CONSTRAINING THE THERMAL PROPERTIES OF AIRLESS BODIES USING MACHINE LEARNING

S. Cambioni*[1], M. Delbo[2], A. J. Ryan[2], R. Furfaro[3], E. Asphaug[1] *cambioni@lpl.arizona.edu
[1] Lunar and Planetary Laboratory, The University of Arizona; [2] Observatoire de la Côte d'Azur, CNRS, Laboratoire Lagrange, [3] Systems and Industrial Engineering Department, University of Arizona

Introduction: We present a new approach to the interpretation of infrared fluxes of airless body. Our technique combines supervised machine learning and Bayesian inversion to determine the surface properties, including rock abundance, and to infer the thermal inertia of the rocks and the regolith separately. We train a neural network representation of the thermophysical behavior of the asteroid, and we employ this in a Bayesian inference of observed infrared fluxes. We validate the method by inverting simulated infrared fluxes of asteroid (101195) Bennu as observed by NASA's OSIRIS-REx mission [1], and then we also invert infrared observations of (25143) Itokawa. On Itokawa, we retrieve a rock abundance of ~85% for pebbles larger than the diurnal skin depth (~2cm). The conductivity of the rock is found to be lower that their meteoritic analog (the LL chondrites), possibly indicating that the pebbles could be fractured. Cracks in rocks can be modeled as pores of very flat shape, and thermal conductivity in meteoritic samples is found to decrease as porosity increases [2]. This is relevant to the interpretation of future infrared observations of (101195) Bennu by O-REx and (162173) Ryugu by JAXA's Hayabusa 2 [3]. Given the small size of the targets and their high rock abundance, differences in thermal inertia could be representative of more or less fractured rocks, rather than indicating the presence of regolith material (i.e., pebbles with size smaller than the diurnal skin depth).

Scientific rationale: Theoretical studies and remote sensing of the surface of airless bodies are crucial to understand their geology, composition, formation and evolution ([4] and references therein). All the asteroid observed so far show a combination of rocks and regolith, the latter produced by the evolution of the former via micrometeoroid impacts and thermal fatigue processes (e.g., [5]). Knowledge of temperatures and determination of thermal inertia of rock and regolith, and relative rock abundance, are key in estimating the "sampleability" of the surface, because they define the thermal and mechanical environment and inform about the average grain size.

Why machine learning? A powerful technique is to infer the surface properties from infrared fluxes emitted in response to the changing diurnal insolation. On asteroids, however, thermal inertia of rock and regolith, and rock abundance, have been never measured from infrared fluxes. State-of-the-art techniques involve the use of look-up tables which are populated by thermophysical simulations, and the matching between the observed flux and its nearest-neighbor flux in the table, e.g., via chi-2 minimization. However, this method is likely to fail if the dimensionality of the parameter space (number of surface properties) is enhanced, e.g., we want to split the contribution to rock and regolith to thermal inertia. A rough sampling of the parameter space is already computational expensive (thermophysical models may require up to 30 minutes in CPU hours to run), and it does not have enough resolution to rule out local minima and saddle points of the objective function (e.g., the chi-2 loss function). Populating a look-up table is therefore misplaced effort, unless the simulations can used to generalize the functional relationship between input (surface properties) and output (infrared flux). We propose to use the simulations in a look-up table to train, validated and test a neural network representation of the thermophysical model. As opposed to the parent model, this tool – once trained – is a fast predictor (~ seconds) which can be effectively employed to sample the posterior distribution of the surface properties by means of more advanced statistical techniques, such as Bayesian inversion aided with Markov Chain Monte Carlo integration of the evidence.

Methodology. *1)* We use a TPM thermophysical model (e.g., the TPM code [6]) to generate infrared fluxes corresponding to different combinations of surface properties and illumination conditions. We assume that the surface has regolith and rock, with two distinct values of thermal inertia. The fluxes relative to the two components are linearly combined by means of the rock abundance. We split the dataset in a training set (70%), a validation set (15%) and a testing set (15%). *2)* We choose a neural network architecture and train it to associate surface properties (e.g., surface roughness, thermal inertia regolith and rock, rock abundance) to an infrared flux. We use the validation set for hyperparameter optimization, and we test the best-validation scheme on the unseen data of the testing set. The performance of the network is assessed in terms of the mean square error between prediction and target, and regression accuracy. We find that a 2-layer network (with 10 neurons in the hidden layer) is a good choice for this application. *3)* We blind-test the trained network by simulation validation, i.e., inverting simulated infrared fluxes whose corresponding surface properties are known. 4) We use the network to sample from the (unknown) posterior distribution of the surface properties, via Bayesian inversion of observed infrared fluxes. We refer to the full manuscript [7], and references therein, for a more detailed explanation of the method.

Model validation: (101195) Bennu. We perform the blind test on simulated infrared flux of asteroid (101195) Bennu as observed by the O-REx Thermal Emission Spectrometer (OTES, [8]) during the detailed survey [1]. The Bayesian inversion uses uninformative prior distributions of the surface properties – that is, we do not assume any prior knowledge. The inversion is successful, because the reference values (34°; 50 SIU; 850 SIU; 30%) of the parameters belong to the posterior distributions (Figure 1).

(25143) Itokawa. We apply the validated method to the inversion of observed infrared fluxes of asteroid (25143) Itokawa [9]. The inference of the surface properties of Itokawa – namely, surface roughness, rock abundance, thermal inertia of regolith and rock components – is supported by prior information, such as lower/upper limit on the thermal inertia of the regolith and rock derived from assumption of homogeneity for the regolith. The resulting posterior distributions are in Figure 2. The surface is confirmed to be rocky at the diurnal skin depth level, and the pebbles have low thermal inertia (with respect to their meteoritic analog, the LL chondrites, [2]), which could indicate that they are fractured. The average thermal inertia of the surface is around 750 SIU, consistently with previous studies [9]. Finally, we use the empirical relationship by [10] to convert the thermal conductivity of the regolith to an average grain size of about 10 mm, consistently with previous studies [11].

Potentialities and future work. We foresee the use of the proposed methodology to forthcoming infrared data of (101955) Bennu and (162173) Ryugu, whose rock abundance can be accurately inferred given the availability of nightside observations. The concept of thermal surrogate model, however, is broader and can be used to inform about surface sampleability also on the Moon, Mars, comets and icy satellites (e.g., NASA's Clipper), provided the availability of infrared data – and accurate "parent" thermal models.

Acknowledgements. MD and AR acknowledge support from the Academies of Excellence on Complex Systems and Space, Environment, Risk and Resilience of the Initiative d'EXcellence "Joint, Excellent, and Dynamic Initiative" (IDEX JEDI) of the Université Côte d'Azur, as well as the Centre National´ Etudes Spatiales (CNES).

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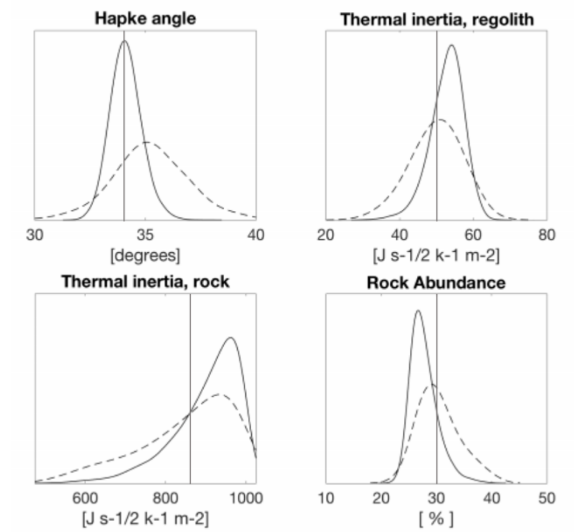

Figure 1. Posterior distributions of the surface thermal properties from simulated disk-integrated fluxes of (101955) Bennu. The dashed curves are solutions when only the daytime observations are processed. The solid curves are solutions when all the observations are processed. In both cases, the reference values (34°; 50 SIU; 850 SIU; 30%) of the parameters (vertical lines) belong to the posterior distributions.

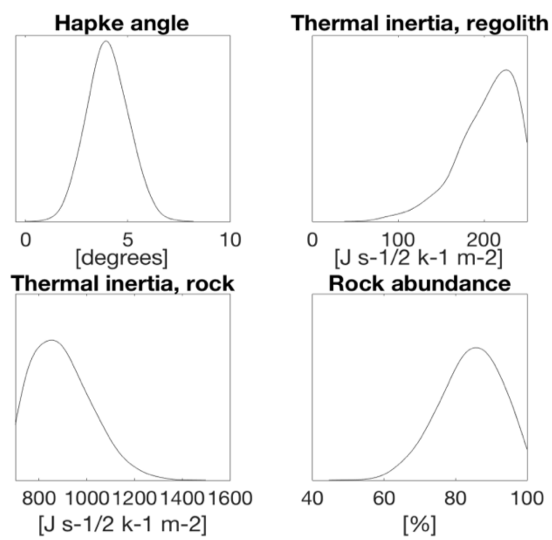

Figure 2. Solution for (25143) Itokawa. The surface is found to be rocky and the pebbles have low conductivity; they could be highly fractured.