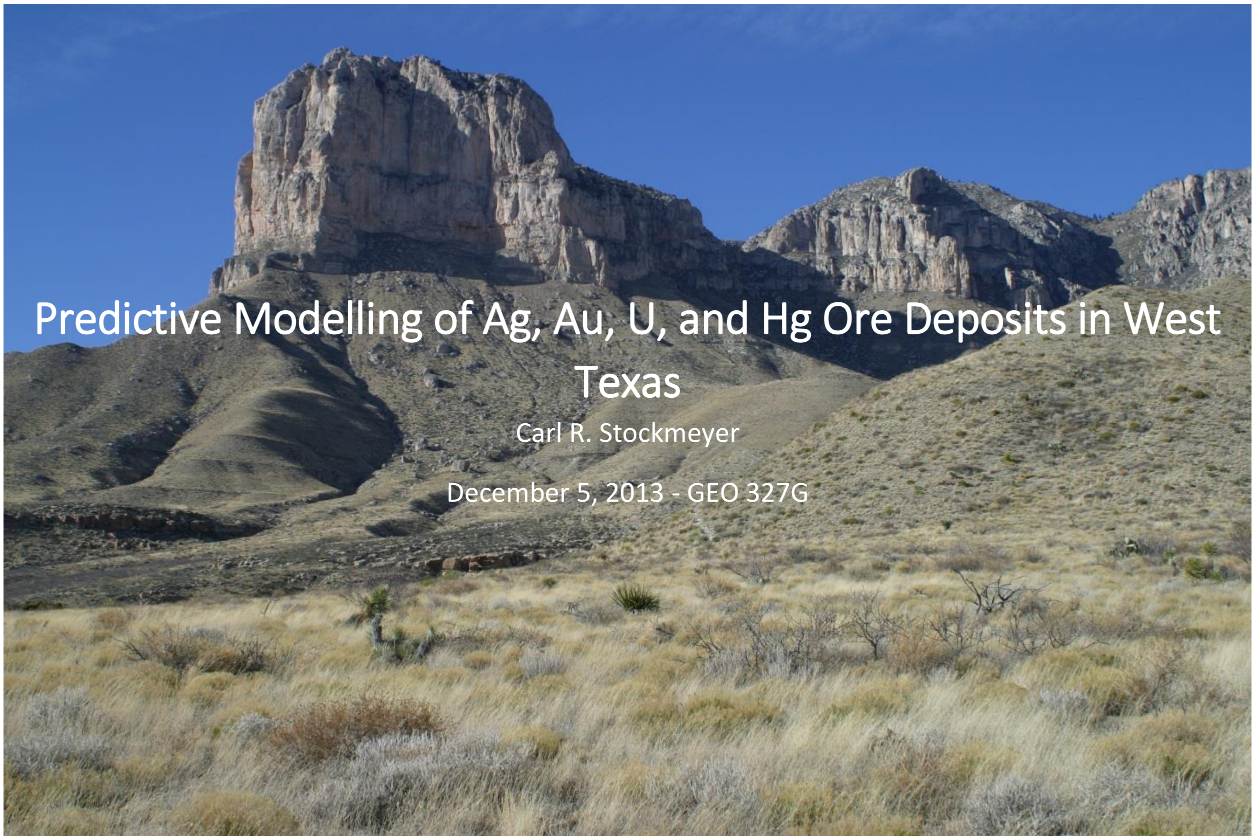

Predictive Modelling of Ag, Au, U, and Hg Ore Deposits in West Texas

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Objectives and Motivations

The goal of this project is to use ArcGIS to create models based on characteristic features that may be useful as indicators of the presence of ore deposits in West Texas, and to use these models to perform a suitability analysis within the region to predict the potential locations of other such deposits that are yet to be discovered. Furthermore, the project intends to serve as a demonstration of the diverse applications for GIS software.

Methods

To achieve this end, I aimed to combine geophysical data representing magnetic and gravitational field anomalies throughout the region in coordination with geologic map data pertaining to the surface geology. My plan called for first examining the surface geologic units, contained in a polygon shapefile (see fig. 1), within the region and determining which of these surface units contain known deposits, included in a point shapefile, of Uranium, Silver, Gold, or Mercury ores. I would then determine the relative quantities of each ore contained within each of the given rock units. Next, I edited the known deposits point shapefile to create four new feature classes, each containing only locations corresponding to one the above elements. I then qualitatively assigned rankings to each rock unit, and for each element, based on the relative levels of occurrence of the given element within the rock layer. These rankings were compared to the host rock units and altered rock units listed for the deposit locations that contained information in these fields, and any adjustments, perhaps arising from an ore being hosted within a subsurface unit, were then made to the rankings. Next, I planned to analyze the geophysical raster data in the attempt of determining which, if any, field anomalies generally correspond to the presence of the ore bodies and/or their host rocks. Finally, I intended to create a raster layer, for each ore type, whose cell values would be the result of the combination of the factors and patterns, after applying appropriate weights, related to the ore type.

Data Collection

The statewide GIS data used in the completion of this project was gathered from the USGS website. Unfortunately, the geophysical datasets (figs. 2, 3, and 4) were at a 2000m raster cell size and higher resolution data could not be found from any source. Due to the low resolution of these raster layers, a high degree of uncertainty was inherent in their application to the model, and so they were only used when it appeared that a strong and quantifiable correlation existed between an anomaly trend and the presence of potential ore-bearing rock units. Several attempts were made to procure higher resolutions geophysical anomaly datasets, but none were found for the entire region and so the 2000x2000m data was used.

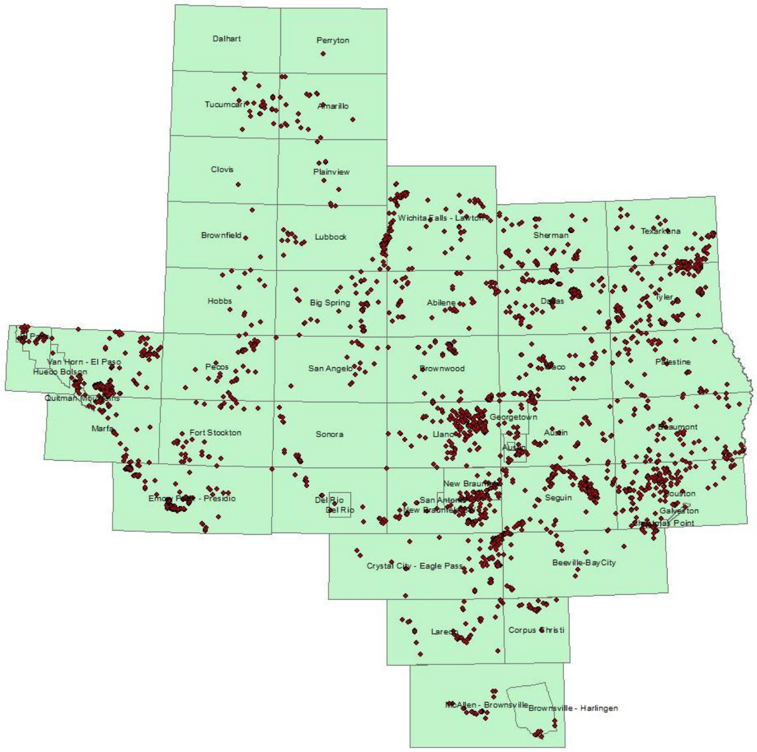

Figure 1 – Statewide rock units polygon shapefile (1:250K) for surface geology

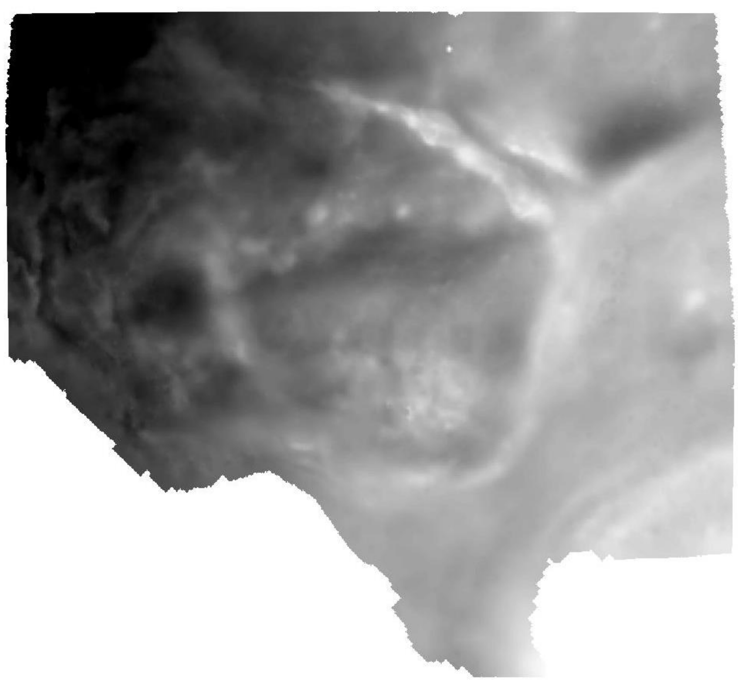

Figure 2 – Statewide Bouguer gravity anomaly layer

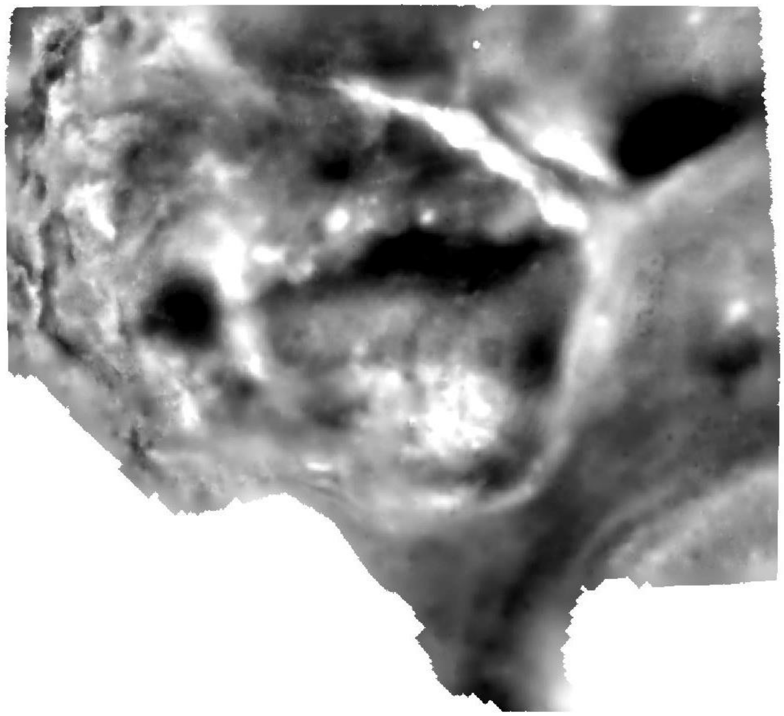

Figure 3 – Statewide isostatic gravity anomaly layer

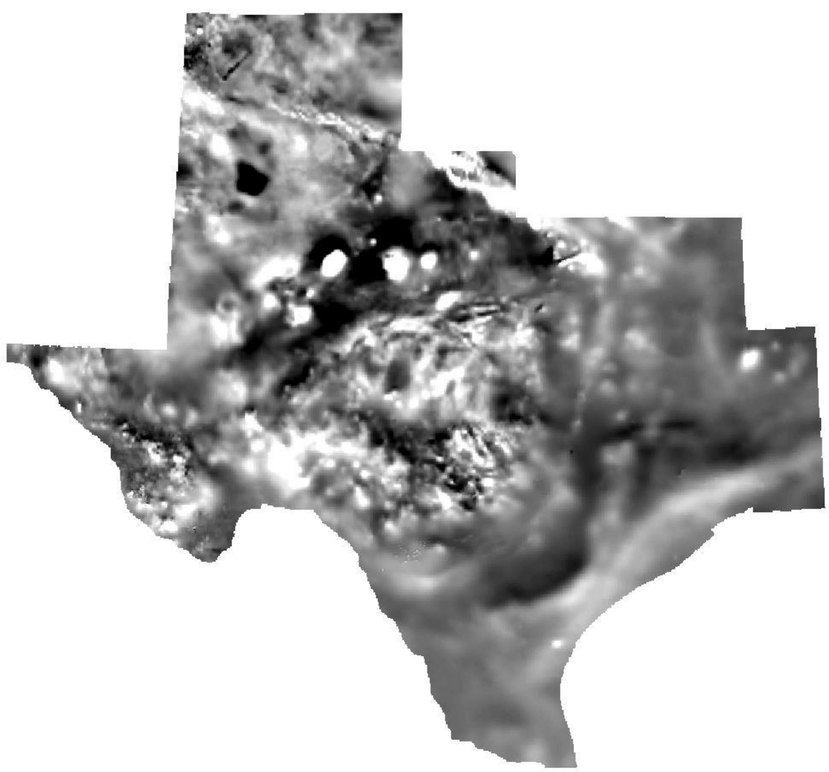

Figure 4 – Statewide aeromagnetic anomaly layer

Preliminary Data Processing

Before beginning to actually create this model within ArcGIS, it was necessary to import all of the relevant data layers into an ArcGIS data frame, and to ensure that all of the imported files had been properly projected into the Texas Albers coordinate system. I then utilized the "clip" tool (see fig. 5) to remove unnecessary data from the known mineral deposit point feature class and the Texas counties and surface geology polygon feature classes by clipping the layers to the counties of interest. For similar reasons, I then used the "extract by mask" tool to remove, or define as null, all of the raster cells not contained within those counties, by defining the clipped Texas counties shapefile as a mask for each of the rasters.

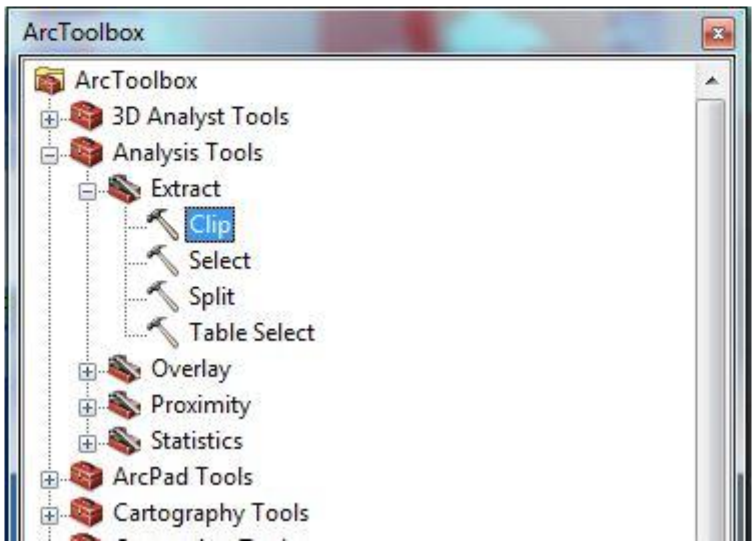

Figure 5 – Clip Tool

Next, the 1:250K rock unit polygon class was then related to its corresponding table in order to allow for more manageable analysis and identification of these units and four separate point feature classes were created to contain the points corresponding the known deposits of each of the four elements of interest (see fig. 6). This allows distinctive symbolization of each deposit type to easily be achieved and altered on a case-by-case basis, as necessary, during preliminary processing and analysis. Additionally, the existence of individual feature classes allowed for the attributes related to the points for each ore type to be exported to separate Excel sheets, which would prove to be important in several processing steps.

After defining the symbols for each of these point classes, I then zoomed in on the map and could finally make the shapefile for the surface rock units visible. This enabled for a detailed qualitative and quantitative analysis of the surface unit polygons containing points for any of these classes (see figs. 7, 8, and 9). Upon determining the rock units containing deposit points on the map, I verified or disqualified the potential for the units to contain such deposit using the aforementioned spreadsheet tables, which contained information on the host and altered rock types for some points. The discrepancies between the apparent host rock on the map and as listed in the attribute tables arises from two possibilities: 1) the large scale (1:250,000) at which the geologic units were originally mapped inherently prohibits small outcrops from appearing in the map, and 2) the ore body may have been covered over by another rock unit, such as Quaternary sediments.

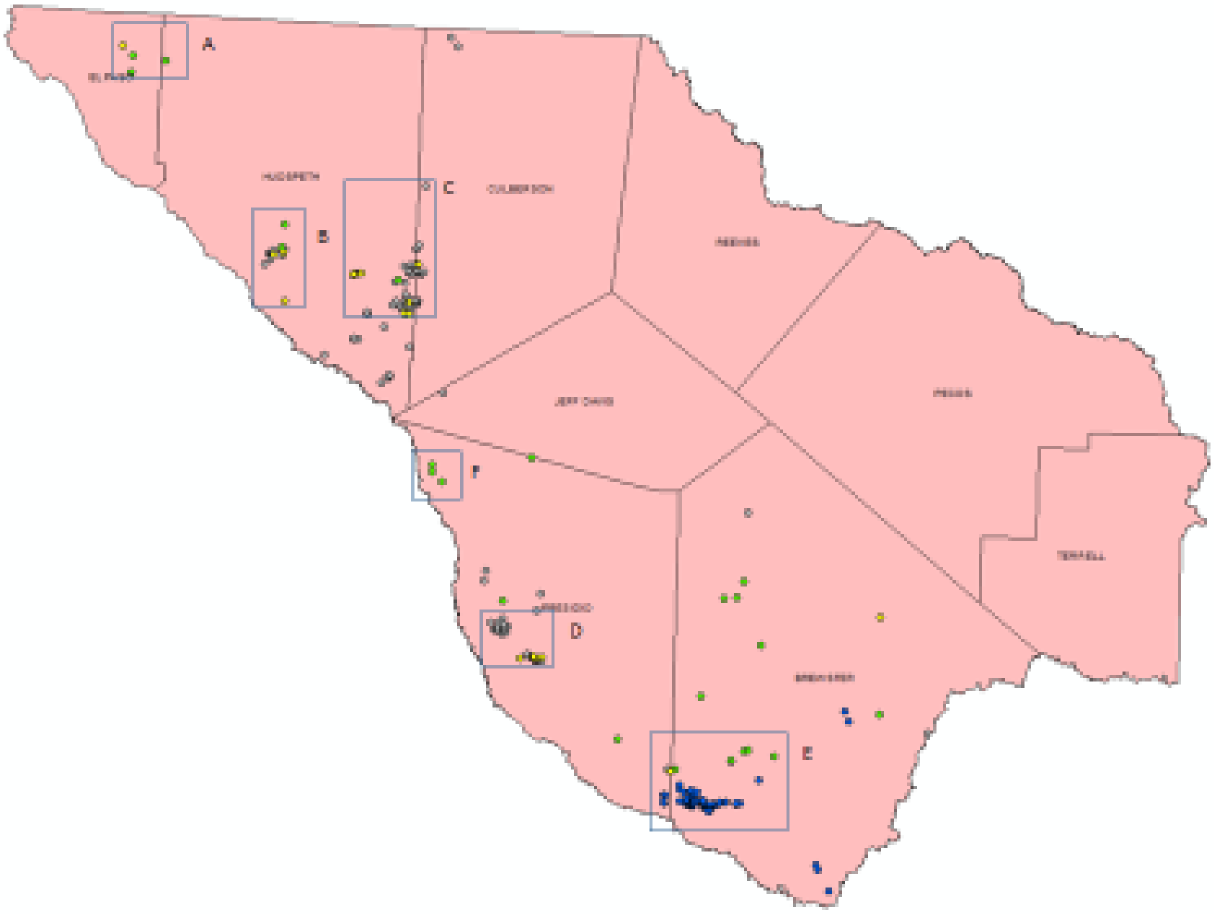

Figure 6 – The clipped Texas counties shapefile. Known mineral deposit locations are represented as follows: grey for silver, yellow for gold, green for uranium, and blue for mercury.

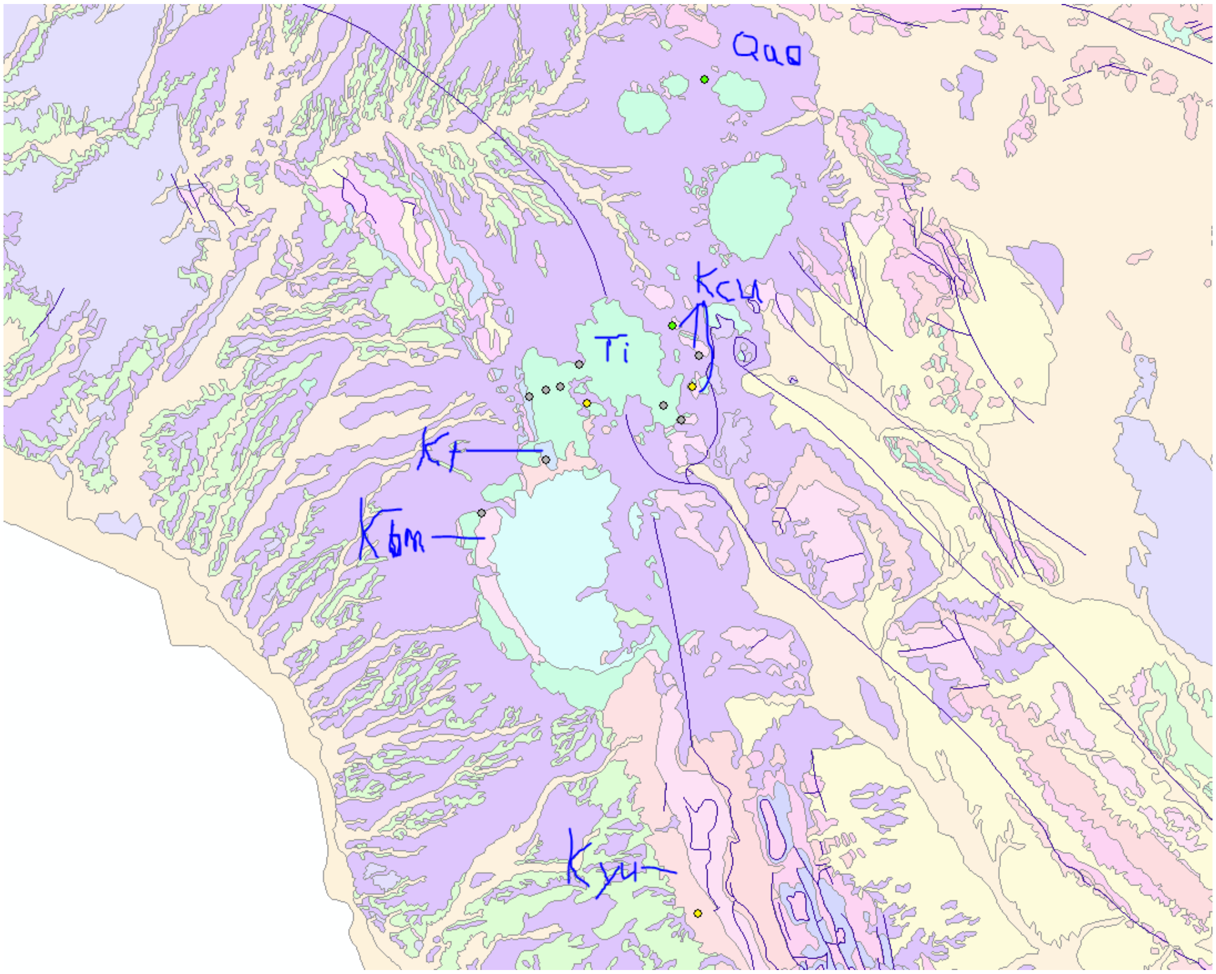

Figure 7 – Labeled map of rock units contained within Box B in figure 6.
Contains Ag (grey), Au (yellow), and U (green) ore deposits.

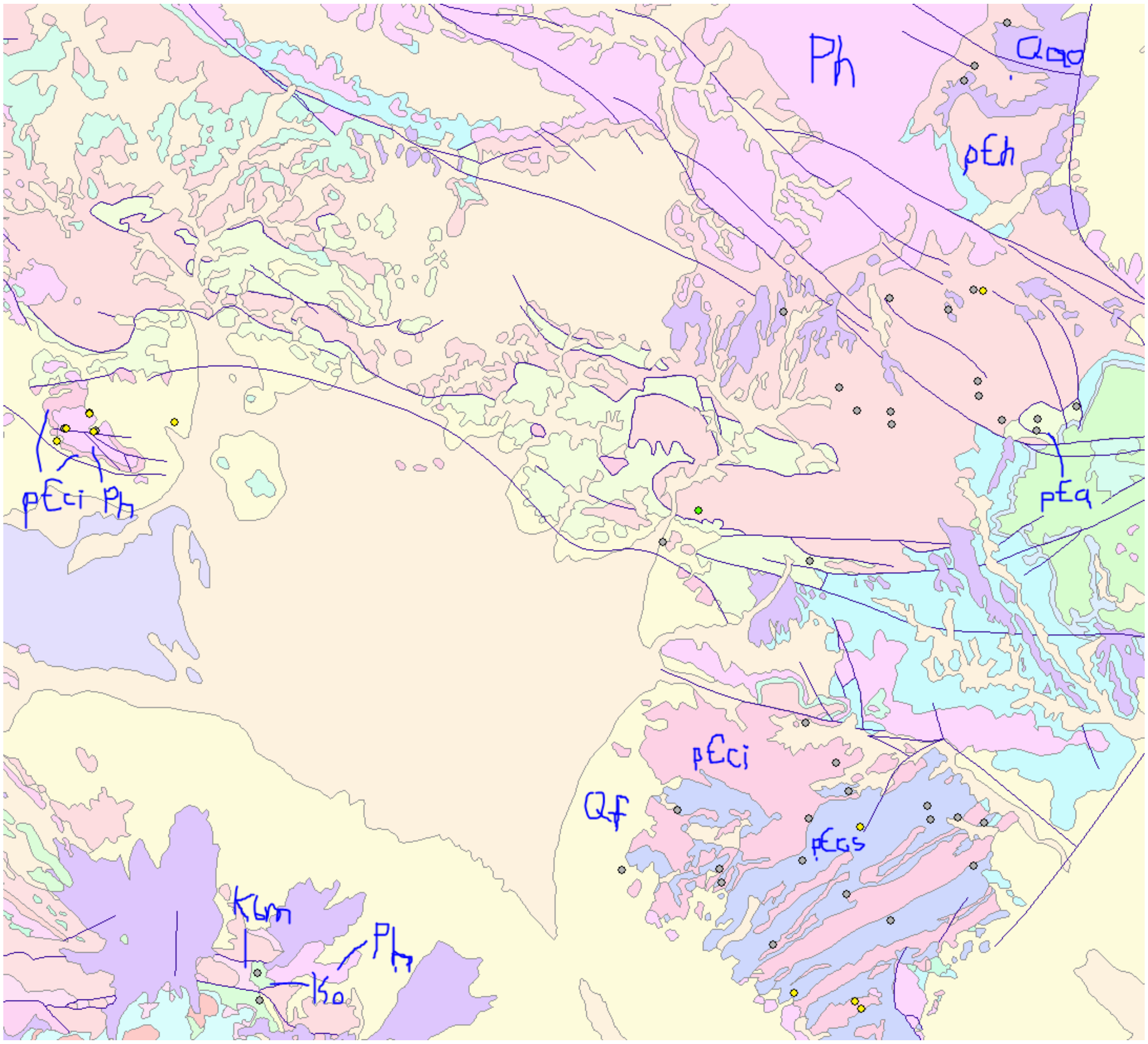

Figure 8 – Labeled map of rock units contained within Box C in figure 6. Contains Ag (grey) and Au (yellow) ore deposits.

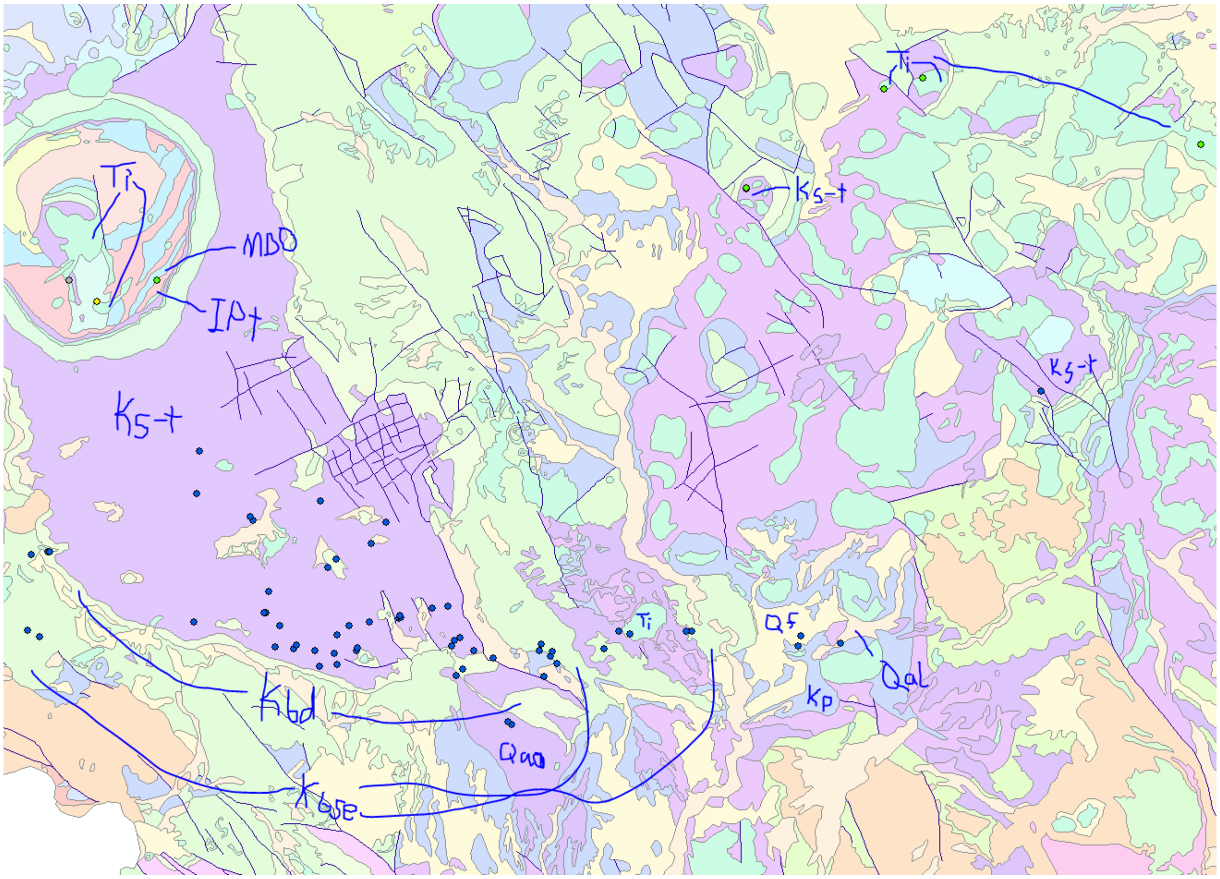

Figure 9 – Labeled map of rock units contained within Box E in figure 6. Primarily contains Hg (blue) and U (green) ore deposits.

Once the relative abundances of each ore type contained within each host rock unit had been determined, a field was added for each element to the rock unit polygon attribute table (see fig. 10), with initial values of the fields being defined as null. These fields for each elements were populated with ranks based on the recently determined relative ore abundances within the corresponding rock unit type, with high ranks being related to a relatively large number of ore deposits and mines being located within that rock type. This was achieved by creating an SQL query script (fig. 11, left) to select the rock units in groups of those units that would be assigned identical ranks, and the field calculator tool was used to populate the relevant field, for all selected entries, with the rank value corresponding to those units (fig. 11, right). This process was repeated until the appropriate ranks had been applied to each rock unit type containing, or possibly containing, a known ore deposit.

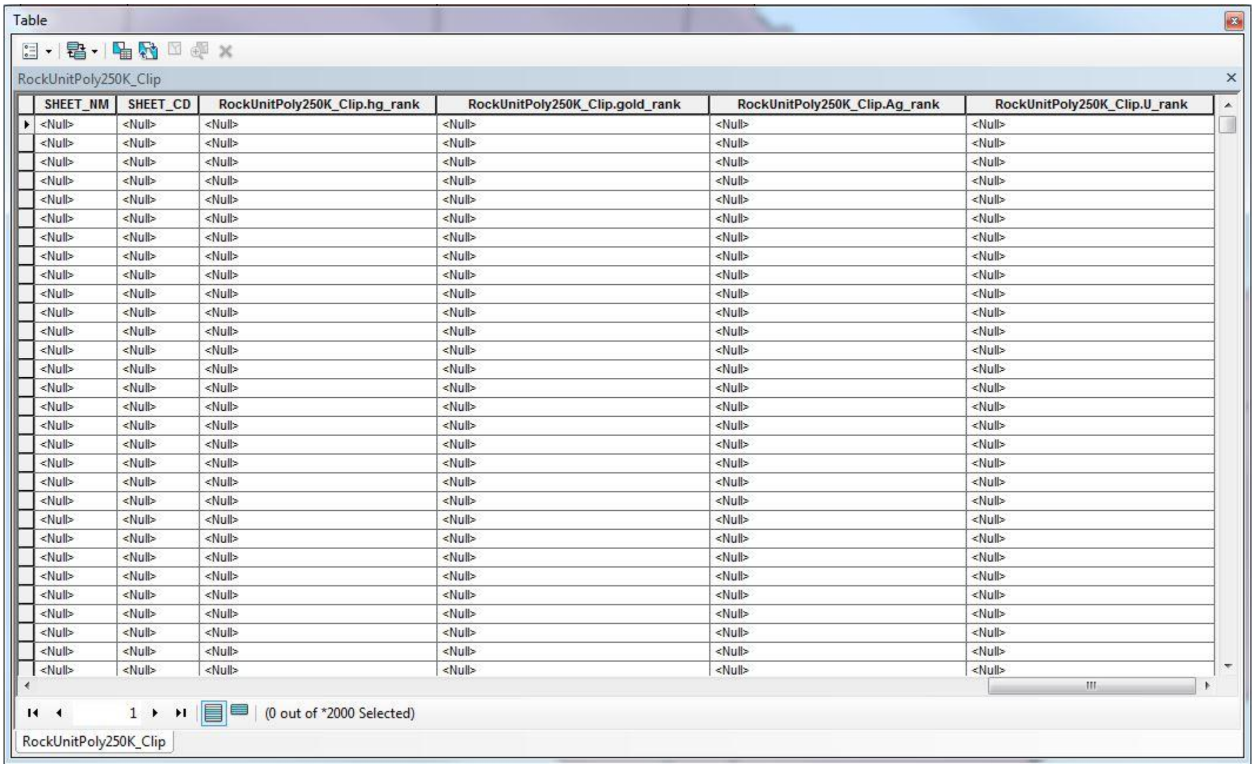

Figure 10 – The attribute table for the rock unit polygon feature class, with the 4 new rank fields having been added to the end of the table.

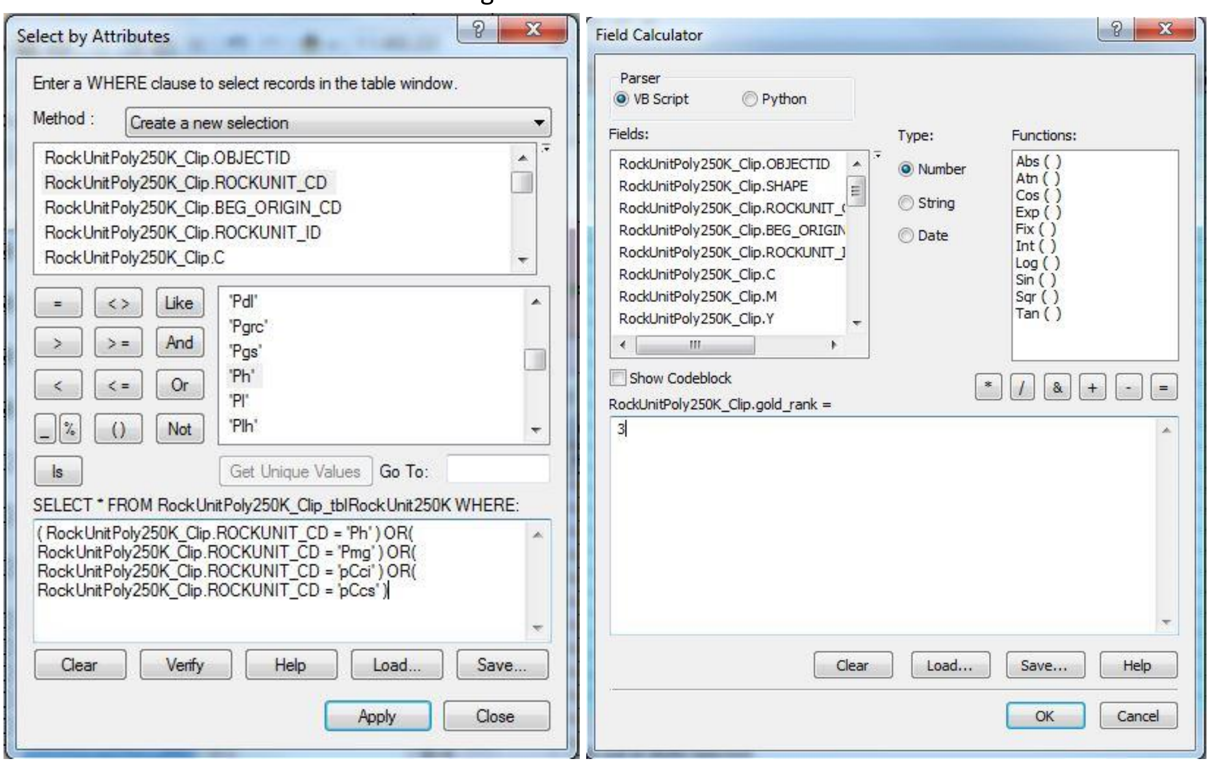

Figure 11 – (Left) The select by attributes tool and SQL query script. (Right) The field calculator tool for defining cell values in the chosen attribute field.

ArcGIS Processing

Perhaps due in part to the resolution of the magnetic and gravitational anomaly data, there was some difficulty in establishing a consistent relationship between the presence of these ore bodies and the existence of local anomalies. No correlations could be determined between mineral deposits and variance in the Earth's magnetic field, however, there did appear to be a fairly reliable connection between the presence of silver and gold ore bodies and the existence of high frequency isostatic gravity anomalies (or relatively large fluctuations in the Earth's gravitational field, which are not due to variations in surface topography) in the vicinity of very large, positive isostatic anomalies. To qualify this relationship, I used the Slope tool (see fig. 12) to create a raster with cell values equal to the slope of the values of the clipped isostatic anomaly raster, with a Z factor of 2000. I then applied the Focal Statistics tool (see fig. 13) to the slope raster to create a focal statistics standard deviation raster with cell values equal to the standard deviation of slope values within a 3-cell x 3-cell neighborhood of the given cell.

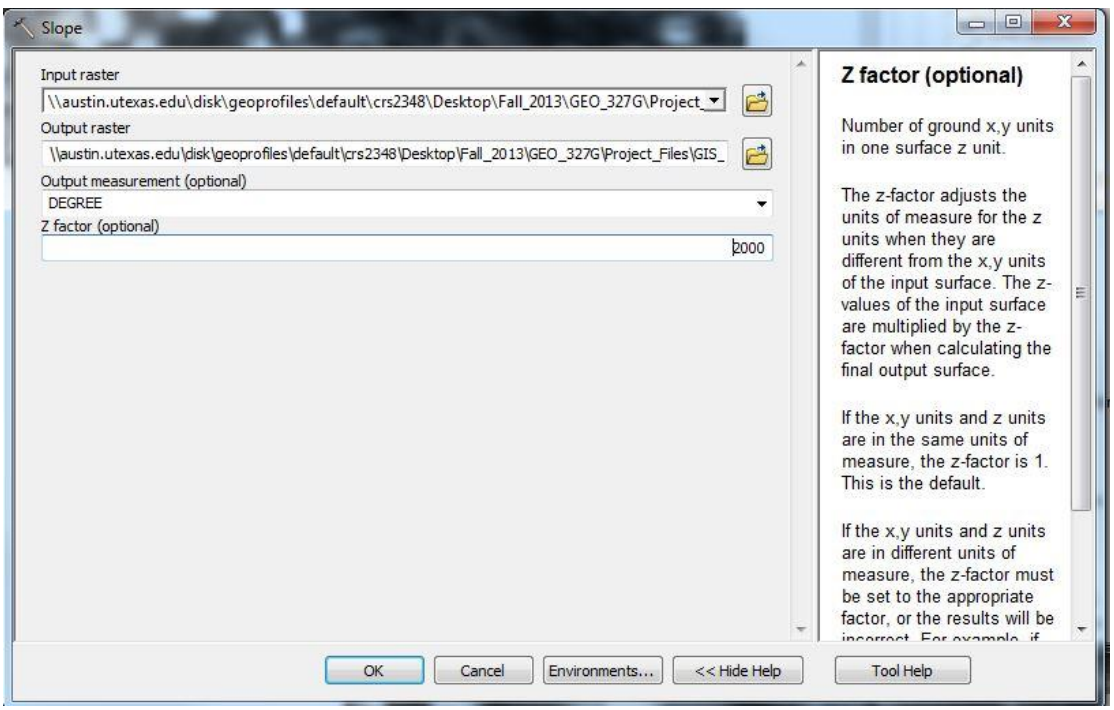

Figure 12 – Slope tool

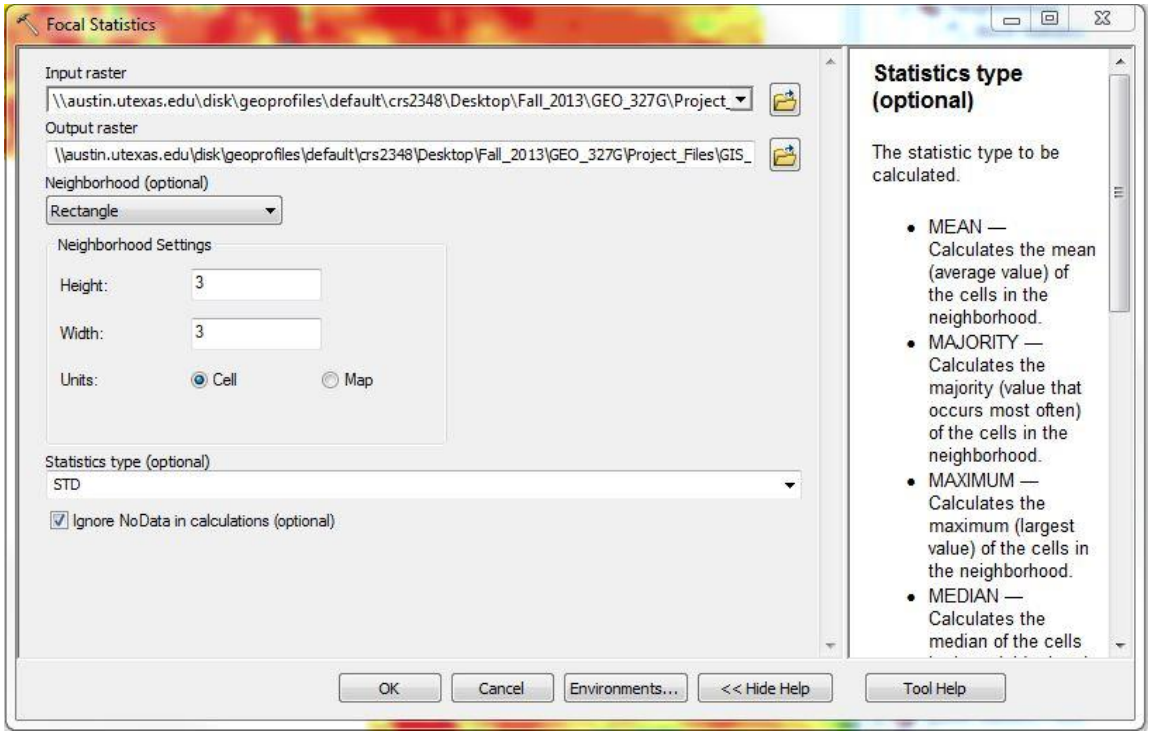

Figure 13 – Focal Statistics tool to calculate the standard deviation of cell values within 3x3 square neighborhood

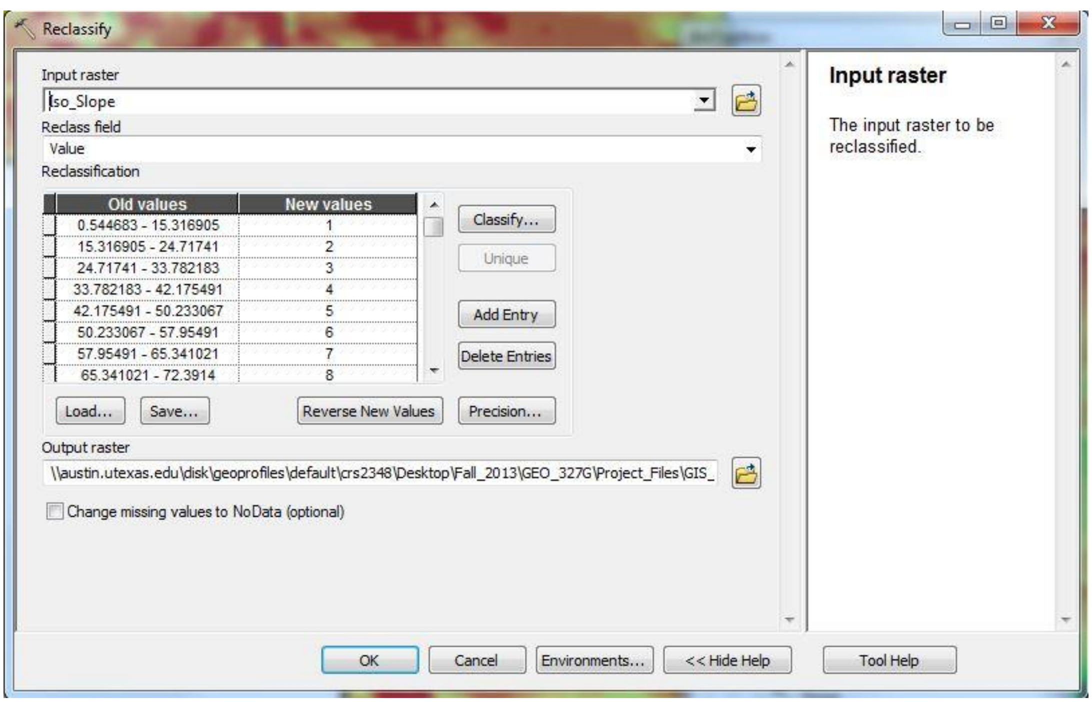

Figure 14 – Reclassify tool

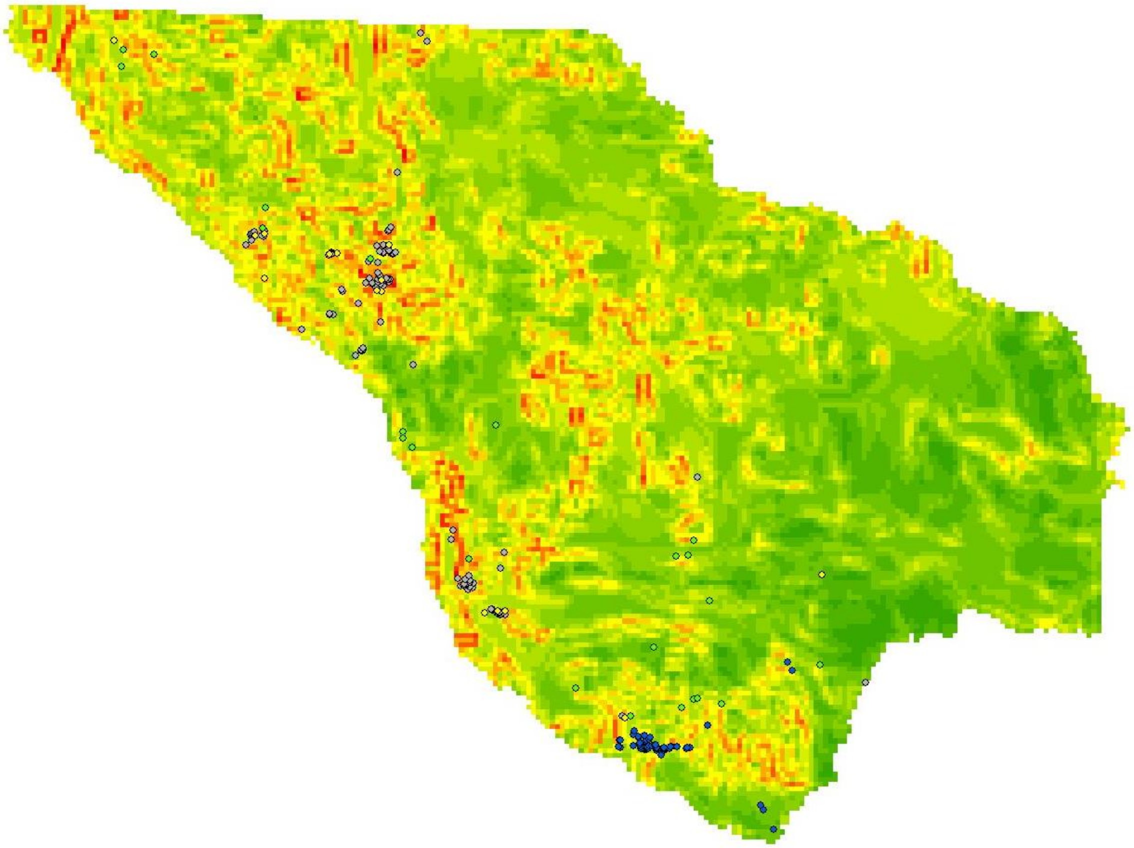

Figure 15 – Iso_grav_analysis raster. Red corresponds to high cell values, which are predicted to indicate areas with an increased probability of containing gold and silver ores.

Next, I used the Reclassify tool (see fig. 14) to create two new rasters by reclassifying the slope and focal statistics rasters with more appropriately weighted cell values. These two new rasters were then added together using the Plus tool to create the Iso_grav_analysis raster (see fig. 15) that would later be used in the creation of the ore deposit suitability analysis rasters for gold and silver ores.

Using the rank values from the four previously populated attribute fields, I then created four rank rasters, one for each ore type, from the rock units shapefile via the Polygon to Raster tool (see fig. 16). From each of those four rasters, I then created two new rasters with the Aggregate tool; one using the SUM aggregation technique, and a second using the MAX aggregation technique. Because I used a cell factor of 20 (original rasters converted from polygons had a cell size of 100m to better represent the distribution and identity of the rock units) and turned off the "Expand extent" option, these 8 aggregate raster have cells of the same size and in the same locations as the anomaly rasters. I then reclassified each of the 8 rasters, based on the relative importance for each element of its corresponding aggregate sum raster to its aggregate max raster, which is another way of saying "based on the relative importance of the amount of potential host rocks contained within a cell to the quality of ores produced from those rock units in controlling the probability of ore being present within that cell". The two rasters for each element were then added to each other using the plus tool to create the final suitability analysis rasters for mercury and uranium (see figs. 17 and 18, respectively) and a two new geology rasters for silver and gold. In the case of silver and gold ores, an appropriate reclassification of the Iso_grav_analysis raster was then added to the newly created sum rasters to create their final suitability analysis rasters (see figs. 19 and 20, respectively).

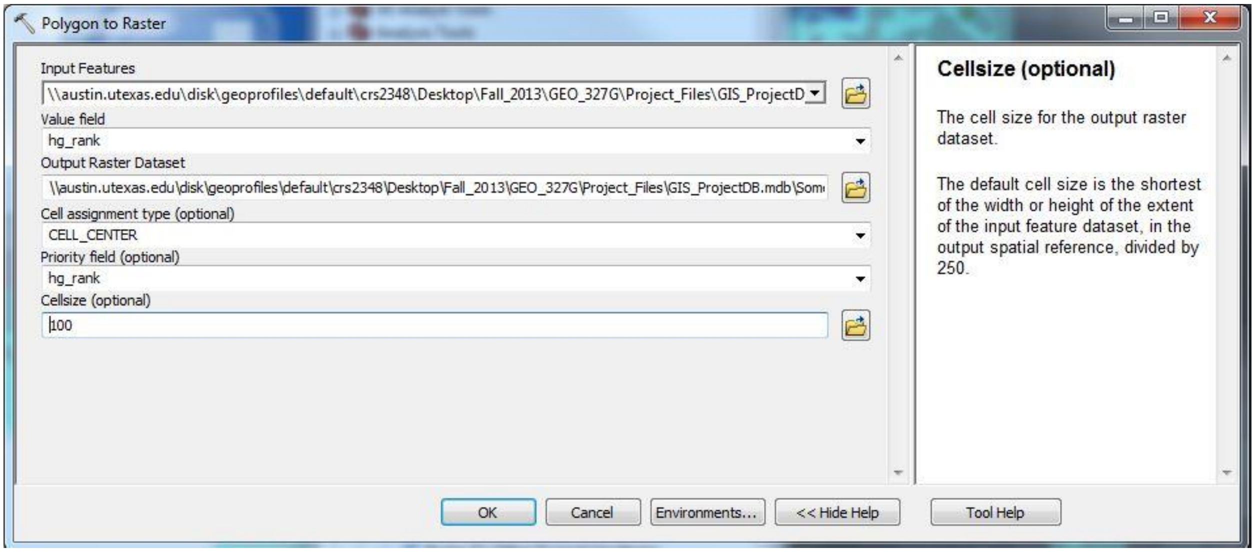

Figure 16 – Polygon to Raster tool set to create raster called Hg_rank, with a cell size of 100m, from the hg_rank field of the rock units polygon class

Conclusions

From the final raster models, we see that the predictions for the locations of silver and mercury ores match up very well with the locations of known deposits, while the predictions for gold deposits match well, they are not quite as precise for those of Ag and Hg, and the predictions for uranium deposits match only moderately, at best. It is likely that the predictions for mercury deposits only match so well because the vast majority of known Hg deposits were found within a single rock unit which only occurs in one area of the map. Obviously that unit had to be given a higher ranking than other rock units, but because it only outcrops in a small area within west Texas, this means that the only area being modelled with a high likelihood of deposits, is the same small area that is already known to contain the vast majority of the deposits. For the gold, silver, and uranium predictive models, I would propose a different explanation. Concerning these ore models, it is my estimation that the predictions for gold and silver are far more accurate than those for uranium because of the correlation that could be made with between Au/Ag and isostatic anomalies. The basis for my conclusion that such a correlation could be drawn lies not only in observation from the map, but also in a line of logic related to the geologic setting within which these ores are found in the region. From the analysis I performed on the host rock setting of Ag, Au, and U in the early stages of this project, I recognized that a large percentage of all three ore types seemed to be hosted within igneous and metamorphic rock, which of course makes sense for these heavy elements. I also recognized that the Ag and Au tended to occur near areas of high, positive isostatic anomalies (indicating a high rock density) which lie in areas with very large, high frequency variations caused by isostatic anomalies. This would indicate to me that these ores do in fact lie in dense igneous (intrusive) and metamorphic rocks, which explains the correlation between their presence and high isostatic anomalies since they lie in much denser rock than the sedimentary rocks of which the majority of the area is comprised. This analysis can be intuitively coupled with an explanation of the rapid isostatic anomaly variations surrounding these rocks by simply recognizing that such anomalies can easily be explained within a large, ancient fault zone, that brought dense old rock into sharp contact with less dense sedimentary rock and, in doing so, created weaknesses through which the magma that formed the igneous rocks could have flowed. Though this certainly does not prove that the correlation does in fact exist, it does seem to fit well with the geology evident from the surface map alone. The reason that uranium does not similarly correlate with the isostatic anomalies and the model prediction may possibly be due to either the low number of known deposits, allowing for greater error within the model through lack of data, or it may be due to the fact that, unlike silver and gold, uranium is somewhat soluble in water, and so much the uranium within these host rocks may have tended to weather out at the surface faster than the other elements, possibly explaining why deposits of it have been found relatively more often in sedimentary rocks than the others.

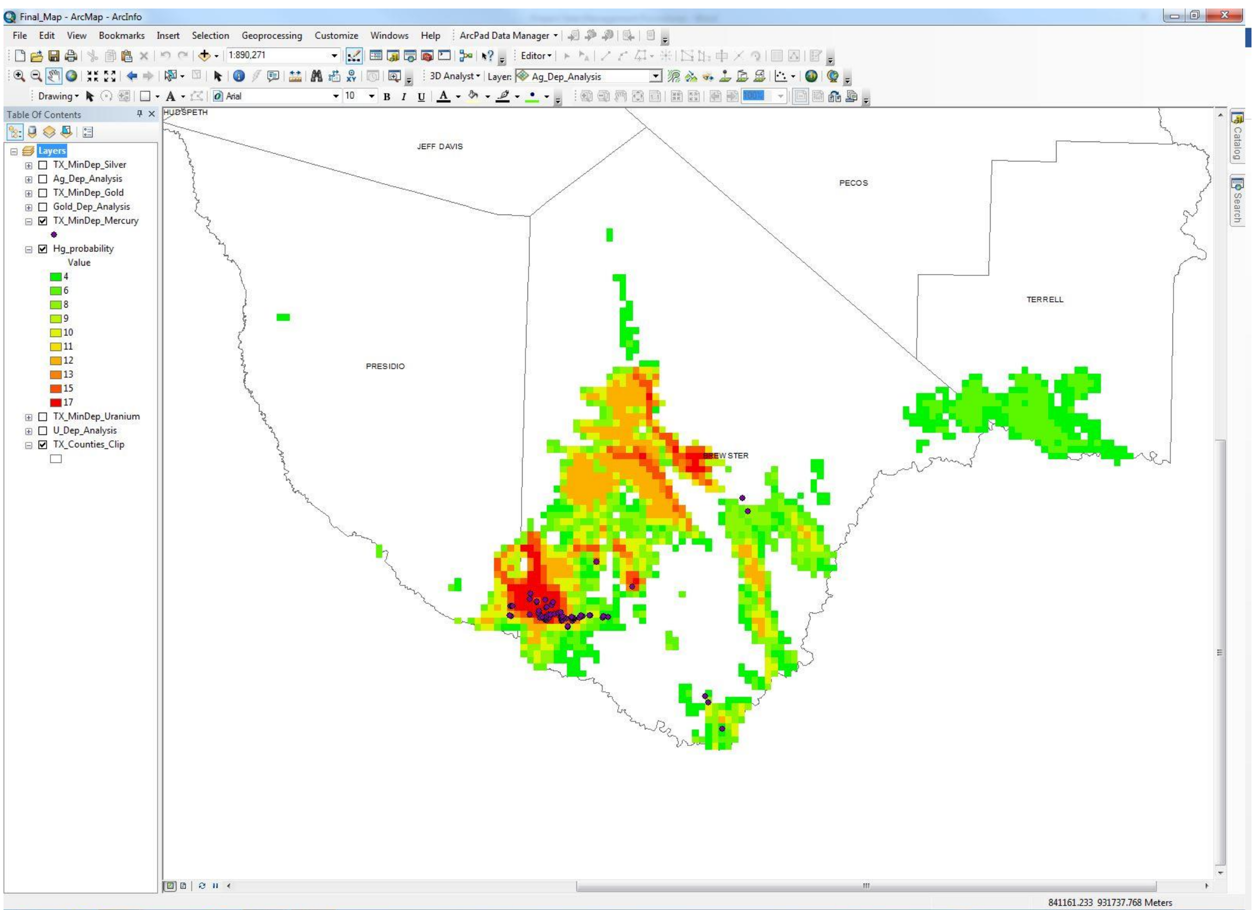

Figure 17 – Suitability analysis raster for mercury ore. Red corresponds to higher probability of ore deposits being found within the cell.

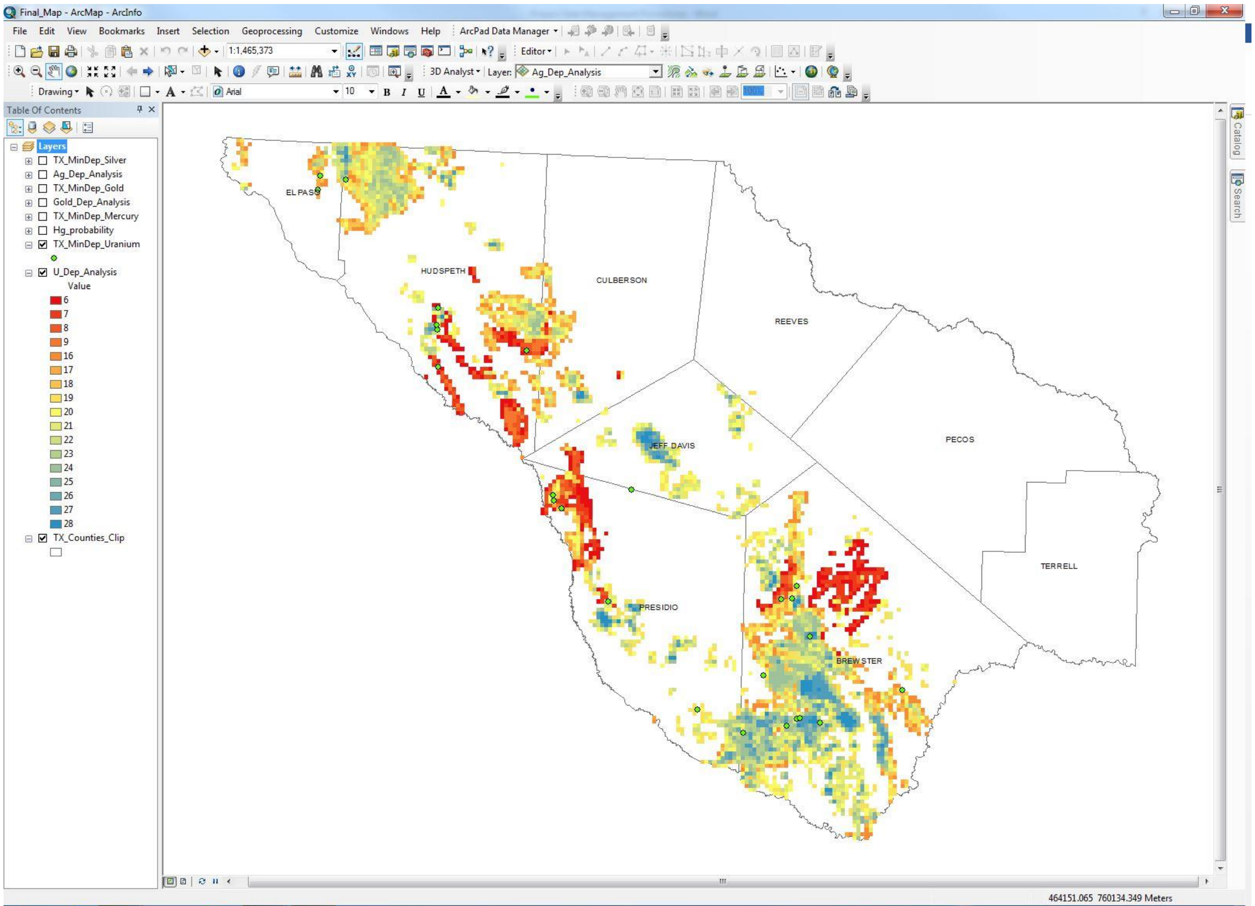

Figure 18 – Suitability analysis raster for uranium ore. Blue corresponds to higher probability of ore deposits being found within the cell.

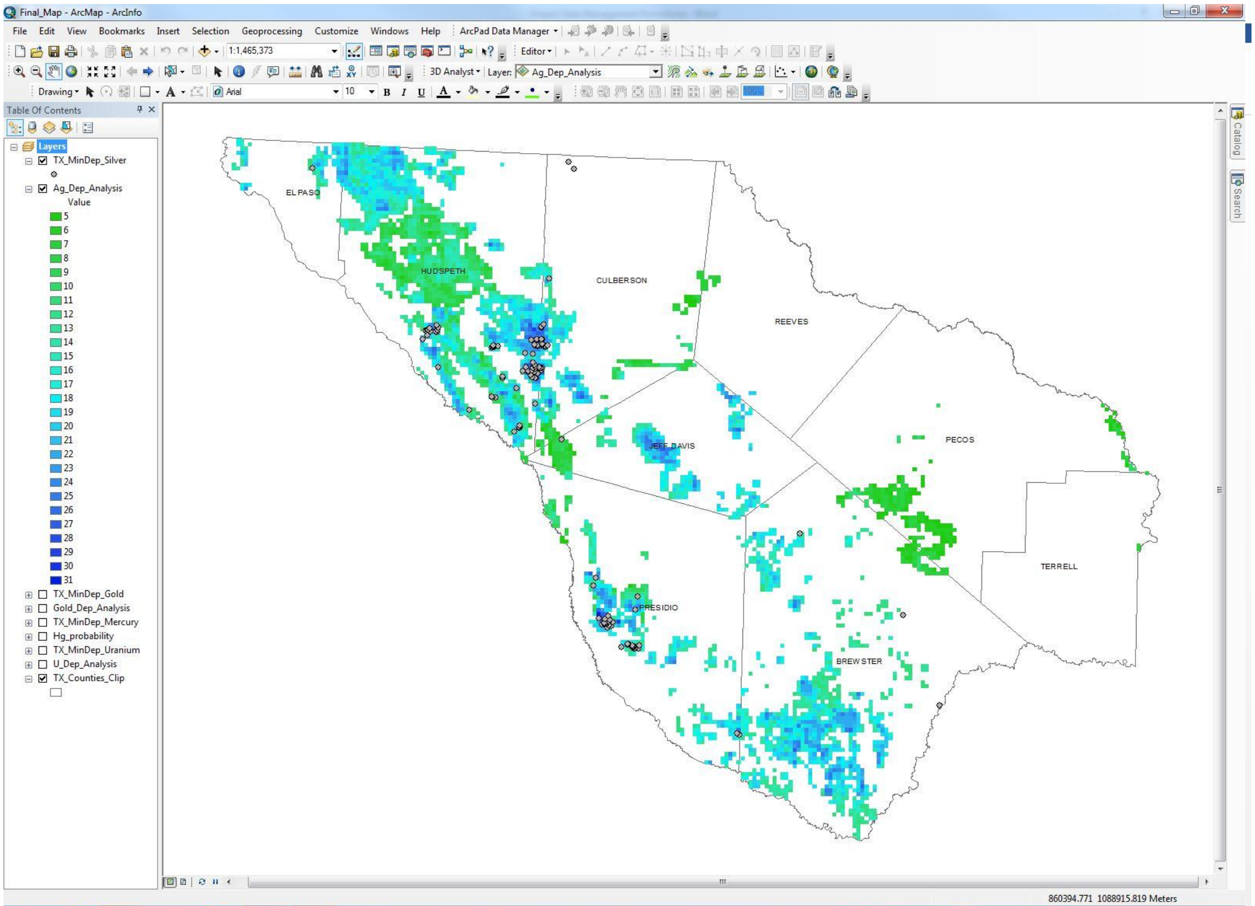

Figure 19 – Suitability analysis raster for silver ore. Blue corresponds to higher probability of ore deposits being found within the cell.

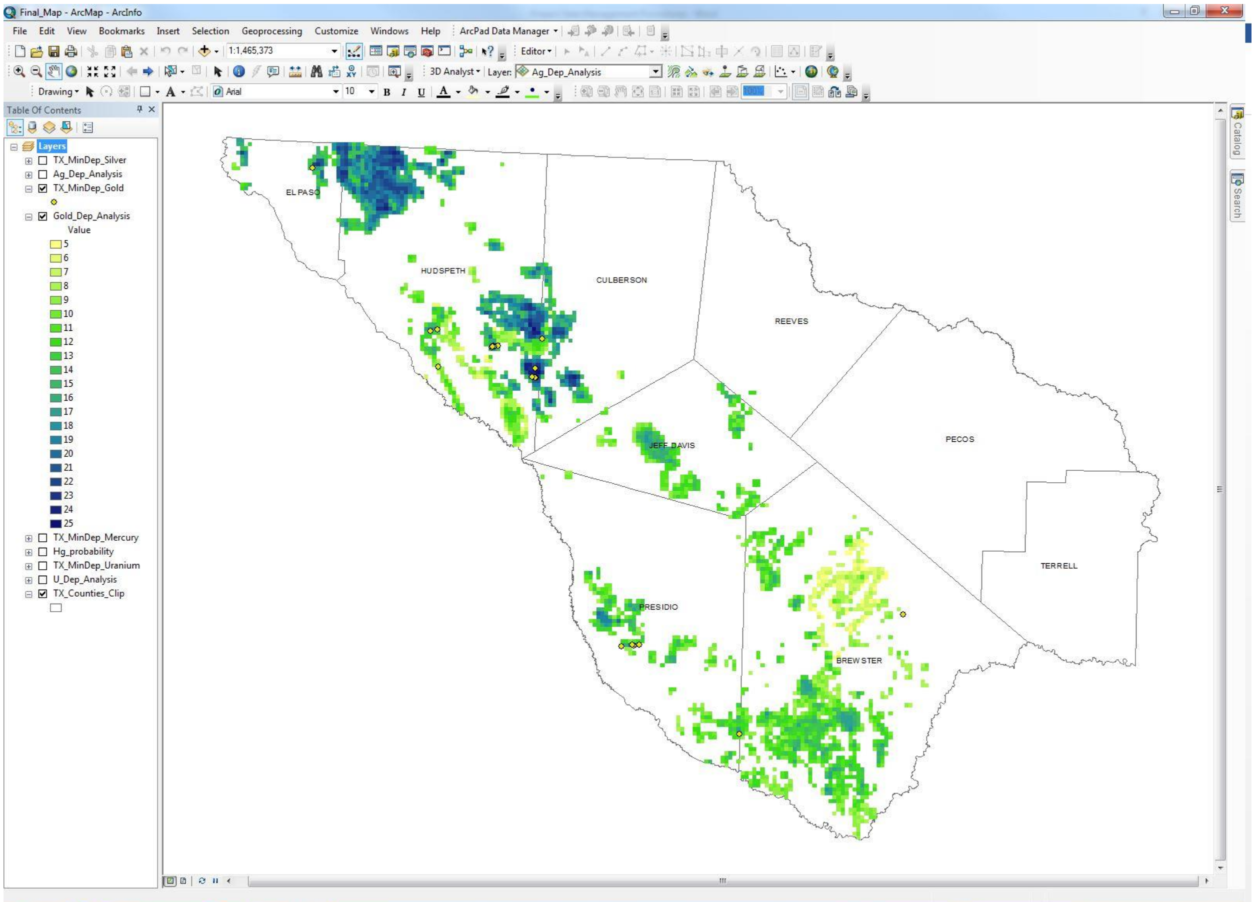

Figure 20 – Suitability analysis raster for gold ore. Blue corresponds to higher probability of ore deposits being found within the cell.

References