Mission Space Lab Phase 4 report outline

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Chosen theme: Life on Earth

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1. Introduction

Over 4 million km^2 of land is being desertified every year – enough land to farm food for half the world's population. Desertification is a real issue – we need vegetation not just to store carbon and reduce climate change, but to provide land for food, communities, and wildlife.

Primarily, we hoped to be able to successfully take photos of the Earth's surface and calculate a range of indices to produce graphical representations of land characteristics. From this, we would be able to identify areas of land across the world that could be reclaimed and turned into farms, forests, parks, or anything green. We set out with the aim to analyse environmental conditions within areas of high vegetation to understand what makes land suitable for greenery, and then find seemingly barren plots that could be converted to more sustainable use.

Despite the fact that this was a very unique experiment, we aimed to discover a correlation between environmental factors and vegetation health. We expected to find that a greater access to water would increase plant health, and that this would be reflected in our results.

2. Method

To identify regions on Earth, we captured Near InfraRed (NIR) images at 13 second intervals and recorded the GPS coordinates in the EXIF data. The colour bands in each image allowed us to calculate the 3 indices that we used to assess the characteristics of a region:

1. Soil Adjusted Vegetation Index (SAVI) – determines landscape type

$$SAVI = \frac{(1 + L)(NIR - Red)}{(NIR + Red + L)}$$

$$L = 0.428\ (ESA\ recommended\ value)$$

2. Normalised Difference Water Index (NDWI) – determines water access

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$$

3. Red Chlorophyll Index (RCI) – determines plant health

$$RCI = \frac{NIR}{Red} - 1$$

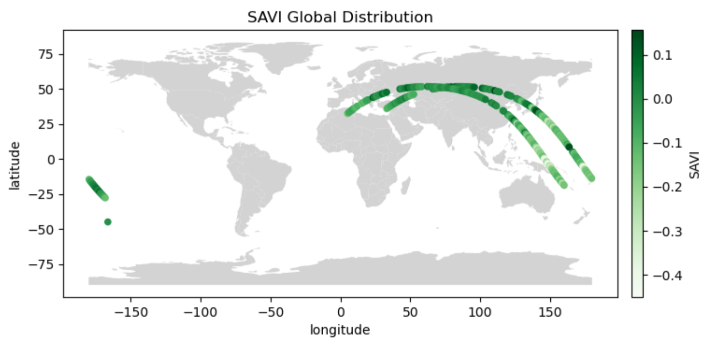
The AstroPi code automatically filtered and discarded invalid images – those that had significant cloud cover, were taken at night, or over the sea – alleviating storage requirements on the AstroPi.

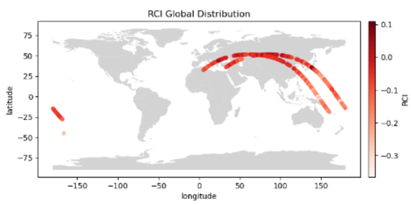
We processed the 352 images on Earth due to the complexity of our calculations. The AstroPi would not have enough time to perform the computations whilst regularly capturing images.

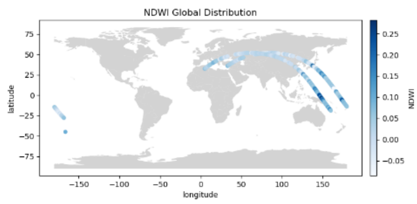
On Earth, we generated index values for every pixel we received to produce images/data tables. We then used the OpenCV and NumPy modules to efficiently average the index value across each image (excluding clouds to increase the accuracy). Finally, we produced a series of graphical maps in Python by plotting the data using MatPlotLib on a basemap generated by GeoPanda.

3. Experiment results

The average value for each index for each image was plotted onto a global map to allow us to locate spatial trends. The darker colours represent desired characteristics (high vegetation cover, high water access, high vegetation health).



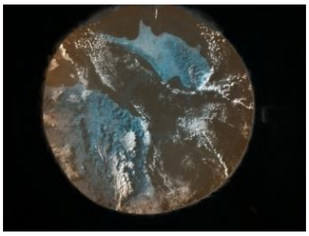




We looked at the maps above to find locations of interest. For each photo, we generated an image for each index and picked a few to look at in detail. The first case-study is Cyprus (the island) and Turkey:

RCI visualisation

NDWI visualisation



Raw NIR photo of Cyprus

Vegetation map

SAVI visualisation

First, we looked at the SAVI image and verified its accuracy against the vegetation map above. Next, we looked at the RCI image to ensure the vegetation was healthy. Finally, we looked at the NDWI image to see what water access makes an area suitable for plant growth.

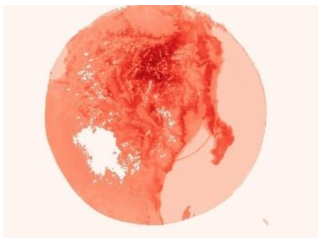
We looked through the data of every image to locate other areas of similar characteristics, finding regions that could be reclaimed. We constructed an equation to calculate the 'entropy' for each image to rank the locations; the closer the entropy was to 1.0, the greater the chance of the image having a desertified area which could be reclaimed. The equation used the average index values for each image:

$$Entropy = \frac{NDWI}{SAVI + RCI}$$

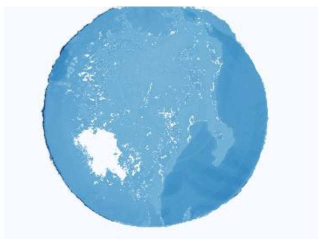
We normalised the values for the entropies across all images on a scale of 0.0 to 1.0. This allowed for a fair and clear comparison. We found our second case-study which had a relatively high entropy and similar latitude to Cyprus, central Japan (the cross is Tokyo City):

Raw NIR photo of Japan

SAVI visualisation



RCI visualisation



NDWI visualisation

Looking at the NDWI, we see plenty of water access. Whilst there are areas of thriving vegetation, we identified the circled regions as barren locations that would be suitable for new vegetation growth. As Tokyo City is a dense urban area we ruled that out.

4. Learnings

Together as a pair, we learned much about how images are used by the agricultural industry to optimise their crop yield. It gave us a wider view on satellite imaging, and we learned how to use and configure a camera with the Raspberry Pi. Image processing was a particularly tough aspect of the project, and geolocating data-points on a graph using Anaconda Python was a challenging, yet insightful experience. To overcome this, we studied the GeoPanda documentation in great detail.

We enhanced our communication skills as we coordinated over text, had in-person meetings, and worked on the report through voice calls. A major challenge was choosing the idea in Phase 1 as we had contrasting ideas – the ordeal of brainstorming pros and cons of each idea was invaluable in developing our teamwork skillset. If we were to do the process again, we would set up a remote SSH terminal so that we could both access the Pi at any time to alter the code. Having to manually copy the program over each time the partner made an edit was a little tedious and relied on both of us being free! To future teams, we recommend doing this if possible.

5. Conclusion

We set out with the goal of successfully analysing land and finding a correlation between environmental factors and vegetation health.

We managed to write successful code, and generate graphical representations of all three indices, which we proved were highly accurate. We also managed to identify regions of good plant health (Cyprus/Turkey) and locate another region with similar characteristics which could benefit from increased vegetation (Japan). We would therefore recommend more trees or outdoor parks to be regrown around central Japan because not only are the characteristics very suitable, but the large population would benefit from increased natural environments.

However, there were some underlying issues with our experiment – we did not have enough images to produce a conclusive correlation, and therefore had to create an entropy ranking system. Despite this, the sea and clouds in images were difficult to filter, resulting in misleading entropy values. Moreover, given the colour bands in NIR images, the indices available were limited. Consequently, water access was the only environmental factor we could assess.

Overall, we proved and successfully demonstrated our idea using case studies, showing its great potential for future application on a larger scale to prosperously reclaim more desertified land across the entire globe.

I. *A big 'thank you' to ESA and the Raspberry Pi Foundation for this incredible opportunity.*
II. *Another thanks to our mentor, Mr Paul Baker, for his help throughout the process.*

III. *All of our code can be found on GitHub here.*