Imperial College London

Department of Earth Science and Engineering

MSc in Applied Computational Science and Engineering

Independent Research Project
Project Plan

Using deep learning to map potential resource distribution of lunar permanently shadowed regions.

by

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Abstract

The polar regions of the Moon contain permanently shadowed regions (PSRs), zones which never receive direct sunlight. These environments remain extremely cold and have the potential to trap volatile materials (such as water) in solid form. A paper published by Brown et al. [1] analytically evaluated 65 PSRs to generate a ranking of those with the highest resource potential. This project aims to achieve the same goal through machine learning (ML) and hopes that a neural network will be able to better identify patterns across datasets and better rank the PSRs with the highest resource potential. A review of published literature indicates that since 2020, ML is increasingly being applied to lunar science however data assimilation exercises such as this remain scarce.

1 Introduction

The presence of water-ice on the Moon was confirmed by NASA following the LCROSS mission in 2009 [2] which propelled an impactor towards the lunar surface. While the mission was able to definitively confirm the presence of water on the Moon in one location [3], remote sensing techniques can be used to indicate its presence and location on a larger scale. It is widely predicted that most will be contained within lunar permanently shadowed regions (PSRs). Primarily located at the poles of the Moon, PSRs are in continuous darkness and can reach temperatures as low as $-238°\mathrm{C}$ [4, 5]. While not constant, temperatures in these regions are consistently low enough to create stable conditions for volatile materials including $\mathrm{CO_2}$, $\mathrm{H_2}$ and $\mathrm{H_2O}$ [6].

1.1 Problem description and objective

This project aims to replicate the findings of a reference paper by Brown et al. [1], titled "*Resource potential of lunar permanently shadowed regions*", using a new methodology. The paper uses analytical methods to assess the resource potential of respective lunar PSRs and ranks them. This project aims to show that machine learning (ML) can be used to enhance these insights.

The final objective is to create a ranking of the same PSRs but using fewer datasets. The list generated using ML will be compared against the list in Brown et al. [1].

If ML is able to recreate this ranking accurately, there are significant implications regarding the potential for data assimilation in lunar resource identification. Higher numbers of datasets, including images, could be incorporated into neural networks achieving an unprecedented level of assurance when debating the best places to search for lunar volatiles.

1.2 Methodology

Brown et al. [1] compiles eight remotely sensed datasets across 65 PSRs and gives each region a score from 0-2 for each dataset (0 = no detection/inconsistent, 1 = consistent, 2 = strongly consistent) for each of the eight datasets. The result is each PSR has a total score from 0 to 16, where 0 indicates no detection of volatile materials across any dataset, and 16 indicates all datasets are strongly consistent for volatile materials. This scoring structure can be seen in Figure 1.

This project will use the same scoring structure to assign synthetic lables to points on a grid and train a neural network to predict the likelihood of volatile materials based on these labels. This type of ML is known as deep learning. Only four of the datasets considered in the reference paper will be evaluated and the same ranges (latitude ranges of $80°$ to $90°$ at each pole) will be considered. These datasets are:

- LRO's Diviner Annual Maximum Bolometric Temperature (Diviner)
- LRO's Mini-RF monostatic CPR (Mini-RF)

- LRO's Lunar Orbiter Laser Altimeter (LOLA)
- Chandrayaan-1's M^3

Four of the original datasets were considered incompatible with this project. LRO's LAMP dataset is unable to provide data for the North Pole due to low signal to noise ratio (SNR). LRO's LEND and LPNS datasets both have a spatial resolution considered too coarse for an ML approach. Finally, LRO's Diviner ice depth stability dataset was discounted as the thresholds are based off model predictions and is without physical rationale for the thresholds. Each of these factors are discussed in Brown et al. [1].

The impact of this selection is discussed further in section 2.

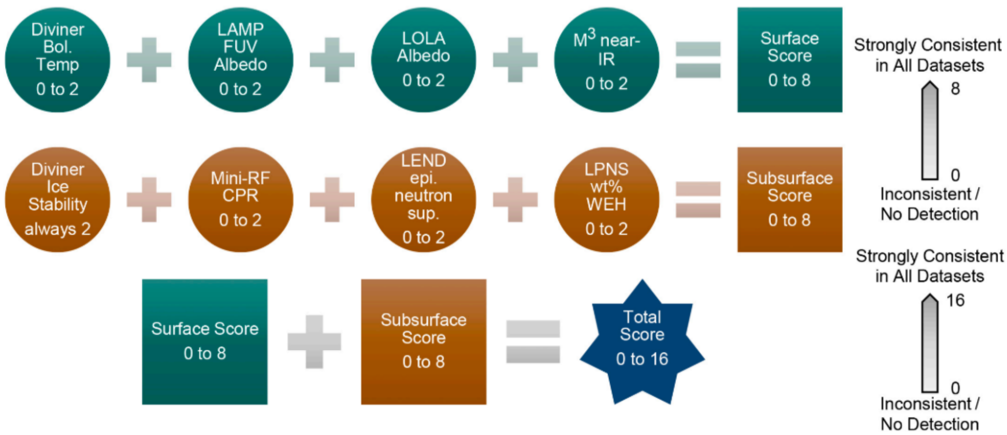

Figure 1: Scoring structure used to rank PSR resource potential in Brown et al. [1]. In this project, the LAMP, Diviner Ice Stability, LEND and LPNS datasets are dropped. Image taken from Brown et al. [1]

1.3 Literature review

As this project seeks to reevaluate existing work through novel means, the review of existing literature is split into three parts. These parts consist of: literature in the field of the work being replicated, literature in the novel means being applied and any additional literature of note.

Evaluation and ranking of PSRs

In addition to Brown et al. [1], Brown, Robinson, and Boyd [7] also takes a holistic view by analysing a larger number of remote sensing datasets to try and analytically rank PSRs. Jia et al. [8] completed detailed analysis of potential lunar south pole landing sites. They created fuzzy cognitive maps and ran simulations, varying certain factors to investigate how they affect these sites. Sites were then ranked for suitability. Additionally, a deep learning tool named HORUS [9] has been developed to denoise PSR images and has been applied to potential Artemis landing sites in Bickel et al. [10]. Barker et al. [11] and Cannon and Britt [12] both considered LOLA data to improve digital elevation models (DEMs). They used mathematical algorithms to improve the models with the aim of improving lander and rover navigation respectively.

Application of deep learning to lunar or remote sensing datasets

In 2021, Varatharajan et al. [13] published a whitepaper titled *Artificial Intelligence for the Advancement of Lunar and Planetary Science and Exploration*. This is one of many publications [14, 15] highlighting the vast potential of AI when applied planetary science and it proposes a range of applications.

The first major application is to make inferences using specific remote sensing datasets. For example, Cambioni et al. [16] uses neural networks to analyse and predict the surface properties of airless bodies, such as asteroids, by using measurements of emitted infrared flux. This approach helps estimate likely surface properties by comparing the observed infrared data with the predictions made by surrogate models. Additionally, Shukla et al. [17] developed a radar scattering model and a deep learning-based inversion algorithm to identify and analyse the physical nature of lunar regolith. This work focuses on the detection of near-surface volatiles such as water ice and Helium-3.

Another application of deep learning to lunar data is through image processing. HORUS is a deep learning tool using convolutional neural networks (CNNs) to identify and reduce noise patterns in lunar images while preserving important geological features [9]. It has been applied to Artemis sites and a range of other PSRs [18, 10]. Similarly, Bickel and Kring [19] developed a feature detection and classification model to identify boulder tracks which had applications to determine slope angles, bearing capacity and surface strength of the sunlit south polar region. These types of ML algorithms applied to image-based datasets have been used in a range of investigations ([20, 21, 22]).

Finally, deep learning has been used for navigation and terrain management. Applications for rovers have been diverse including Wu et al. [23] who introduced a method for lunar rover localization by generating a synthetic lunar environment and training a Siamese convolutional neural network to match surface-perspective images with satellite imagery. Many other publications have been made regarding rover navigation ([24, 25]). In addition to rovers, Gaudet, Linares, and Furfaro [26] used reinforcement learning to develop an integrated guidance and control system able to optimize the descent and landing of a planetary lander.

Other literature of significance

For a deeper understanding of how volatile materials behave, Crotts [27] and Zhu et al. [6] were consulted with Cannon and Britt [28] helping to understand how impacts can redistribute/bury ice and the mixing efficiency of ice in regolith.

Conclusion

Literature which evaluates or ranks PSRs on a large scale seems scarce. Several have achieved this analytically ([1, 7, 8]) but current efforts in machine learning (as applied to lunar science) appears more directed at specific capabilities such as image enhancement, rover navigation and building models around specific datasets. These applications certainly have importance, informing future orbiter, rover and manned missions to the Moon, but deep learning should also be applied to data assimilation exercises to continue to develop a big-picture understanding of the Moon.

By far the most common deep learning architecture in the literature reviewed was the CNN, however other architectures feature in special cases such as Siamese neural networks [23], reinforcement learning [24], value iteration [26] and more. There are also opportunities for current research areas to be combined. For example in the future, the ML algorithms which denoise PSR images and those which allow rovers to navigate autonomously in lit regions could be combined to enable rovers to traverse into PSRs.

It is also interesting to note that many publications in the field of ML applied to lunar datasets are very recent. Of all 23 publications considered in this section, 18 were published in the last five years (2019-2024) with the earliest in 2012.

2 Progress to date

In addition to the work described in this plan, ranked lists of PSRs considering the full eight datasets and the four chosen datasets have been compared. Kendall's Tau value was 0.8816 and Spearman's Rank Correlation was 0.9426. This gives sufficient confidence that this selection is satisfactory. Additionally, the process of processing the data from each instrument has begun with preliminary scripts developed.

3 Future plan

Here is presented the intended roadmap to complete the project outlined in section 1.1.

- Project plan and literature review
- Data collection and transformation
- Grid generation
- Synthetic label generation
- Data cleaning and augmentation
- Model training and validation
- PSR ranking
- Comparison with Brown et al. [1]

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