

Extraction and Characterization of Mining Highwalls from a LIDAR Digital Terrain Model

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Highwalls are an artificial landform that results from mining activity. They are characterized as a length of steep, possibly unstable, slope that scars the landscape and can pose a hazard to people or property. In Appalachia, most highwall features are artifacts of auger mining that occurred along ridges where coal beds outcropped at the surface (figure 1).

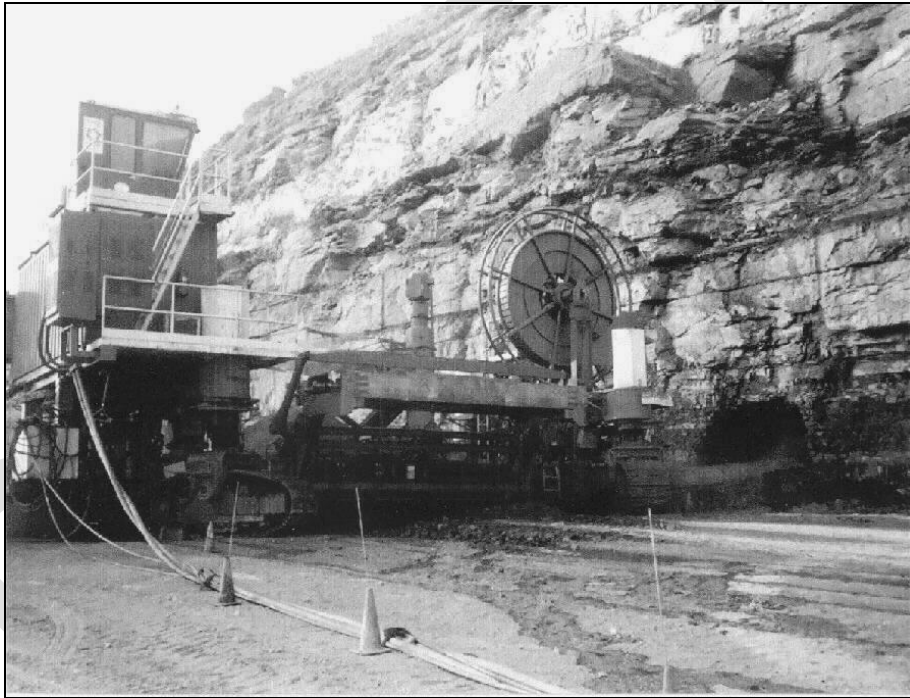


Figure 1. Auger mining against a highwall. Augering equipment rests on a flat bench cut onto the hillside at the elevation where coal outcrops at the surface. Photo courtesy of West Virginia Office of Miners' Health Safety & Training.

The Surface Mining Control and Reclamation Act (SMCRA) of 1977 provided a mechanism for reclaiming abandoned mine hazards, and ultimately led to the creation of inventories of potentially hazardous features. In West Virginia, highwalls, along with other features, were delineated on mylar topographic maps, which subsequently were converted to digital format for use in Geographical Information Systems (GIS).

Since the creation of West Virginia’s highwall inventory, high resolution digital elevation models (DEMs) have become much more common. The level of detail apparent in these data sources, particularly data from LIDAR sensors, suggests it may be possible to extract highwall features in a systematic way. Furthermore, high resolution data sources could be used to attribute individual highwall sections with estimates of height and slope.

This project examined the feasibility of creating and attributing a mining highwall dataset from a 3-meter LIDAR elevation grid for Wyoming county, West Virginia (figure 2).

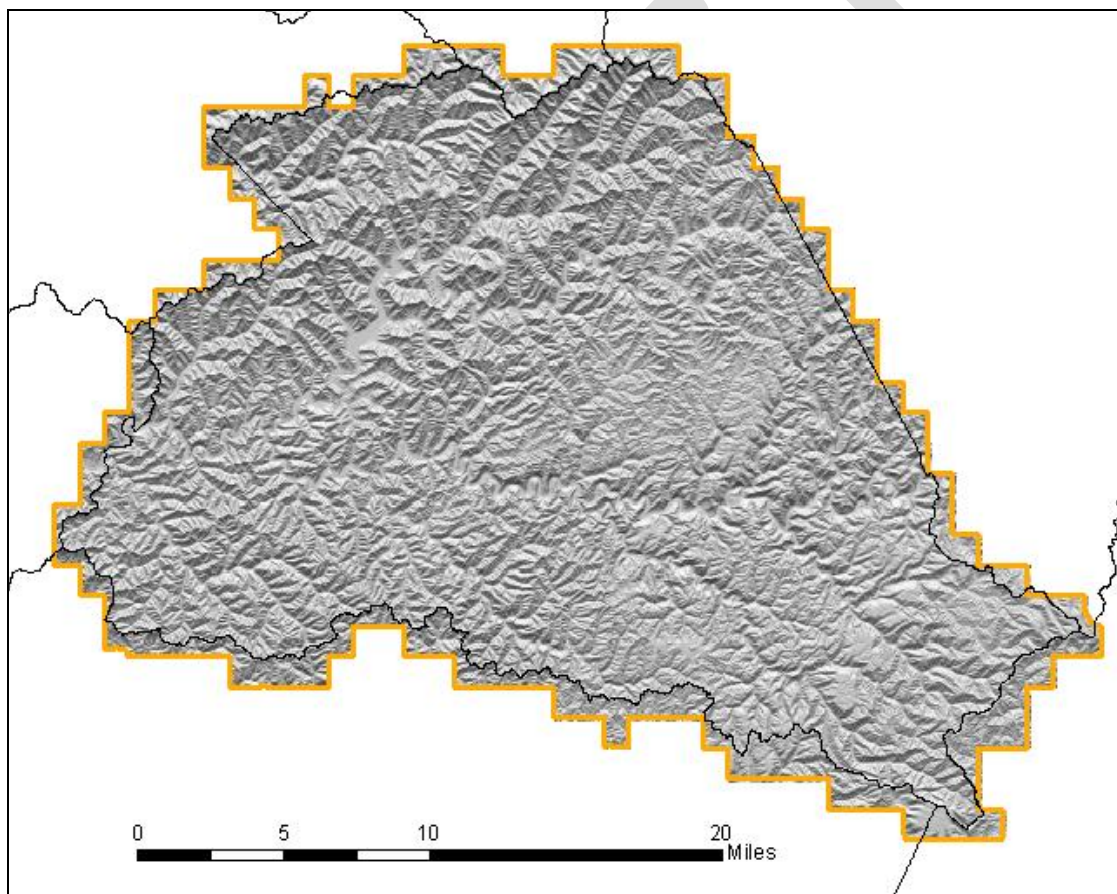


Figure 2. LIDAR elevation model of Wyoming County, West Virginia.

The data, originally collected to facilitate a floodplain mapping project, covers an area over 575 square miles and includes several areas of extensive auger mining activity. Figure 3 shows a portion of Wyoming county where auger mining has followed coal outcrops around an entire

mountain at two elevations. The red line in Figure 3 defines an west-to-east elevation profile reproduced in Figure 4, showing highwalls cut into the mountain on each side.

Method

Isolating highwall features involves the creation of derivative data products that relate to salient characteristics of the features, the most notably slope. The average slope calculated for the Wyoming county dataset was approximately 26 degrees, with a standard deviation of 10.14. Assuming a normal distribution, areas where the slope exceeds 45 degrees would constitute less than 3.1% of the study area. Visual examination of the data suggested that 45 degrees represented a good compromise between isolating the desired features without truncating them, and not producing an overwhelming number of spurious noise artifacts. Figure 5 depicts slopes greater than 45 degrees occurring in the same area depicted in figure 3.



Figure 3. Aerial photograph of auger mining in within the study area.

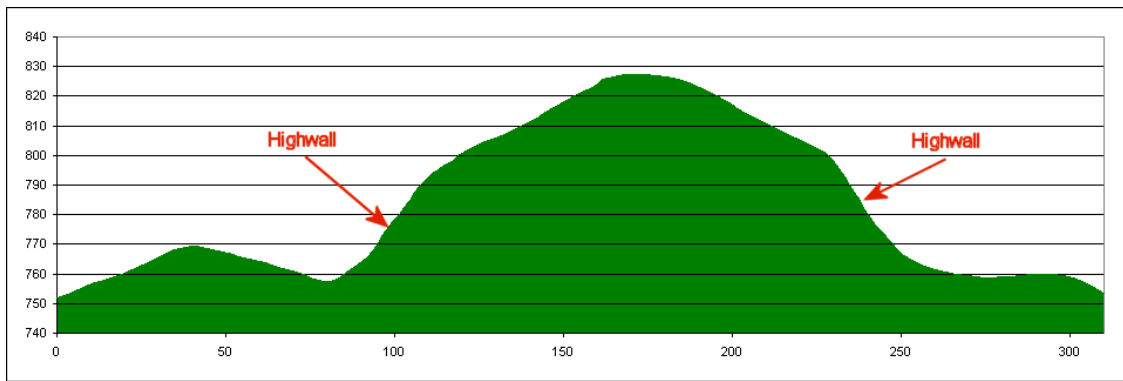


Figure 4. elevation profile for the red line depicted in figure 3, showing highwalls on both sides of the hill.

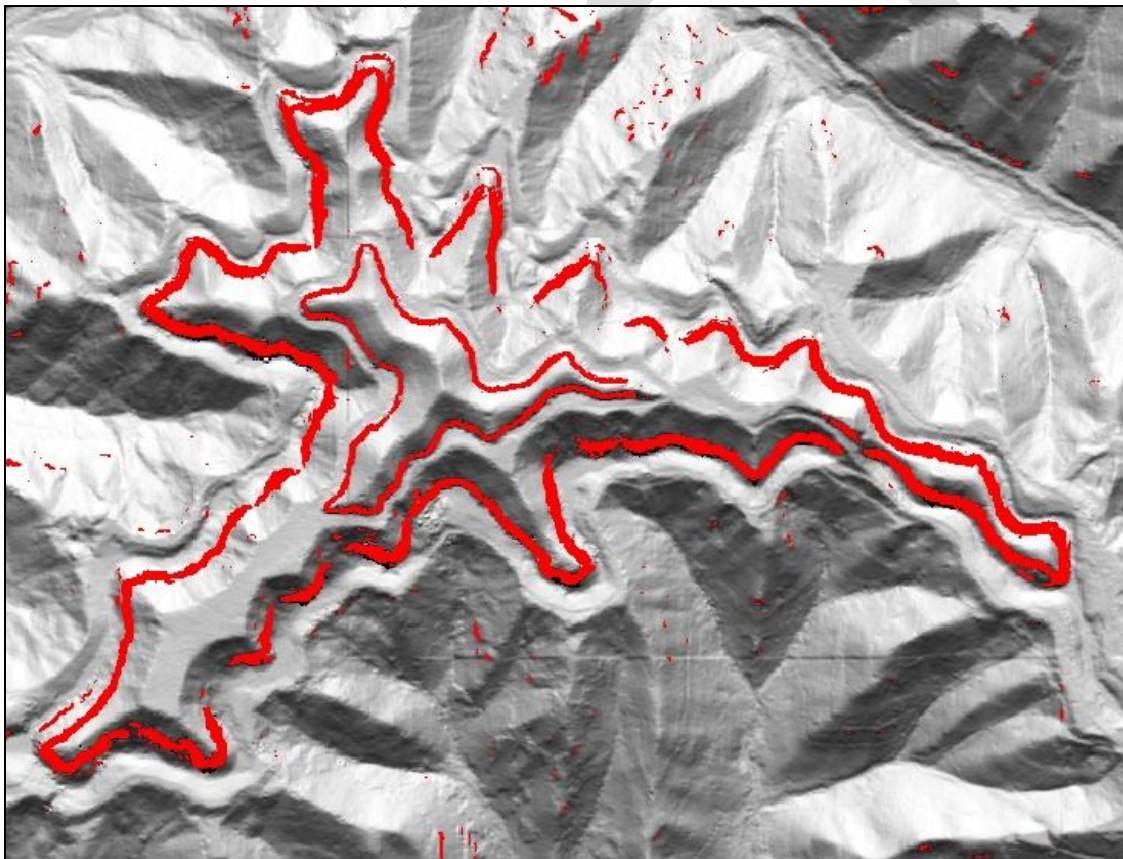


Figure 5. Slopes greater than 45 degrees, shown in red.

Cells in the elevation grid with a slope over 45 degrees were reclassified to a value of 1; all other cells were assigned a null value. After some experimentation, the steep slope areas were expanded by 1 cell prior to running a thinning routine. The thin routine is part of ESRI's spatial analyst extension, designed to condition line work depicted on scanned maps prior to conversion

to a vector data format. This algorithm proved very effective at reducing the thickness of the high slope areas, greatly facilitating the conversion from a raster grid representation to vector lines (Figure 6).

Following the conversion to vector format, the central challenge in the analysis was to discriminate between actual highwalls and various noise artifacts, natural cliff features, and man-made features such as road and railroad cuts.

Computers do not approach human capacity for pattern recognition. Using a combination of aerial photography, topographic maps, and hillshade renderings of the elevation data, an analyst can correctly identify mining highwalls much more accurately than a computer algorithm. However, the initial vector conversion produced over 20,000 features, which presented a significant workload for manual interpretation. Therefore, some combination of an initial algorithmic selection, followed by manual interpretation of the results, could be expected to maximize the quality of the final product while minimizing the total time invested in the process.

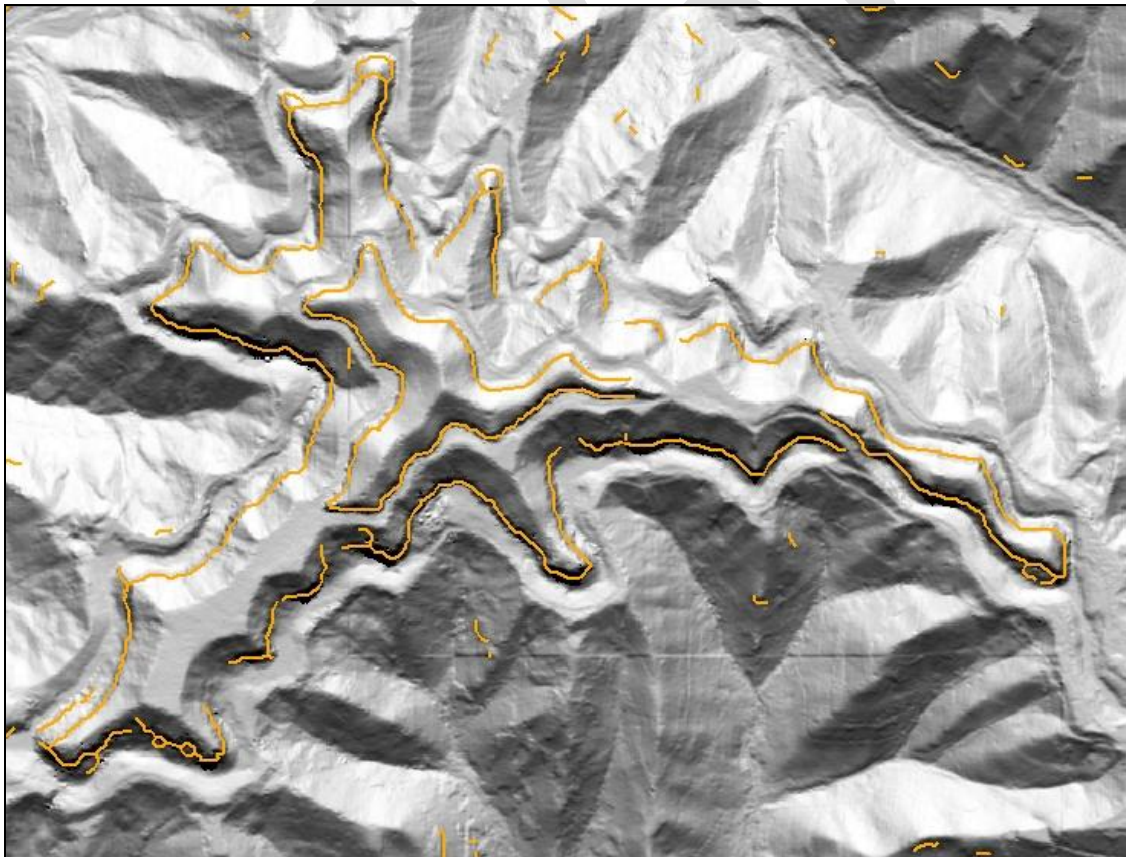


Figure 6. Result of the *thin* operation and initial conversion from raster to vector format.

Automated selection of highwall features was based on a set of calculated attributes designed to isolate likely candidates. First, all features longer than 250 meters were included automatically, since there are relatively few natural occurrences of long, linear, steep slopes in this area. Second, coal beds in this area are relatively flat, resulting in an auger mining pattern that follows the contour of a mountain at a relatively constant elevation. Therefore, the average change in elevation along the length of the highwall should be relatively small. Third, auger mining requires a flat bench for equipment, so auger highwalls often are spatially associated with a relatively flat area. Figure 7 shows areas of less than 10 percent slope in relation to the vector highwall candidates.

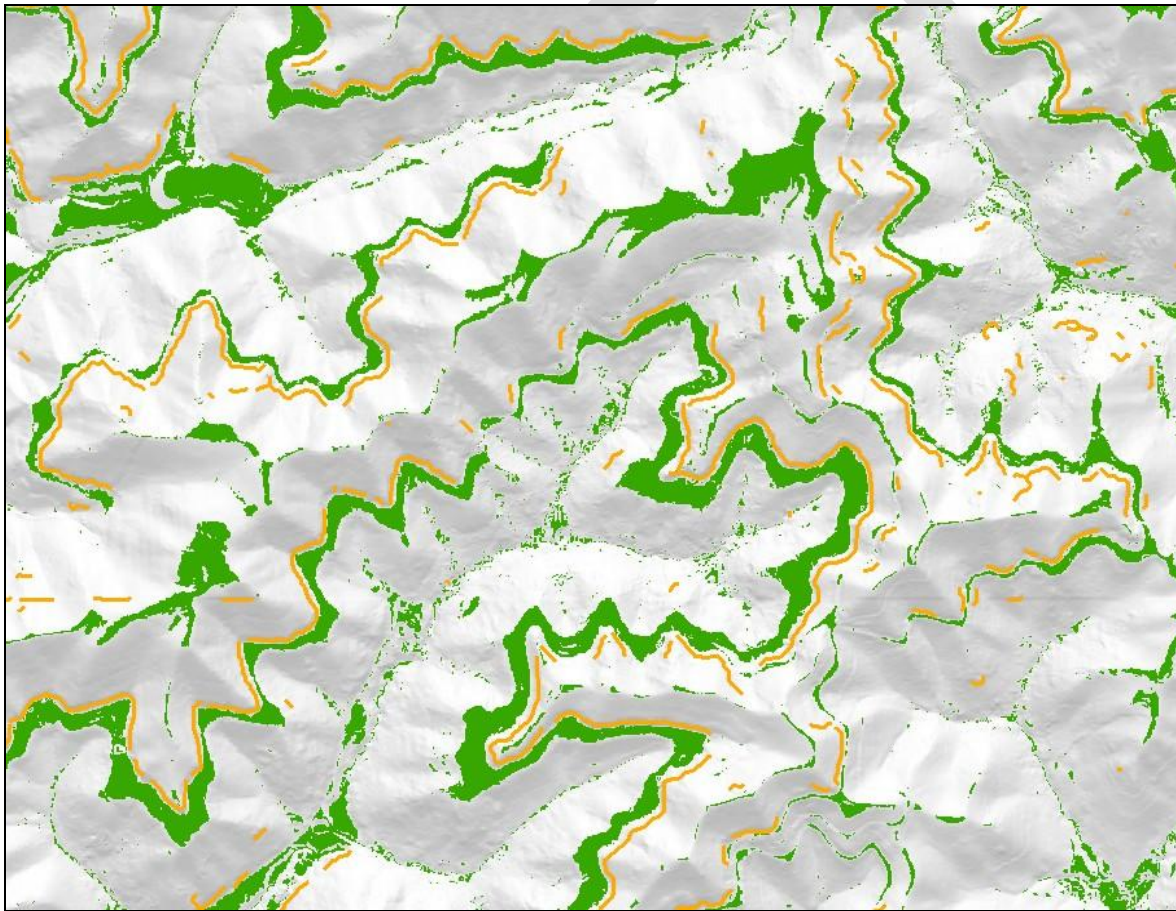


Figure 7. Areas of slope less than 10 degrees, shown in green, and their relationship with potential highwall features, in yellow.

Two parameters, *Drop* and *Proximity*, were calculated using grid representations of the highwall features. *Drop* was defined as the elevation range divided by the length of the feature, where

elevation range is the difference between the maximum and minimum elevation values sampled for each grid cell along the length of the feature. *Proximity* was calculated as the average distance from each highwall grid cell to a cell with less than 10 degrees slope. A more rigorous application of proximity would have used flat areas *down* slope of the feature only, rather than any flat area. However, visual examination of the data indicated that this restriction probably wouldn't have affected the results significantly, so it was not implemented.

In order to determine thresholds to use with the attributes, 100 manually-verified highwalls were selected randomly from the candidate set. Mean and standard deviations were calculated for the *Drop* and *Proximity* attributes:

Sample *Drop* Mean (D_s) 0.0831, standard deviation (σ_{DS}): 0.050748

Sample *Proximity* Mean (P_s) 16.73, standard deviation (σ_{PS}): 7.72

The sample means and standard deviations were used to set upper thresholds for selection of potential highwall candidates. Here, standard deviation was considered a useful measure of spread in the data for setting a threshold; it was not used to extrapolate statistically valid assertions about the population. As stated previously, the selection equation included a candidate if its length was greater than 250 meters. It also included a candidate if 1) its *Drop* was less than the mean of the sample plus three times the standard deviation, and 2) its *Proximity* was less than the mean of the sample plus two times the standard deviation:

$$L_c > 250 \text{ OR } (D_c < D_s + 3\sigma_{DS} \text{ AND } P_c < P_s + 2\sigma_{PS})$$

Where:

L_c length of a highwall candidate, in meters
 D_c candidate *Drop*
 D_s sample *Drop* mean
 σ_{DS} sample *Drop* standard deviation
 P_c candidate *Proximity*
 P_s sample *Proximity* mean
 σ_{PS} sample *Proximity* standard deviation

This equation selected 6,102 candidates from the initial pool of 20,364, effectively reducing the candidate set by 70%. However, the initial selection committed errors of commission, in which

non-highwall features were included in the selection set, and errors of omission, in which actual highwall features were incorrectly left out.

One significant source of commission error was highway and railway cuts. A standard TIGER transportation layer was used to select features within 10 meters of railways, US highways, and state highways. Despite the limited spatial accuracy and completeness of this data source, the operation eliminated 413 candidates from the initial set without including any instances of highwalls. An additional 173 candidates were determined to be associated with active mining operations and also were removed from the selection set. Finally, 2,617 candidates were removed through manual interpretation. Some of these features were additional transportation cuts that fell outside the 10 meter buffer. However, a post-analysis examination indicated that the buffer value could not have been increased without including a significant number of real highwall features. The majority of the remaining commission errors were typically short features scattered throughout the study area representing natural cliff features or noise artifacts.

Manual interpretation also identified 503 omission errors. Many of these candidates were relatively short sections that formed part of a pattern, or chain of highwall features occurring along a ridge, and thus were relatively easy to identify. In total, approximately 8 hours was devoted to manual interpretation of the candidate set following the preliminary selection process. Extensive use was made of hillshade renderings, aerial photography, and topographic maps, which often depicted past mining activity, to make determinations regarding candidate status.

total candidates	20,364
rejected, by equation	14,262
selected, by equation	6,102
omission errors	503
commission errors	2,617
active mining highwalls	173
rejected, road/railroad cuts	413

Calculating Feature Attributes

After finalizing the highwall feature set, the elevation model was used to generate a series of height and slope estimates for features identified as highwalls. First, every highwall feature was split at each vertex into sequence of line segments. Then a perpendicular profile line was calculated for each line segment (figure 8). The profile lines were used to sample the top and bottom of the highwall, thereby allowing an estimation of height and slope for each segment. The length of each profile was determined by the 45 degree slope criteria originally used to identify the highwall features. In other words, the endpoints of each profile were clipped to the boundary representing the area of greater than 45 degrees slope.

The decision to clip the profiles at the 45 degree slope line was based on an investigation of curvature. The curvature function in ESRI's spatial analyst extension can be used to calculate the rate of change in slope for an elevation surface. One of the products of this function measures change in the direction of maximum slope, producing negative values for convex, and positive changes for concave, surface trends. These trends relate to the structure of a highwall. Viewed in profile, the extent of a highwall is determined by a convex break at the top, and a concave break at the bottom (figure 9). The curvature function was useful for delineating these breaks visually, though it was not considered consistent enough for modeling the top and bottom of the highwall algorithmically.

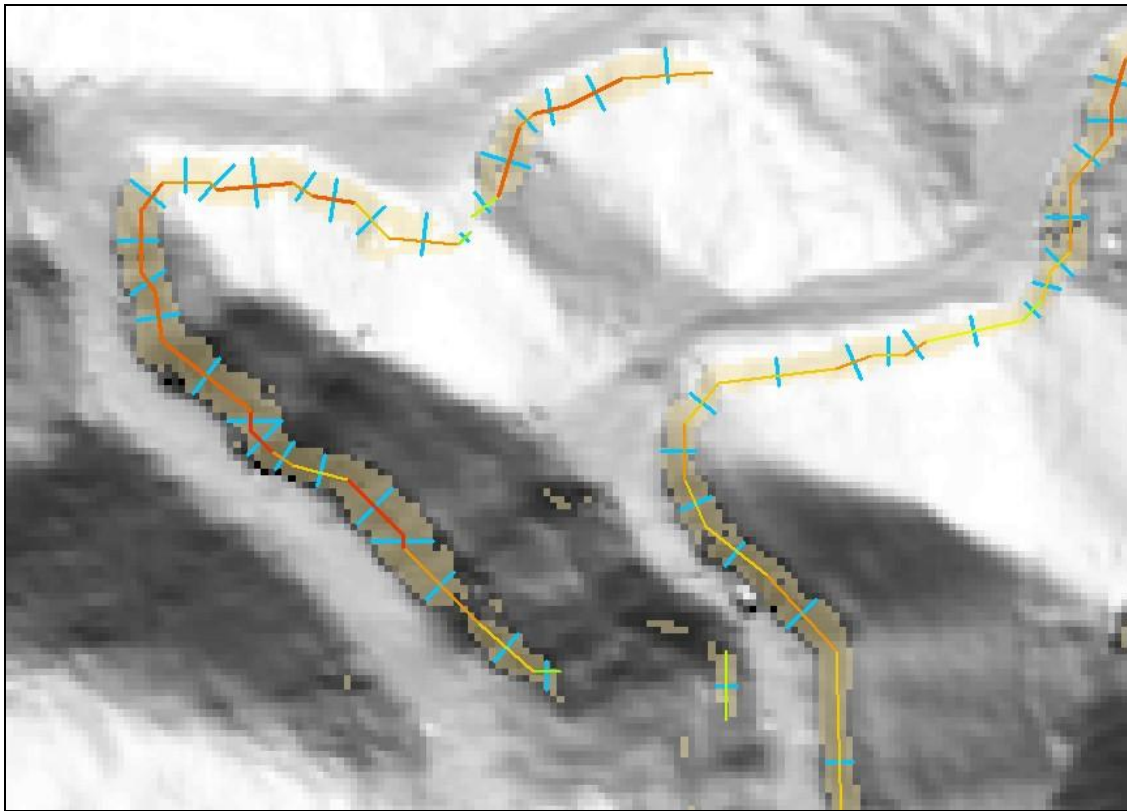


Figure 8. perpendicular profile lines, in blue, used to estimate highwall height and slope for each line segment. The semi-transparent yellow areas represent slopes greater than 45 degrees.

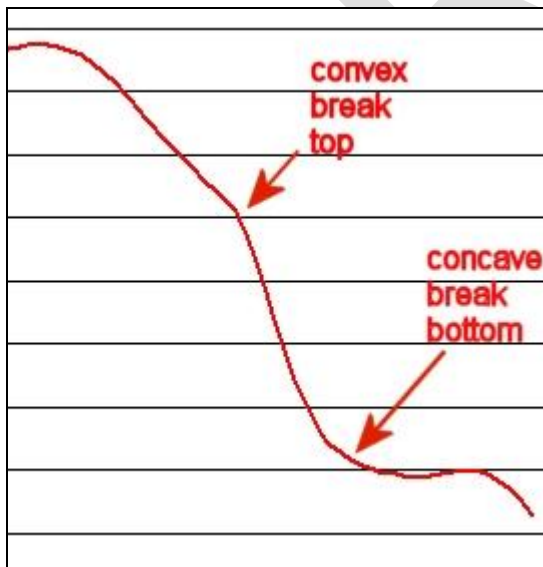


Figure 9. highwall profile.

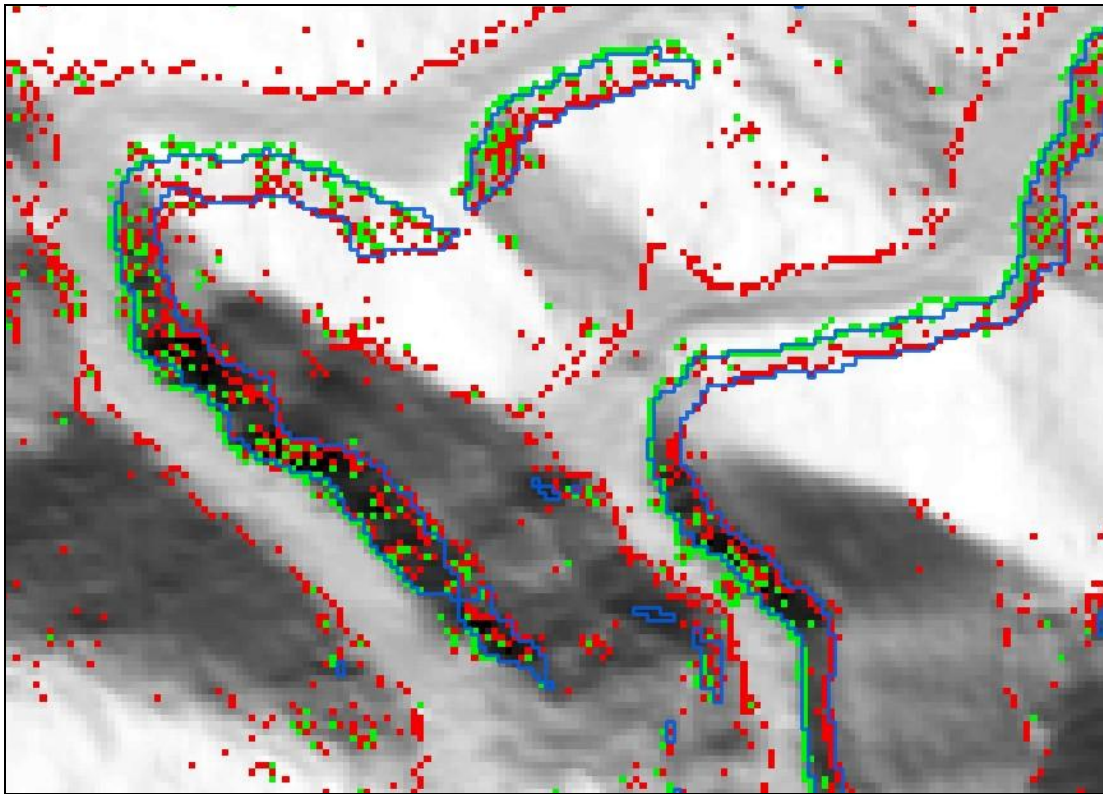


Figure 10. comparison of curvature and areas greater than 45 degrees slope. Convex breaks on slope are depicted in red, concave breaks in green.

Figure 10 illustrates the correlation between the output of the curvature function and the slopes greater than 45. The Red pixels in figure 10 represent pronounced convex breaks in slope, which occur at the top of a highwall, and at the outer edge of the bench cut into the side of the hill. Green pixels represent concave breaks in slope at the bottom of the highwall. The blue vector lines represent areas over 45 degree slope, which typically correspond with the top and bottom highwall breaks within one grid cell (3-meters). The high degree of correlation observed between slope breaks and the 45-degree slope cutoff suggests that the 45-degree slope cutoff value produces a reasonable delineation of highwall width, and consequently, is a reasonable basis for sampling the elevations at the top and bottom of a highwall segment to estimate overall height and slope.

While the process of estimating highwall height and slope works reasonably well, it should be noted that quirks in the highwall line segments can result in profiles that do not cross the highwall feature at an appropriate angle. Figure 11 shows profile segments generated for a small highwall segment. Profiles at A and B cross the highwall at an angle, due to the way the GIS

software converted the line segment from a raster to a vector representation. In many cases the error may be negligible, though not in all cases. These profiles usually are associated with short segments and could be filtered out based on segment length when calculating average statistics for a longer feature.

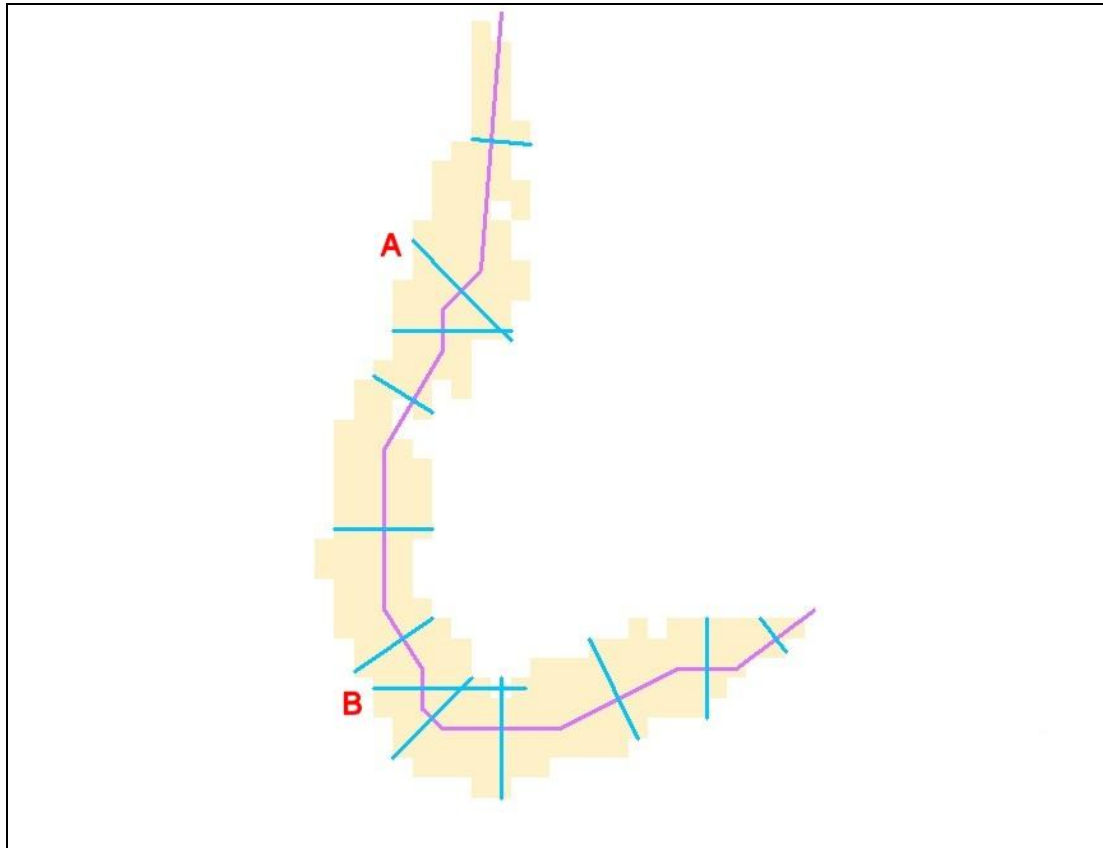


Figure 11. example of spurious profile segments that could create error in highwall height and slope estimates.

Conclusions

This paper demonstrates a semi-automated process for identifying mining highwall features that improves on an existing manually-delineated inventory in several ways. First, the project identified over 493km (306.5 miles) of highwalls within the study area, in contrast to 244.6km (152 miles) in the existing inventory. Figure 12 illustrates one of several areas of highwall mining identified by the study that were completely absent from the existing inventory. Second, the process created a more precise depiction of the location and extent of highwall features. This

fact is apparent in Figure 13, which depicts highwall features delineated by this study along with manually delineated features from the existing inventory.

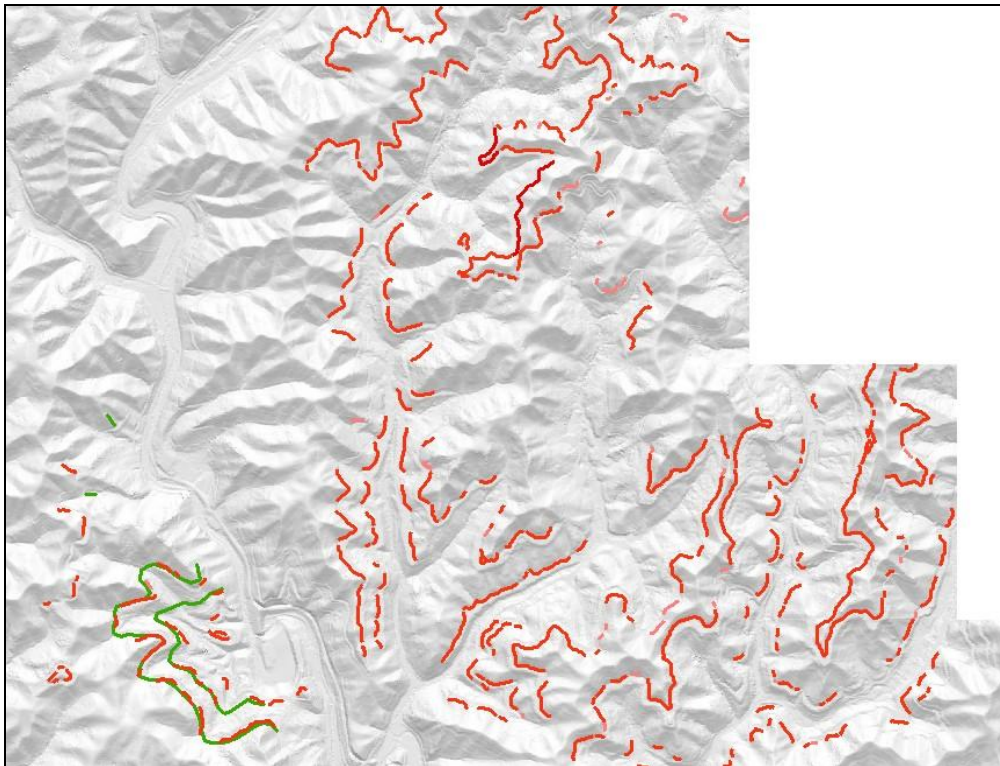


Figure 12. highwalls found by the study not currently in the highwall inventory.

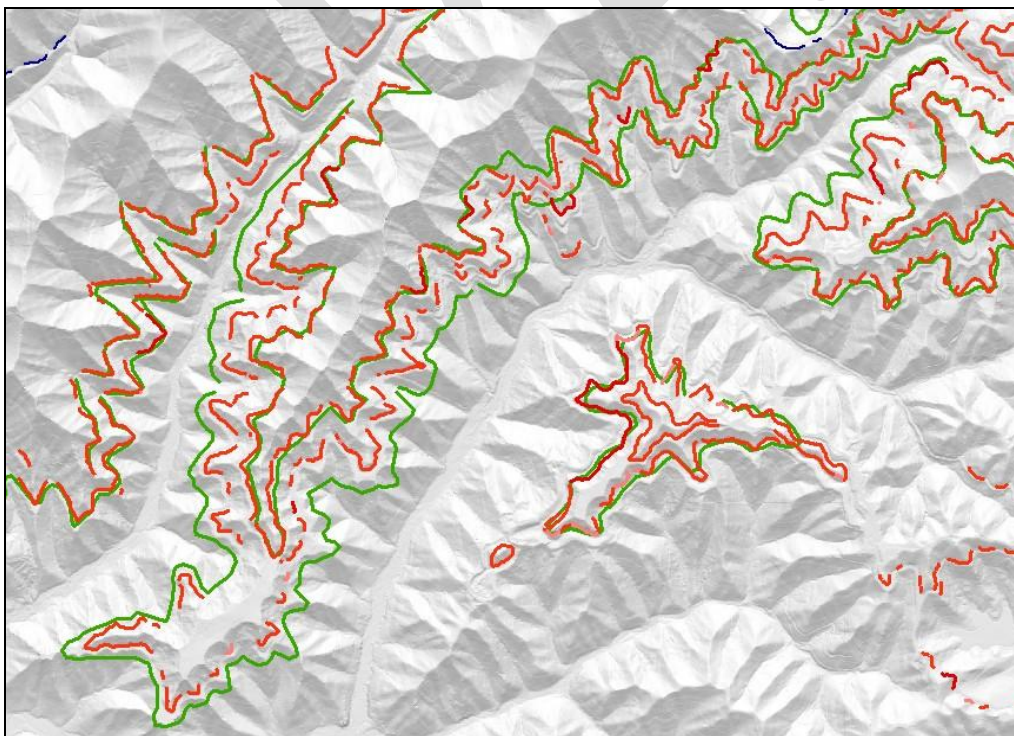


Figure 13. comparison of highwalls created by this analysis (red) with manually delineated highwalls in the current highwall inventory (green).

The newly delineated highwall segments are more complete, detailed, and accurately located. The third advantage of this process is the ability to estimate height and slope of individual highwall segments, which can be visualized with GIS systems. The estimation of these parameters allows highwall segments to be classified and visually evaluated in ways that were not previously possible.

Finally, the results of the study arguably are more consistent than results obtained from manually digitizing highwall features from aerial photography. This is because an objective criterion was applied based on the morphology of the feature, rather than relying on the visual presentation of the feature from above. However, the process does have limitations. No completely reliable method was found to isolate highwall features from noise fragments without some error that required manual correction. Additionally, the study was conducted using LIDAR elevation data, which is the most detailed and accurate source for elevation data currently available. Therefore the results represent a best case example. Employing a similar process with less precise data sources would produce less detailed results.