# Mapping the Surface of Imja Glacier


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## Introduction

In recent decades, a significant manifestation of climate change has been warmer-than-average alpine temperatures across the globe, from the Andes to the Himalaya. As a consequence, previously stable glaciers in affected alpine regions have begun to melt, the runoff pooling and giving rise to glacial lakes. As melt water accumulates and a glacial lake swells in size, the risk of the impounding structure experiencing a catastrophic failure increases rapidly. Such an event is known as a glacial lake outburst flood (GLOF) and can have devastating consequences for downstream communities. Research efforts are currently focused on modeling the evolution of glacial lakes and their parent glaciers, with the goal of providing predictive capacity and risk assessment in order to aid downstream communities with disaster preparation and planning.

This project focuses on Imja Tsho (or Imja Lake) in the Himalaya, shown both on the previous page and below in Figure 1. Imja Tsho has been identified as one of the fastest growing and most dangerous glacial lakes in the region[1]. It is perhaps not a coincidence, then, that Imja Tsho is also one of the most extensively studied glacial lakes in the Himalaya. The work performed herein is in collaboration with David Rounce, a PhD candidate at the University of Texas at Austin. Working under Dr. Daene McKinney, David's doctoral research centers on Imja Tsho and its main contributing glaciers, Lhotse Shar and the Imja Glacier. One of the goals of his research is to develop an energy balance melt model for the Imja Glacier. Such a model will require, among other things, knowledge of the variation in debris thickness (non-ice materials covering the glacier) over the surface of the glacier.

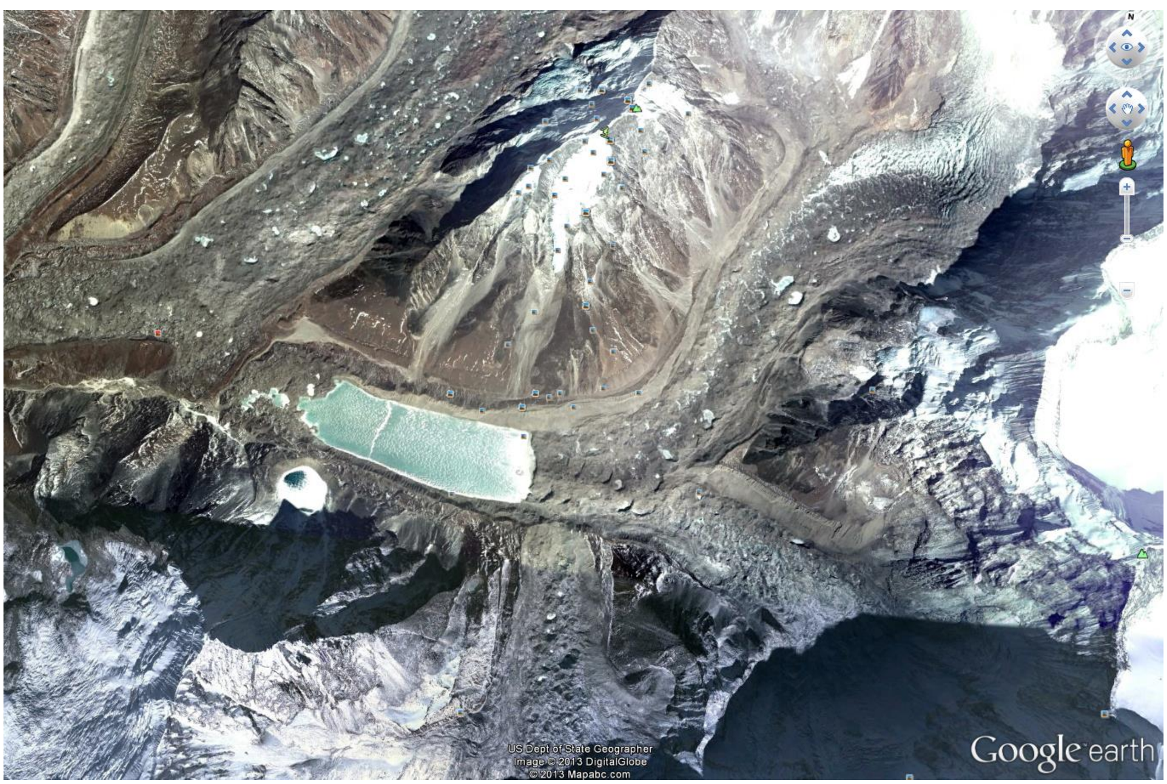



**Figure 1: Google Earth image depicting an aerial view of Imja Tsho (center) and Imja Glacier (directly right of lake)**

## Data

David recently returned from a field expedition to Imja Tsho where he acquired twenty-two direct measurements of debris thickness from one area of the glacier. We are also is in possession of a 5-meter resolution digital elevation model (DEM) that was generated by D. Lamsal et. al. in 2011[2]. Moreover, David wore a GPS tracking device throughout the duration of his fieldwork, providing geographic information about the surfaces he traversed. Taken together, these data may be used to paint a picture of the glacier surface.

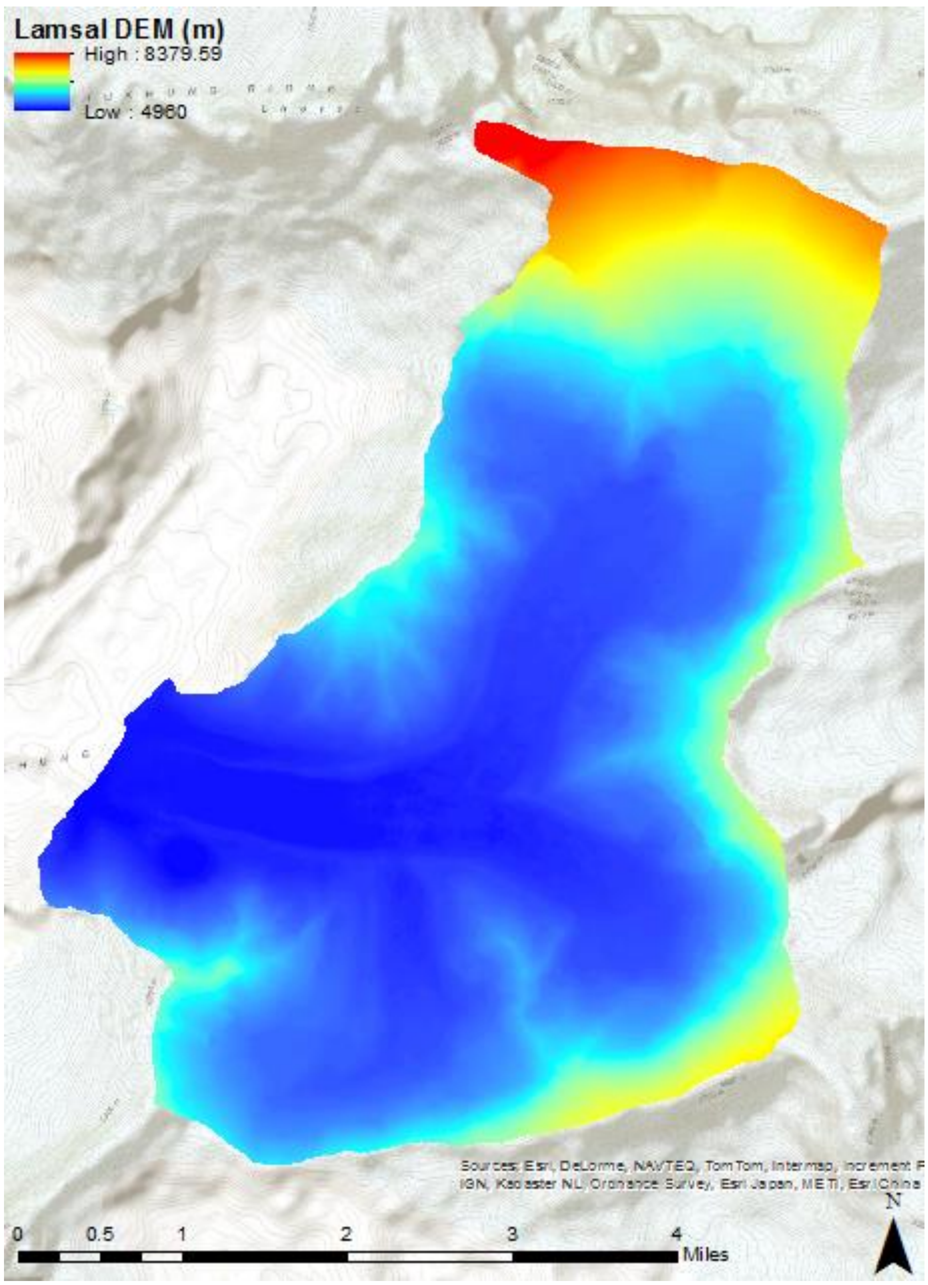



**Figure 2: The 5m spatial resolution DEM of the Imja Tsho basin. This DEM was derived from the Advanced Land Observing Satellite's Panchromatic Remote-sensing Instrument for Stereo Mapping (ALOS PRISM), by D. Lamsal et. al. 2011[2]**

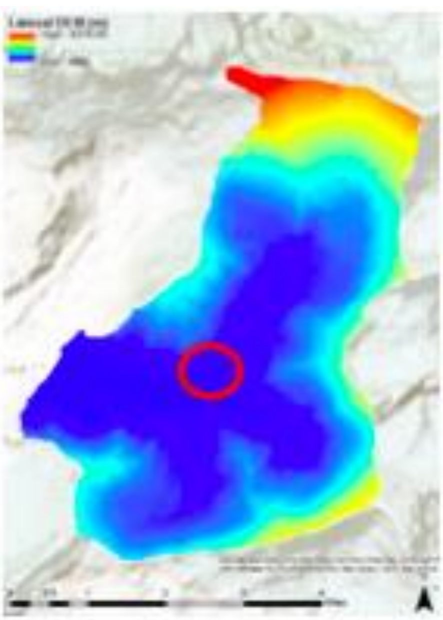
## Research Goals

The initial goal of this research was to attempt to use field data of debris cover thickness in conjunction with the fine scale DEM to derive a predictive relationship. Using this relationship, the debris thickness across the glacier surface could be inferred. Unfortunately, it quickly became obvious that the goal was not feasible – we lacked the volume of data sufficient to make meaningful spatial correlations. The analysis then turned towards developing other relationships between DEM-based spatial variables and debris thickness, identifying possible errors with the slightly outdated DEM, and generally to learn about the dynamic nature of the debris covered glacier surface.

## Methods & Results

*Attempts at Geostatistical Interpolation*

The first step in the analysis was to visualize the data with ArcGIS. For each sampling point, the latitude and longitude (m), GPS elevation (m), and debris thickness (cm) were known. These data were imported into ArcGIS as point features and overlain on top of the Lamsal DEM (Figure 3). Bilinear interpolation was used to enhance the display of the DEM. The sample points were displayed to take a size proportional to the debris thickness at that point. Debris thickness values ranged from less than 17cm to almost 100cm. The elevation at Dave's field site is roughly 5050m above sea level.



**The red circle indicates the general location of sampling within the basin.**

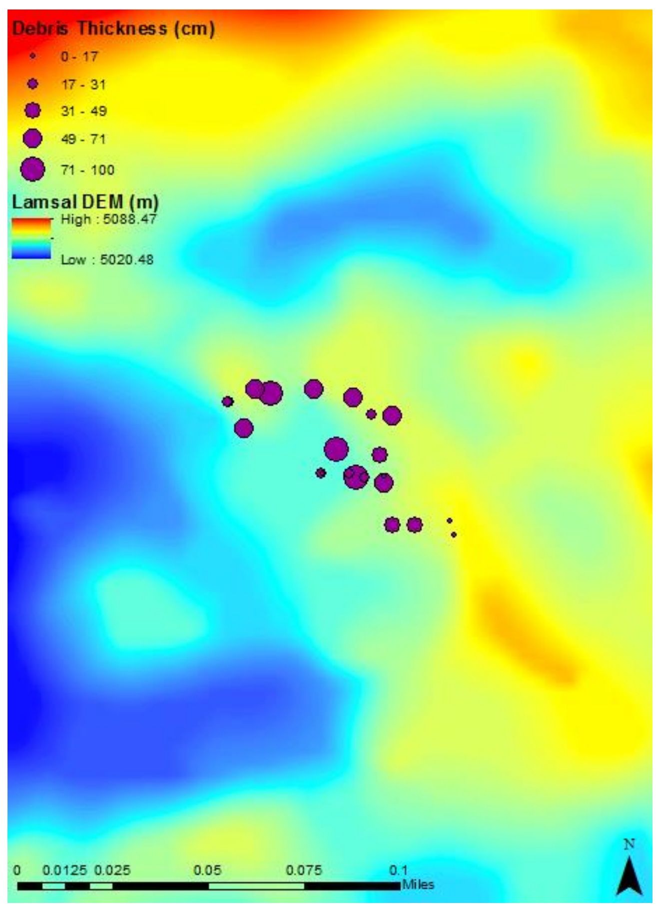



**Figure 3: Map showing sample locations on the glacier surface**

Inspection of the map above (Figure 3) does not reveal any obvious spatial patterns between debris thickness (point size) and elevation (surface color). The relative sparseness of the dataset also becomes apparent when visualized in this manner. Despite reservations about having an insufficient sample size, an attempt was made to find a spatial relationship in the debris thickness by using a geostatistical technique known as kriging. Kriging is a method of interpolation whereby intermediate values are estimated based on the covariance of known points in the spatial field. The mathematics behind kriging can become quite sophisticated, but fortunately ArcGIS provides a kriging tool within the Spatial Analyst toolbox. The tool takes as inputs the point features containing the information to be interpolated and the field where the variable values are to be found. While there are a number of other optional inputs, the tool was run with the default settings: a spherical semivariogram-type model, default cell size, and default search radius. The output raster of the tool is shown below in Figure 4.

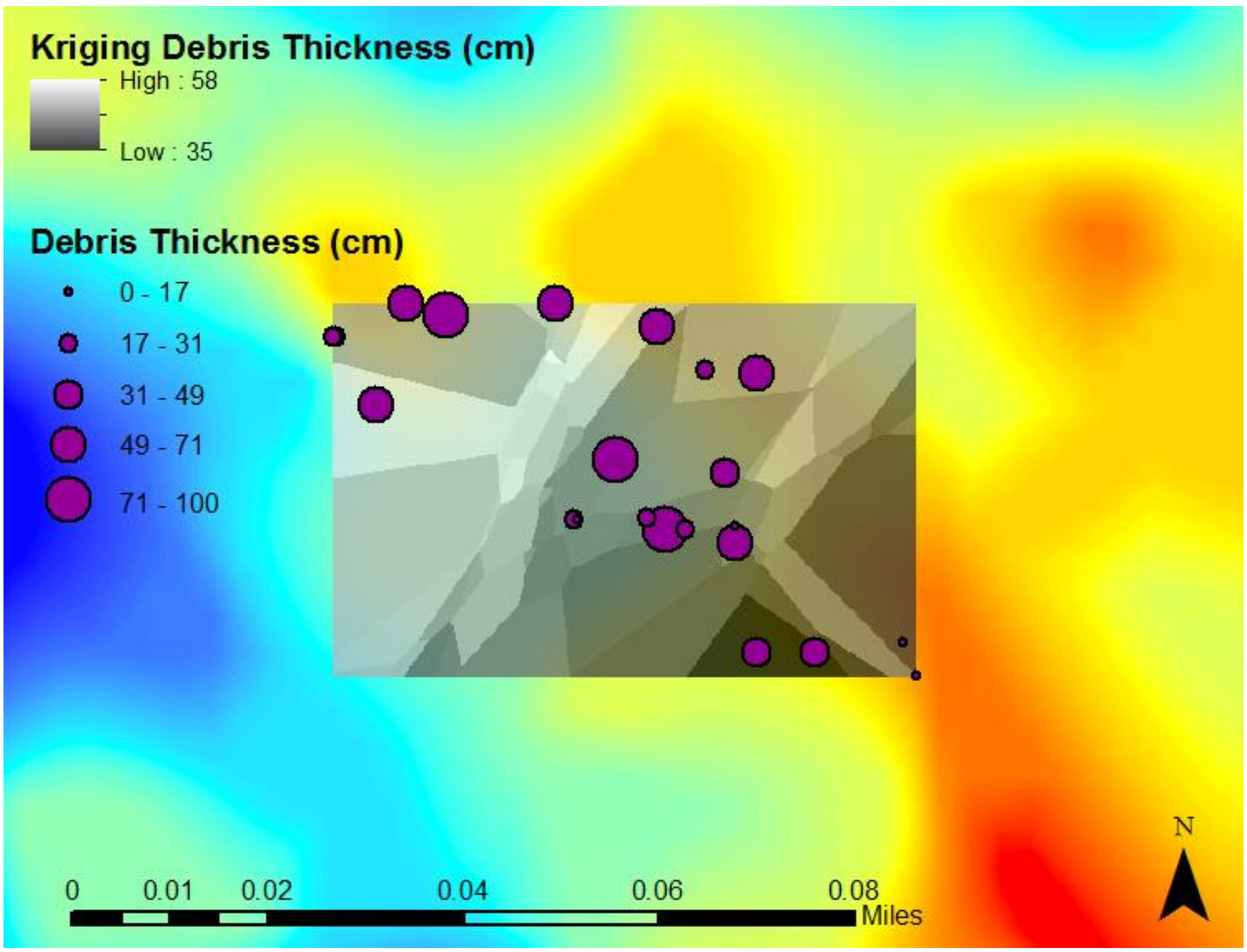



**Figure 4: The result of applying the kriging method to debris thickness data in ArcGIS**

While there is an obvious complexity to the kriging solution, closer inspection reveals the result to be garbage. The kriging raster does not accurately capture the range of samples points (compare the high and low extents of the two layers in the legend). The explanation is that there is simply not enough data to produce a meaningful result.

*Exploration of DEM-based Correlations*

The failed attempt to utilize kriging suggested that interpolation by any method was unlikely to produce favorable results. Instead, other relationships to debris thickness were sought. The idea came that perhaps by integrating the information contained within the DEM, a useful correlation could be found. In a physical sense, one would not expect debris thickness to be correlated with elevation. However, it seemed at least somewhat feasible that slope, aspect, or surface curvature may have some relationship to debris thickness: a steeper slope may be less able to hold thick layer of debris than a flatter surface; the direction a slope faced may affect differential melting or debris deposition on the surface; upwardly concave surfaces could conceivably act as debris traps, while convex surfaces might shed debris.

Subsequently, the ArcGIS tools Slope, Aspect, and Curvature were employed to calculate slope, aspect, and curvature rasters of the Imja Tsho basin. These maps are shown below in figures 5, 6, and 7, respectively.

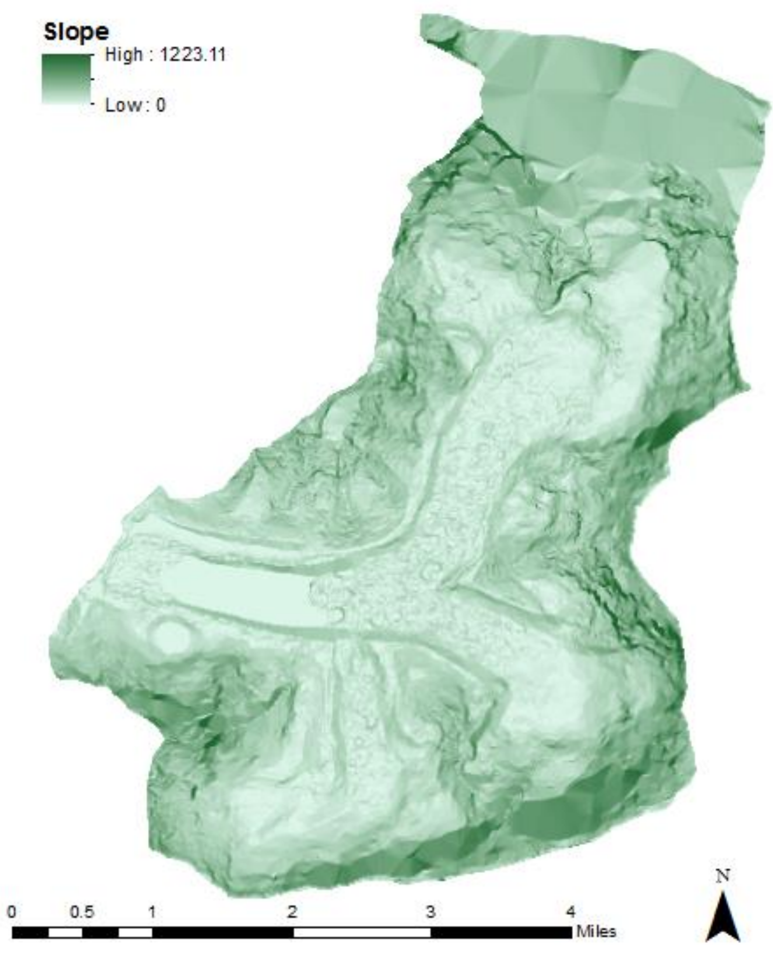



**Figure 5: Slope raster of the Imja Tsho basin.**

The units of the slope were specified to be percent rise when the Slope tool was run. The legend display, showing a maximal value of 1223.1, is probably the result of an error within the DEM.

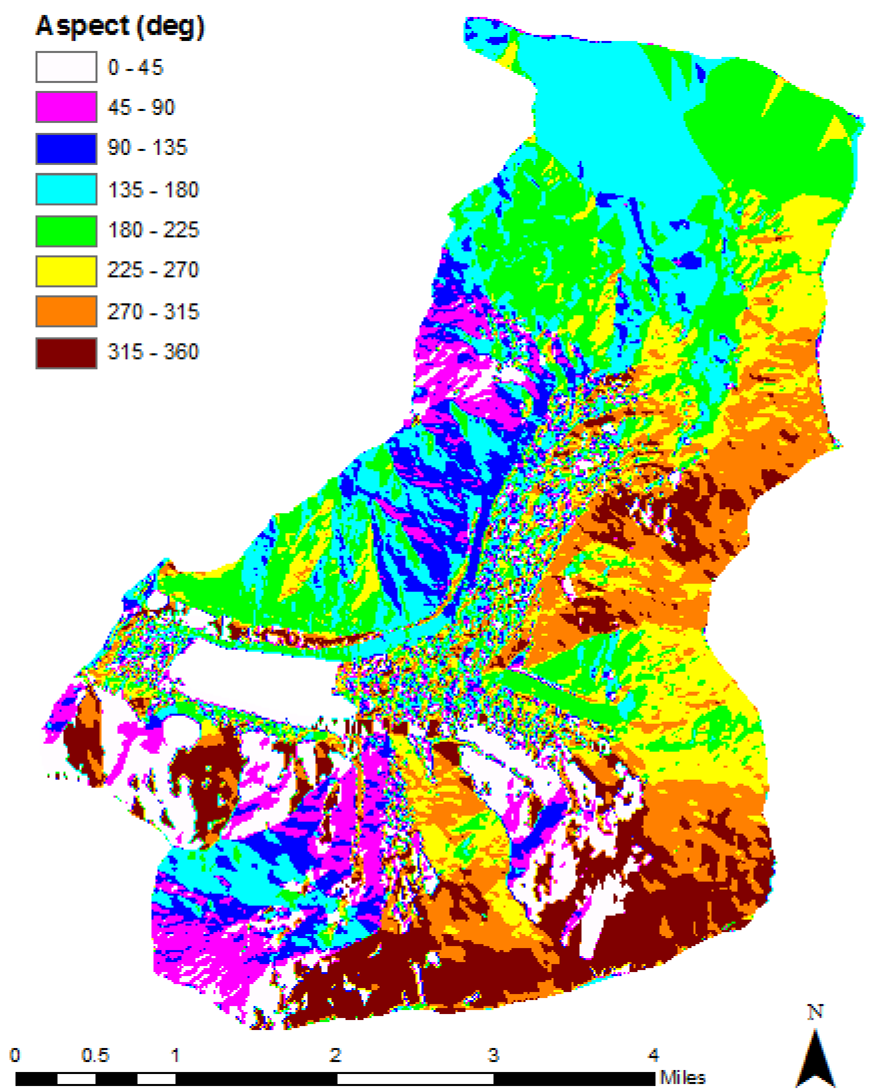



**Figure 6: Aspect raster for the Imja Tsho basin.**

In Figure 6, the legend gives surface aspect in degrees from north, where north is indicated on the map as being towards the top of this page. Flat surfaces or those with indeterminate aspect appear to be given a value of 0 as well – i.e., Imja Lake in the center of the map is white.

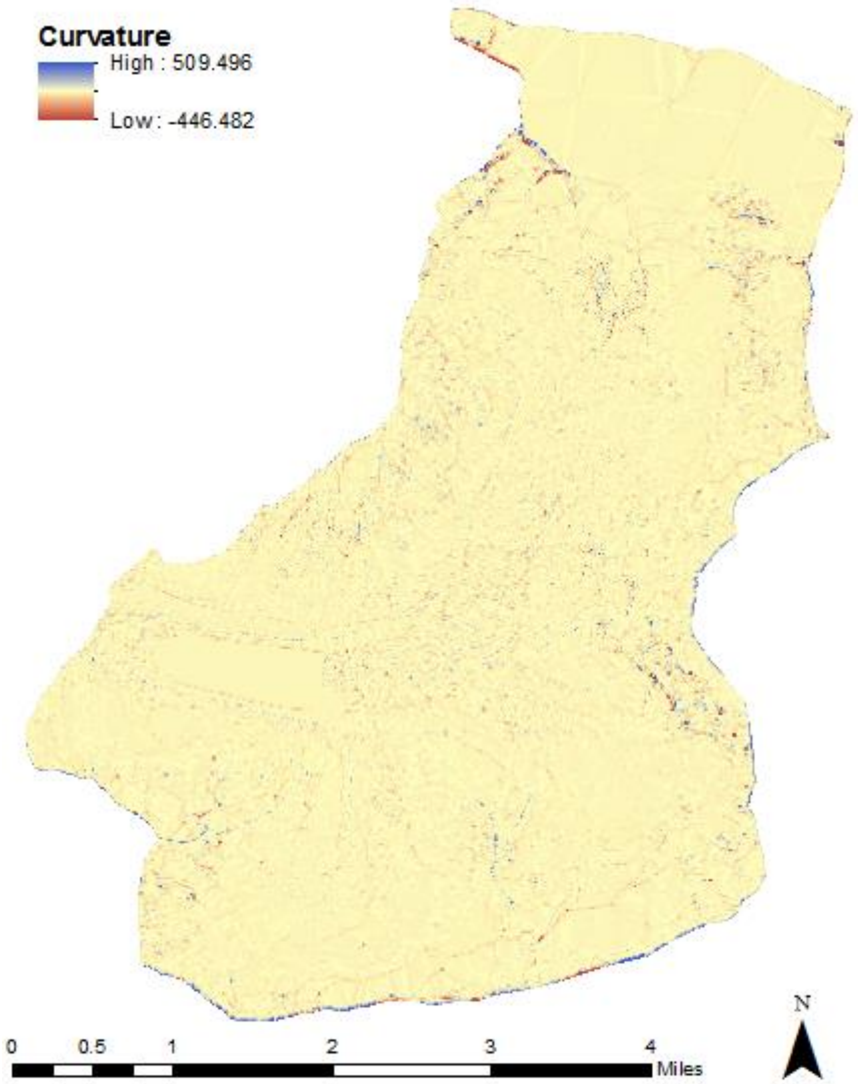



**Figure 7: Curvature raster for the Imja Tsho basin.**

Curvature is the derivative of slope, or the second surface derivative of elevation at a point. Because it is a surface vector, there are two orthogonal components to curvature: profile curvature and plan curvature. The profile curvature is oriented in the direction of maximum slope, and the plan curvature is oriented perpendicular to the direction of maximum slope. The default, primary output of the curvature tool (displayed above) is the cell-by-cell curvature, computed by using the curvatures of 8 adjacent cells (in a similar manner as R8 flow direction determination). Large positive curvature values indicate an upwardly convex surface, like the top of a hill, while large negative values indicate the opposite: a downwardly convex surface, like a bowl. ESRI advises that curvature values will seldom exceed |4|, but here they are around |500|. The source of this error may be the same issue that resulted in unreasonably high slope values in Figure 5. A closer view of the curvature raster, with sample locations overlain, is given below in Figure 8.

Having now calculated three new raster layers, we sought to compare this information with the debris thickness data. The values of each raster surface at the points sampled were extracted using the ArcGIS tool Sample (Figure 9). The tool allows the capability to sample from multiple rasters at once and collate the information in a table. The resultant table was exported to Microsoft Excel, where the data pairs were plotted against one another in search of any kind of correlative relationship. These charts are shown below (Figure 10).

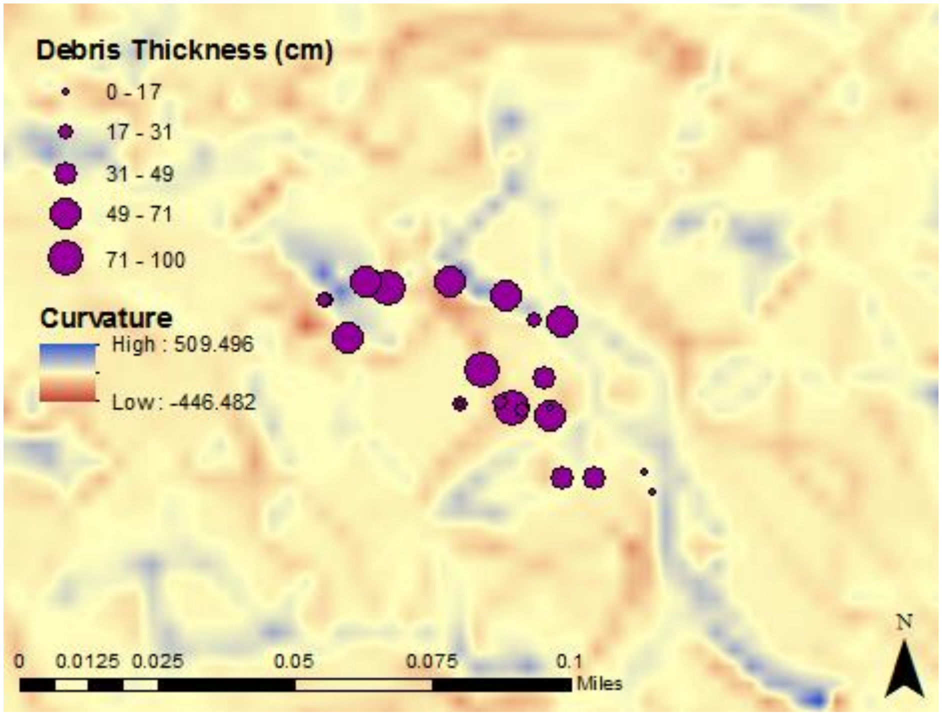



**Figure 8: Sample points overlain on the surface curvature raster**

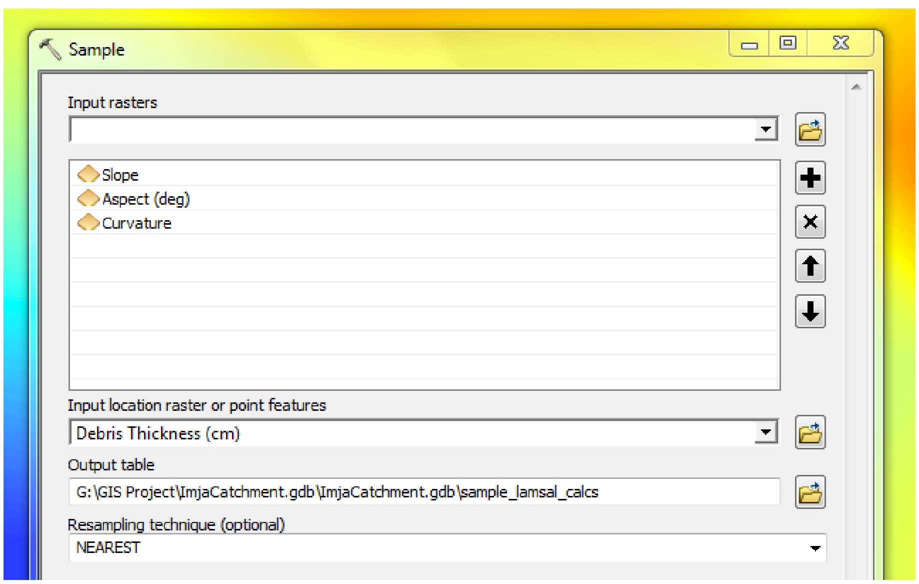



**Figure 9: Screenshot of the Sample tool**

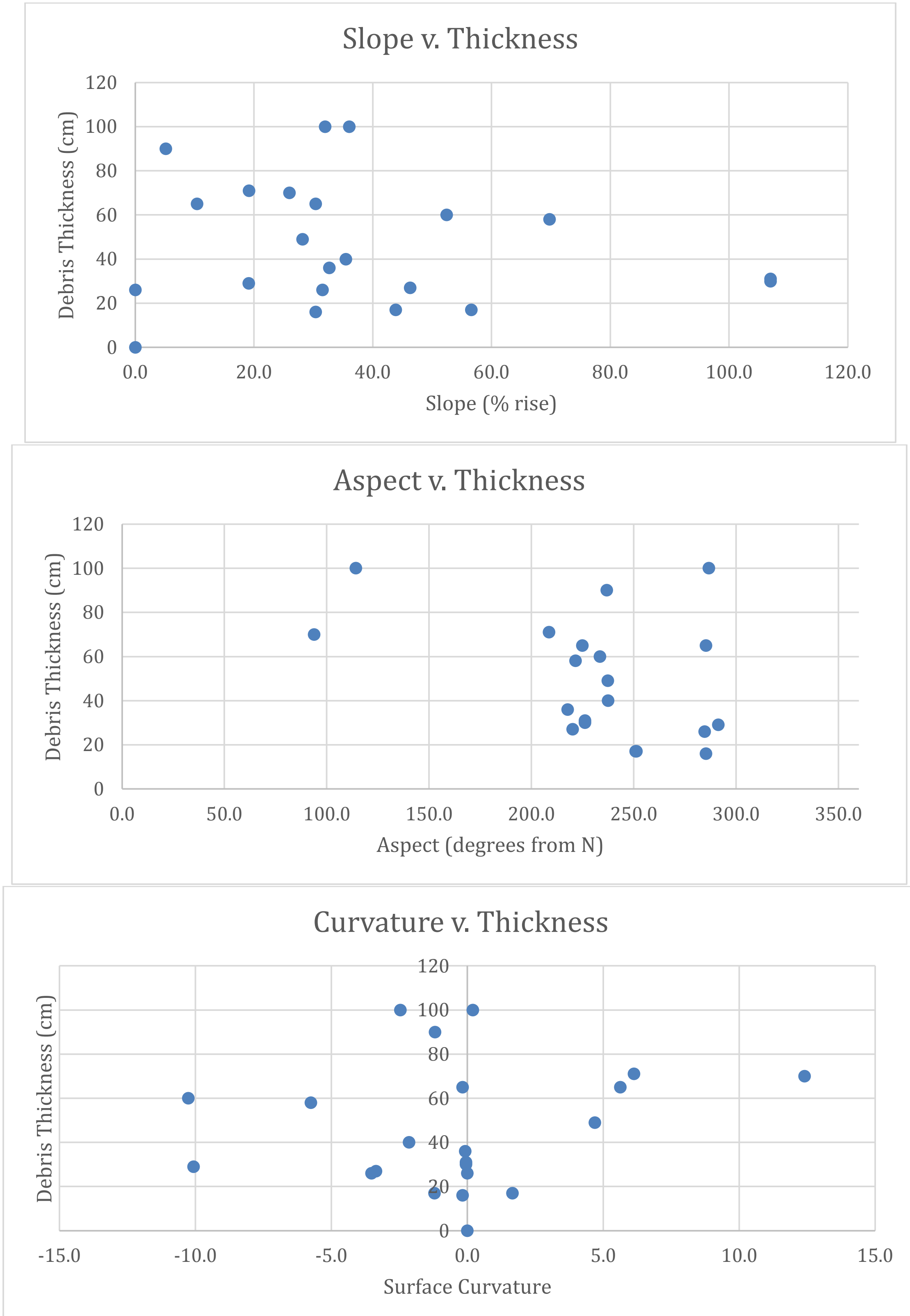



**Figure 10: Debris thickness plotted against slope, aspect, and curvature at each sample point**

Unfortunately, we can see no meaningful correlation between any of the variables analyzed. Perhaps there is some semblance of a negative trend in the Debris Thickness vs. Slope plot, but remove the high slope point and the trend turns to noise. We might again blame the small sample size for the lack of meaningful results, but the possibility exists that there is in fact no meaningful correlation between any of these variables and debris thickness, no matter how large the sample.

*Comparison of GPS Tracker Elevation with DEM Elevation*

One possible issue with the previous analysis is that Lamsal's DEM dates to 2006, whereas the field data was collected very recently (September 2013). If the glacier surface changed appreciably in the interim, then the sample points (lat/long) cannot be reliably mapped to the DEM elevation values, and therefore the above analysis is invalid from the start. While we do not have access to a more recent, fine-scale DEM, we do have the GPS tracker data that recorded elevation measurements as Dave traversed the glacier surface. An analysis of the discrepancy between the GPS elevations and the DEM elevations would reveal to what extent the DEM misrepresents the glacier surface of today.

This task was accomplished first by importing the GPS tracker data from Excel into ArcGIS, creating a point feature class (Figure 11). Again using the Sample tool, DEM elevation values were extracted at the points defined by Dave's trajectory over the glacier. This tabular data was exported back to Excel, at which point statistical analyses could begin. There were a total of 1324 locations sampled.

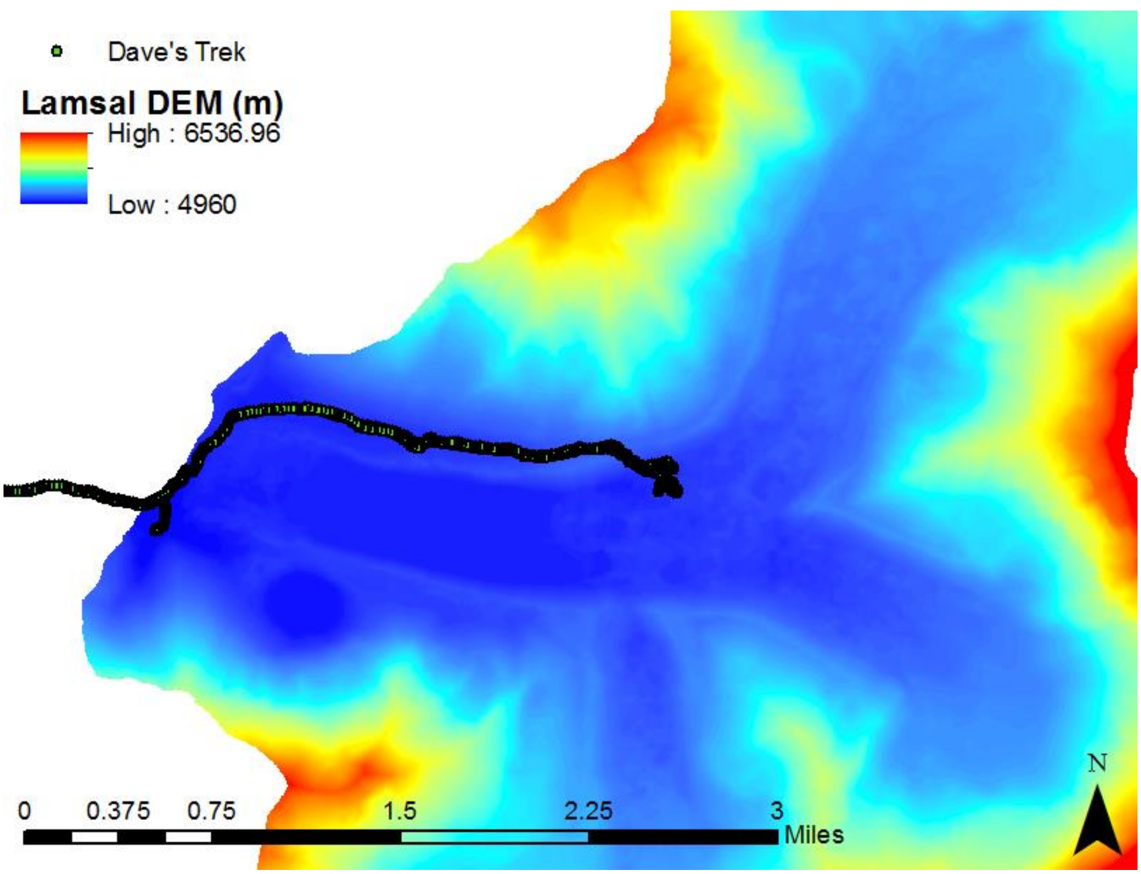



**Figure 11: The sequence of points shows Dave's trajectory over the surface of the glacier**

First, the GPS elevation and the DEM elevation values were plotted in series, showing a profile view of Dave's elevation during his trek (Figure 12). Dave took an out-and-back path, hence the symmetry about the midpoint of the graph.

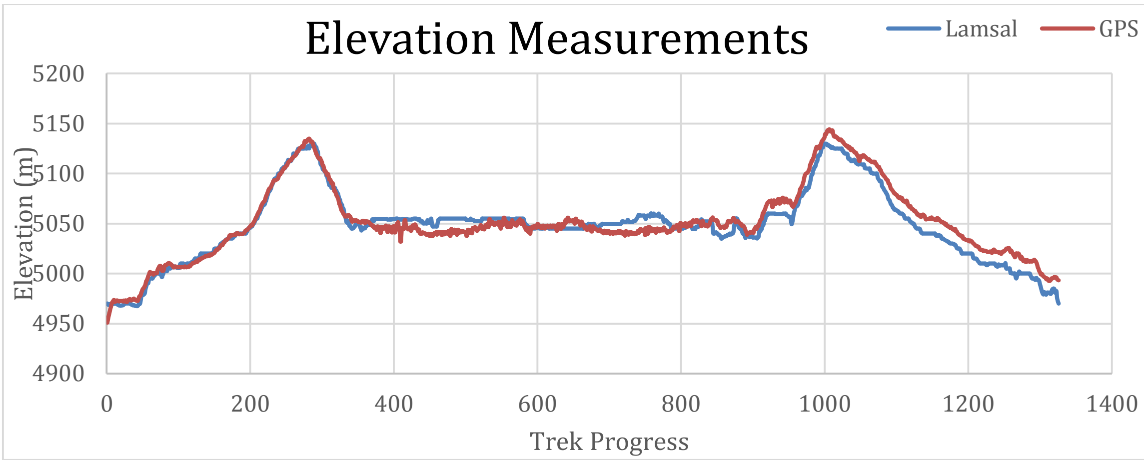



**Figure 12: Elevations passed through during the field campaign, according to GPS data and DEM information**

Then, pairs were subtracted (GPS-DEM), resulting in the "Elevation Discrepancy". With this data, summary statistics were calculated (Table 1) and a histogram was constructed to visualize the distribution of the discrepancy (Figure 13). Additionally, a normal probability plot was constructed for the discrepancy data (Figure 14). A normal probability plot is built by ranking a set of data, assigning quantiles to each rank according to a formula (in this case Blom's plotting position was used), and then inverting the quantiles to derive normal z-scores. These standard normal variates are plotted against the z-scores of the original data, and the extent to which the plot follows the line y=x is an indication of the normality of the dataset. Conversely, the deviation from y=x, especially at the tails, can suggest non-normal distribution.

| *Statistic* | *GPS Elevation (m)* | *DEM Elevation (m)* | *Discrepancy (m)* |
|---|---|---|---|
| *Average:* | 5051.00 | 5048.17 | 2.83 |
| *Variance:* | 1300.47 | 1284.15 | 89.28 |
| *Standard Dev:* | 36.06 | 35.84 | 9.45 |
| *Skew:* | 0.42 | 0.12 | -0.17 |

**Table 1: Summary Statistics for Elevation Discrepancy**

From this table we see that the discrepancy is centered on 2.8m with a standard deviation of 9.5m. The mean is positive, implying that on average the GPS elevation is greater than the DEM elevation.

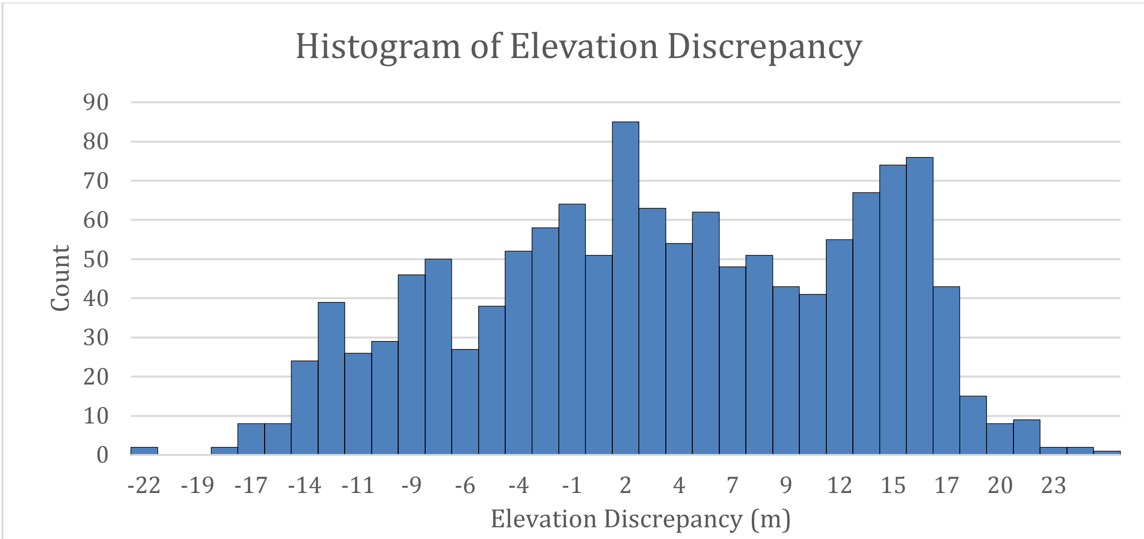



**Figure 13: A histogram showing the distribution of the discrepancy between GPS and DEM elevation values**

Looking at the histogram, we observe a somewhat symmetric shape, although there appears to be a slight bimodal tendency, with a second peak at the upper (positive) end of the distribution.

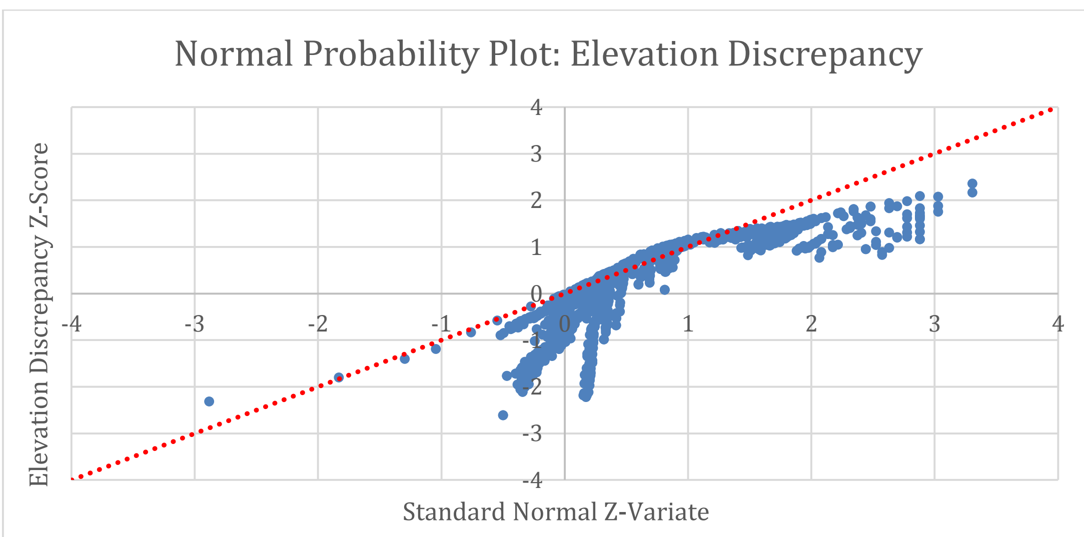



**Figure 14: Normal Probability Plot for Elevation Discrepancy**

The normal probability plot shows deviation from the line y=x at both the positive and negative tails in the same direction, indicating that the elevation discrepancy might not be normally distributed – there may be some trend or skew inherent in the difference between GPS and DEM elevations.

The question arose: how significant is a 2m discrepancy in the context of this dataset? To answer this question, we can use hypothesis testing. Hypothesis testing facilitates quantitative comparisons between datasets. In our case, the null hypothesis would be that there is no difference between the two groups, whereas the alternative is that a difference does exist. Through the test, this statement would either be disproven or not disproven. There are a wide variety of tests to choose from, but an appropriate test in this case would be the Wilcoxon signed-rank test. This test does not require any assumptions about the normality of the dataset. Given what we know from the normal probability plot, assuming normality may not be a valid anyways. The test was performed in MATLAB and the results are shown below in Table 2.

*Wilcoxon Signed-Rank Test*

| | | |
|---|---|---|
| *p-values:* | *two-tail* | *8.75E-25* |
| | *right-tail* | ***4.38E-25*** |

**Table 2: Wilcoxon Signed-Rank Test results for Elevation Discrepancy**

The p-value represents the probability that the given samples would be observed if the null hypothesis were true. Because it is so extremely small in this case, we reject the null hypothesis: the test says that there is a significant difference between the two groups. In other words, the 2.5 difference in level between the GPS elevation and the DEM elevation is real and significant, not just the product of random sampling errors.

*On-Glacier vs. Off-Glacier*

Why would the elevation across the glacier have *risen* since 2006, given that the glacier is melting? One might expect the opposite to be true – that the elevations on the glacier are lower now than they were in 2006 due to underlying glacial ice melting and the glacier surface slowly lowering. Revisiting the trajectory Dave took to his field site, it became apparent that Dave was only on the actual glacier itself for a short part of that journey – the rest was presumably traversed on montainsides, trails, and other more stationary landscape features. Examining figure 15 below, it appears that as Dave approached his field site, he climbed to the crest of a moraine adjacent to the Imja Glacier before descending the slope and accessing the glacier. The points on glacier can be identified as those near to the sampling points, as well as those points leading up to the visible "edge" of the glacier. This edge is most clearly shown by the slope raster calculated earlier. Figure 16 depicts Dave's path as moving down a long, consistent slope before finally meeting the edge of the glacier. Once on the glacier, Dave circled around as he sampled and eventually made it back to his entry point to the glacier, where presumably there is some sort of trail that he used to traverse back to his origin.

The same analysis performed above for Dave's entire trek in the Imja Tsho basin was repeated, but this time only considering the subset of points corresponding the glacier surface. The points that were selected for analysis are highlighted in Figure 17 below. The reduced dataset contained 618 points. The summary statistics are shown in Table 3.

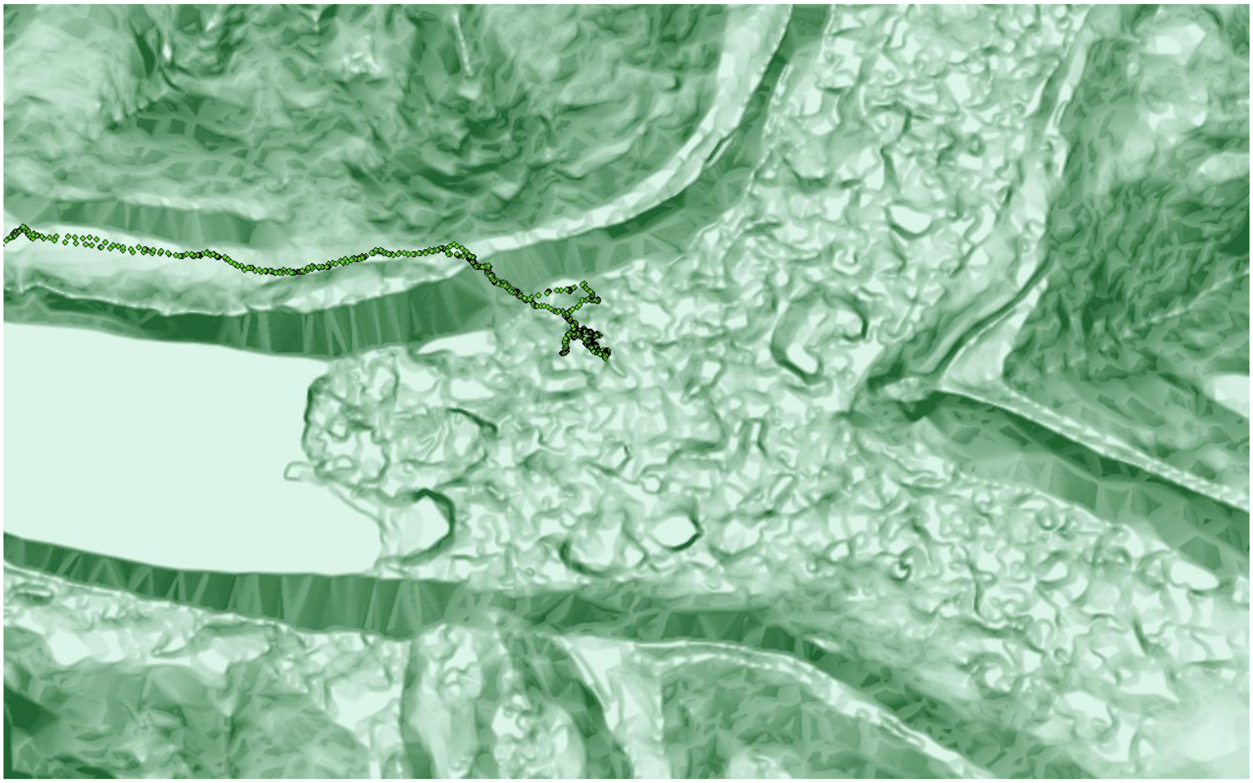


**Figure 15: View of Dave's traverse overlain on the Imja Tsho basin slope raster**

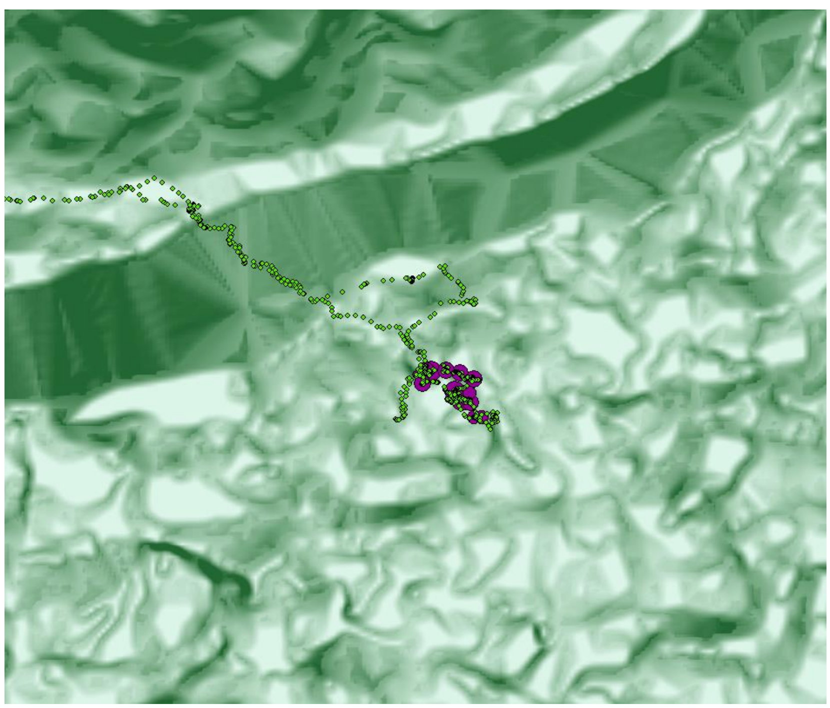


**Figure 16: Depiction of the edge of the glacier at where Dave's path splits into a loop. Sample points are shown in purple.**

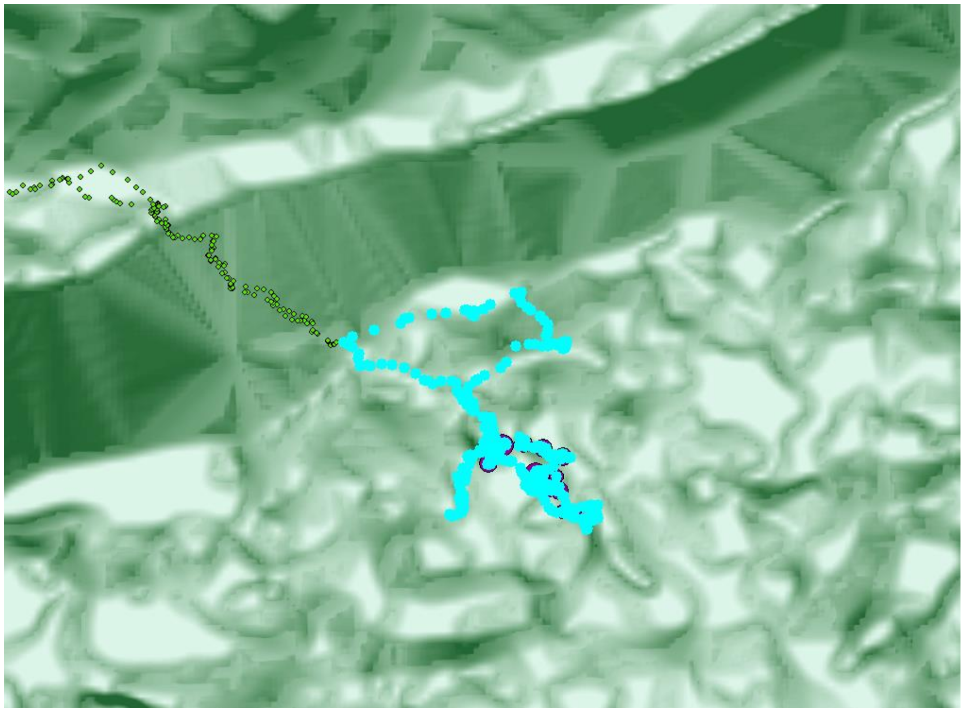


**Figure 17: Selected points for on-glacier analysis**

| *Statistic* | *GPS Elevation (m)* | *DEM Elevation (m)* | *Discrepancy (m)* |
|---|---|---|---|
| Average: | 5047.86 | 5050.37 | -2.51 |
| Variance: | 58.44 | 33.32 | 77.69 |
| Standard Dev: | 7.64 | 5.77 | 8.81 |
| Skew: | 1.74 | -0.57 | 0.30 |

**Table 3: Summary Statistics for Elevation Discrepancy On-Glacier**

Interestingly, with on-glacier points the elevation discrepancy average is -2.5m, indicating that the surface is lower as compared to the 2006 DEM. The on-glacier elevation profile, histogram, and normal probability plots are given below:

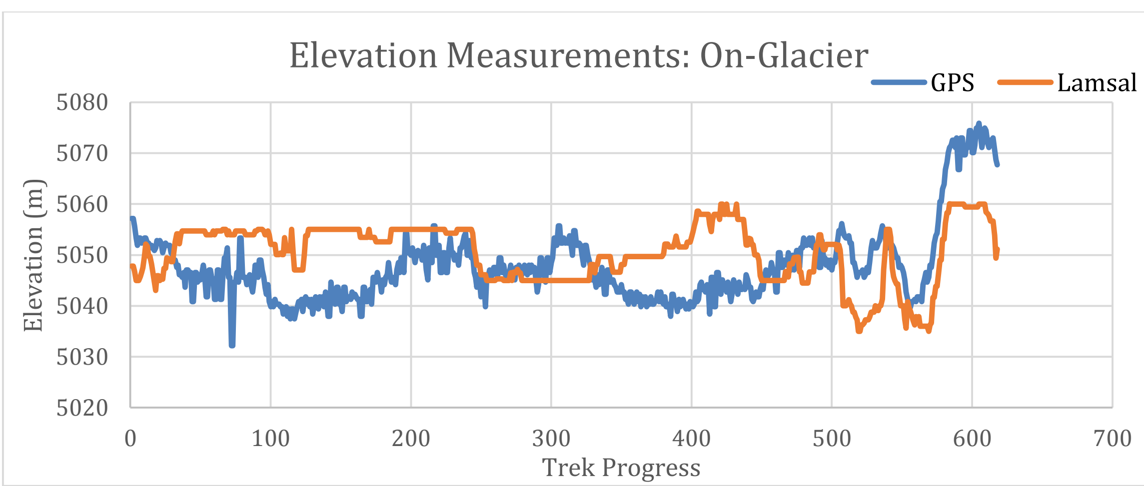



**Figure 18: Elevation profile, on-glacier**

The relationship between GPS elevation and DEM elevation is not as close as with the larger dataset. It does appear that for a significant portion of the points, the GPS elevation is below the DEM elevation, but there are some cases of the opposite scenario.

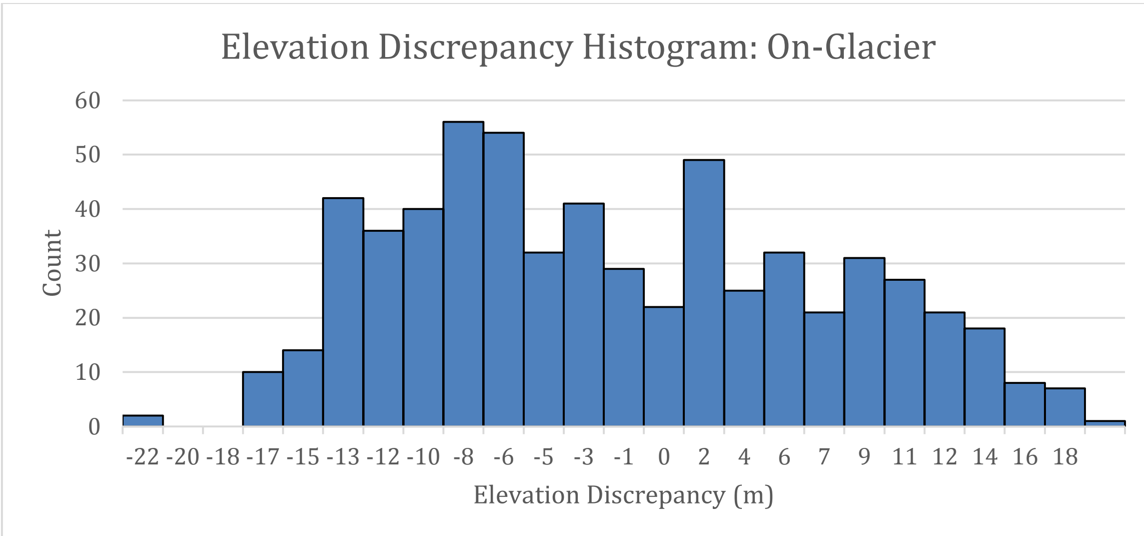



**Figure 19: On-glacier elevation discrepancy historgram**

The histogram of elevation discrepancies has slight positive skewness, but appears more symmetric than the histogram of Figure 13.

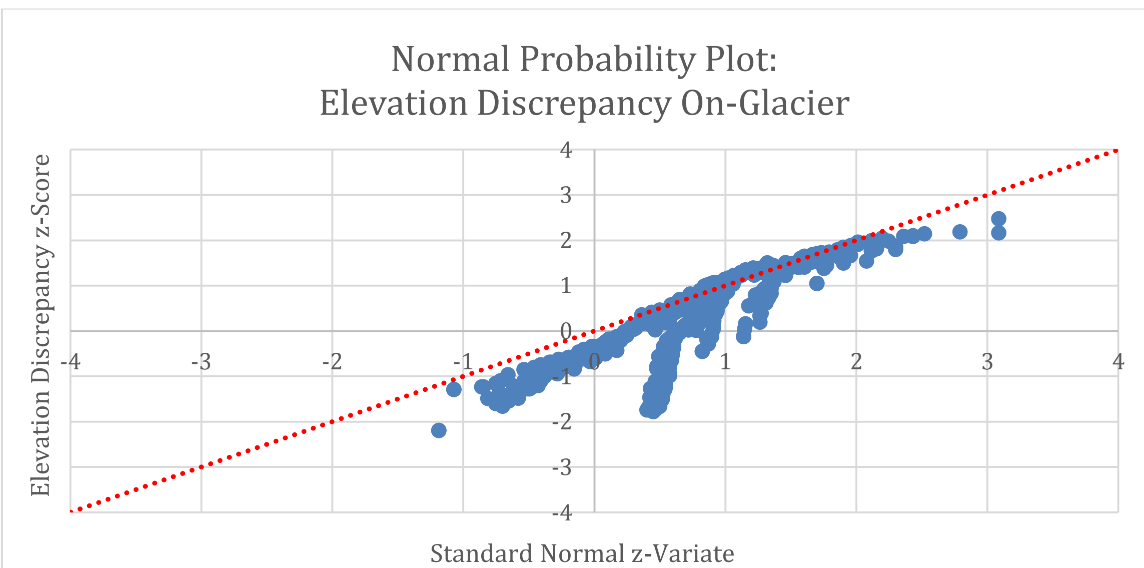



**Figure 20: Normal Probability Plot for On-glacier Elevation Discrepancies**

The normal probability plot shows significantly less deviation from y=x at the tails, suggesting that the distribution of the elevation discrepancies between these points on-glacier is much more normal. Most of the points do lie below the line y=x, however, indicating perhaps some difference level.

For consistency's sake, the Wilcoxon signed rank test was applied to this dataset, despite possibly more normal distribution. The low p-value resulting from the left-tail test indicate that the difference is very significant between the two groups – GPS elevations are on average 2.5m lower than DEM elevations. The two elevation measurements do not likely come from the same population.

*Wilcoxon Signed-Rank Test*

| | | |
|---|---|---|
| p-values: | two-tail | 8.80E-12 |
| | left-tail | **4.41E-12** |

**Table 4: Wilcoxon Signed-Rank test results for on-glacier elevation discrepancy**

## Summary of Results & Conclusions

The initial research goal for this project – interpolating debris thickness across the Imja glacier surface – quickly proved to be difficult to accomplish. Instead, the investigation was taken down a different path, a more exploratory path. Correlations were sought between DEM slope, aspect, curvature and debris thickness, but to no avail. Questions arose as to the validity of the methods and the accuracy of the DEM itself.

Through a selective comparison of GPS tracker recorded points and the Lamsal DEM from 2006, it can be concluded that there has been a significant decrease in the overall elevation of the Imja glacier surface since 2006 (at least in the area near Dave's field site). Whether this is attributable to subsurface melting or some other factor is beyond the scope of this investigation. Additionally, the distribution of residuals between GPS measured elevations and DEM elevations has been determined to be approximately normal. This might facilitate predictive modeling of the elevation difference, hence allowing some coarse method of correction to the existing DEM. An assessment of the stationarity of this trend in time would first need to be made.

While these results may not directly aid in the formulation of a melt model for the Imja glacier, understanding of the dynamics of the glacial surface is an important piece of modeling the dynamics of glacial lake formation. In this task, GIS has proven to be an indispensable tool.

**References**

1. Watanabe, Teiji; Lamsal, Damodar; Ives, Jack D. "Evaluating the growth characteristics of a glacial lake and its degree of danger of outburst flooding: Imja Glacier, Khumbu Himal, Nepal" *Norwegian Journal of Geography* 63 (2009) 4: 255-267
2. Lamsal, Damodar; Sawagaki, Takanobu; Watanabe, Teiji. "Digital Terrain Modelling Using Corona and ALOS PRISM Data to Investigate the Distal Part of Imja Glacier, Khumbu Himal, Nepal" *Journal of Mountain Science* (2011) 8: 390-402