Satellite Image Analysis for Climate Change Monitoring

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Introduction

Climate change is widely considered to be the top global threat we currently face [1]; and equally requires a global effort to solve. It is predicted that there will be an average warming of 1.5°C within a decade [2] and we are in the extraordinary position of experiencing average global temperatures that humankind hasn't experienced before. It is crucial to understand and analyse the consequences of global warming in order to predict future affects and what can be done to avoid (or more often, mitigate) the damage.

The effects of climate change are broad, this proposed project will focus on its impact on permafrost. Permafrost is defined as ground (sediment, soil, or rock) which is continuously frozen for at least 2 consecutive years [3]. Permafrost can be found around the world from high altitude regions to under the sea, it is predominately found in the Northern Hemisphere in which 24% of the land has permafrost underneath it [4].

The regression of permafrost has many consequences on both a local and global scale. Firstly, thawing permafrost causes the ground to contract, leading to earth caving in and cracking. Infrastructure on top becomes increasingly unstable as the permafrost melts. This is a massive threat to the roughly 35 million people that live in the permafrost zone [5] and a huge amount of infrastructure. For example, the city of Yakuts is built on continuous permafrost.
Secondly, landscapes are drastically changed by melting permafrost. Soil becomes more vulnerable to landslides and erosion as it softens, resulting in increased coastal erosion. Additionally, wetlands drain as the permafrost underneath melts, allowing the water to sink deeper into the ground and dry out the terrain above which increases its susceptibility to wildfires. An example of these affects is the recent record amount of coastal erosion in Alaska [6] which coincides with 85% of Alaska being permafrost [7].
Finally, a major concern of melting permafrost is the release of carbon. Methane is stored within permafrost as either Methyl Clathrates (methane molecules frozen into ice crystals) or in the form of organic matter (dead plants and animals) which have been frozen for thousands of years. As the permafrost melts the methane is released, it is estimated that there is 1400 gigatons of carbon frozen in permafrost, approximately 1.5x the amount of carbon currently in our atmosphere [4]. The artic permafrost is currently a carbon sink (it absorbs more carbon than it produces), if enough permafrost melts it would become a carbon source (it produces more carbon than it absorbs), this is the domino tipping point at which the carbon produced would lead to warming, which leads to more permafrost melting etc.

The objective of the proposed project will be to develop a model from deep learning techniques that can be used to identify permafrost from satellite imagery. This could then be used to analyse the regression of permafrost and formulate correlations with other determining factors involved in the melting of permafrost. The methodology, motivation and project plan are further explained throughout this proposal.

Related Work & Relevance to the Proposed Project

There are many past papers/articles/projects that relate to this proposed project, a selection of information relating to permafrost analysis, remote sensing of permafrost and deep learning models used on satellite imagery are explored throughout this section and linked to the proposed project.

Previous analysis on the remote sensing & modelling of permafrost includes an article reviewing the progress and challenges of studying permafrost in the Tibetan Plateau using satellite remote sensing and models [9]. In-situ instruments and on-site observations have been used to measure permafrost temperature, thickness and more in the Tibetan plateau since the 1970s, the article is critical of these measurements because of their sparseness and limits on observational periods. Furthermore, the article suggests that the extrapolated results entail large uncertainties when combined to assess the permafrost state across the whole plateau. This is due to a lack of data and inconsistencies in the measurement methods across the different sites. From this critique of in-situ methods, a motivation for this proposed project is further demonstrated.
The article proceeds to recommend satellite remote sensing data combined with process-based models as a more effective method to study permafrost. The article examines the different types of satellite data used to analyse the permafrost, which relates to my proposed project as a dataset will have to be chosen to train the deep learning model. Microwave remote sensing can be effective as it is particularly sensitive to the dielectric changes on the surface, this allows the datasets acquired with microwave remote sensing to easily identify the soils' frozen or thawing state. Additionally, microwave remote sensing can operate under all weather conditions. However, current microwave sensors have relatively low spatial resolutions and can be confused by other factors such as dry snow on top of the permafrost, both of which can add large uncertainties to data classifications – which is crucial to a deep learning model.
Alternatively, optical and thermal infrared remote sensing could be used (such as MODIS, Landsat & Sentinel-2), this has a high spatial resolution but is affected by cloud coverage. These factors will be considered when deciding a dataset for the proposed project.

Another related body of work is a project in which a team developed a deep learning convolutional network algorithm to characterize ice-wedge polygons (a permafrost subsurface feature caused by repeated ice-vein growth) [10]. The project displays a successful example of a deep learning model being used to identify a permafrost feature. While the proposed project is unlikely to use the same convolutional neural network, the proposed project can expect to encounter some similar problems in relation to the subject matter – permafrost. For example, the paper explains that the deep learning model can become biased due to the different types of vegetation across permafrost tundra, reducing its reliability. This issue might be even more pronounced in the proposed project because the proposed project aims to characterise all permafrost rather than a specific feature, this exposes the proposed project to even more variation in surface topography and features i.e. vegetation. The paper proposes a solution to this issue would be to refine the deep learning model by increasing the variability of training samples and exploring more sophisticated pre-processing steps.

Recently numerous papers and projects have examined the carbon release of melting permafrost. For example, the PULSE methane concentration map [11] displays the concentrations of methane in the atmosphere. However, this does not determine the source of the methane. This highlights another motivation of the proposed project, that it can be used in conjunction with other data to identify correlations. For instance, if the proposed project can characterise permafrost it would be possible to analyse areas of melting permafrost; if a large area of melting permafrost correlates with a high methane concentration it further proves the permafrost carbon feedback process. As a result, the proposed project must be tested thoroughly and deemed reliable in order to conclude accurate correlations.

Objectives & Motivation

As mentioned in the introduction, the melting of permafrost has major consequences on both a local and global scale. It is estimated that permafrost regions occupy nearly 23 million square kilometres within the northern hemisphere [4]. While there is infrastructure within permafrost areas, a huge portion is extremely remote, for example, the peaks of the Tibetan Plateau. This makes in situ measurements time consuming, costly and in some cases dangerous. It is these problems that make using satellite imagery to monitor permafrost so attractive. The primary objective is a deep learning model that can be used to identify permafrost from satellite imagery, throughout this section I further explain my motivation and the benefits of this approach.

Within the last 20 years there have been massive improvements in the standard of quality of satellite data. Additionally, there is now a significant amount of satellite data publicly available. Each dataset has different variables, including spatial resolution (the m^2 area represented by a pixel of the image), spectral resolution (segments of the electromagnetic spectrum that are being measured) and temporal resolution (the amount of time between an image of a surface area being collected and the next time an image is collected of the same surface area). This means different datasets have varying suitability to different research projects - this is explored more in the proposal methodology. This is of particular relevance as a deep learning models' effectiveness is heavily dependent on the data with which it is based off [8]. So, the wide range of datasets available allows the proposed deep learning model to utilise the most relevant and effective data.

Another motivation for this proposal is its re-usability in future research. As previously stated, permafrost is widespread but often in remote areas. Once a deep learning model is proven to effective it can be applied to permafrost in a range of different locations. This also highlights one of the key challenges and objectives of the proposal; in that the deep learning model will need to cope with the many ways permafrost forms, for example: 'Thuthur' are large lumps in the ground caused by permafrost underneath, 'Pingos' are hills up to 50m high formed by thick underground ice pushing up the top layers of soil [4]. Both of which indicate permafrost but appear very different.

Finally, using deep learning-based processing techniques combined with the latest satellite image analysis has been proven successful in monitoring other natural resources across the globe – As shown in 'Related Work'. The relatively quick speed at which these methods can be applied is particularly relevant in this case due to the rapid changes in permafrost areas. In comparison to in-situ measurements which require extended periods of planning and setting up.

Methodology & Analysis

The proposed project will follow an agile methodology allowing the project to be continuously tested and improved until a satisfactory standard is achieved. This methodology allows the project to be flexible and responsive to problems that arise. Additionally, continuous attention should be given to making the project more efficient.

The first stage of research will be to decide on a dataset to use as sample data for the deep learning model. This will also be done in conjunction with deciding on a deep learning approach. The first phase of research will be qualitative; conceptual information on the different methods of deep learning networks and the different datasets will be collected and compared. In the second phase of research, quantitative data on the satellite image datasets such as spatial resolution, spectral resolution and temporal resolution will be compared.

To develop the deep learning model 3 classifiers will be used: permafrost soil, melting permafrost & no permafrost. From these classifiers the proposed project should be able to predict a mask representing the permafrost in the given data.

As soon as it is possible the deep learning model will be consistently analysed and tested. One such method to do so is to compare the model results to real images (real images can be acquired from Google Earth Engine). Additionally, classification accuracy can be continuously recorded after short bursts of training to monitor if the model is approving. Training and testing should be reproducible throughout the project, this means that changes to the model can be tested in the same exact way, so the results show an accurate representation of the change.

Once a reliable level of accuracy has been reached the deep learning model can be used to determine correlations. Some examples of possible correlations to investigate are factors causing permafrost to melt and carbon concentrations around melting permafrost areas. Data used in conjunction with the project to form correlations should be assured to be reliable, equally the developed model should be accurate to mitigate the risk of deducing inaccurate correlations.

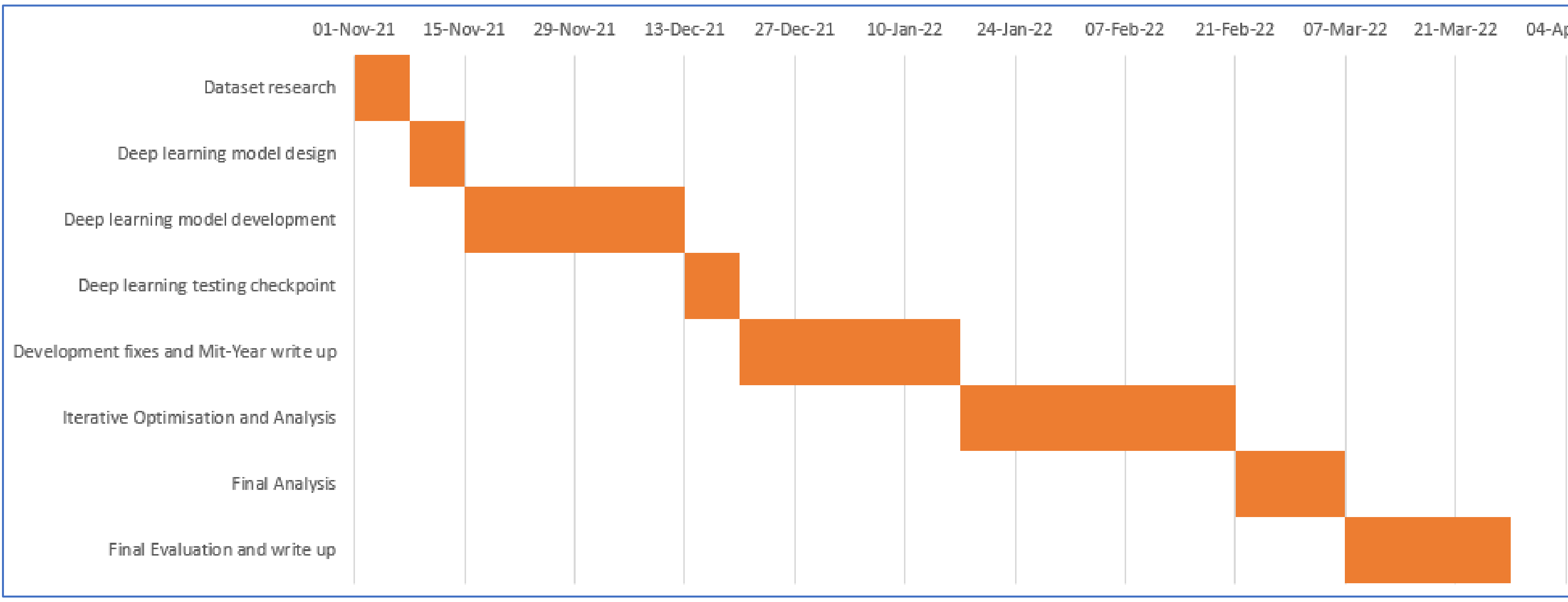
Workplan

The proposed project will be broken up into the following stages:

- Dataset research & comparison – Comparative research into different satellite image datasets to deduce which are best suited for a deep learning model to characterise permafrost. This should take around 1 week.

- Deep learning model design – Research and design the intended deep learning model, during this stage different methods of deep learning networks should be compared to deduce the most suitable for this project. This should take around 1 week.
- Deep learning model development – Developing the deep learning model, throughout the development; iterative testing will be performed and recorded. This should take 4 weeks.
- Deep learning testing checkpoint – Planned and recorded quantitative testing of the deep learning model so far, the tests should be reproducible so that later developments of the model can be tested in the exact same way. This should take 1 week.
- Development fixes and Mid-Year write up – Over the Christmas break any major issues should be fixed so that the project is at least functional before the next term. Over the break all progress, notes and test results should be accumulated into a single report. This should take 5 weeks.
- Iterative Optimisation and Analysis– Repeatedly measuring quantitative values and developing to improve them, comparisons to other models should be noted and test results compared to previous results. This should take 5-6 weeks.
- Final analysis and correlation investigating – A final analysis on the developed deep learning model and its effectiveness in a multitude of measurements. The model can then be used in conjunction with other resources to formulate correlations in relation to climate change. This should take 2 weeks.
- Final evaluation and write up – Evaluate all gathered data, test results and correlations. Final write up to conclude progress and development. This should take 2-3 weeks.

This schedule is displayed in the following Gantt chart:



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