CALIBRATING HEIGHT DATA FOR A CARBON BIOMASS ESTIMATION IN SONORA, TX

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Calibrating height data for a carbon biomass estimation in Sonora, TX

1 BACKGROUND

The purpose of this project is to further existing carbon biomass estimation techniques by improving upon current vegetation height estimation practices. Carbon biomass estimation is an important tool for quantifying carbon biomass quickly and accurately in study areas through remote sensing techniques. Typically, this is done by measuring vegetation height with a macro-scale, easily processed, low-resolution dataset and then calibrating these height measurements with heights obtained from higher resolution data across a smaller sample area. Several estimation methods exist, and estimates have increased in accuracy as higher resolution datasets become available. However, physical sampling has long remained the most accurate, yet most labor intensive, method of calibration. Calibrated height measurements are typically one parameter of the allometric equations¹ that provide the final biomass estimation (Fatoyimbo, 2008).

To improve upon current methods, we used vegetation height data derived from interferometric synthetic aperture RADAR (IFSAR) data as our macro-scale dataset across our study area. Then, we employed height data collected using terrestrial laser scanning (TLS), a technology providing more accurate, more thorough, and more easily attainable data than physical sampling, to calibrate our IFSAR height data. This yielded samples of highly accurate vegetation height data across our study area, resulting in a robust calibration equation. Additionally, we encountered several complications in processing the TLS data, which provided for a fruitful learning experience. Therefore, we include some step-by-step methodology we employed to provide a troubleshooting resource for those working with similar data in the future.

1.1 STUDY SITE

The Texas Sonora AgriLife Research Station in Sonora, TX served as the location of this project. The site, whose vegetation profile is composed of well-known, indigenous plant species, was the subject of a prescribed burn regime from 1987 to 1996 (Washington-Allen, unpublished). The result is a stark vegetation profile from north to south, shown in Figure 1 below.

¹ Allometric equations take input parameters to estimate vegetation mass, which is correlated with total carbon content. They are species specific. Dominant species in the study site are Ashe Juniper, Oak, and assortment of woody shrubs (Washington-Allen, unpublished).



Figure 1: AgriLife Study Site

2 DATA

2.1 INTERFEROMETRIC SYNTHETIC APERTURE RADAR

We used interferometric synthetic aperture RADAR (IFSAR), an aerially collected radar dataset, for our macro-scale dataset. NEXTmap, a remote sensing technology company, has compiled IFSAR for the entire United States and made it commercially available for use. IFSAR has 5m x 5m resolution with ± 30-cm to 3-m vertical accuracy. Two IFSAR swathes were purchased for the Sonora area in GCS_North American_1983. The first, the digital surface model (DSM), represent the first return of the radar. The second, the digital terrain model (DTM), is "created by digitally removing, to the extent possible, the cultural features contained in a DSM, exposing the underlying terrain" (IFSAR product handbook).

2.1.1 Complications

IFSAR data is compiled in the band-interleaved by line (.bil) file extension. While normally ArcMap can read this file extension once it has been changed to a float (.flt) file, the IFSAR files did not have header files in ESRI short .hdr format. To solve this problem, we used Global Mapper to open the data and export in .bil with the proper .hdr format. Once this step was complete, we used the Float to Raster tool

to import the data to ArcGIS, and then used the Define Projection tool to set the geographic coordinate system to GCS_North American_1983, the coordinate system required by the IFSAR data.

2.2 TERRESTRIAL LASER SCANNING

A research team at Texas A&M obtained terrestrial laser scanning (TLS) data from the research site using a Leica Scan Station 2 with a 360° horizontal and a 270° vertical field of view. This machine fires a 532 nm green laser at a rate of 55,000 points per second. A typical scan contains upwards of 11 million points with x, y, and z information. Generally, researchers created four 30m x 30m plots arranged in an equilateral triangle, with a fourth reading taken at the midpoint, although Plot 2 contains only 2 scan points.

2.2.1 Complications

Raw LIDAR data is in .xyz format sorted into three columns, each row representing one data point and column representing x, y, or z. X and y are typically in latitude and longitude, while z represents elevation (ATLAS). However, this is not the case with our data, as shown by Figure 2.

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L	29.674	7 0	.4739	0.01	17
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Figure 2: xyz TLS data

As a result, when the data was uploaded to ArcGIS, it could not be spatially oriented with the IFSAR data. Figure 3 shows how all five plots are aligned relative to (0, 0) on the Cartesian plane and not relative to their geographic position. This prevented us from directly relating IFSAR data to TLS data geospatially.



3 METHOD

3.1 IFSAR VEGETATION HEIGHT

We extracted vegetation height (H) from the IFSAR data using Equation 1, where DTM is the cell elevation value of the digital terrain model raster and DSM is the cell elevation value of the digital surface model. Due to the definition of both, the height remaining after subtraction should be any ground cover above the surface, in our case this is vegetation.

$$H = DSM - DTM$$
 (meters) (1)

Figure 4 gives a schematic representation of how this calculation was conducted. The Raster Calculator tool provided this functionality.



Figure 4: Raster calculation schematic

A polygon feature was first used to create a mask around the study site. Figure 5 shows the resultant raster. Notice how the burn gradient is clearly visible from north to south, with high vegetation height values found in the south and mostly bare ground visible in the north.



Figure 5: IFSAR vegetation heights

The height data across the study area was randomly sampled with N = 4576, the number of TLS plot points.

3.2 TERRESTRIAL LASER SCANNING VEGETATION HEIGHTS

The green dots shown in Figure 5 represent the Leica system placement locations. Figure 6 provides a snapshot of the raw data extracted from the TLS at Plot 1. The data is so fine a resolution that individual branches of trees and shrubs can be seen.



Figure 6: Raw TLS data

Because of the complications encountered while analyzing the TLS data, the following provides step-bystep guidance to aid future users in importing raw data.

The raw .xyz data (which had been decimated² by a software provided by the scanner manufacturer) was imported to ArcGIS by using the ASCII 3D to Feature Class tool shown in Figure 7. Once imported as a feature class, we were able to analyze the data in ArcGIS and ArcScene.

² Reducing the number of points to a processable size while outliers removing outliers.

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Figure 7: importing .xyz data

Feature class data was then converted to a triangular irregular network (TIN) surface from which vegetation height data could be extracted. Figure 8 shows the tool while Figure 9 shows the TIN of Plot 1. Notice the distinct peaks created by vegetation ranging up to 6 meters in height. Appendix A includes TINS for the other four plots.

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Figure 8: creating a TIN surface



Figure 9: Triangular irregular network surface of Plot 1

The Add Surface Information tool, shown in Figure 10, extracts data from TIN files to feature classes. It was used to associate a height with each point in the plot feature classes. The natural neighbor method gave the min, max, and medium height between each triangle.

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Figure 10: Extracting height values from a TIN

Once vegetation heights were appended to the plot feature classes, they could be extracted using dbase tables.

4 RESULTS AND DISCUSSION

In order to calibrate vegetation height data obtained from the IFSAR data, we plotted Y vs. H data across sample locations, where Y is TLS height data and H is IFSAR height data, in a Quantile-Quantile plot shown by Figure 11. Unfortunately, due to the complications we discussed regarding the alignment of TLS and IFSAR data, heights from spatially aligned portions of TLS and IFSAR data could not be obtained. However, by randomly sampling an equal number of IFSAR points to compare with TLS points, we yielded a robust linear regression, Equation 2 below.



Y = 1.023(H) + 0.0565 (2)

Figure 11: IFSAR to TLS vegetation height calibration

Figure 12 shows calibrated IFSAR vegetation height data plotted against uncorrected IFSAR heights. Despite the lack of spatial accuracy in Equation 2, the results in Figure 12 are encouraging. Equation 2 marginally readjusts vegetation heights across the distribution. However, worryingly, negative heights caused by the overlap of the DTM and DSM layers persist through the calibration, justifying the need for a spatially accurate calibration equation.



Figure 12: Calibration of IFSAR data

Figure 13 shows the range of heights founds in the TLS data. Comparison of Figures 12 and 13 is encouraging, since Figure 12 reflects the bulk of the height range of the distribution in Figure 13.



Figure 10: Height range of TLS data

The richness of vegetation height data collected from TLS demonstrates the technology's usefulness for improving current biomass estimation practices.

5 FUTURE WORK

With properly geo-referenced TLS data, the methodologies explored herein could further advance carbon biomass estimation techniques. Geo-referencing would align TLS scan points to their given location an IFSAR layer. Thus, masks sized in the dimension of the TLS plots could extract raster cell values from the IFSAR layer. Using similar 5m x 5m raster data and 30m x 30m scanner plots, each scanner plot would contain approximately 30 IFSAR points, which would then be compared to the average TLS height within each raster cell. This would build a more powerful dataset approaching the true distribution of height values to which the calibration equation could be fit.

Additionally, to fully complete biomass estimation, additional parameters need to be estimated such as tree density, number of trees, and various other morphological characteristics of vegetation in the study site. Theoretically, TLS data can be used to accomplish this task as well.

6 CONCLUSION

While eliminating early complications proved instructive and successful, the lack of spatial alignment in the two datasets undermined the overall objective of the project. Regardless, we made strides towards improving biomass estimation techniques by exploring a robust method for vegetation height calibration independent of proper geo-referencing. Studies such as this one set the groundwork for further improvements in carbon biomass estimation techniques as well as remote sensing practices in general. Improving technology will also continue to motivate better methods.

6.1 ACKNOWLEDGEMENTS

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APPENDIX A: ADDITIONAL FIGURES



Figure A2: TIN Plot 3



Figure A3: TIN Plot 4



Figure A4: TIN Plot 5

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