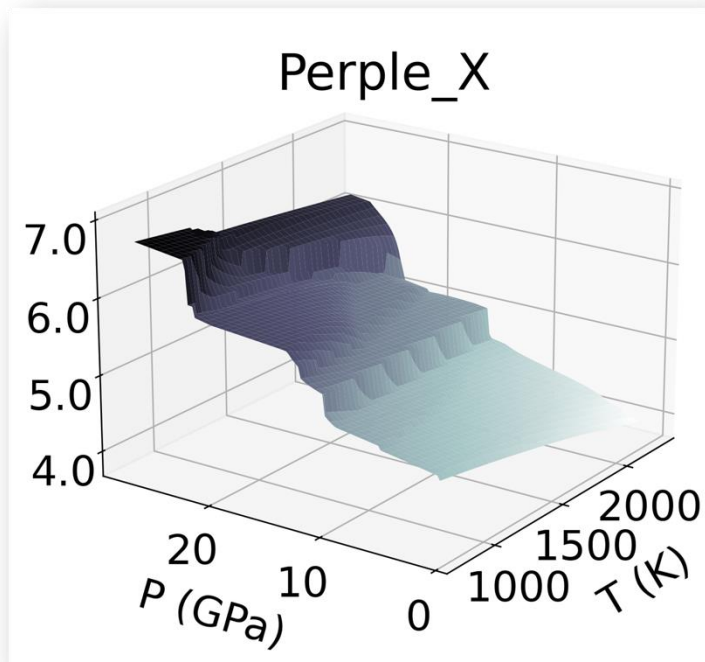


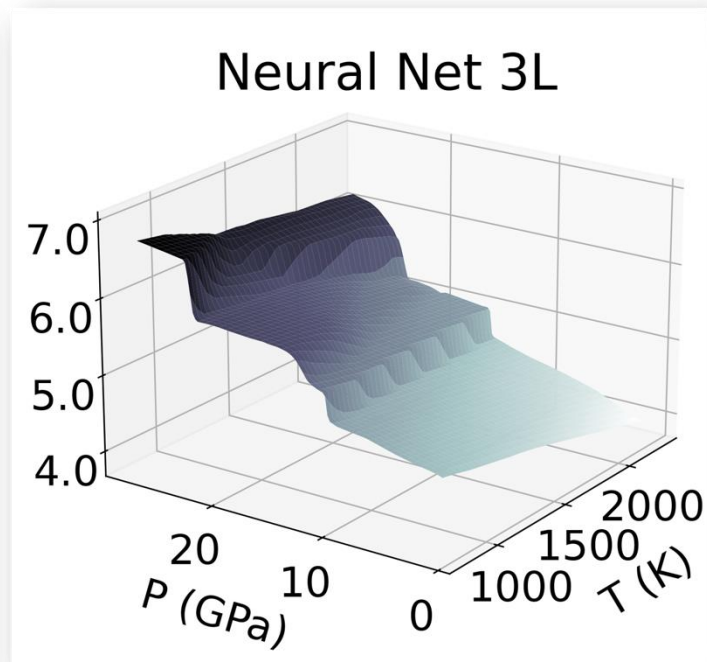
RocMLMs

Predicting Rock Properties through Machine Learning Models

Training Dataset



RocMLM Predictions



¹Buchanan Kerswell

¹Nestor Cerpa*

¹Andréa Tommasi*

¹Marguerite Godard

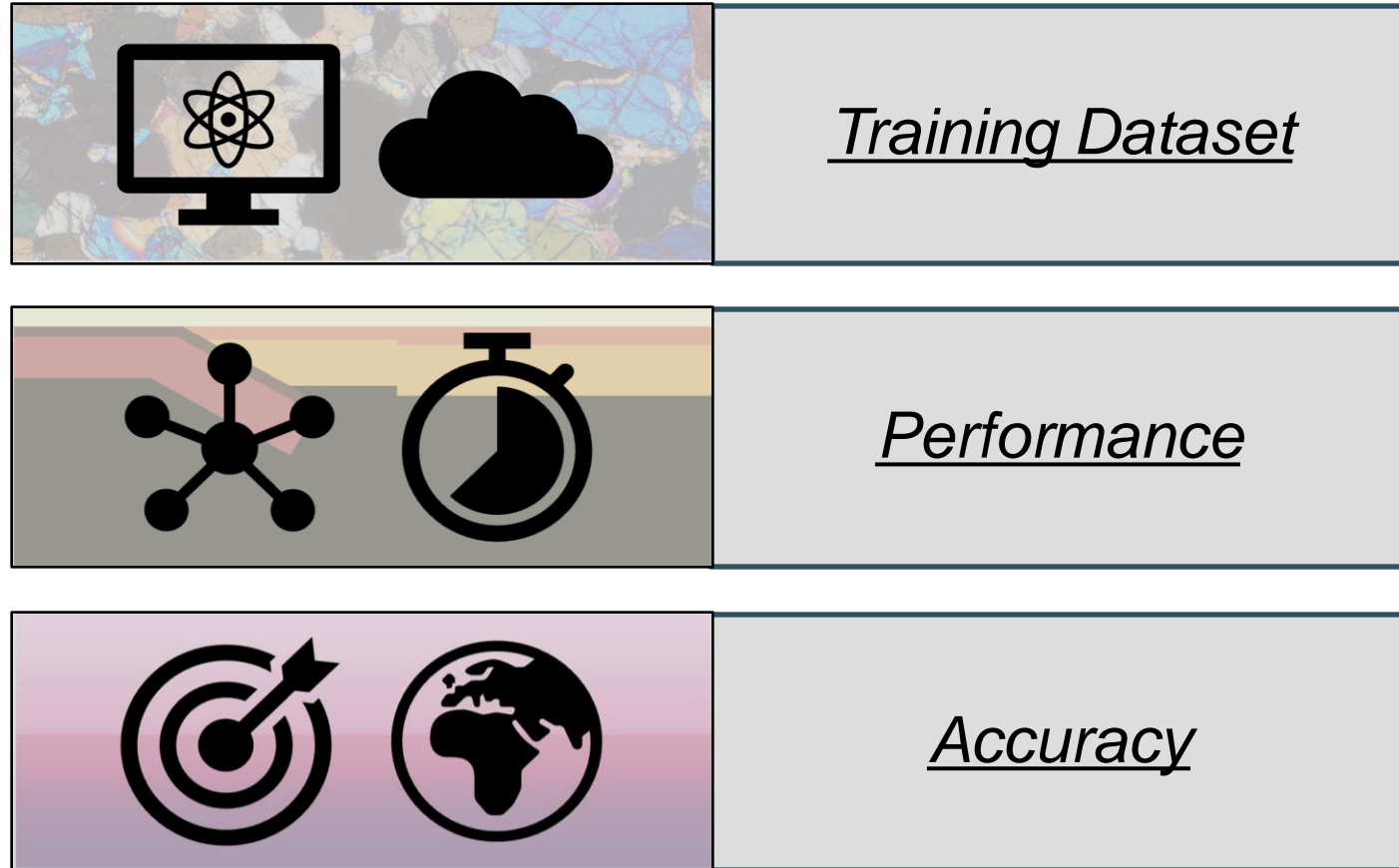
²José Alberto Padrón-Navarta

¹CNRS, Géosciences Montpellier

²Andalusian Earth Science Institute

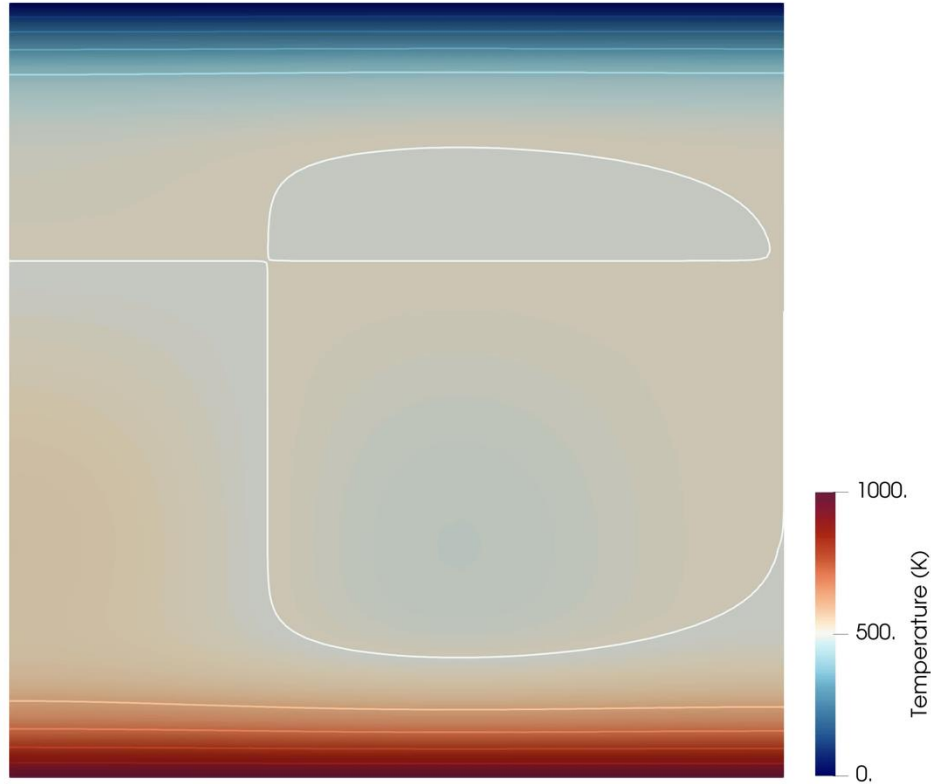
April 15, 2024

We developed RocMLMs to emulate dynamic phase changes in numerical simulations of mantle convection



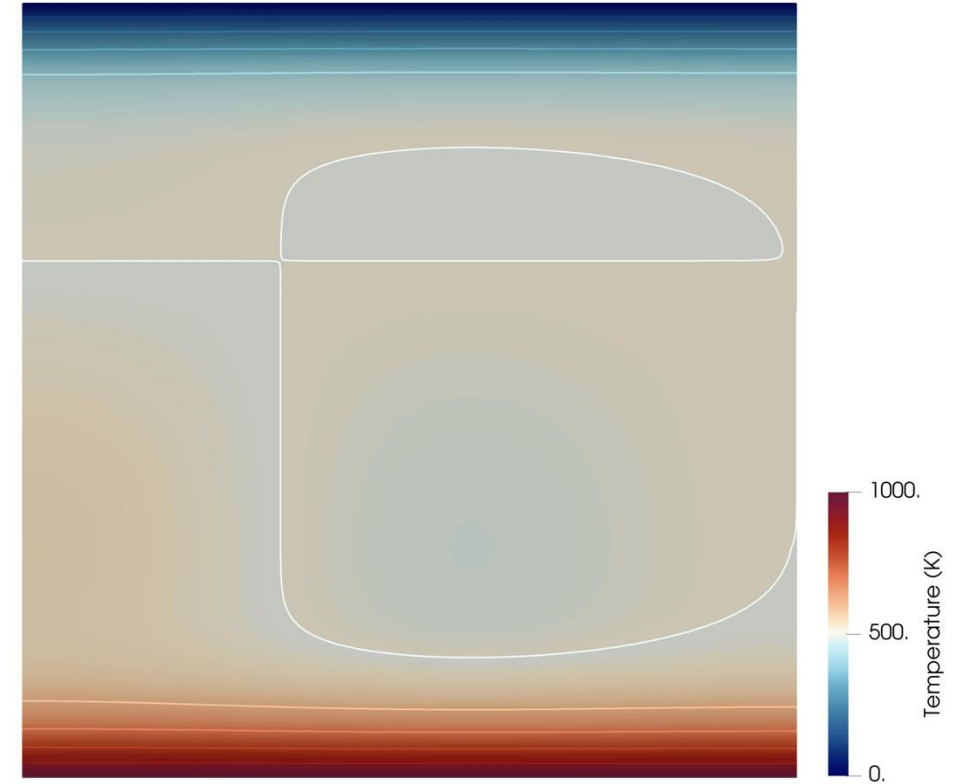
Phase transformations strongly impact mantle convection

No phase change



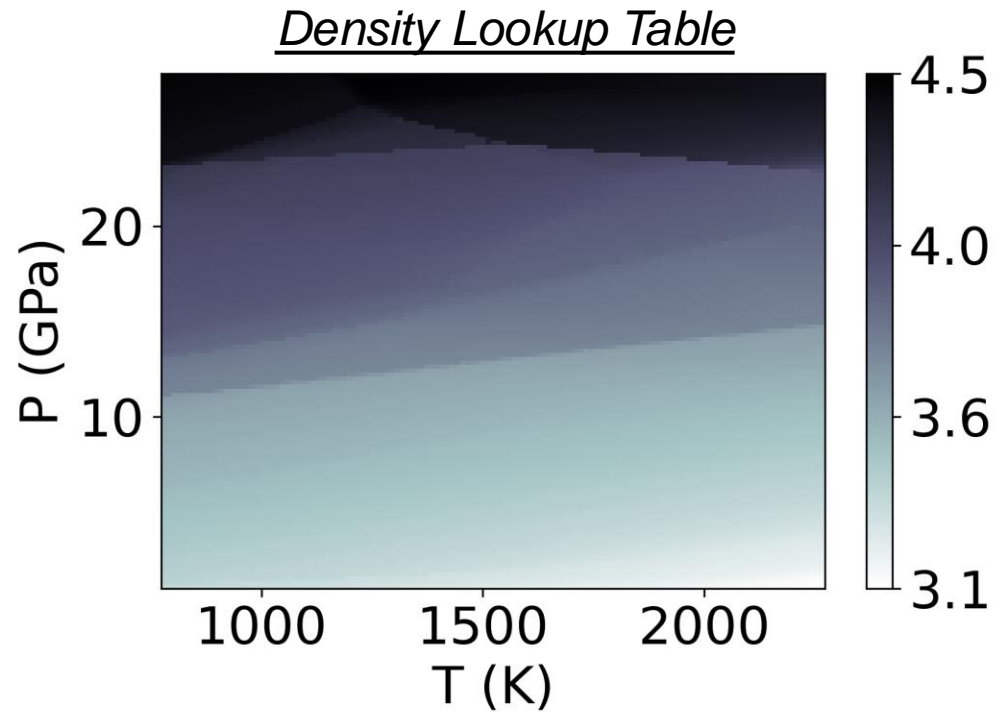
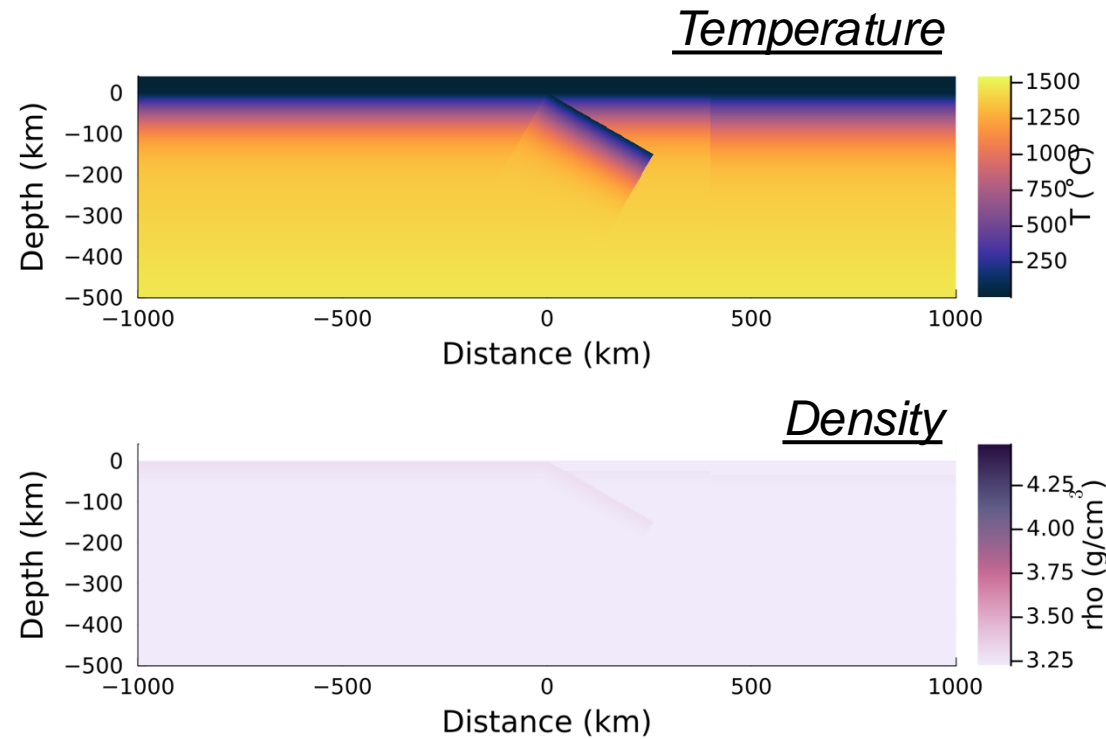
Blankenbach et al. (1989; *GJI*)

Phase change with: $\rho_1 > \rho_2$

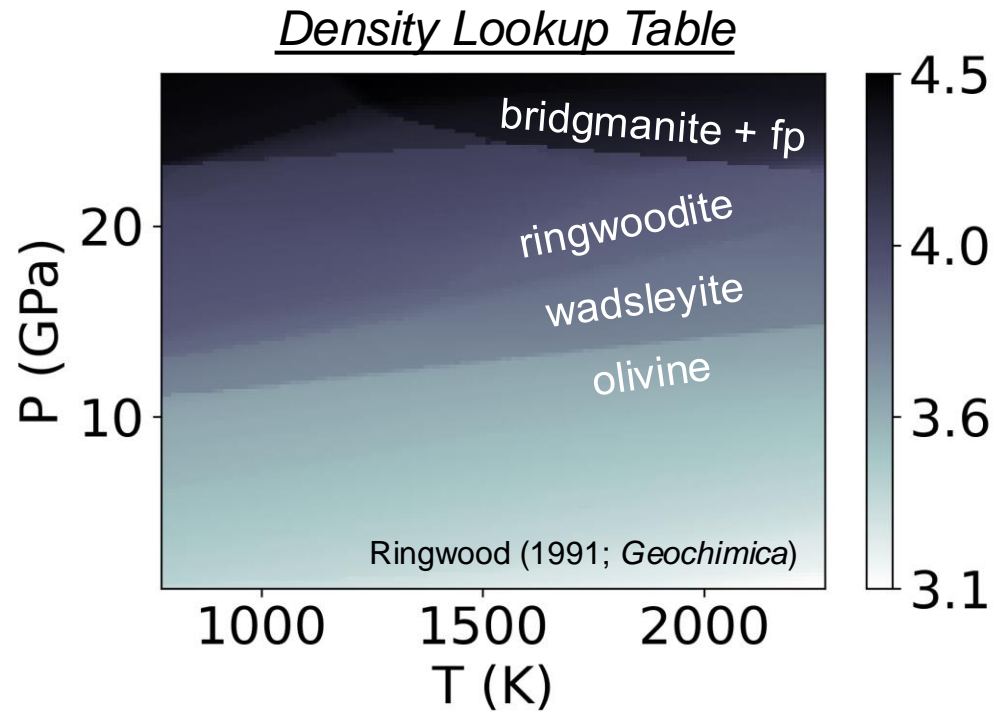
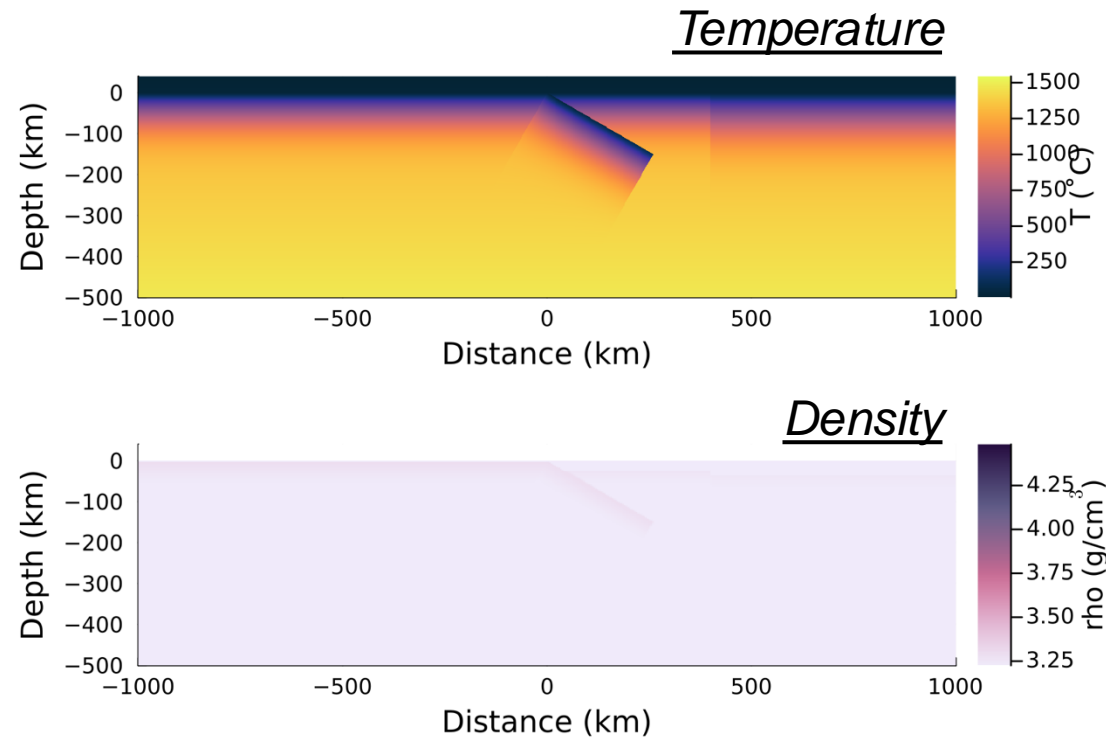


Christensen & Yuen (1985; *JGR:SE*)

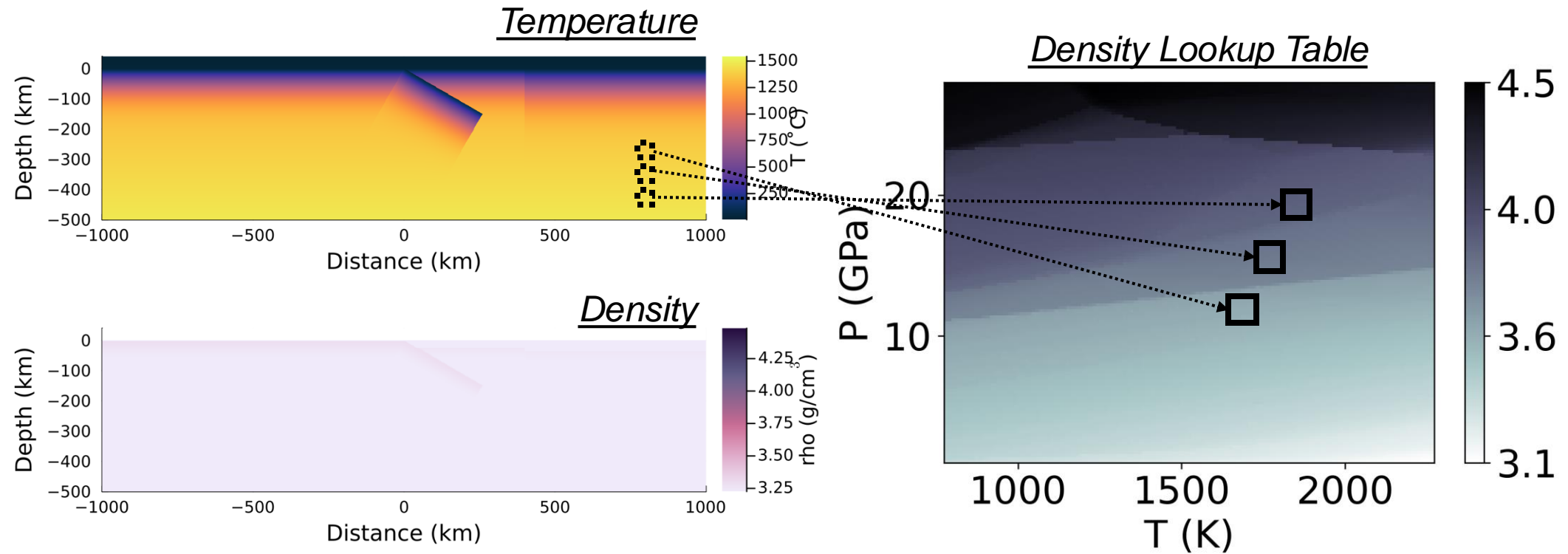
Lookup Tables are effective at implementing phase changes



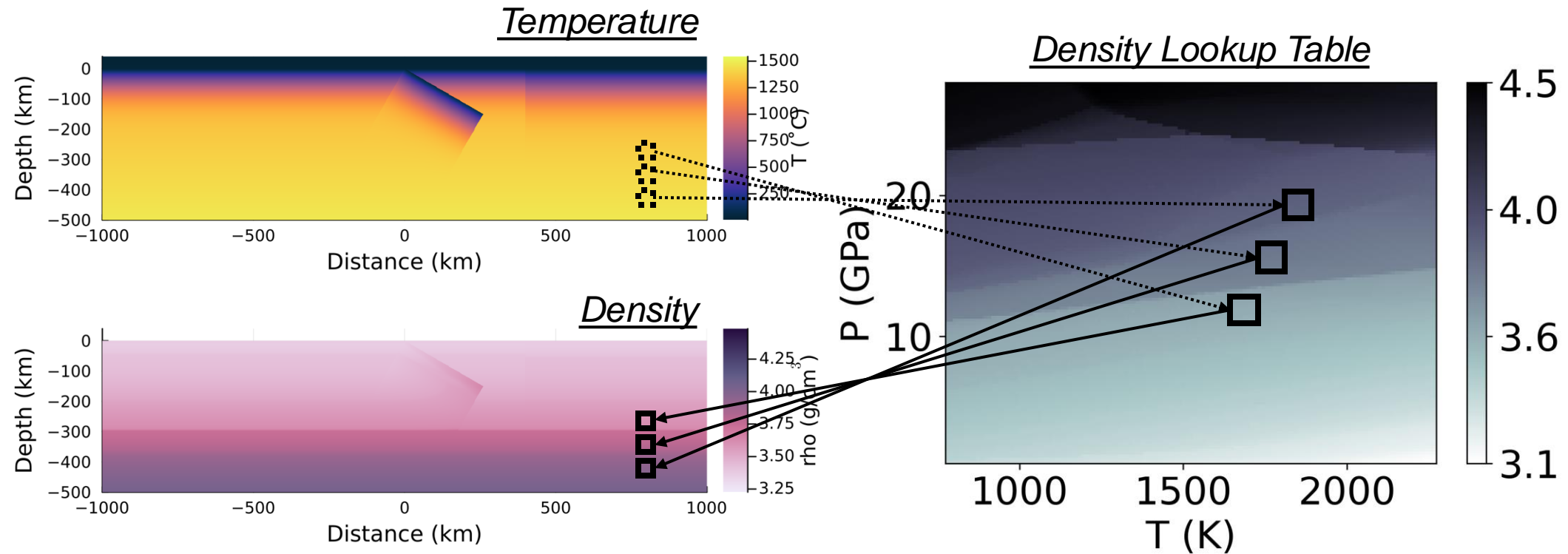
Lookup Tables are effective at implementing phase changes



Lookup Tables are effective at implementing phase changes



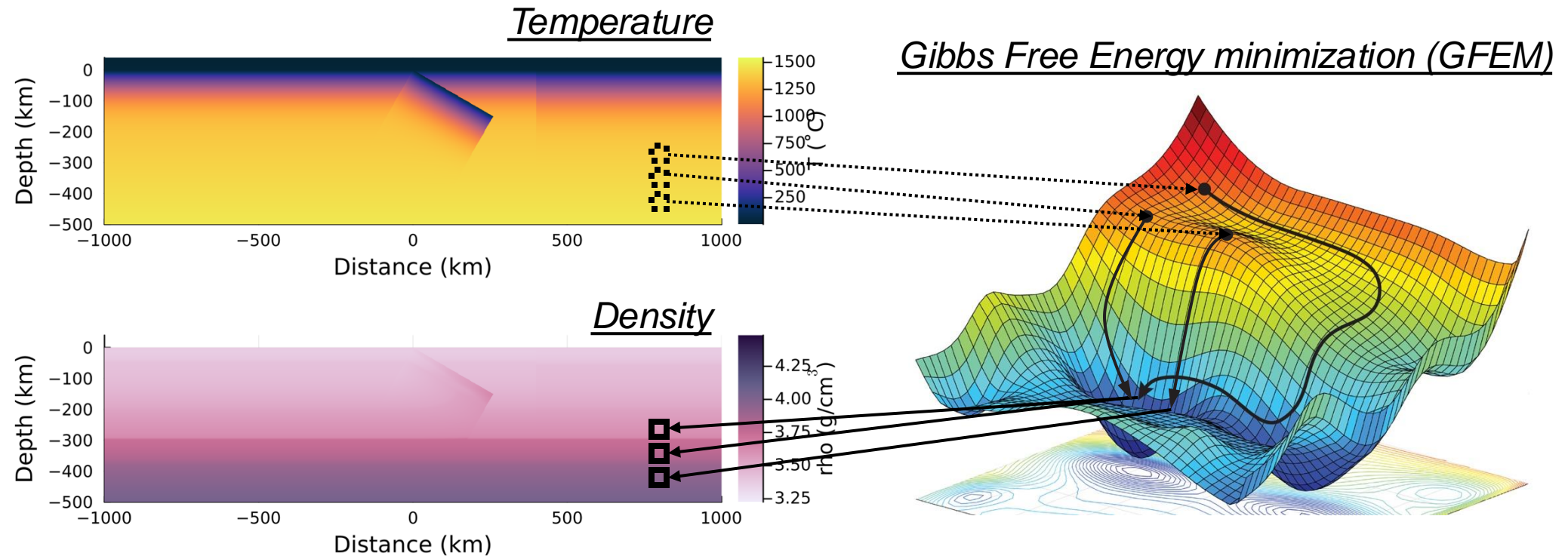
Lookup Tables are effective at implementing phase changes



+ : adds a degree of thermodynamic self-consistency

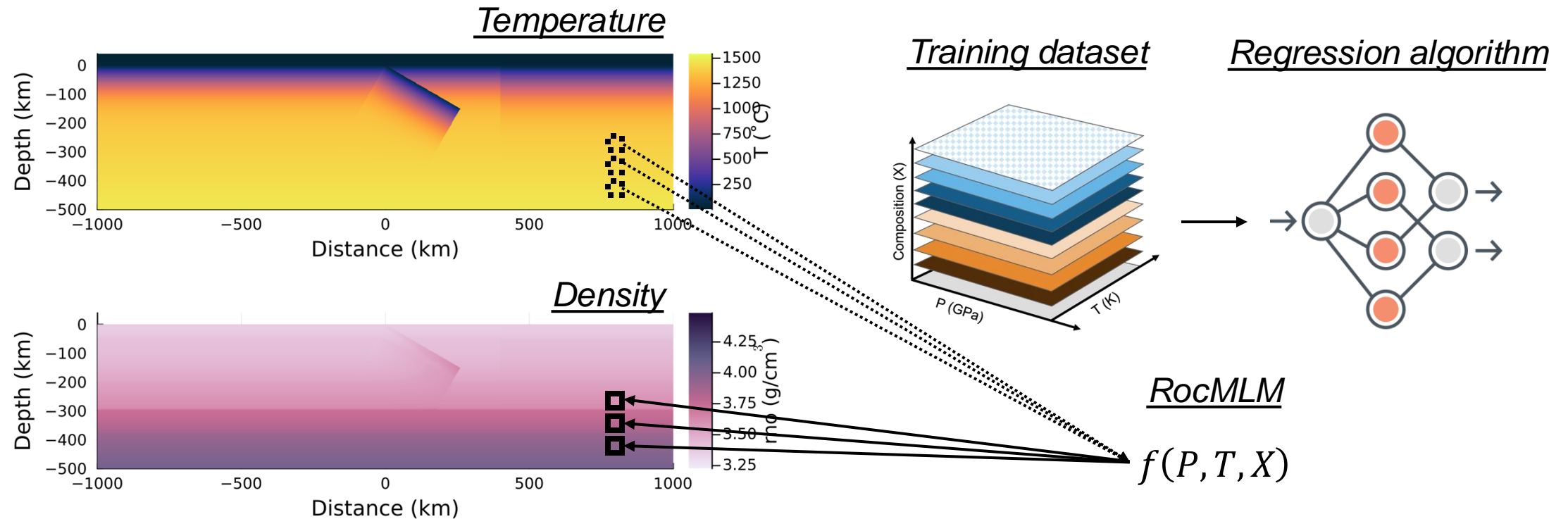
- : need Lookup Tables for each rock composition and rock property

Phase equilibria modeling is more effective, but slow



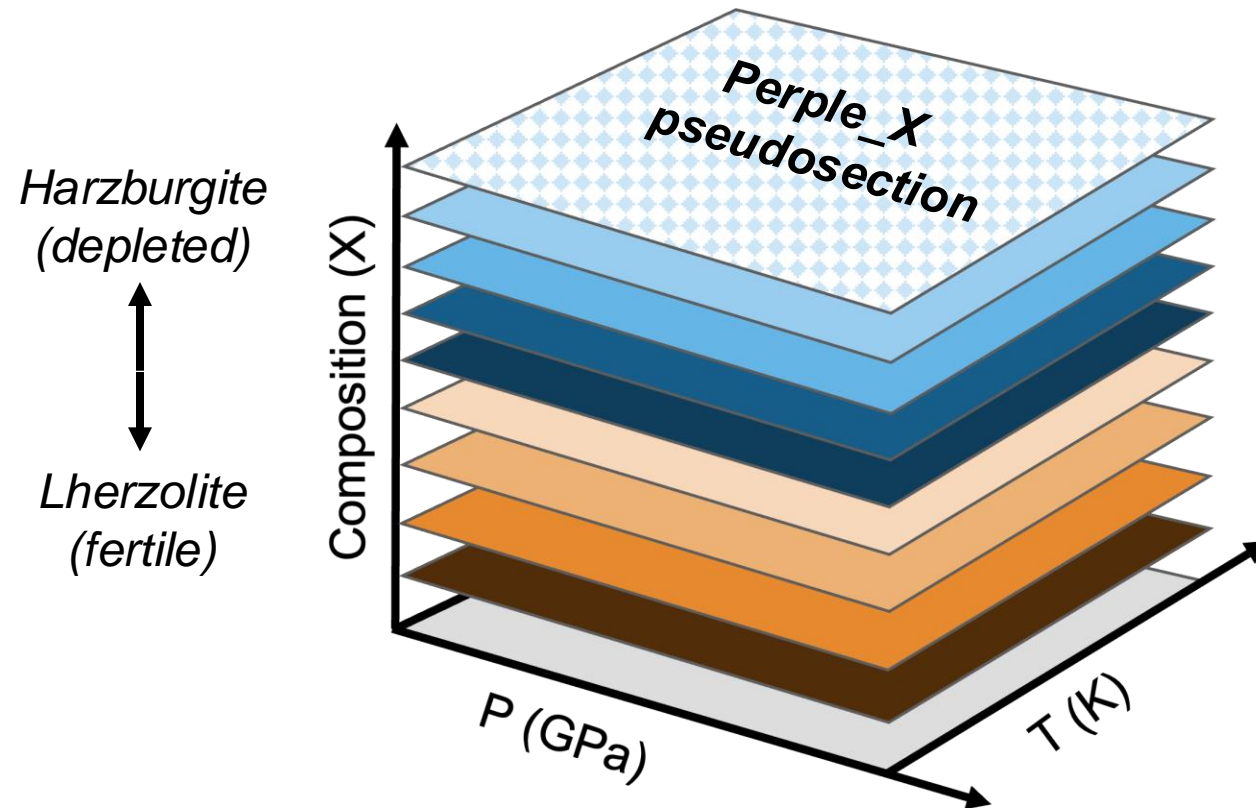
- + : thermodynamically self-consistent, can handle changing compositions***
- : computationally expensive to run (too slow for high-res simulations)***

Machine learning models (*RocMLM*) are effective and fast

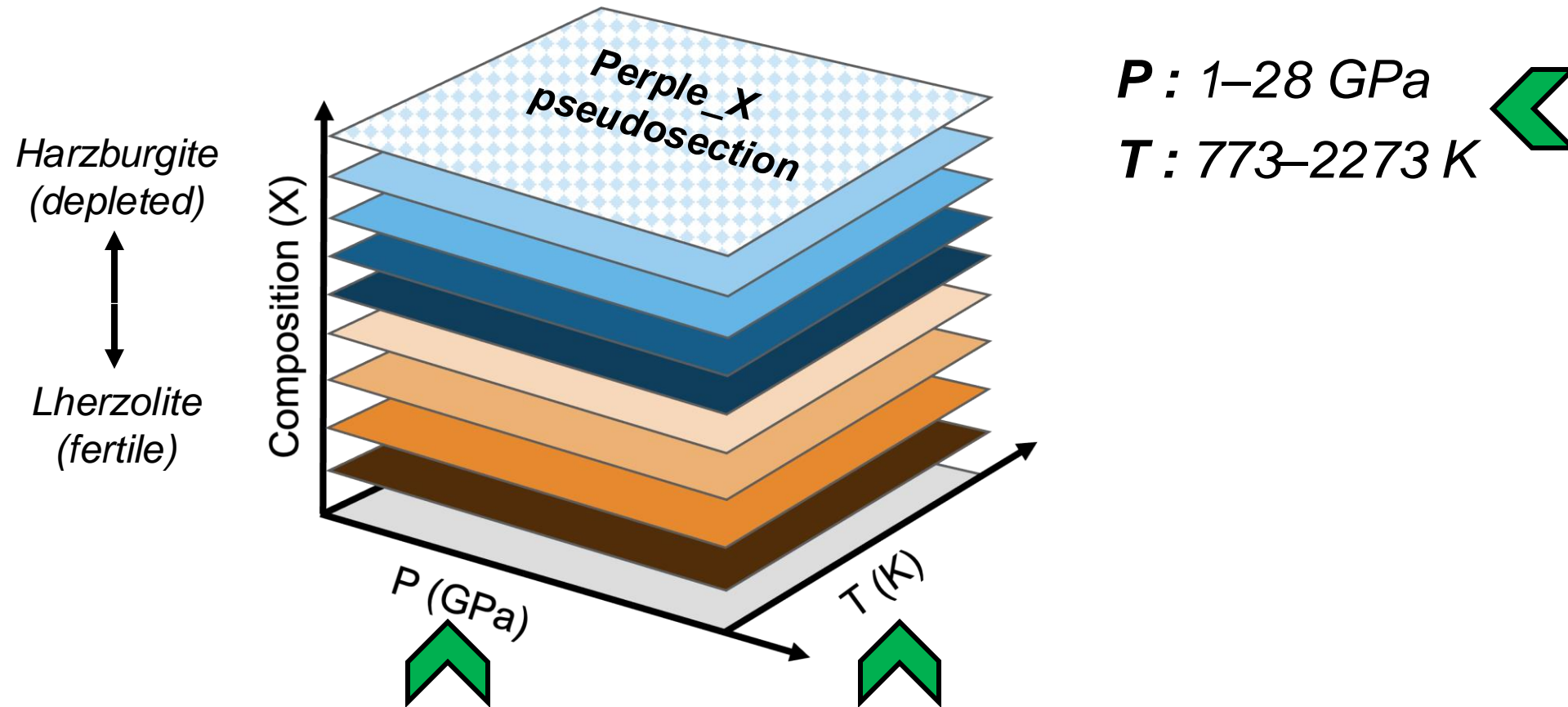


- + : *potentially much faster than Lookup Tables and GFEM*
- : *requires building and training on a large dataset*

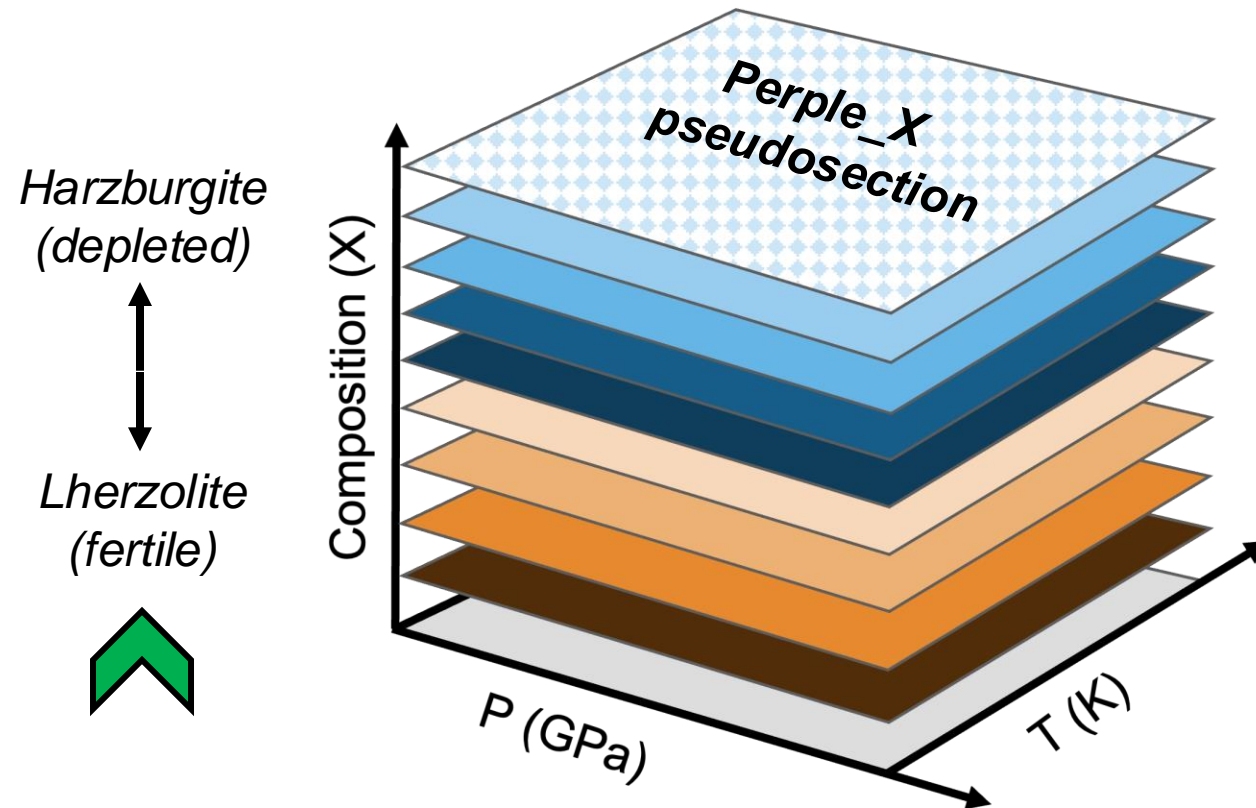
RocMLM training data were designed to be relevant for convection in the upper mantle



RocMLM training data were designed to be relevant for convection in the upper mantle



RocMLM training data were designed to be relevant for convection in the upper mantle



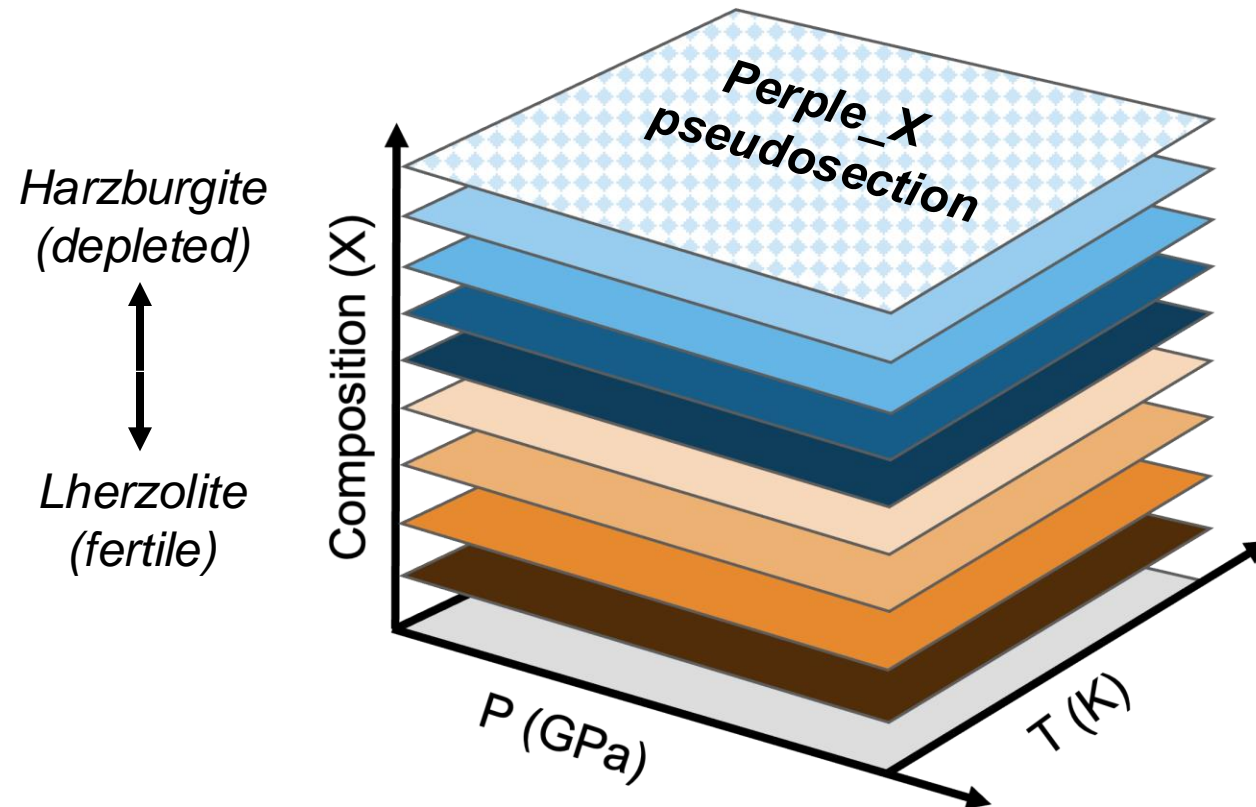
P : 1–28 GPa

T : 773–2273 K

X : [Na_2O - CaO - FeO - MgO - Al_2O_3 - SiO_2]



RocMLM training data were designed to be relevant for convection in the upper mantle



$P : 1\text{--}28 \text{ GPa}$

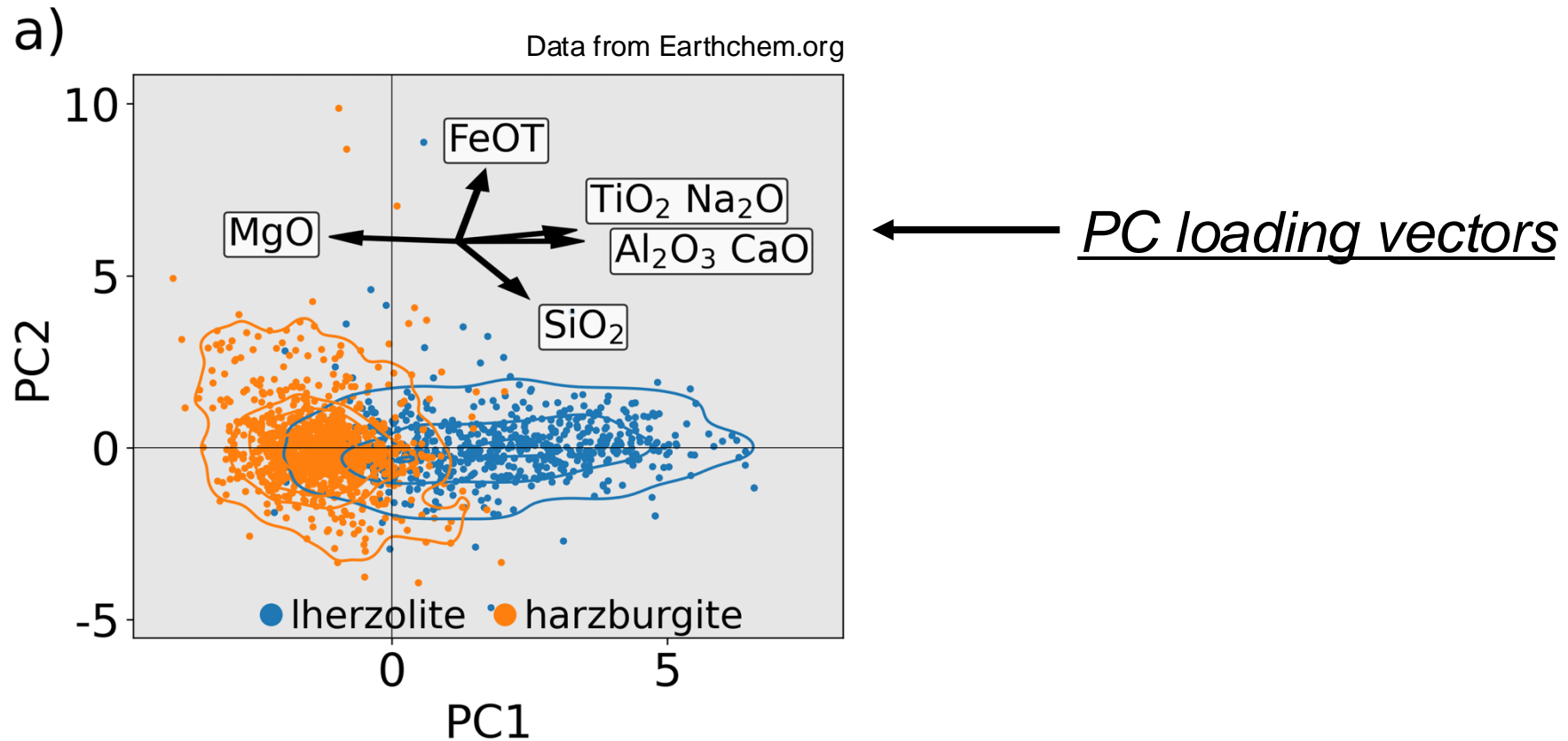
$T : 773\text{--}2273 \text{ K}$

$X : [\text{Na}_2\text{O-CaO-FeO-MgO-Al}_2\text{O}_3\text{-SiO}_2]$

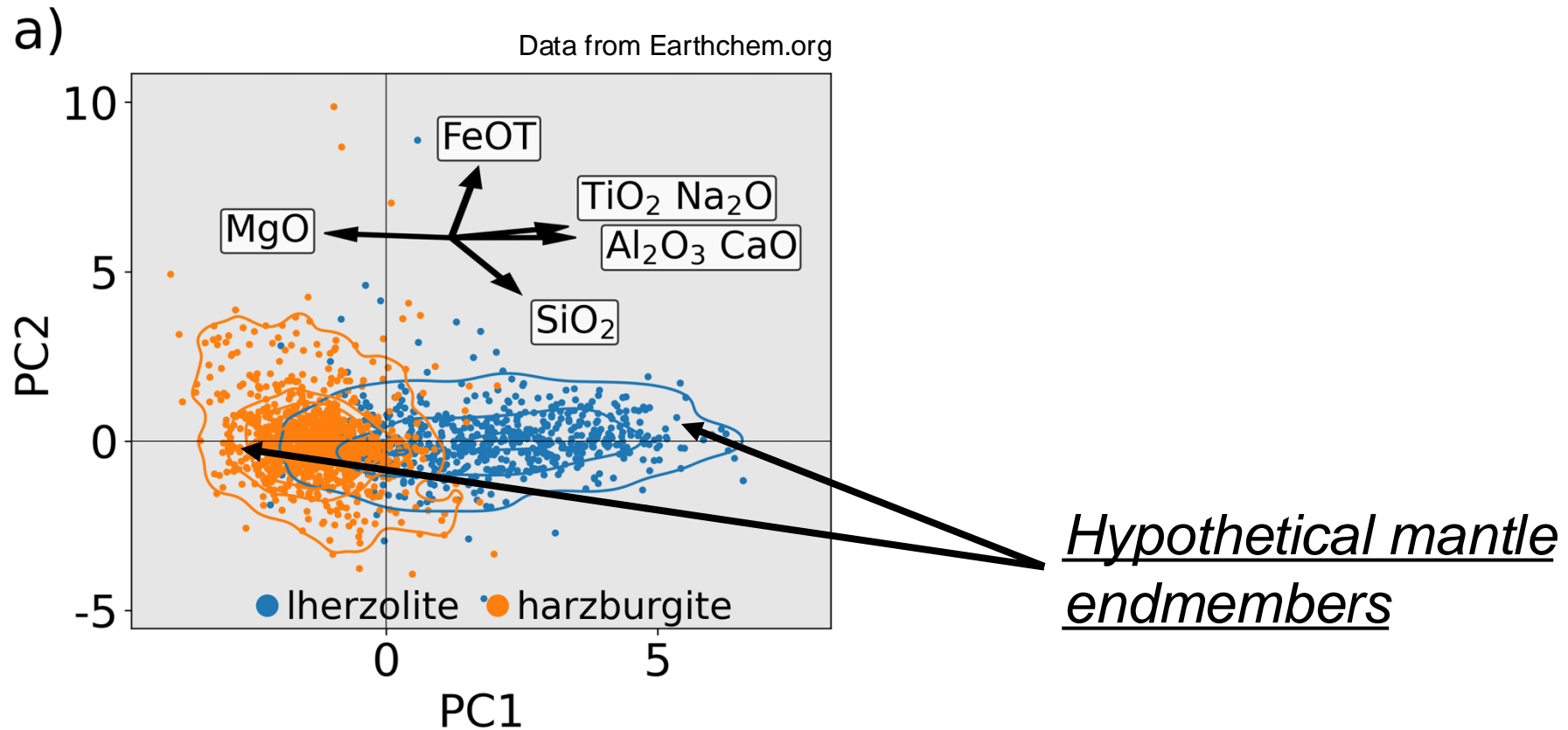
Dimensions : 2 + 6 = 8

Need to reduce this !

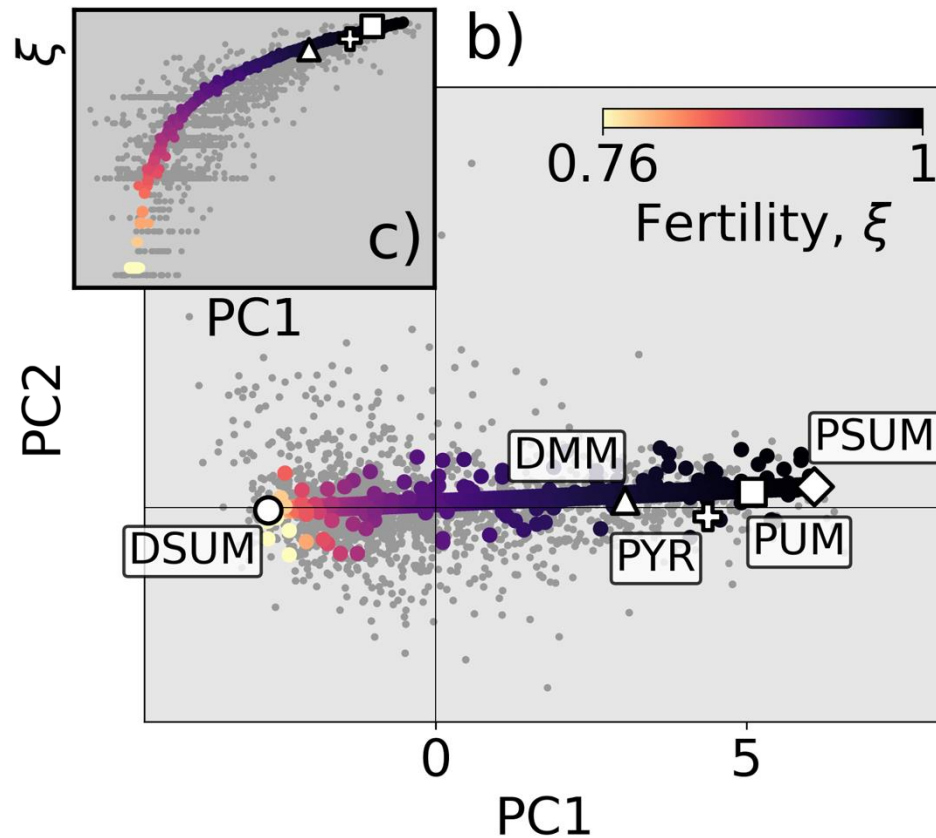
3111 natural peridotite samples were reduced by PCA to 2 “chemical” components: PC1 & PC2



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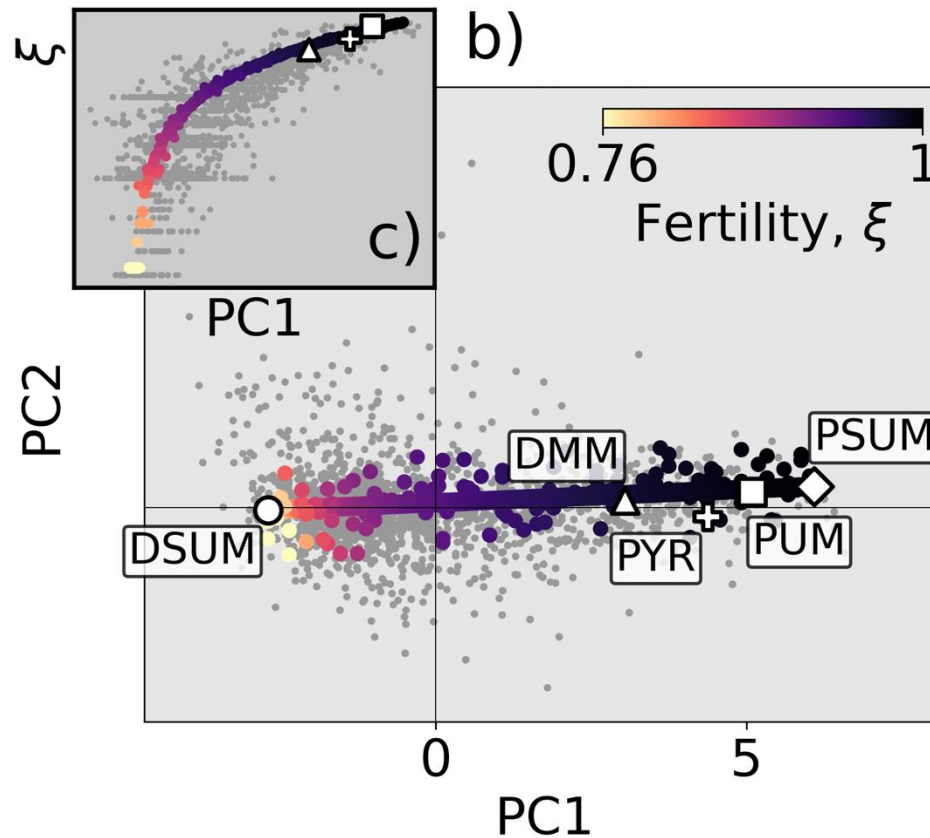


A hypothetical mixing array was used to sample synthetic bulk compositions for RocMLM training



*Synthetic samples used for
RocMLM training*

A hypothetical mixing array was used to sample synthetic bulk compositions for RocMLM training



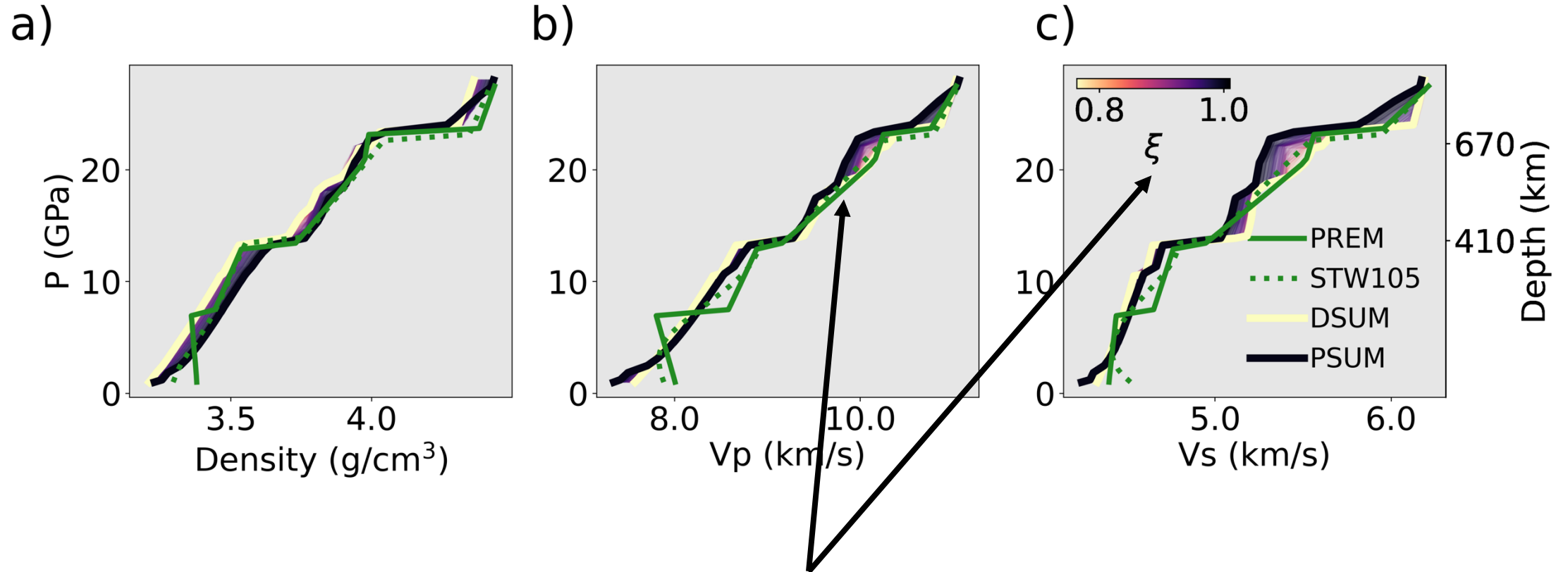
ξ Fertility Index parameter represents composition

$\xi : [\text{Na}_2\text{O}-\text{CaO}-\text{FeO}-\text{MgO}-\text{Al}_2\text{O}_3-\text{SiO}_2]$

$$\xi = 1 - F = R^{\frac{1}{(\frac{1}{D_0}) - 1}}$$

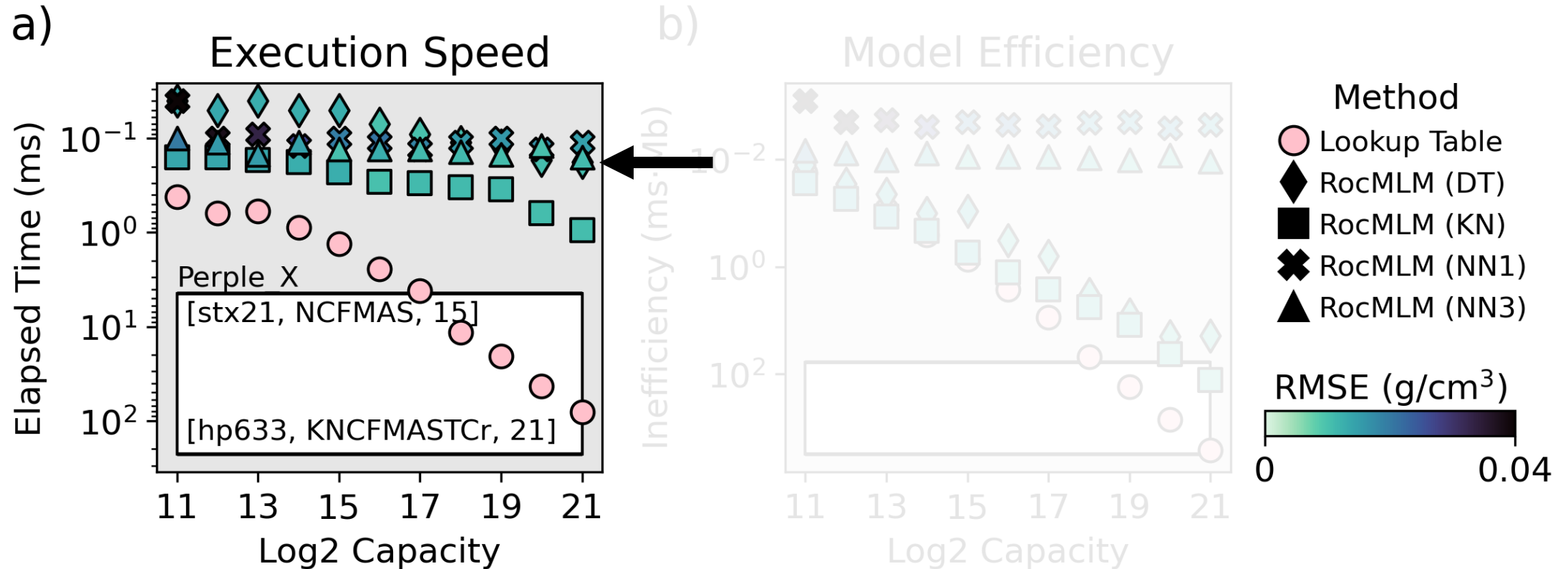
Shaw (1970; *Geochimica*)

RocMLM training dataset contains 2^{21} (~2.1M) phase equilibria across an array of 128 mantle comp's from fertile → depleted

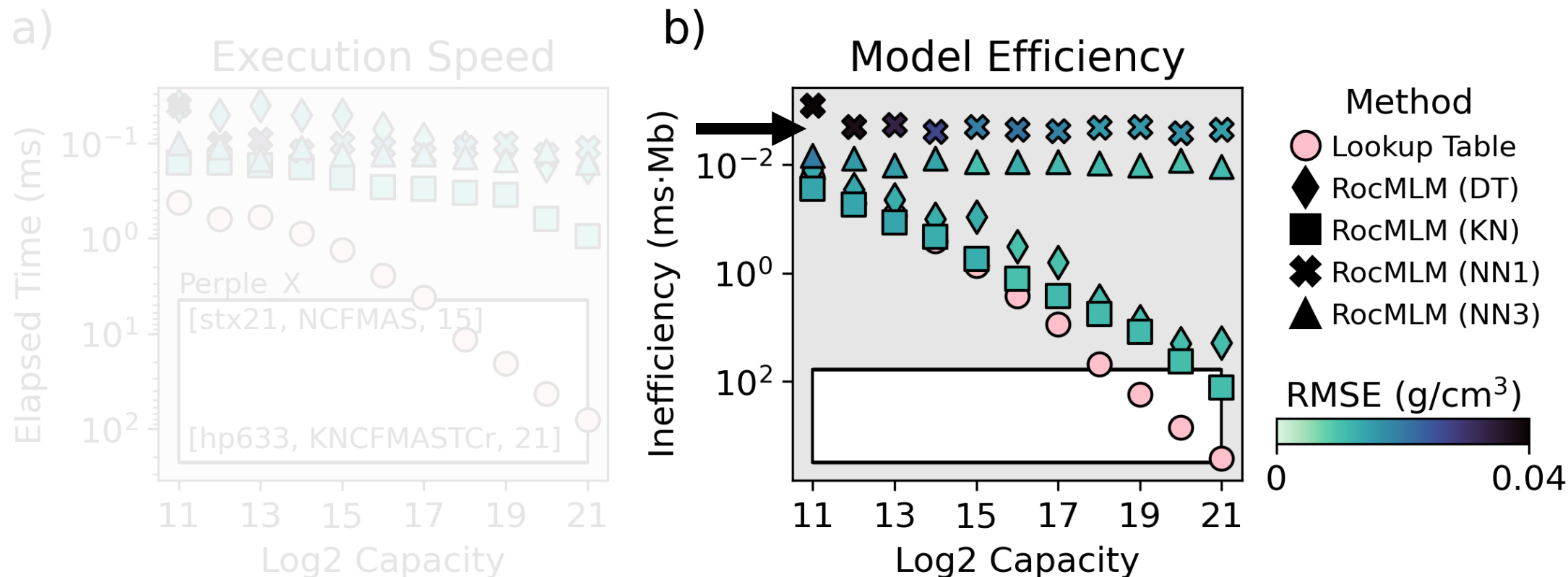


Training data are sensitive to mantle composition

RocMLMs are 10^1 – 10^3 times faster than common methods

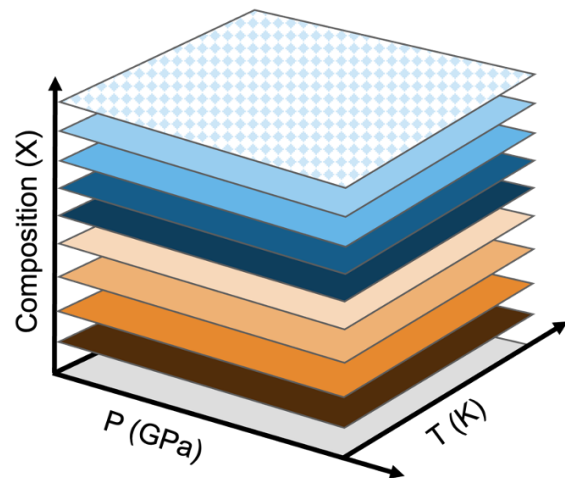


Neural Networks are more scalable than other algorithms

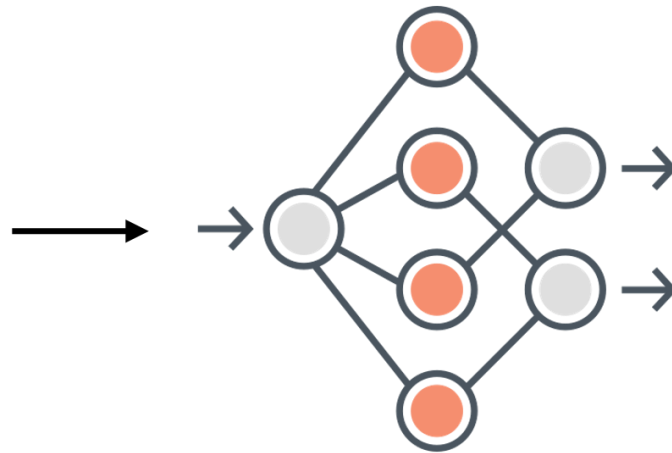


In summary, RocMLMs overcome practical limitations for emulating dynamic phase changes in numerical simulations of mantle convection

Training dataset



Regression algorithm



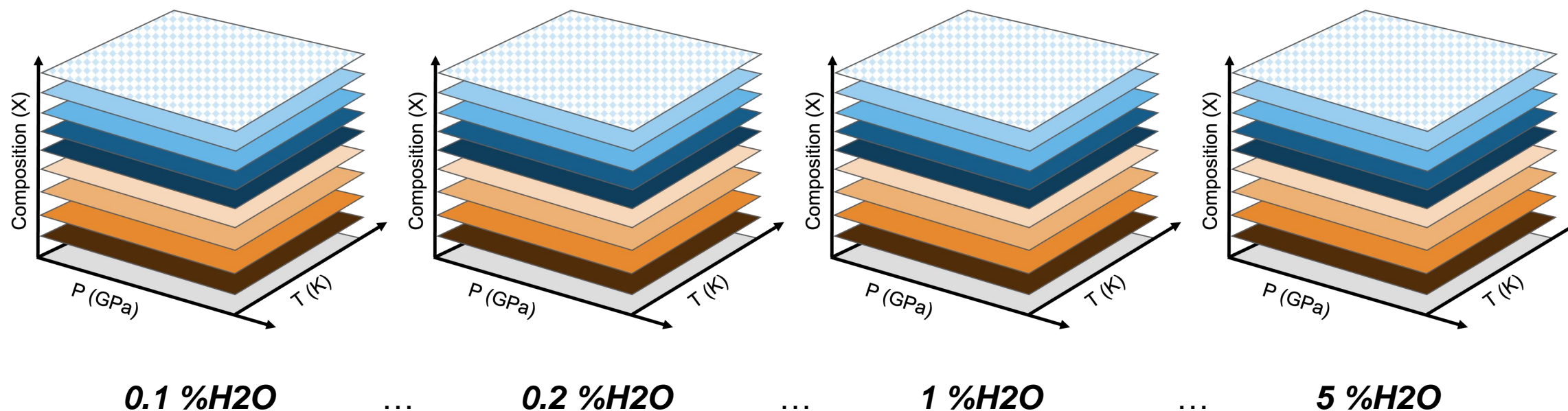
RocMLMs are 10^1 – 10^3 times faster than GFEM programs and Lookup Tables

RocMLMs trained with Neural Networks are more efficient compared to other regression algorithms

RocMLM training data show good agreement with PREM and STW105 for an average mantle geotherm

Questions?

RocMLM2: extending training dataset to include H2O



P : 1–28 GPa

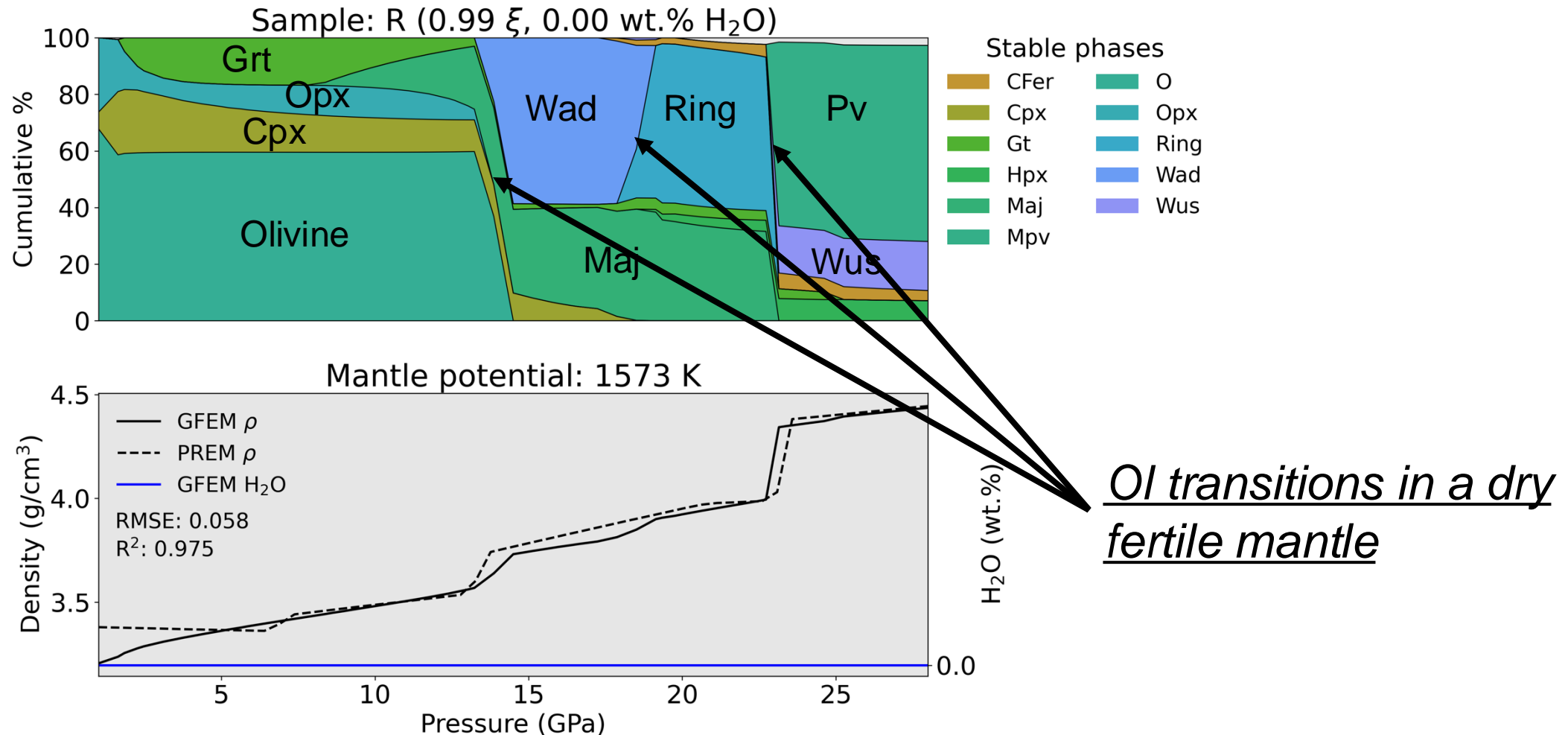
T : 773–2273 K

X : $[Na_2O-CaO-FeO-MgO-Al_2O_3-SiO_2-H_2O] \rightarrow [\xi, H_2O]$

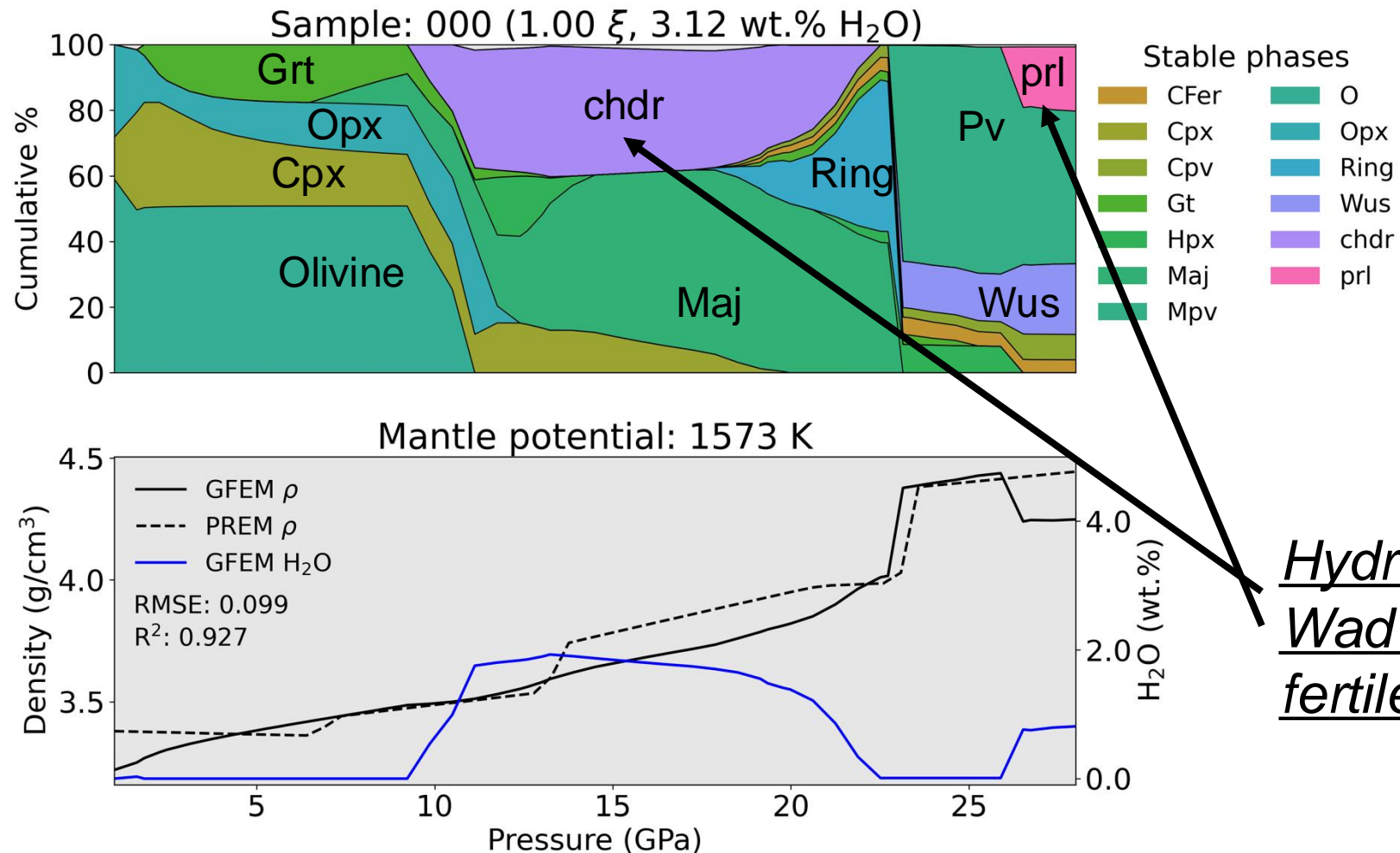
Dimensions : 2 + 2 = 4

Size : 5,292,032

Dry mantle compositions show sharp density discontinuities where Ol transforms into denser Mg-Fe-rich phases

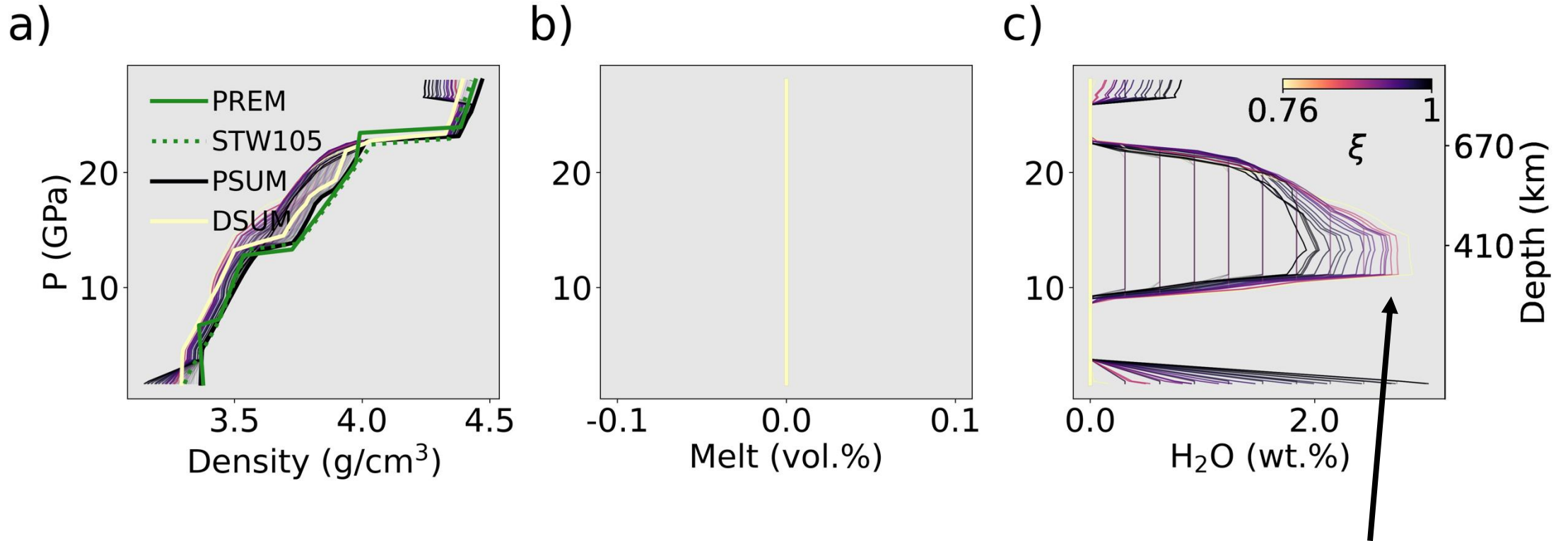


Adding water hydrates the MTZ by stabilizing high-density Mg silicate minerals



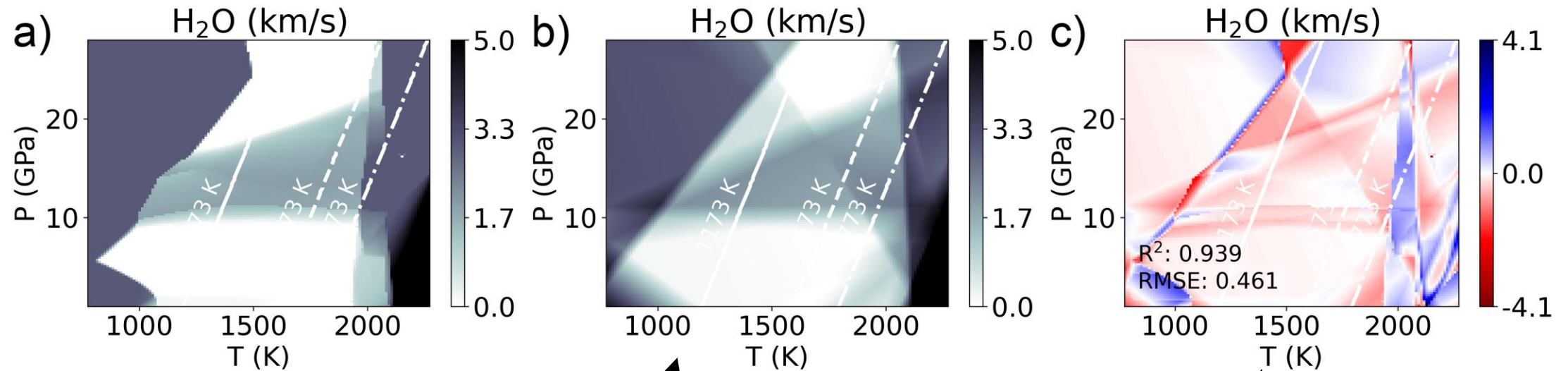
Hydrous phases replace Wad and Pv in a wet fertile mantle

Adding water smooths out sharp density discontinuities within the MTZ but does not produce melting



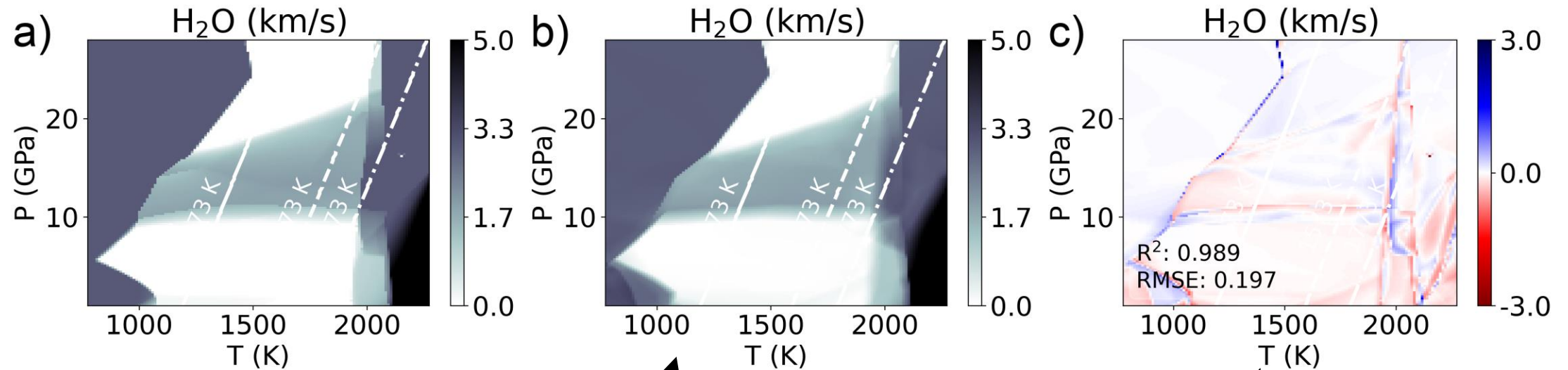
More depleted mantle compositions can potentially store more water

Some ML algorithms (small NN) show bias due to strongly irregular training data distributions



Artefacts induced from density distribution = large residuals

Larger NN (and other ML algorithms) show better predictions and higher internal accuracies



Artefacts from density distribution disappear = small residuals

RocMLM performance continues to exceed GFEM and Lookup Table approaches

