Geospatial Science Portfolio

**A satellite image of a land

Description automatically generatedTask #1:**

The image above, of a dense, scaled, and orientated point cloud showing a research site at Prior Park in Bath, UK, which was created through VisualSFM and CloudCompare. By using photo-matching and entering ground control points into Visual SFM, and then selecting the ground control points in the photos taken, I was able to construct a dense point cloud. I then exported the cloud to CloudCompare, which I used to clip the cloud and produce the image above.

A diagram of a blue and pink scale

Description automatically generated with medium confidence

I used three given control points to reach a better understanding of the accuracy of the two models. For two of the three control points, the multi-angle model was more accurate, and the average failure of the multi-angle was smaller, although marginally (0.167 vs. -0.174, and we are considering absolute difference). The multi-angle tends to overestimate whereas the nadir-only tends to underestimate. This could be inferred from the map above, as the multi-imagery model was usually larger in the elevation values it generated, as we can see from the greater amount of space in blue rather than red.

It is essential to have strong photo coverage when creating 3D models using Structure-from-Motion photogrammetry as the process relies on the photos being used having overlapping areas covered to create a useful model. For example, in both of the maps I created above, areas with poor photo coverage have been clipped out as there are lots of gaps in the data in those portions, leading to an unhelpful 3D model with holes. The importance of this overlap is noted in the module textbook in reference to photos being taken from the sky, writing, “In the case of aerial photographs, it is usual to have 60% overlap along each flight line and 30% overlap between flight lines.”[[1]](#footnote-2) In short, “The amount of overlap defines the area for which a 3-D model can be created.”[[2]](#footnote-3)

A satellite view of a red river

Description automatically generated with medium confidence**Task #2:**

In this map, I used bands 1, 4, and 7, also known as Blue, Near Infrared (NIR), and Shortwave Infrared 2 to focus on the Venetian Lagoon in Northeast Italy. This combination was helpful in delineating clear borders between land and water, as well as some underwater topography, and finally, provided a clear way to examine the swampy areas to the northeast of Venice. This was likely possible due to the NIR and SWIR 2 bands, which according to USGS, are useful for mapping “biomass content and shorelines” and “improved moisture content of soil and vegetation,” respectively.[[3]](#footnote-4)

A green and purple surface

Description automatically generatedThis second map, focused on the mountains in Northern Italy, uses bands 1, 6, and 5. Band 5 is another SWIR, and Band 6 is a Thermal Infrared band. I believe this combination is able to identify topography well, as well as snowy areas (in the purple/red rising from the green). This is likely due to Band 6 and Band 5 both being useful for identifying soil moisture (which would change with elevation gain), and Band 6 being particularly useful for thermal mapping, which could help identify snow. The thermal mapping may also be the reason the pink clouds in the bottom of the image are so pronounced. USGS notes that these bands are useful to penetrate thin clouds, so the clouds here are likely on the denser side.[[4]](#footnote-5)

A graph showing the number of miles

Description automatically generatedA map of a river channel

Description automatically generated

A map of a river

Description automatically generated

A map of a mountain range

Description automatically generated**Task #3:**

A black text on a white background

Description automatically generatedA topographic map of a mountain

Description automatically generated

This exercise aimed to identify locations to build a research station with visibility of many landslides. I began by creating a Boolean MCE to use root cohesion, wetness, and slope together to be able to evaluate the landslide risk on a scale of 0-100 for any area in our region of the San Gabriel mountains. For my model, I weighted the slope at 0.7, the root cohesion at 0.2, and the wetness at 0.1. The authors of *Geographic Information Science and Systems 4th Edition* writes that, “it is possible that multiple views might exist about appropriate functions and weights, particularly when modeling a decision over an important development with impact on the environment,”[[5]](#footnote-6) so this is not the one “correct” weighting to use.

I put this evaluation over a hillshade, and used a color ramp with red indicating the highest risk and green indicating low risk.

I next selected 9 catchments across the map, aiming to select a variety of areas and risk could guess from the first look, to reach an idea of how the process worked. I was then able to color the catchments on a different color ramp that showed their risk level. I examined the risk level based on both maximum and mean values (unfortunately median was not available as an option), and the catchment focused on in the second map for this task had the highest value for both statistics, so I felt it was a high-risk area and decided to attempt to find a location that could see many landslides in this catchment. If I had been forced to choose between mean and maximum as my statistic to determine “most landslide prone”, I would have chosen mean. The maps above indicate the mean risk of the catchment, not the maximum. I attempted to use the Viewshed2 tool to find locations that could see this catchment as well as its closest catchment to the west, as this had high risk values as well, but the tool struggled to complete this task.

Using the Viewshed tool, I created the light yellow layer visible in the map to indicate which locations could be seen from the pour point for the catchment, as those locations would be able to see the pour point, and more importantly, see any landslides from the catchment passing through the pour point.

One obvious limitation is that my catchments only cover a small portion of the map, so there are many other areas that are potentially more landslide-rich and should be focused on instead. Additionally, my MCE focuses heavily on slope, and not much on wetness. I was led to heavily weight slope from both the practical example, as well as the textbook example, which showed slope being used as the most important factor in a MCE for “vulnerability to runoff”[[6]](#footnote-7) using slope, land use, and distance to stream. It also makes sense logically that slope would be a highly important factor in the likelihood of a landslide. However, wetness plays an important role as well, and a different MCE with higher weighting for that factor would change my results. The textbook notes that when creating models such as these, the discussions on how to use it should take place before the implementation, writing, “all the controversy should be over once the factors, functions, and weights are decided, and the solution they produce should be acceptable to all because all accepted the inputs.”[[7]](#footnote-8)

**A map of a city

Description automatically generatedTask #4:**

**A close-up of a sign

Description automatically generatedA black and white compass

Description automatically generatedA chart of a number of colors

Description automatically generated with medium confidence**

In the map above, I performed a Getis-Ord GI\* analysis to visualize the hot and cold spots of the raccoon sightings in the dataset. First, I used ten Moran’s I calculations to analyse the spatial autocorrelation, producing a chart which showed a peak close to 1400 meters. Following this, I used the Getis-Ord GI\* tool on the aggregated racoon data to identify the hot and cold spots. Most of the parameters were fairly straightforward (ICOUNT and FIXED\_DISTANCE\_BAND for Input Field and Conceptualization of Spatial Relationships, respectively), and Euclidean rather than Manhattan distance as raccoons do not exclusively travel on the sidewalk, like humans, and are able to reach places more quickly with diagonal movement. The only parameter I chose that was not instructed to me to choose by the practical instructions was when I set the Distance Band to 1400 meters, as this was the peak in Z-Scores in the chart produced earlier. The map above also contains a layer of an IDW interpolation to further visualize the hot and cold spots, which I will discuss in more detail below.

A map of different colors

Description automatically generated

A table of numbers and symbols

Description automatically generated with medium confidenceA map of different colors

Description automatically generated

A map of a city

Description automatically generated with medium confidence



A graph with blue bars and numbers

Description automatically generatedA graph with numbers and a bar chart

Description automatically generatedThese three methods produced fairly distinct interpolations. The textbook writes that spatial interpolations are “fairly intelligent guesswork,”[[8]](#footnote-9) and so our task was to determine which method is the most intelligent and produces the best guesses. For the IDW, I used a power of 1 to avoid over-weighting particular areas as racoons are mobile and the dataset could have included multiple sightings of the same individual. I set the variable to 15 as that seemed appropriate based on the density of sightings I was seeing in my mapping of the aggregate data. This map is the one I believe to be the most helpful, largely because it does not run into the issues that the others did, which I will detail below. I believe this method is best due to its acceptable accuracy, and being able to deal with the fact that it is interpolating on a dataset where each point should not be weighted too heavily, as it is of something that moves around, rather than say, a dataset of elevation values, which we know will stay constant. The chart to the right, made with Excel to determine the accuracy of the method, shows that the method was fairly accurate in its interpolation, as there is little skew, and values are fairly concentrated around a difference of 0.

While the IDW method was fairly accurate, the Spline method, in which I used a regularised spline and weight of 0.1, was more accurate, as we can see from its histogram, as the values are more tightly centered around 0. While this is excellent, I still felt the IDW was better as it did not create hot and cold spots in the interpolation where there should not have been, as the Spline was more prone to do. Part of the reason for this is actually due to a commonly cited downside of the IDW method, that “no point on the interpolated surface can have an interpolated z that is more than the largest measured z, or less than the smallest measured z,”[[9]](#footnote-10) effectively limiting the range of interpolated values. An example of an unnecessary hot/cold interpolation can be seen as I moved the title of the Spline map to the lower left corner to highlight an example of an unnecessary cold spot near the top left corner. Perhaps a Spline with a higher weight would have avoided this issue, but this may have sacrificed some accuracy as well.

Finally, the Thiessen method, creating smaller polygons and assigning them values, ran into the opposite issue as the Spline: a lack of accuracy. I was unable to create a histogram as there were points included that had such a large difference that it threw the data visualization off completely. I assume this is more likely to happen with a Thiessen interpolation as it is applying one value to a larger area than the other two methods, leading to more errors, or as put by the textbook in reference to Thiessen polygons, “they leave something to be desired, however, because the sharp change in interpolated values at polygon boundaries is often implausible.”[[10]](#footnote-11) On the bright side, the method generally avoided creating hot and cold spots where there should not have been any.

1. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 8.3.2.3 Photogrammetry.* (pp. 185). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBH92/geographic-information/photogrammetry [↑](#footnote-ref-2)
2. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 8.3.2.3 Photogrammetry.* (pp. 185). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBH92/geographic-information/photogrammetry [↑](#footnote-ref-3)
3. “What Are the Best Landsat Spectral Bands for Use in My Research?” *What Are the Best Landsat Spectral Bands for Use in My Research? | U.S. Geological Survey*, USGS, www.usgs.gov/faqs/what-are-best-landsat-spectral-bands-use-my-research. Accessed 3 Jan. 2024.  [↑](#footnote-ref-4)
4. “What Are the Best Landsat Spectral Bands for Use in My Research?” *What Are the Best Landsat Spectral Bands for Use in My Research? | U.S. Geological Survey*, USGS, www.usgs.gov/faqs/what-are-best-landsat-spectral-bands-use-my-research. Accessed 3 Jan. 2024.  [↑](#footnote-ref-5)
5. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 15.4 Multicriteria Methods.* (pp. 352). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBKU2/geographic-information/multicriteria-methods [↑](#footnote-ref-6)
6. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 15.4 Multicriteria Methods.* (pp. 352). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBKU2/geographic-information/multicriteria-methods [↑](#footnote-ref-7)
7. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 15.4 Multicriteria Methods.* (pp. 352). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBKU2/geographic-information/multicriteria-methods [↑](#footnote-ref-8)
8. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 13.3.6.1 Thiessen Polygons.* (pp. 313). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBJS5/geographic-information/thiessen-polygons [↑](#footnote-ref-9)
9. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 13.3.6.2 Inverse-Distance Weighting.* (pp. 315). John Wiley & Sons. Retrieved from   
   https://app.knovel.com/hotlink/pdf/id:kt011BBJT2/geographic-information/inverse-distance-weighting [↑](#footnote-ref-10)
10. Longley, Paul A. Goodchild, Michael F. Maguire, David J. Rhind, David W.. (2015). *Geographic Information Science & Systems (4th Edition) - 13.3.6.2 Inverse-Distance Weighting.* (pp. 314). John Wiley & Sons. Retrieved from   
    https://app.knovel.com/hotlink/pdf/id:kt011BBJT2/geographic-information/inverse-distance-weighting [↑](#footnote-ref-11)