# Can Artifical Intelligence help us understand how planets evolve?

## Unravelling the interior evolution of terrestrial planets using Machine Learning

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**In Short**

- The mantle of rocky planets behaves like a highly viscous fluid over geological time scales. Key parameters and initial conditions to the non-linear partial differential equations governing mantle flows are poorly known.
- Using a dataset of $10,000$ evolution simulations, we trained a Neural Network, that can predict the entire 1D temperature profile at any time in the evolution with an accuracy of $99.7\%$.
- We also inverted synthetic observables to constrain model parameters using Mixture Density Networks.
- We propose creating a more sophisticated thermo-chemical dataset for future ML studies on the long-term interior evolution of Mars.

Studying how rocky planets like Mercury, Venus, the Earth and Mars evolve over billions of years requires modelling mantle convection, the main driver of planetary evolution. The physics of the mantle can be quantified by solving equations of conservation of mass, momentum and energy for an extremely viscous fluid. These non-linear partial differential equations are typically solved numerically using sophisticated fluid dynamics codes like GAIA [1]. The parameters and initial conditions governing mantle convection are poorly known. However, certain outputs of the simulations can be "observed" (directly or indirectly) via remote-sensing or in situ measurements performed by spacecraft missions. These observations can help constrain key parameters and initial conditions, thus elucidating the basic physics and evolution of planets.

As shown in Fig. 2, we randomly generate several values of five parameters and feed these to 2D forward simulations, performed with our finite-volume mantle convection code GAIA on a quarter-cylindrical grid. We then process the 2D temperature fields output by GAIA and laterally average them to obtain 1D temperature profiles. These can be processed further to arrive at observables such as heat flux at the surface, core-mantle boundary (CMB) temperature, and elastic lithospheric thickness.

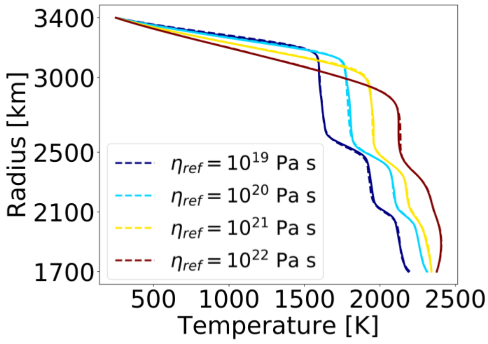


***Figure 1:*** *Comparison of temperature profile predictions from the trained NN surrogate (dashed lines) and GAIA simulations (solid lines) for selected simulations from the test-set.*

In [3], we trained a Neural Network (NN) to predict the full temperature profile at any point in the evolution from $0$ to $4.5$ billion years. For that study, we built a dataset with $10,453$ evolution simulations for a Mars-like planet. The prediction results on selected simulations in the test-set are shown in Fig. 1. On average, the NN can predict any point in the temperature profile with a high accuracy of $99.7\%$. It represents a significant advance over studies that only predict the surface heat flux.

We then investigated the *inverse problem*, where, we generated a higher spatial resolution dataset with the same setup as [3], to overcome some convergence issues and obtain a more balanced dataset. Using Mixture Density Networks (MDNs) [2] and their corresponding loss function, we quantified the degree to which each parameter can be constrained given different number and combinations of synthetic observables. Among the extensive results described in [4], which is under reviewed, particularly interesting is Fig. 3, which shows which quantities need to be measured to constrain different parameters.

In the 2021 accounting period, we plan on learning high-dimensional surrogates. While the 1D temperature profiles already contain a wealth of information on the thermal and compositional state of the interior, they lack characteristic convective structures such as downwellings and plumes. Similarly, we also plan on inverting the 2D temperature fields to infer the same five parameters.

We propose generating a new and more realistic dataset of 2D simulations of Mars interior evolution. The datasets generated so far are already quite advanced and provided a good starting point, but employ simplifications that make them unsuitable for a direct comparison with actual Mars data. We will complement our purely Eulerian, grid-based simula-

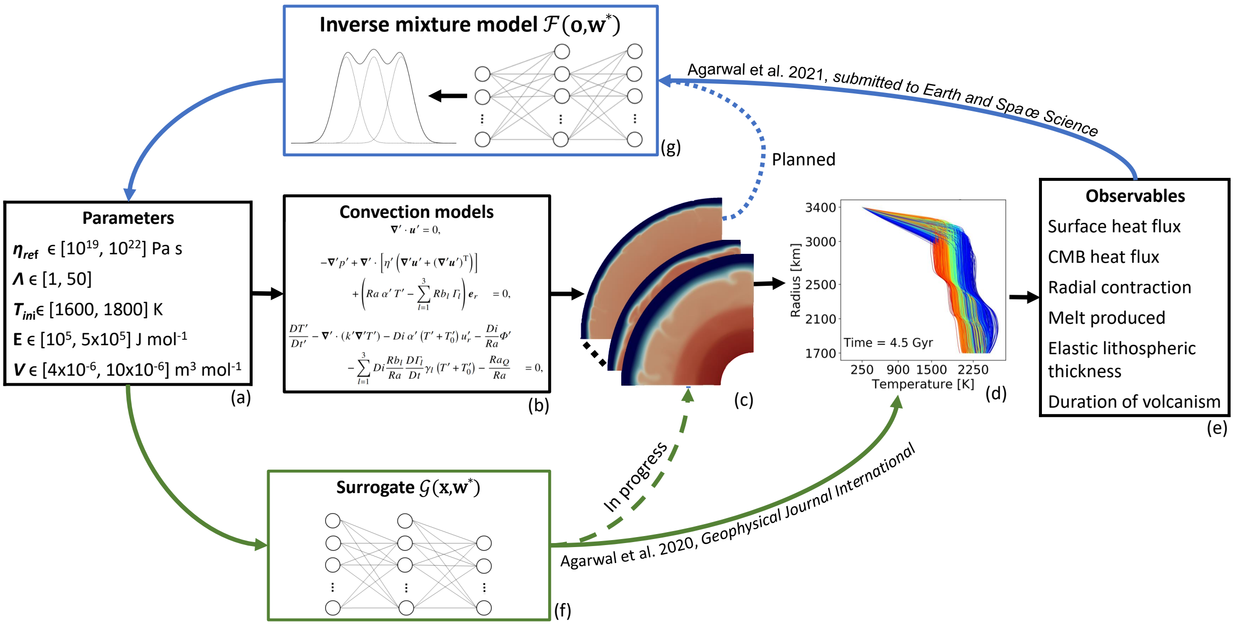


***Figure 2:*** *Using ML to study constraints on Mars' thermal evolution.*

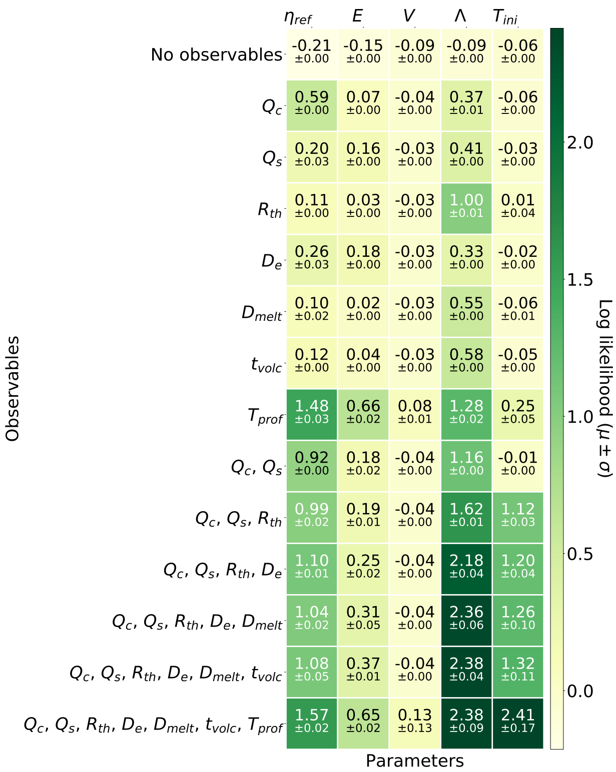


***Figure 3:*** *Constraints on parameters for different observables and some selected combinations thereof as defined by the log-likelihood (the higher is its valu, the better constrained is a parameter). The observables are surface heat flux ($Q_\mathrm{s}$), CMB heat flux ($Q_\mathrm{c}$), accumulated radial contraction ($R_\mathrm{th}$), elastic lithosphere thickness ($D_\mathrm{e}$), equivalent thickness of the melt produced ($D_\mathrm{melt}$), duration of volcanism ($t_\mathrm{volc}$), and temperature profile ($T_\mathrm{prof}$). The parameters are reference viscosity ($\eta_\mathrm{ref}$), activation energy ($E$) and volume of diffusion creep ($V$), enrichment factor of heat sources in the crust ($\Lambda$), and initial mantle temperature ($T$).*

tions with a self-consistent treatment of melt generation and extraction using an already implemented Lagrangian particle-in-cell method along with a variety of accompanying processes, namely i) changes in the composition and density of the mantle upon partial melting and melt extraction, ii) mantle depletion in incompatible elements (such as water and heat-producing elements), and iii) their enrichment in the crust. We will run the simulations in a 2D spherical annulus geometry that we recently implemented in our code GAIA. This preserves the correct inner-to-outer-boundary surface ratio of a realistic 3D spherical shell geometry and hence delivers more closely matching temperature distribution.

## WWW

https://sites.google.com/site/nictosi/

## More Information


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