Identifying deep moonquake nests using machine learning model on single lunar station on the far side of the Moon

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Key Points:

- As a part of the future space mission NASA will deploy a new seismic station to Schrödinger Basin on the far side of the Moon.
- We propose a machine learning model trained to classify deep moonquakes using the lunar orbital parameter.
- The models perform with accuracy greater than 70% when trained to classify combinations of four or fewer nests.

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Abstract

One of the future NASA space program includes the Farside Seismic Suite (FSS) payload, a single station with two seismometers, on the far side of the Moon. During FSS operations, the processing of the data will provide us with new insight into the Moon's seismic activity. One of Apollo mission finding is the existence of deep moonquakes (DMQ), and the nature of their temporal occurrence patterns as well as the spatially clustering. It has been shown that DMQs reside in about 300 source regions. In this paper we tackle how we can associate new events with these source regions using the single station data. We propose a machine learning model that is trained to differentiate between DMQ nests using only the lunar orbital parameters related to DMQ time occurrences. We show that ML models perform well (with an accuracy $> 70\%$) when they are trained to classify less than 4 nests.

Plain Language Summary

The future space missions will provide us with various new lunar data, one of which will be ground vibration measurement. The studies of these measurements from the Apollo era in 70s, showed that Moon can host various events. The most intriguing ones are deep moonquakes (DMQs), which are events associated with the displacement deep within the lunar interior. It has been shown that DMQs occur in the specific locations, which are called nests, and that their temporal occurrence is related to the monthly motion of the Moon around the Earth. In this paper we tackle how we can associate new events from only one station located on the far side of the Moon with these known locations of DMQs. We propose a machine learning model that is trained to classify DMQ nests, only using the information about their temporal occurrences, e.g. time of the event, described in terms of different lunar events. We report that models are performing well (with an accuracy $> 70\%$) when they are trained to classify 4 or fewer nests. This gives us a good first approximation about the nest identification.

1 Introduction

We are at the beginning of a golden age of lunar exploration as many nations, together with private companies, are establishing numerous efforts to obtain new scientific measurement of the Moon (Weber et al., 2021; Pickrell, 2022; Kawamura et al., 2022). In light of this, NASA established the Artemis program which should land a crewed mission at the lunar south pole (Witze, 2022). This would be the first attempt of a crewed landing after the successful Apollo missions in 1970's. Before Artemis missions land on the Moon, NASA has also established the Commercial Lunar Payload Services (CLPS) program to land scientific payloads on the Moon using commercial landers. The Farside Seismic Suite (FSS) is one of the selected payloads, and it will deliver two seismometers to Schrödinger Basin on the far side of the Moon (Panning et al., 2021; Standley et al., 2023; Cutler et al., 2023): one vertical Very BroadBand seismometer, and Short Period sensor, both spare or derived from the SEIS experiment sensors (Lognonné et al., 2019, 2020) from the InSight mission to Mars (Banerdt et al., 2020).

The Apollo missions showed the importance of deploying sensors on the surface of the Moon, since a great deal of our knowledge about the Moon comes from the analysis of data acquired during the Apollo era (Lognonné & Johnson, 2015). Thus, analyzing ground motion measurements provided the community with the first constraints on the lunar interior and the activity at the surface (Nakamura et al., 1982a, 1982b; Khan et al., 2000; Khan & Mosegaard, 2002; Khan et al., 2014; Lognonné et al., 2003; Gagnepain-Beyneix et al., 2006; Weber et al., 2010; Garcia et al., 2011; Kawamura et al., 2017; Garcia et al., 2019; Nunn et al., 2020). It has also revealed that the Moon can host events of various origins, such as shallow and deep moonquakes, meteoroid and artificial impacts (Toksöz et al., 1974; Dainty et al., 1975; Lammlein, 1977a; Nakamura, 1983, 2003, 2005).

Today, we have more than twelve thousands events, out of which the deep moonquakes (DMQs) form the most numerous group (Nakamura et al., 1981; Nakamura, 2005).

DMQs are a distinctive group of seismic events that originate from depths between 700 and 1200 km, at high pressure and temperature conditions, where little brittle deformation is expected. Due to very high waveform similarity between quakes, the DMQs have been clustered into about 300 source regions or nests (Nakamura, 2003). This has interpreted to be a consequence of DMQs occurring repeatedly at the fixed nests, which are located mostly on the near side of the Moon. It has been shown that time occurrence of the DMQs is correlated with the monthly motion of the Moon around the Earth. Thus, DMQ occurrences exhibit tidal periodicities and furthermore, the associated high strain rates might explain brittle processes (Kawamura et al., 2017). However, the real causes of their origins are yet to be discovered. There are two puzzling fact about their origin: a) cyclic tidal stresses, caused by the monthly motion of Moon around Earth, are far less than the estimated confining pressures where DMQs occurs (Cheng & Toksöz, 1978; Minshull & Goulty, 1988a); b) do we need both, tectonic and ambient tidal stresses, to explain their mechanical origin (Frohlich & Nakamura, 2009).

To better constrain the lunar interior and unravel the cause of DMQs, it is important to locate new events and associate them with the known nest locations from Apollo with future lunar missions like FSS. These new observations will add, for each new nest, a new differential $t_s - t_p$ measurement constraining the deep interior with a different epicentral distance. However, due to the mission requirements, it is extremely likely that, at the beginning, we might have only one lunar station at the disposal. Therefore, in this paper we study the problem of DMQ nest identification without using waveform information. This is due to the new location of the recording station, which will not match existing Apollo-era waveform templates due to different propagation paths. We propose a machine learning (ML) model that is trained to identify nests within the set of nests of similar differential travel times. The main features used for the model training are related to the fact that different nests respond differently to lunar cycle.

Very early studies have shown correlation between lunar transient events and position of the Moon related to the Earth (Middlehurst, 1967; Cameron & Gilheany, 1967; Moore, 1968). This further encouraged observations that some moonquakes occur with periods that reflect Earth-Moon-Sun relationship (Ewing et al., 1971). Later, it has been shown that the occurrence of DMQs are related to tidal stress cycles, and correlations between DMQs occurrence times and lunar monthly tidal cycles have been indicated (Lammlein et al., 1974; Toksöz et al., 1977; Lammlein, 1977b; Cheng & Toksöz, 1978; Minshull & Goulty, 1988b). The lunar cycle can be explained with three lunar months: synodic, draconic, anomalistic. Synodic month is the period of lunar phases such as New Moon, First Quarter, Full Moon, Last Quarter. Draconic month is the period between two nodes, ascending or descending, where the nodes are points at which the Moon's orbit plane crosses the ecliptic plane towards which it is inclined of about 5.14°. Anomalistic month is the period between two extreme points, perigee and apogee, since the Moon's orbit approximates an ellipse rather than a circle. Earlier studies counted the number of events per day as a function of time and found 0.5 and 1 month signals in the occurrence times related to anomalistic and draconic period of 27 days (Lammlein et al., 1974; Lammlein, 1977b). The same studies also indicated 206-day and 6-year periods, related to the Sun's perturbation on the lunar orbit and the relative precession of the perigee of the Moon's orbit. Subsequently, many recent papers studied and confirmed tidal periodicities of DMQs and more (Bulow et al., 2005, 2007; Bills et al., 2008; Frohlich & Nakamura, 2009; Weber et al., 2009, 2010; Turner et al., 2022).

Based on the previous papers, it is clear that DMQ nests exhibit some clear temporal patterns in their occurrences, and that these are correlated with Moon-Earth system. Therefore, the open question is whether we can design features which would reflect these temporal patterns and to further use those features to study the nest identification with one lunar station. In this paper we tackle the question of defining optimal features and the machine learning model. The paper is organised as follows: first, we discuss data used in the analysis, the existing catalog of DMQ events. Second, we discuss the feature design. Third, we introduce a machine learning model. Fourth, we discuss successes and pitfalls of the machine learning model for nest identification applied to different combination of nests. We conclude how this study can offer some first estimates of the nest location in the future lunar missions.

2 Data

We start with the existing catalog of lunar events (Nakamura et al., 1981), which was updated in 2008 and modified in 2018 (Nunn et al., 2020). Catalog contains a list of events (shallow and deep moonquakes, meteoroid and artificial impacts) with attributes such as date and time of the event occurrence, signal envelope amplitude as measured in mm on a standard plot, data availability per station, and the nest (source) classification for DMQs. It is important to note that the source classification is not an exact location defined by latitude and longitude, rather a result from the waveform cross-correlation and single-link cluster analysis (Nakamura, 2003). This analysis positively clustered around 7k DMQs into 77 nests, where the largest nest is associated with label A1. This nest contains 443 quakes and it is placed on the near side of the Moon.

2.1 Catalog processing: nest sets based on travel time information

Earlier studies published lunar interior models and location of DMQ nests in terms of latitude and longitude by picking P and S travel times on the quake waveforms (Garcia et al., 2019, review of these picks). Using lunar interior models and nest locations we can define nests that are close by in distance if we consider only the t_{sp} travel time measurements. To do so we assume that a) our single lunar station is located on the far side in Schrödinger Basin (FSS landing site at 71.378°S, 138.248°E), b) nests' latitudes and longitudes from (Lognonné et al., 2003), c) calculated P- and S- wave travel times (t_p and t_s, respectively) using lunar velocity model between landing site and locations of DMQ nests. By having t_s and t_p we can calculate $t_{sp} = t_s - t_p$ for all nests and models shown in Figure 1 (see Text S1 and Figure S1 for further explanation). Next, we count for each nest how many there are with the similar t_{sp} travel time measurement assuming a picking error of 5 seconds as shown in Figure 1A, consistent with the average picking error in Lognonné et al. (2003). This count provides us with the different sets S_i, shown in Figure 1A, that contain nests N_j of similar travel times. In other words, if we are able to measure t_s and t_p of the new lunar event with accuracy within 5 seconds, we are not able to differentiate between nests that belong to different sets S_i. Therefore, to further tackle the nest identification problem we proceed to associate each event with a combination of lunar orbital measurements.

2.2 Feature selection based on the lunar orbital information

It has been shown that the DMQ temporal patterns in time occurrences are related to different lunar cycles and that these patterns differ from nest to nest. Three lunar cycles are synodic, draconic, anomalistic, and they all have similar periods, but are marked by different motions, either as the motion between two Full Moons phases, or two nodes, or two apsis, respectively. One can list all the events when Moon is in the Full Moon (New Moon) phase, passing through ascending (descending) node or perigee (apogee) by simply looking at the Moon's ephemeris (Meeus, 1991). To make sure that we take into account the temporal patterns, we design the main three features as a time difference between the time of the quake in the nest and the time of the Moon's Full Moon, ascending node and perigee, denoting it as $\Delta t_{FullMoon}, \Delta t_{AscendingNode}, \Delta t_{Perigee}$, respectively. We can achieve the same effect by taking the other three time axis as referent one (New

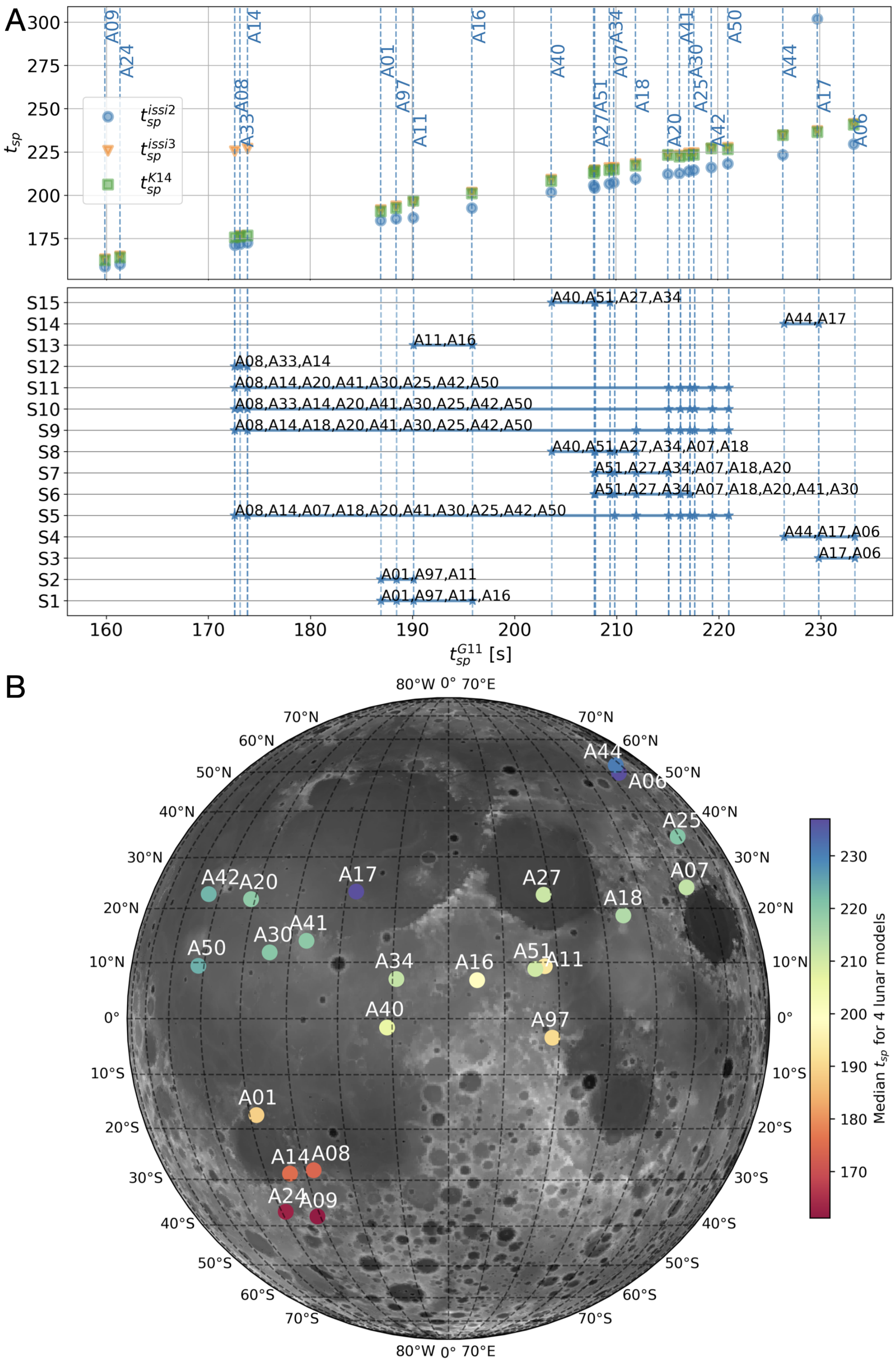

Figure 1. Location study of the DMQ nests from the perspective of $t_{sp} = t_s - t_p$ travel time measurements if we place station in the Schrödinger Basin and consider four different lunar models. A) Upper panel: t_{sp} travel time measurements for four lunar models from Garcia et al. (2011) (G11), Garcia et al. (2019) (issi2, issi3), (Khan et al., 2014) (K14) with nest labels; A) Lower panel: Sets S_i which represent nests with similar travel times if we consider a travel time error of 5 seconds. B) Lunar map with the nests locations where the color indicate the median t_{sp} for four lunar model.

Moon, descending node, and apogee). The next feature is related to the Moon position within its orbit as in Frohlich and Nakamura (2009). The angle between the direction of perigee and the current position of the body, as seen from the main focus of the ellipse, is called the true anomaly, denoted further as γ. Further, as one of the feature we also use the interval time between two quakes in the nest, noted as $e_{i+1}-ei$, as in Weber et al. (2010). And the last two features are related to the position of the Moon with respect to the Earth, and these are the distance, d, itself and the rate of the distance change, $\dot{d}$, as in Bills et al. (2008).

The selected features all have different ranges and we refer to them as raw data. To train a model that is able to generalise well for a given problem sometimes it is necessary to transform raw data to a form that is more suitable for training (Langer et al., 2019). By applying transformation on the raw data we may obtain a mapping which better reveals patterns in our data. Therefore, we chose to apply trigonometric transformation of the true anomaly angle γ, to properly address the jump discontinuities in the feature when angle goes from 2π to 0, due to it's cyclic nature. This is addressed by transforming true anomaly angle γ to pair of $[\cos\gamma, \sin\gamma]$. An example of all eight features are shown in Figure S2 for nest A1.

3 Methodology

When new lunar data arrives, we shall be able to differentiate events in groups based on the waveform similarity measurement. And we shall be able to measure their P and S travel times, and thus form set of nests from Section 2.1. Final step would be to associate these new events with the existing Apollo nests if possible. This nest identification from a single lunar station is a supervised classification problem. The model is trained in a predictive way by taking into account nest locations as labels and nest lunar orbital parameters as input data. Since we want to predict a class (nest), but we do not have statistically large data set (as previously mentioned A1 has 443 quakes), we choose to train a Random Forest (RF) Classifier, since RF can perform well with any size of datasets and tend not to overfit (Ho, 1995; Breiman, 2001).

Random Forest (RF) is a machine learning technique that is based on decision trees (Breiman et al., 1984; Quinlan, 1986) and bootstrap aggregating (Breiman, 1996), where the main output is reached by majority votes among an ensemble of randomised decision trees. A main building unit, a decision tree, is a tree-like learning algorithm where each internal node tests on attribute, each branch corresponds to attribute value and each leaf node represents the final prediction. Usually, during the training phase thresholds, order and number of inequality operations within internal nodes are learned. The hyperparameters that define a RF structure, such as the number of trees, and measure which maximises diversity between classes, are determined beforehand (see Text S2 and Figure S3).

RF also provides an assessment of the feature or input variable importance which might give us an insight of how the model reached its prediction. To assess the feature importance, the RF removes one of the features while it keeps the rest constant, and it measures, among others, the accuracy decrease (Breiman, 2001). RF models are able to solve regression and classification problems, as well as two- and multi-class problems. It has been show that RF can perform with high accuracy even though there are only a few parameters to tune.

In our case, during the training phase, the RF model has access to the extracted features of the individual quakes and the nest labels. The training is performed on a subset of the data, while the model performance is evaluated on the test subset, which the model has never seen. Evaluation is accomplished by comparing the model's predicted class (nest) with the ground truth one. The statistical performance of the model is presented with confusion matrix and Receiver Operating Characteristic (ROC) curve. We expect that in the case of the ideal RF Classifer the diagonal of the confusion matrix is equal to 1 (and off-diagonal elements are zero), while ROC curve is passing through the left upper corner.

4 Results and discussion

4.1 Training and testing on two largest nests

We first test the hypothesis whether it is possible to differentiate two DMQ nests using the lunar orbital parameters (features). For this, we select the two largest nests, A1 and A8, with a total size of 768 events and ratio A1:A8=0.57 : 0.43 (see feature distributions in Figure S4).

Training and testing our base RF model (see Text S2) with the normalised and not normalised input data, we end up selecting to work with the normalised input data since this model performed better (see Figure S5 and S6). The base model trained with the normalised input data performed with an accuracy of 89%, while precision, recall and f1-score for the A1 nest is 88%, 94%, 91%, respectively, and for A8 is 90%, 80%, 85%, respectively (see Figure S6B) with only the occurrence time knowledge. The ROC curve is above the random classifier curve, meaning that the base model is not randomly classifying A1 and A8 nests (see Figure S6C). Out of eight features, the first five most important are $cos(\gamma)$, $\Delta t_{Perigee}$, d, $\Delta t_{AscendingNode}$, $e_{i+1} - e_i$ (see Figure S6D). We notice that $cos(\gamma)$ is the feature with the most important contribution to the model learning. This might be because A1 and A8 have reversed distributions for $cos(\gamma)$ feature (see Figure S 4D).

We proceed into testing learning robustness of our base model in a series of experiments (see Text S2 and Figures S7-S12), all of which indicate that the model is stable. This implies that the base model generalizes well, and not over fit the results. Further, if we examine why the base model sometimes mislabels the nests (Figure S13), we notice that the 2D manifold (see Text S3) of feature space spanned by the input data, calculated by t-sne method (van der Maaten & Hinton, 2008), is not perfectly separated. It seems this segregation might be dominated by a single feature, and that is $\Delta t_{AscendingNode}$ (see Figure S14 and S15A).

4.2 Training and testing on three and more nests

In this section we study how the performance of our base RF model from Section 4.1 changes by adding more nests. We carry out three tests for the next combinations and their ratios: A1-A8-A18 (45%-33%-22%), A1-A8-A18-A6 (38%-28%-18%-15%), A1-A8-A18-A6-A14 (33%-25%-16%-13%-12%), where the three added nests are the three largest nests besides A1 and A8.

The analysis shows that by adding more nests, the performance of our base model deteriorates since the accuracy drops from 88% to 59% (see Figures S16-S19). By adding a 3rd nest, and we notice that A1 and A8 recalls deteriorate slightly, and 50% is A18 events are classified either as A1 or A8 (see Figure S16). Yet, the precision of A18 is the highest. Features, $e_{i+1}-e_i$ and $\dot{d}$, gain importance. Yet, the importance of all features become more equalized. By adding a 4th nest, A6, the recall of A1 nest improves, recall of A8 nest deteriorates even more than before, recall of A18 improves notably, and the new added nest A6 has a recall of 46%, by having most of its events misclassified only as A1 nest, and not a single event as A18 (see Figure S17). This might implies that A18 and A6 nests have completely different source mechanisms. Less notably than before, the importance of all features is becoming more equalized. Lastly, by adding a 5th nest, A14, the recall of A1 and A8 become the highest, and three other nests perform with recall less than 50%, and their most mislabelled data points are associated with A1 nest (see Figure S18). The importance between features is almost equalized, yet the interval time $e_{i+1} - e_i$ is the only feature that stands out.

These results might imply that by adding more nests, we add more complexity into the problem, since we might be adding nests that have similar source mechanisms. Having similar source mechanisms means that sources are triggered by tides is the same way, so their lunar orbital features have similar characteristics, and we cannot differentiate between nests without having more data. Furthermore, it seems that the only significantly important feature is the interval time, the only feature that does not reflect the lunar orbital information.

Checking the two dimensional representation of the feature space constructed by the feature combination of nests A1-A8-A18-A6-A14, we might conclude that for this particular set it is to some degree impossible to completely differentiate between nests due to the lack of data (see Figure S20).

4.3 Training and testing on nest sets

Using the same base RF model from Section 4.1, we proceed to train and test how well we can differentiate nests that belong to the same set shown in Figure 1. We analyze them in three separate groups by the frequency of the nest they contain: A) S1, S2, S3, S4, S12, S13, S14, S15; B) S5, S6, S7, S8; C) S9, S10, S11. The results are shown in Figure 2A, B, and C, respectively.

We observe high value of recall for most of the nests, as well as high accuracy for most of the sets (see Figure 2). Sets that have $<= 4$ nests perform better than those with more nests, as in sets from group A shown in Figure 2B. When the nest's recall is very low or zero (A11, A30, A41, A42, A50), it signifies a nest with very few events (see ratio of nests in all sets in Figure S18). If we take an example of nest A20, we notice that it has constant recall in many sets (see Figure 2B and C), even though it is not the biggest nest in the set (see Figure S21). Thus, not only the size but probably also the uniqueness of the features determine the success of identifying the nest.

The importance of different features is shown in Figure 3 for all three groups. On one hand, removing just one nest could change the feature importance, as in the case of S2 (where we remove A16) versus S1. On the other hand, we notice that the feature importance does not drastically change when comparing results for sets S3 and S4, where we add nest A44, even though the nest itself is large in size (see Figure S21). For the sets in group B, the feature importance is stable with respect to adding or removing nests. It is quite similar for group C, where only one set S8 has different feature importance. We notice that sets which contain $<= 4$ nests (as in group A), there is usually one or two important features, while for sets with > 4 nests there is equalisation of the feature importance (as in groups B and C). This might imply that a single lunar orbital parameter is enough to explain the occurrence of the nests, which are unique in nature. Mixing more nests suggests that we might be mixing nests with similar temporal patterns, thus learning how to differentiate them is more challenging. Moreover, the feature importance changes for sets that have unique combinations of nests, which may hint that these nests have different source mechanisms.

If we consider a 2D manifold spanned by the sets from groups A, B, C (see Figures S22, S23, S24, respectively), we notice that unique segregation in this space correlates with the RF model accuracy. Nests that form closely spaced homogenized clusters in the 2D manifold tend to be correlated with models that scored high recall for these nests.

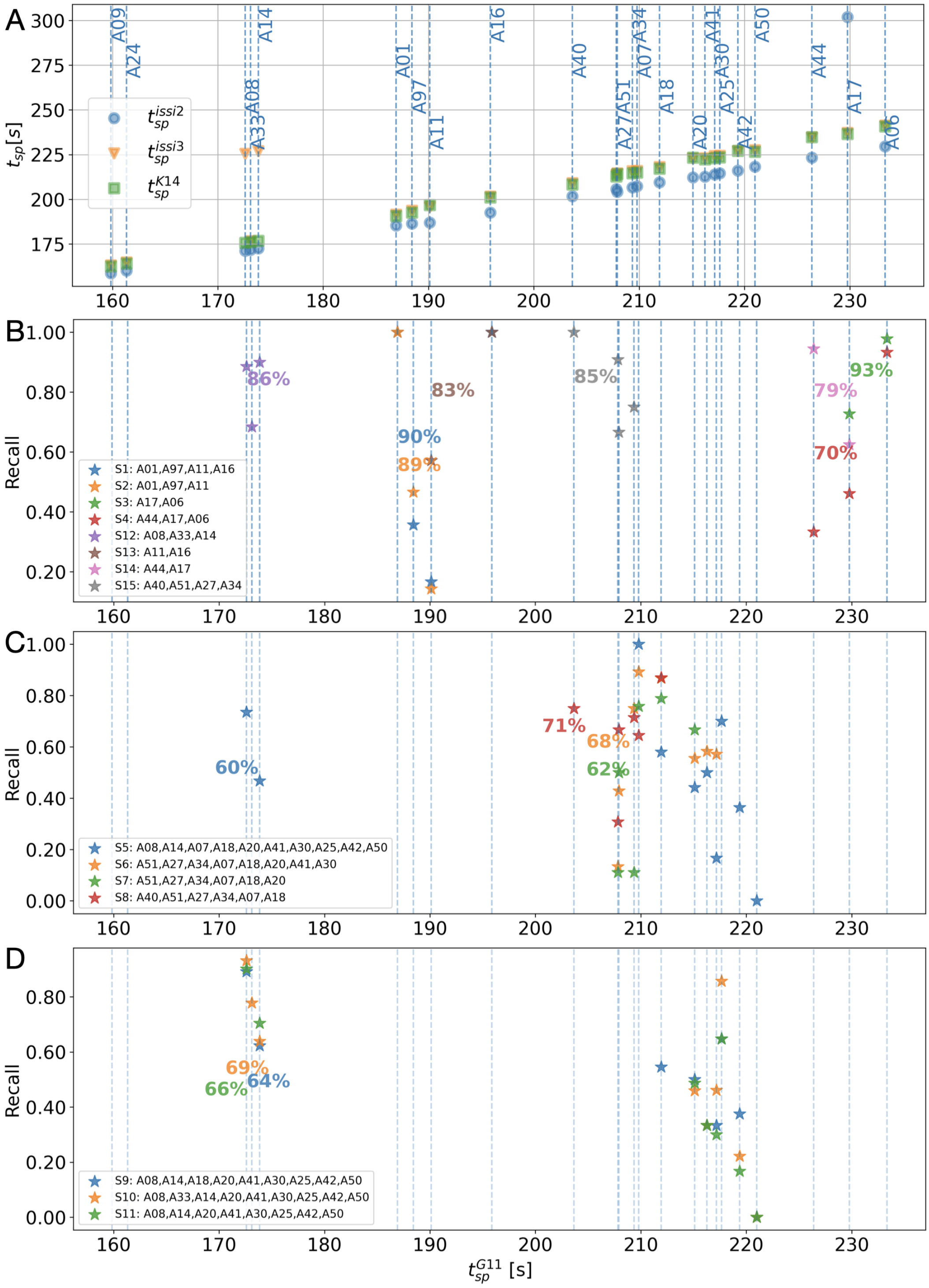

Figure 2. Performance of RF models designed to classify nests within different sets. A) Travel times t_{sp} for four lunar model from Garcia et al. (2011) (G11), Garcia et al. (2019) (issi2, issi3), (Khan et al., 2014) (K14) with nest labels. B) Recall for individual nests within each set with respect to their travel times labeled with sets to which they belong and the scored accuracy of this set. C) and D) same as B) just for different group of sets.

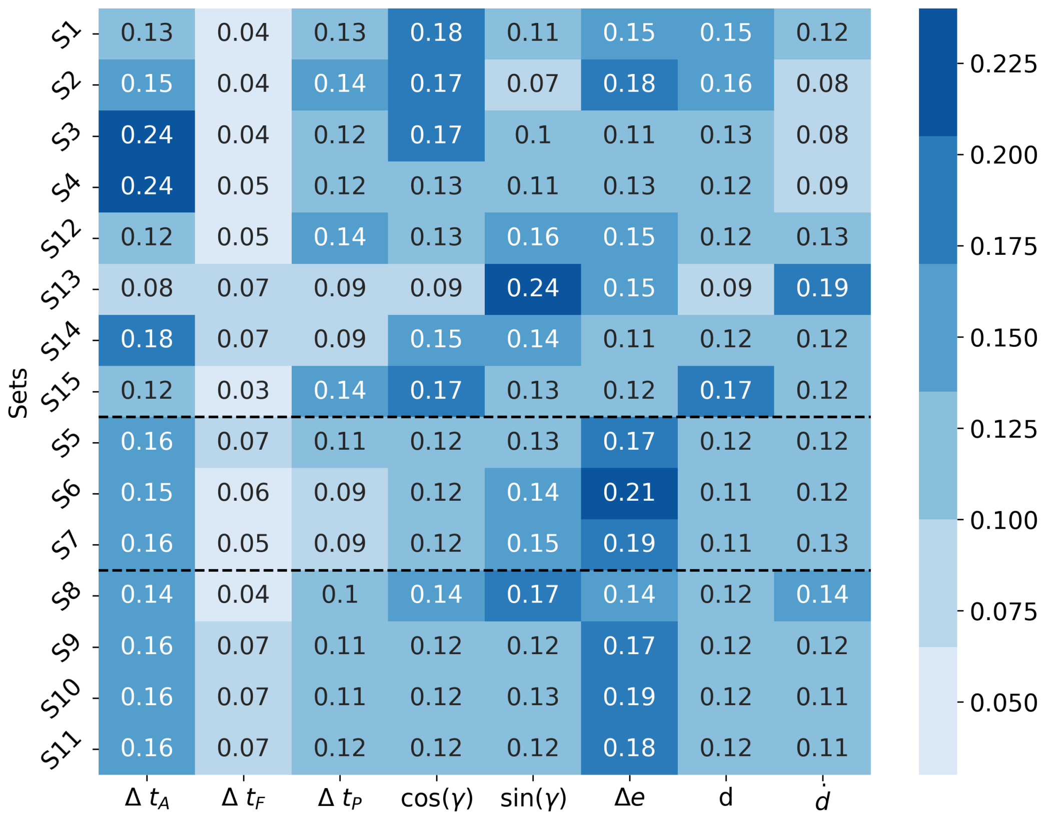

Figure 3. Feature importance for Random Forest models associated with different travel time sets shown in Figure 1.

5 Conclusion

In this paper we propose how to tackle DMQ nest identification during future lunar missions that will likely host only one station on the far side of the Moon. We propose constraining their location by using differential time travel measurement t_{sp} and parameters related to the temporal patterns of the DMQ occurrence. First, in our analysis we assume that we cannot differentiate between nests whose differences in travel time are less than 5 seconds. Thus, we form set of nests that have similar travel times. Second, for each event within the nests we calculate features that are used to build a Random Forest model. This model is trained to differentiate between distinct nests. The features used for training are build by associating each event in all nests with the time difference between events' origin time and time of lunar ascending node, Full Moon phase, perigee, then position of the Moon in its orbit expressed by true anomaly angle, distance of the Moon from the Earth, rate change of this distance, and the time between two successive quakes. We show that by training Random Forest models to differentiate between distinct nests within sets, we can obtain models with high accuracy (more than half of the models score above 70% accuracy). Yet, the performances of these models depend on the number of nests within the set. More nests implies that the problem is more difficult to solve, probably because a) nests might have similar source mechanisms, b) the number of events within nests is unbalanced, and c) we don't have enough data. Since RF models also arrange features by their importance to make a final classification decision, we observe that the importance of the features change with different sets. This complements the findings of previous papers, since it signifies that nests do correspond to different lunar events, which eventually might be connected to the distribution of tidal stresses during these events. Finally, our model provides a good first approximation of the nest identification. And as the catalog of new events grows, it will be straightforward to retrain RF model with the new enlarged dataset.

Open Research Section

The deep moonquake catalog used in this study is published in Nakamura et al. (1981), and revisited in Nunn et al. (2020). Python package Skyfield used to calculate Moon's orbital parameters based on JPL ephemeris can be found on the website `https://rhodesmill.org/skyfield/` (Rhodes, 2019, Software). For our implementation of the Random Forest algorithm we use Scikit-learn machine learning Python library (Pedregosa et al., 2011).

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