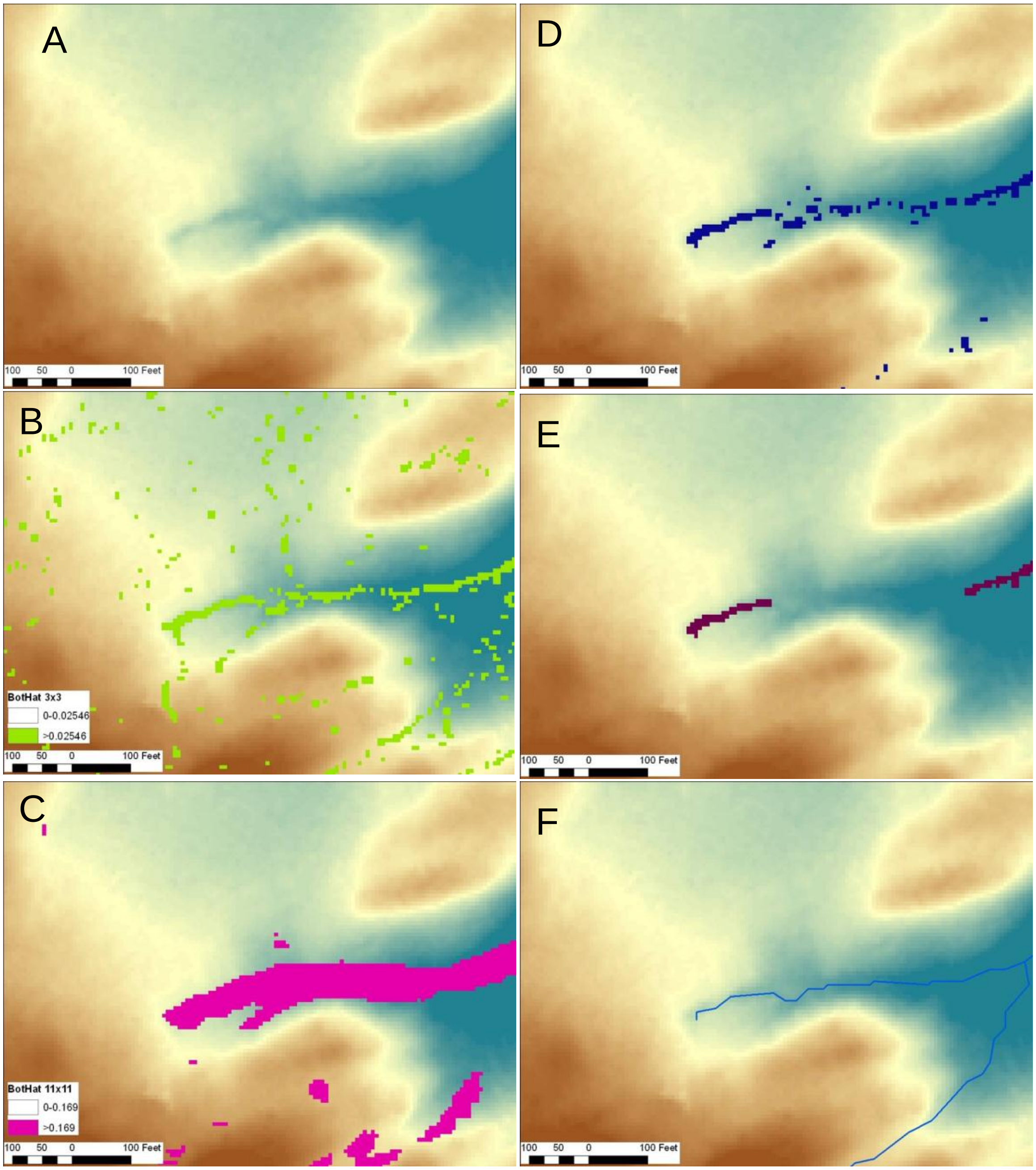

Figure 4. Step-by-step process outlined in text, showing some of the intermediary data layers.

Thresholds

A number of steps in the work flow require the use of threshold values to refine the population of target cells for subsequent processing. Presumably those values should be optimized for differences in topographic relief and roughness inherent in filtered elevation datasets for different geographic areas (i.e., Seacoast region versus White Mountains) as wells as the scale of the target features. A goal of this project, however, was to develop a method that was as automated and free of subjectivity as possible. Although the results for any given area could potentially be refined through exhaustive trial-and-error testing of site-specific threshold values, such an approach was avoided in order to make the entire work flow more efficient and reproducible. For this reason, thresholds were based on the statistical properties of the input images at different stages of the analysis (Step 3, Step 5, and Step 7), namely positive exceedance of the population mean by a multiple of the standard deviation. The initial processing was done in the Seacoast region, and two different threshold values (1 standard deviation or 2 standard deviations above the mean) were chosen as a starting point. During initial exploration of the dataset, it was found that displaying the BotHat layer by 1 standard deviation did a good job of highlighting the channel/valley features, and so this approach was used as an initial starting point for thresholding the original BotHat layer.

The flow accumulation threshold of 500 cells (Step 8) was based on a cursory visual inspection of the dataset using 1 foot aerial imagery that seemed to indicate that this was a minimum amount a flow accumulation needed to initiate channel formation. A majority of streams initiated at higher thresholds, but the minimum threshold was chosen so as not to exclude the smallest of headwater streams. Even after filtering and overlaying the BotHat layers, some number of isolated false positive cells remained. The data exhibited a non-normal distribution, with a large number of small, isolated pixels and an increasingly diminishing number of large, connected pixels. The threshold on the grouping results (Step 7) was chosen to be consistent with the thresholding method of the original BotHat layer. Two different thresholds were created, one at 1 standard deviation and one at 2 standard deviations, and then the results were checked for accuracy in the field.

DEM resolutions

Because of different specifications and timing of LiDAR data collection in the Seacoast region and the White Mountain, the resulting DEMs had different resolutions. The White Mountain dataset is a 1-meter ground surface dataset, as opposed to the Seacoast dataset which is a 2-meter dataset. In order to evaluate the potential effects caused by the different DEM resolutions, the methods developed in the Seacoast area were applied to the original White Mountain dataset and to a re-sampled 2-meter version of the dataset. Only the second, higher threshold developed in the Seacoast was applied here since it was found to produce more accurate results. Both extracted networks were then field checked.

Run times

Work was performed through python scripting in Python 2.7.5, utilizing ArcPy in ESRI 10.1, with a Windows 7 machine equipped with 4GB RAM and Intel Core2 Duo 3.0 GHz processor. The run time for a given HUC 12 was between 31 minutes and 2 hours 35 minutes with a mean time of 1 hour 10 minutes and a median time of 52 minutes.

Field Work

In the Seacoast region, the two threshold methods were used to extract two different networks and random points were created along these networks. In addition, a network was created based solely on a 500 cell flow accumulation threshold applied to the original DEM. This served to evaluate how much the accuracy of extraction results was improved by application of the BotHat method compared to flow accumulation alone. Each site was located using a handheld GPS and a photograph was taken. The site was scored on a scale of 0 to 4, as follows:

0= No water

1= Water in pools only

2= Water present, no flow

3= Interstitial flow

4= Continuous flowing water

A total of 80 sites were visited in the Seacoast region between December 2011 and January 2012. The White Mountain sites were located along the BotHat derived 1 meter and 2 meter DEM networks, but not along the flow accumulation only network. A total of 37 sites were visited in the White Mountain area between August 2013 and October 15, 2013. No significant rainfall was observed within the 7 days preceding field work.

Permanence

Although the project focused on the spatial distribution of the extracted streams, the temporal charcteristics of flow in these headwater streams was also of interest. A number of sensors were deployed in stream channels to log the presence/absence of water, allowing time intervals when water is flowing to be measured. Nine sites were equipped with monitoring equipment as outline by Bhamjee and Lindsay (2011) and monitored between August 2013 and December 2013. The percentage of time that the sites were flowing ranged between 19 and 100, with a mean of 52 and a median of 41percent. Although USGS standards do not tie permanence characteristics to hard and fast percentages (NHD feature catalog USGS 2009), these streams could be classified as either “ephemeral” (flowing for only part of the year only after rain storms or snowmelt), “intermittent” (flowing for only part of the year, but more than just after rainstorms and at snowmelt) or “perennial” (flowing all year unless under extreme drought conditions). Based on the results for this period of record, none of the streams monitored fit the definition for “ephemeral” (contains water only during or after a local rainstorm or heavy snowmelt). The results from sites A-03 and B-01 show the difficulty in using flow accumulation alone as a proxy for flow. A-03 and B-01 are located only 200m apart and have flow accumulations of 180,224 m^2 and 172,220 m^2, respectively. Despite these similarities, site A-03 was only flowing for 23 percent of the time while B-01 was flowing for 89 percent of the time. When percent of time flowing is plotted against upstream flow accumulation area of all the sites, the resulting scatter plot indicates no apparent correlation between the two variables (figure 5). Clearly, other first order controls, such as the water storage capacity of subsurface materials and the configuration of the underlying bedrock surface relative to the surface topography are drivers of stream permanence.

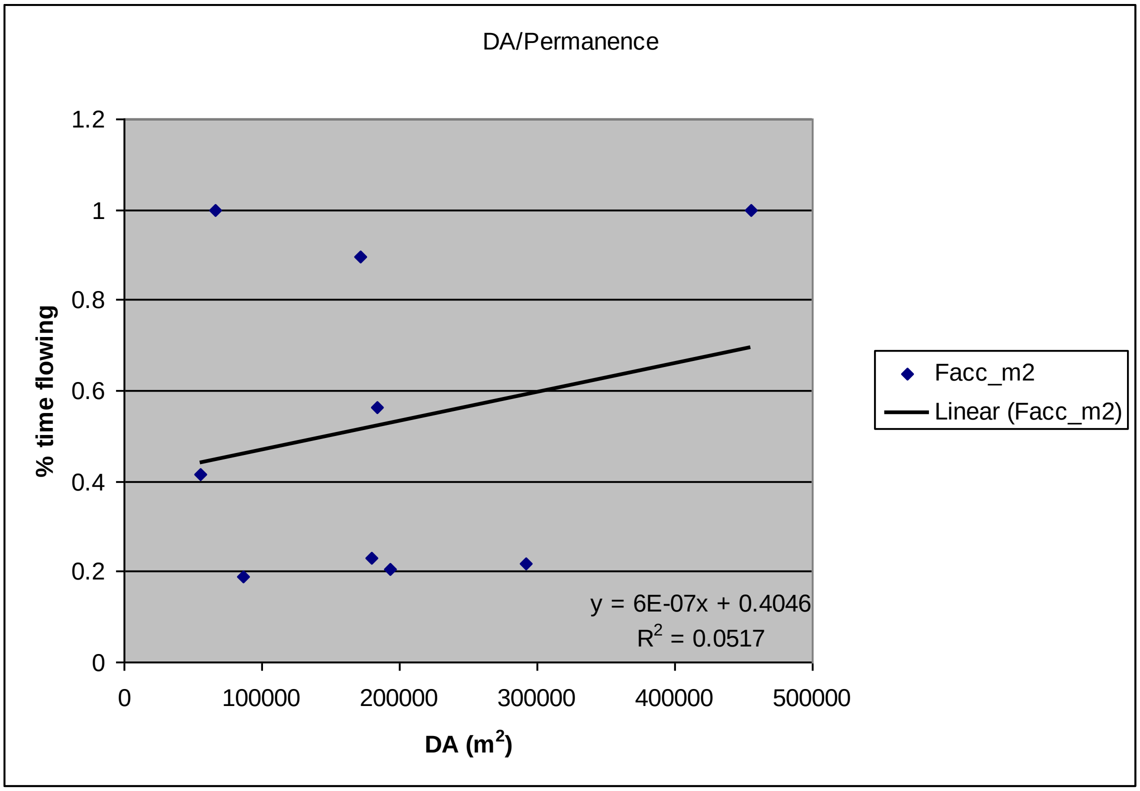

Figure 5. Lack of correlation between the percent of time a site is flowing and the drainage area.

Hydro-enforcement

Hydro-enforcement is the process of removing spurious pits and blockages that prevent the modeled flow of water from moving freely downslope across the DEM surface. The increased detail in high resolution DEMs derive from LiDAR data sources and the retention of road elevations at cells corresponding to stream crossings creates a blockage each time a stream goes through a culvert. After an initial run, it became apparent that there was a problem with blockages caused by roads and other anthropogenic features that affected the performance of the flow accumulation algorithm by creating unrealistic flow paths in the proximity of culverts and bridges. Hydro-enforcement was implemented in an iterative manner. First the locations where the pre-existing NHD intersected the road network were examined to determine if there was a blockage caused by the DEM. If it was, a line was drawn from the upstream to the downstream part of the blockage. These lines were then used for zonal statistics, in which the minimum value of the DEM was extracted to the entire line. The resulting grid was then mosaiced back to the original DEM, replacing the original DEM values with the minimum values. This modified DEM was then used to extract the higher resolution network. At this time, another intersection between the stream network and the road network was performed. Each intersection site was inspected to see if damming was occurring (evidenced by parallel flow lines and other straightening of the flowline or a shift in the flowline position so that it crossed at another location) and if the crossing was being forced to a different location due to the damming. Elevations were then adjusted in the same manner as above to re-enforce the DEM. A total of 478 crossings were identified in the Seacoast area, and a total of 114 crossings were identified in the White Mountain area. Although some effort was focused on attempting to implement an efficient version of the automated breaching algorithm outlined in Poppenga et al. 2010, a satisfactory implementation had not been achieved at the time of writing. Automation of the flow enforcement would be an ideal next step, as this represents one of the more labor-intensive steps in the process.

Pruning

Inspection of the stream network revealed that there were some very short sections of extracted channel that resulted from the seed areas being wider than 1 pixel. In order to remove these spurious segments, the following process was implemented:

1: To Node summarized as a table

2: From Node summarized as a table

3: A relation between the To Node codes and the From Node codes

4: A relation between the From Node code and the stream reaches

5: Switch of the selection

6: Sort these selected features by length and delete the reaches that are less than 30.4 meters.

The length requirement was picked somewhat arbitrarily, but 30.4 meters (100ft) seemed to be the lower limit of a true reach. Inspection of the histogram of stream lengths indicated that this cutoff represented some kind of break point in lengths, but no formal analysis was performed. Overall, the percentage of total length pruned from the results was less than 2 percent of the total stream length (table 1).

HUC12	010600030902	010600030903	0106000030904	010700010202
Prune length (meters)	6285	5052	4249	4988
Total length (meters)	303258	346869	287005	262575
% pruned	2	1.4	1.5	1.9

Table 1. Summary of length of features pruned.

Results

The 28 Seacoast field-check sites (figure 6) that were predicted to be streams based on the final analysis using the 2 standard deviations threshold (in Steps 7) had an average score of 3.18. A score of 4 (Continuous flowing water) was recorded for 53.57 percent of the sites, and only 7.14 percent scored 0 (No water). The 46 field-check sites on the network derived from the 1 standard deviation grouping threshold (Step 7) had an average score of 2.87. A score of 4 was recorded for 43.48 percent of the sites, while only 10.87 percent scored a 0. However, if sites that were also predicted by the 2 standard deviation extraction are excluded so that the focus is only on the 18 headwater 1 standard deviation sites, the average score decreases to 2.33 (27.78 percent with scores of 4 and 16.67 percent with score of 0). The random flow accumulation network that was used as a test for errors of omission had an average score of 1 (Water in pools only). Of the 34 sites, 2.94 percent were recorded with scores of 4 and 47.05 percent scored 0. In the preceding analysis, the presence of 0 scores represents an error of commission or a false positive, while sites with scores of 4 in lower threshold (1 standard deviation in Step 7) network represent errors of omission or false negatives in the higher threshold (2 standard deviations in Step 7) network.

In the White Mountain area, only the best performing thresholds from the Seacoast were used, and applied to a 1 meter native DEM and a 2 meter resampled DEM. With the native 1 meter DEM, the average score was 2.21, and 31.58 percent of the sites scored a 4 while 31.58 percent of sites scored a 0 (total of 19 sites). With the resampled 2 meter DEM, the average score was 3.44, with 83.33 percent of sites scoring a 4 and 11.11 percent of sites scoring a 0 (total of 18 sites).

Another means of calculating under-prediction, or errors of omission, is comparing the results of the extracted stream to reaches in the NHD. In the White Mountain area, all NHD reaches were represented at least in part by extracted streams. In the Seacoast region, 10 km worth of NHD streams, distributed between 13 reaches, were not represented by the extracted network. This is compared to 298 km total NHD length in the Seacoast region, distributed between 293 reaches.

Drainage density is a measure of stream length per unit area, which is a useful way of comparing lengths of streams in different watersheds. The drainage density increased significantly for all HUCS. The original densities and the densities for some of the thresholds are provided in the table 2 below.

HUC12	010600030902	010600030903	0106000030904		010700010202
NHD drainage density (mi/mi^2)	2.06	2.06	1.86	NHD drainage density (mi/mi^2)	2.01
1 SD drainage density (mi/mi^2)	8.67	9.03	8.66	1m grid DEM drainage density (mi/mi^2)	12.95
2 SD drainage density (mi/mi^2)	6.15	6.36	6.17	2 m gird DEM drainage density (mi/mi^2)	5.89

Table 2. Drainage densities (mi/mi2) for each study site.

Discussion

The perfect algorithm for identifying unmapped streams based on analysis of high resolution topographic data is extremely challenging to develop. If the threshold for detection is set too high, then some streams will be missed. If the threshold is set too low, then some features will erroneously be predicted as streams where no channels exist. The advantage of the method outlined here is that it at least accommodates the possibility that drainage density varies spatially. By interrogating the terrain directly, it allows for stream detection and extraction process to be driven by topographic controls on the collection and transport of water and sediment. By comparison, methods based on flow accumulation alone will sometimes yield high values in non-channelized landscapes.

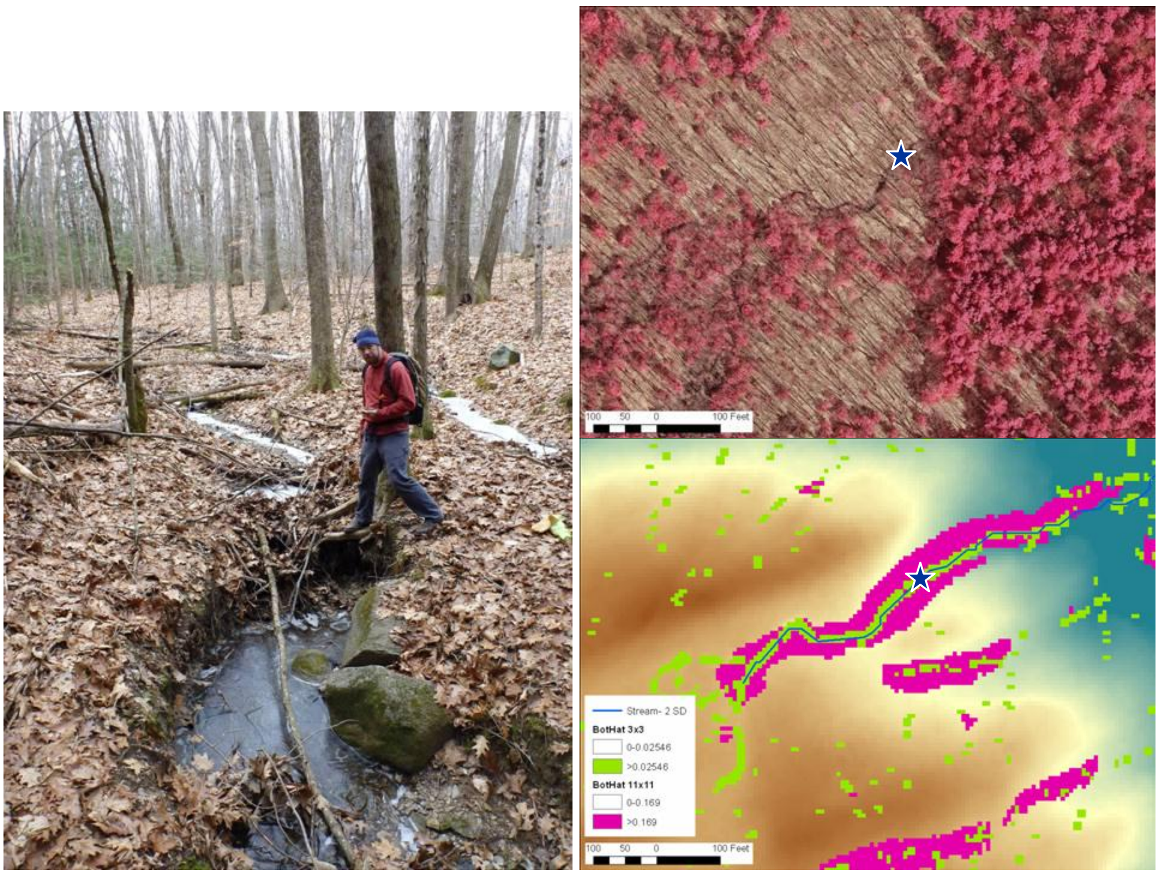

Figure 6. Field photo of a detected stream (left) and the corresponding false color aerial image (top right) and DEM with BotHat layers (bottom right).

Problems

Setting a hard threshold to define a stream versus a non-stream results in some cases of under- or over-prediction. Sequential adjustment of the threshold values enabled fine tuning of the balance between errors of commission and omission, but ideally an end result would reflect more of a probability of stream presence rather than a binary yes-no. There were some areas where the model did not perform as hoped. For one, the inclusion of roadside ditches and other anthropogenic stormwater features could be viewed as problematic. From another perspective, however, these features are important to consider in rainfall-runoff modeling because they convey water and potential contaminants more quickly during storm events. Another issue that could perhaps be resolved by the use of a different flow direction algorithm was that sometimes channelized reaches would enter a wetland area and then not exit, as the flow would enter into the groundwater system from this point on. However, because of the fill and spill nature of the flow algorithm, the channelized flow was forced to continue downstream. Other problem areas existed where channels sometimes developed in the flats, such as in channelized, drained wetlands. In this case, the channelized portion did not show up because there was no valley component that could be detected.

Next Steps

The ideal endpoint of this project would be to integrate the extracted higher resolution streams into the nationally distributed NHD. However, that effort should reasonably be deferred until complete LiDAR coverage is available for the state. In addition, the automated pruning and hydro-enforcement routines should be fully automated to facilitate cost-effective and efficient production. The inclusion of a multi-flow direction algorithm as opposed to the default 8-direction flow method that was used here could lead to more accurate horizontal positioning of the streams.

Conclusions

The BotHat morphological filter effectively highlights channelized features that are likely to represent natural stream channels but have not been previously mapped. Thresholds to determine what constitutes a stream can be modified as desired, but a threshold that tended to minimize errors of omission (false positives), was preferentially chosen.

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