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342 - Fall 2016

Using LiDAR to Detect Abandoned Mines

Summary

A significant portion of the work I do for the California State Department of Conservation Abandoned Mine Lands Program is focused on finding and inventorying abandoned mines throughout the state. Before going into the field to do inventory work we must do pre-field target identification to determine where major sites are, and optimize our time in the field by having accurate targets. We currently use aerial imagery as the main driver of our pre-field target identification which has large drawbacks, especially in deeply forested areas where the surface is completely obscured leading to many features being impossible to detect. As more LiDAR data becomes available, high resolution elevation models are becoming an interesting alternative for identification of abandoned features using their distinct surface expression and the LiDAR products being able to essentially “see through” canopy and display the surface below. For this project I am doing an initial exploration of a high resolution dataset from Tahoe National for mine feature identification and exploring a potential method for automating the process using the topographic position index algorithm. The LiDAR dataset allowed for a significant improvement of manual detection of mine features in the Tahoe area compared to the previous aerial imagery interpretation method. The automated method I explored was effective at detecting features but had a lot of false positives due to natural features also being detected and preliminary attempts at noise reduction didn’t completely mitigate this issue.

Purpose

The purpose of the project is to explore the viability of LiDAR bare earth elevation data for detecting abandoned mine features using a 1 meter resolution comprehensive dataset of Tahoe National Forest which features extensive historic mine workings. The dataset will be used to manually detect features that were previously impossible to detect given the heavy canopy cover obscuring them.

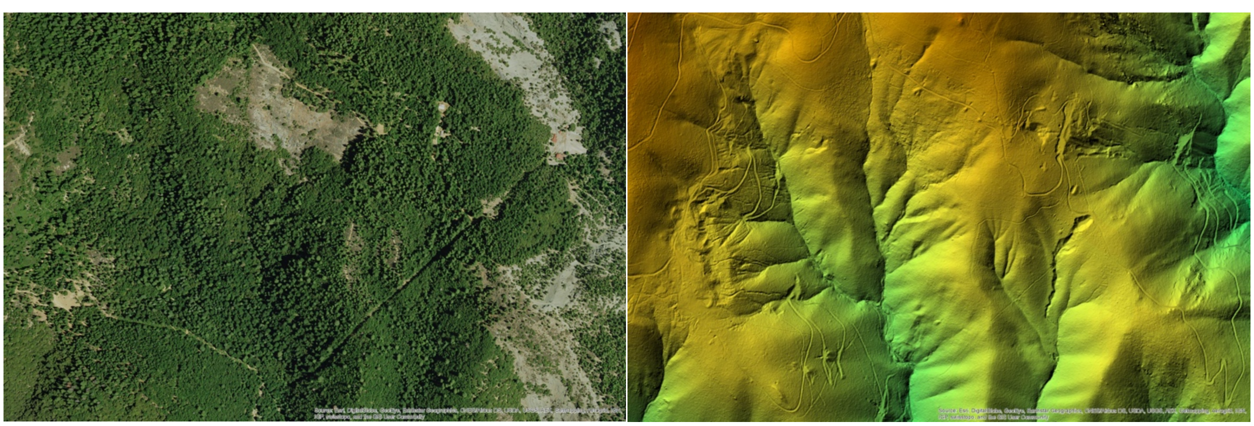

Figure 1: Aerial imagery vs LiDAR DEM example

Waste piles which frequently have a distinct positive topology and shafts, adits (mine tunnels), and prospect excavations which all have negative topology will be manually classified using the dataset. Also a possible method for automating the detection of these features will be explored using a topographic position index algorithm. As the national inter-agency 3DEP project continues to expand the state's comprehensive high resolution elevation model footprint these methods will be useful for future mine working detection in the Department of Conservation.

Methods

For this project I acquired a 1 meter horizontal resolution bare earth LiDAR based DEM of the entire Tahoe National Forest area from the Tahoe National Forest field office in Nevada City. The dataset had already been processed from the raw data, and was filtered to only use bare earth detections.

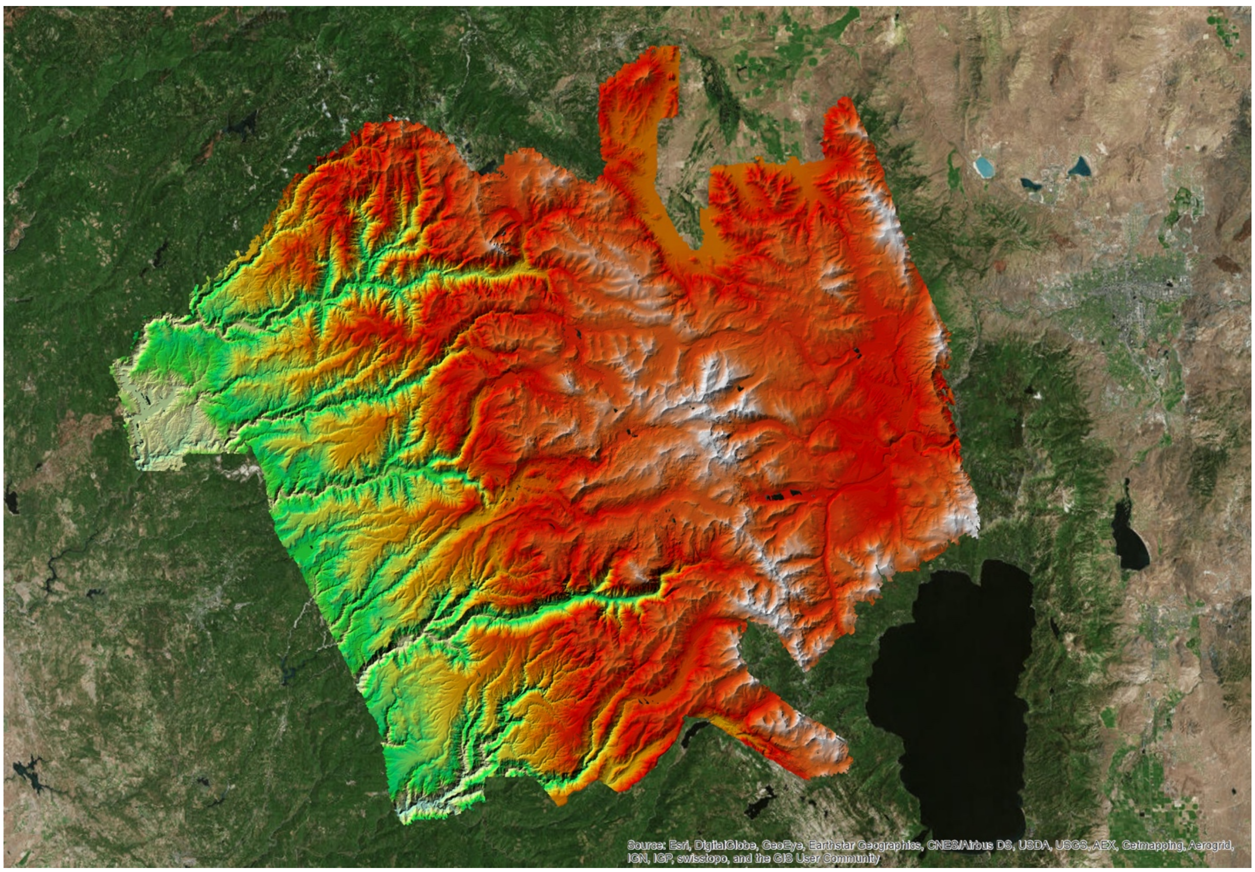

Figure 2: Overview map of Tahoe National Forest DEM

The first step was to create several topographic position index (TPI) rasters to determine optimal inputs for use in this project. TPI is a landscape analysis algorithm developed by Andrew Weiss (2001) to be able to detect valley and ridge landforms in a DEM at different scales. The equation compares the elevation of each pixel to the mean elevation of a specified annulus neighborhood, outputting positive values for ridges, negative values for valleys, and zero values for plateaus. The inner and outer radius of the annulus can be adjusted to look for these landforms at different scales e.g. a 1-5m annulus sees mounds and ditches whereas 100-500m detects actual ridges and drainages in mountains. The equation as entered in Raster

Calculator is given below (DEM is the variable for the input DEM, IRAD is inner radius, ORAD outer radius):

Int((<DEM> - FocalStatistics(<DEM> NbrAnnulus(IRAD, ORAD, "CELL"), "MEAN", "DATA")) + .5)

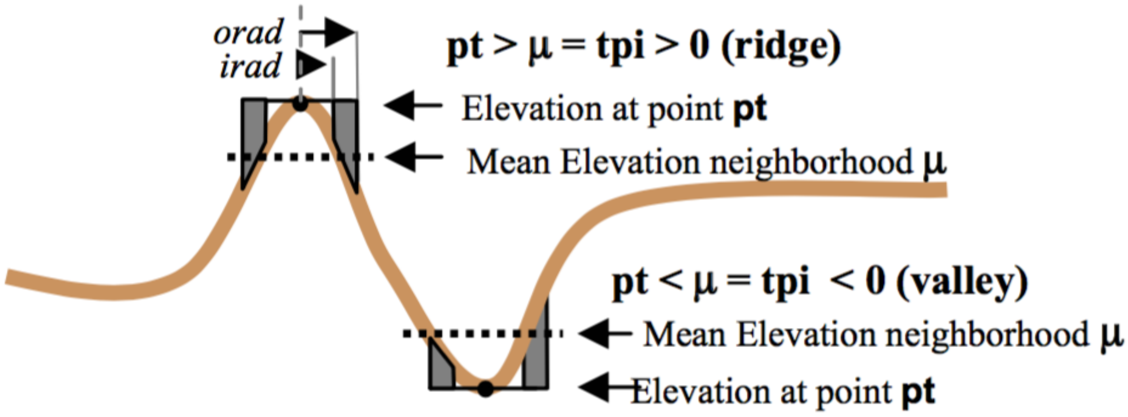

Figure 3: Visualization of how TPI works

I created TPI rasters using the following inner and outer radii: (1,5), (2,4), (5,8), (5,10), (10,20), (10,30).

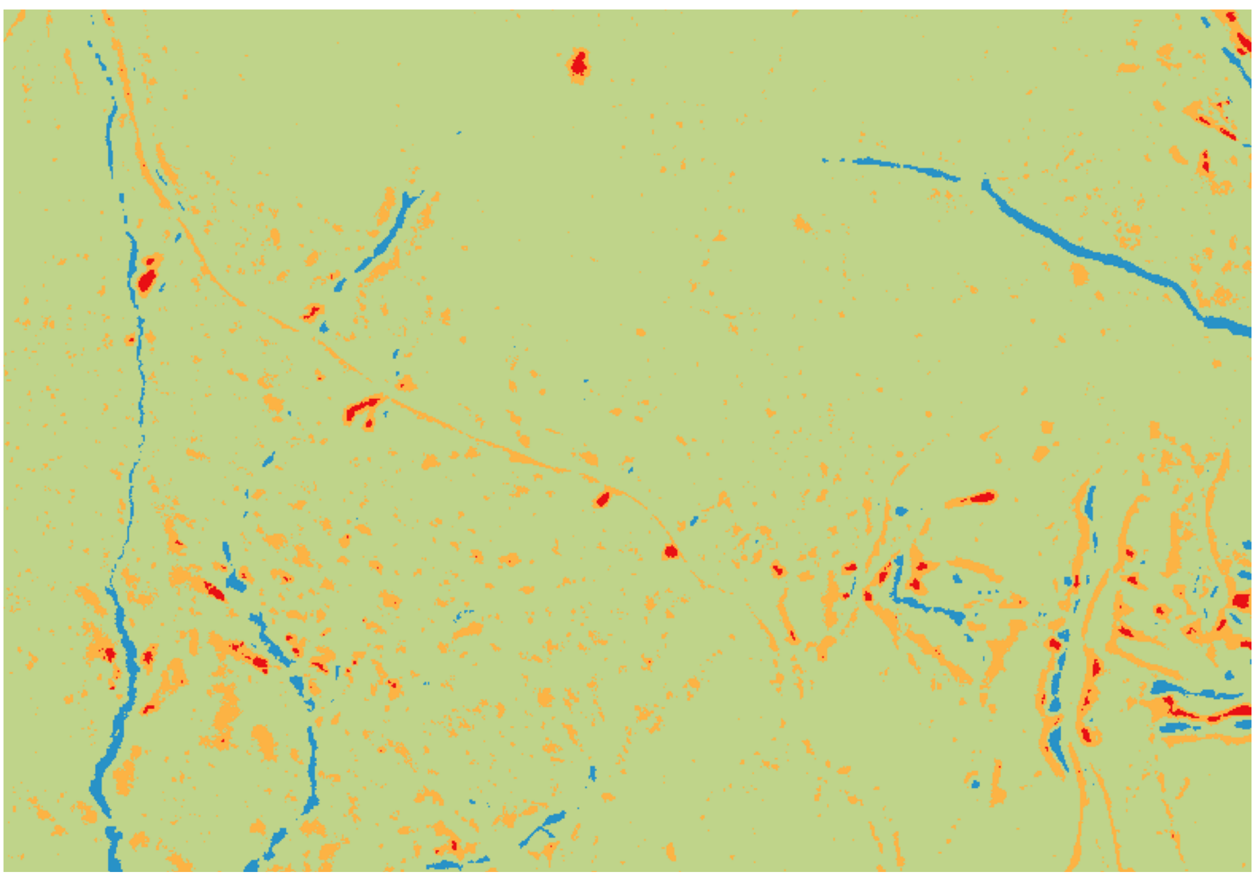

Figure 4: Example TPI (ridges are warmer colors, valleys are cooler colors, plateaus are green)

I determined that the 5, 10 m annulus was best for detecting all types of features by comparing manual classification to the values of the raster. I queried the values of known mine features to determine what TPI values would best be used to classify them. I created a Raster Calculator conditional statement to classify the raster with 1 being the value of negative topological features (e.g. excavations), 2 the value for waste piles (positive relief) and NoData for all other values.

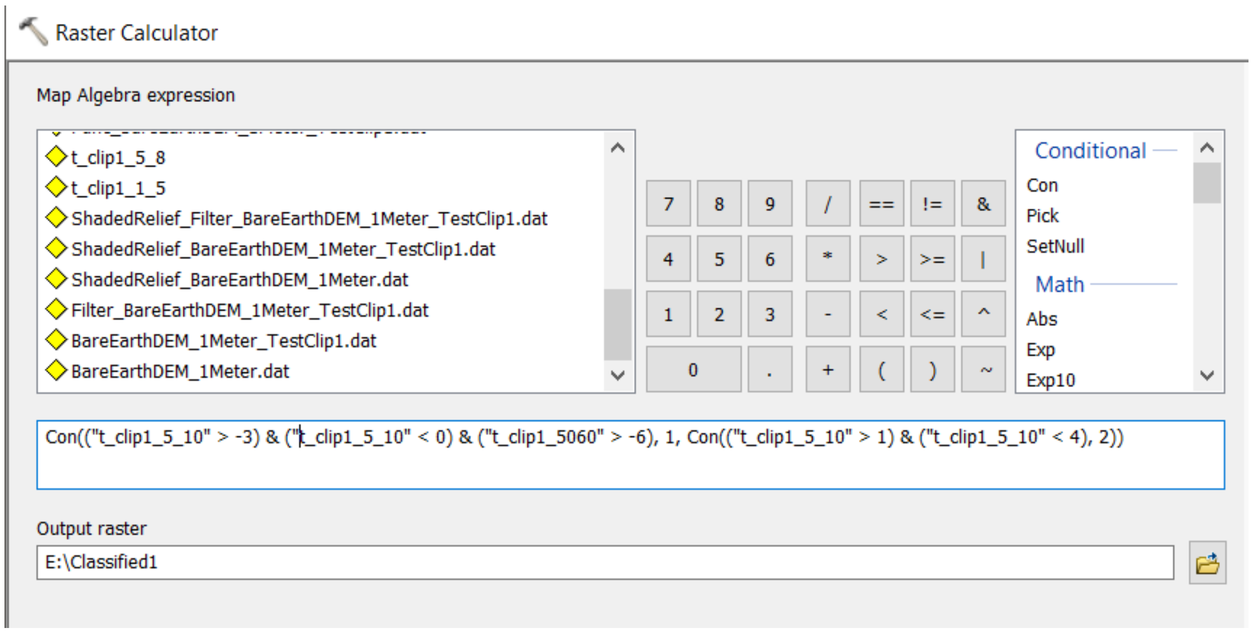

Figure 5: Raster Calculator statement for feature classification

The desired product is a raster and polygon with features of negative and positive relief however some noise reduction is necessary first.

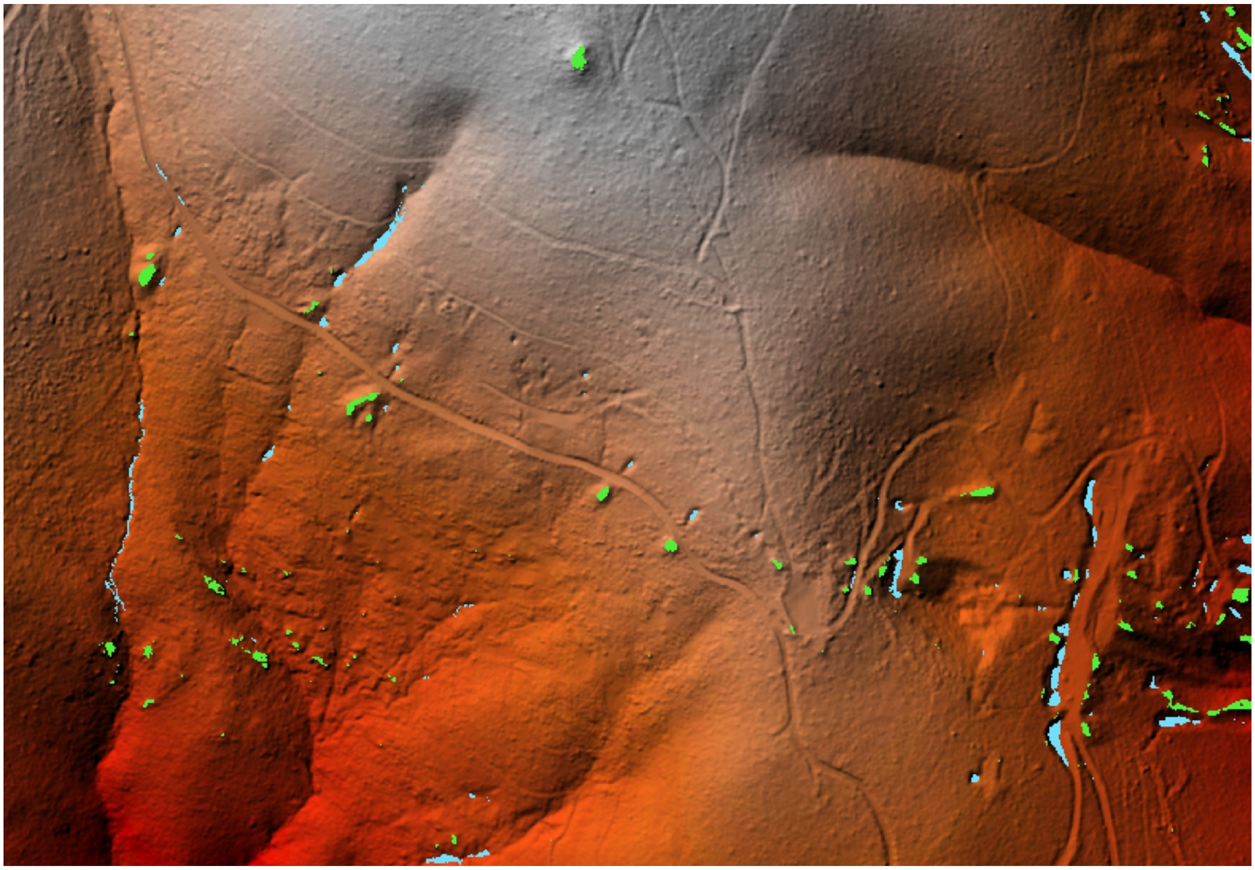

Figure 5: Classified TPI raster (blue are possible excavations, green are waste piles)

As seen in figure 5 above the TPI raster has a lot of noise that is not mining related; road cuts, drainages and general natural "noise" also are detected. To mitigate this I developed a method to connect more linear noise artifacts and then remove them. The first step is to use the Expand tool to increase the radius of every depression pixel domain (the ones that have the most noise) by 5 pixels. This connects groups of pixels into larger merged areas. Then run the Shrink tool to decrease the area of pixel domains by 4 to leave groups slightly bigger than before but reduce the artificial size increase. I then convert the raster to polygon and can then delete all polygons larger than 100 square meters (Figure 6).

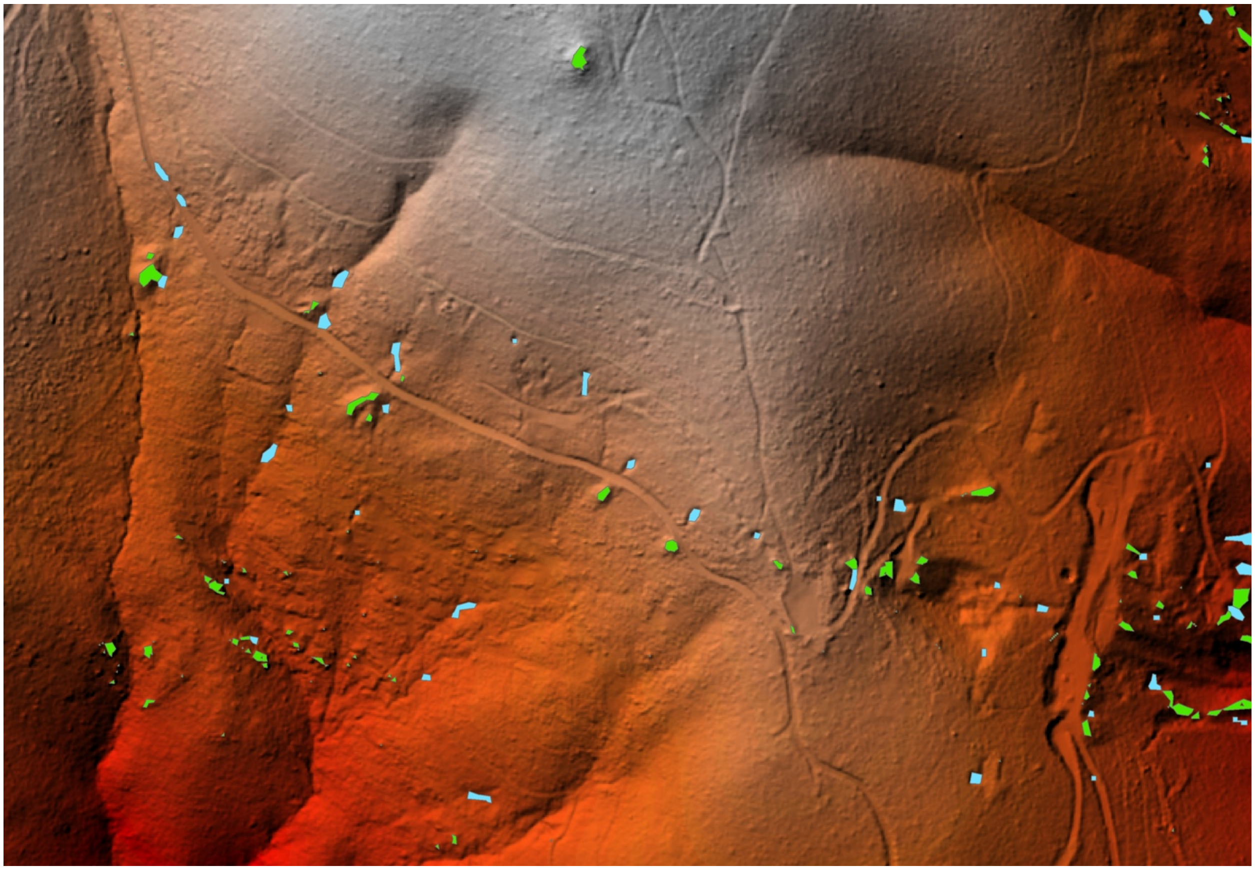

Figure 6: Classified raster after noise reduction attempt

Results and Discussion

The LiDAR dataset provided a huge advantage to previous methods of manual mine feature detection in the region. The ability to “see” through the trees and see the ground directly was incredibly helpful.

I would hazard to guess the method is likely very helpful in areas with sparse tree cover as well for manual detection since the only texture difference on the surface is caused by shadows while doing detection with imagery dark rocks and other natural features are easily mistaken for features. The auto-classification method I explored was good at finding likely features but had many false positives in the form of noise from topological features that weren't mining related. Further refinement could help but in the end the effort involved would likely still not be warranted as a trained eye is hard to beat with noisy data. If I could develop other raster parameters and do image classification using multi-band methods it may also help reduce the noise, but most parameters I explored were too co-dependent with TPI to be treated as an additional band of data.

References

Weiss, A., 2001. Topographic positions and landforms analysis. Proceedings of the Twenty-first Annual ESRI User Conference (Map Gallery Poster), San Diego, CA.