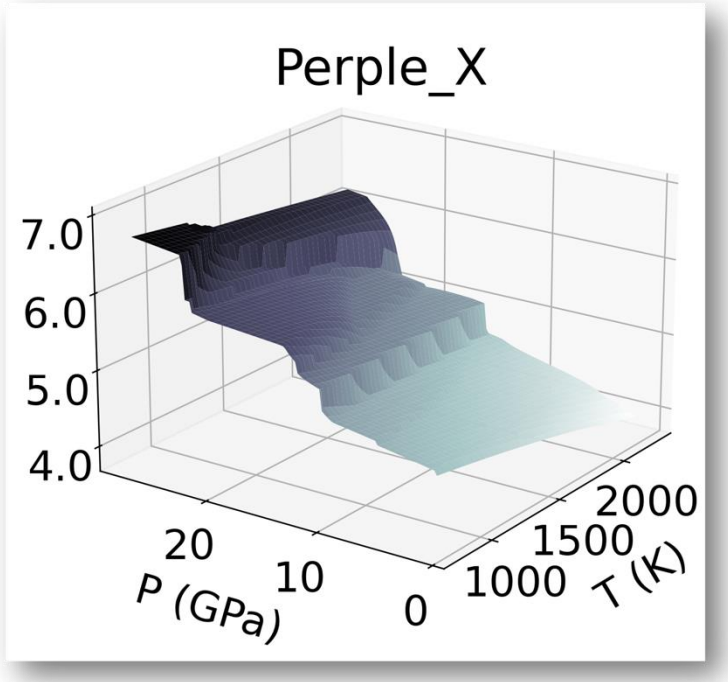
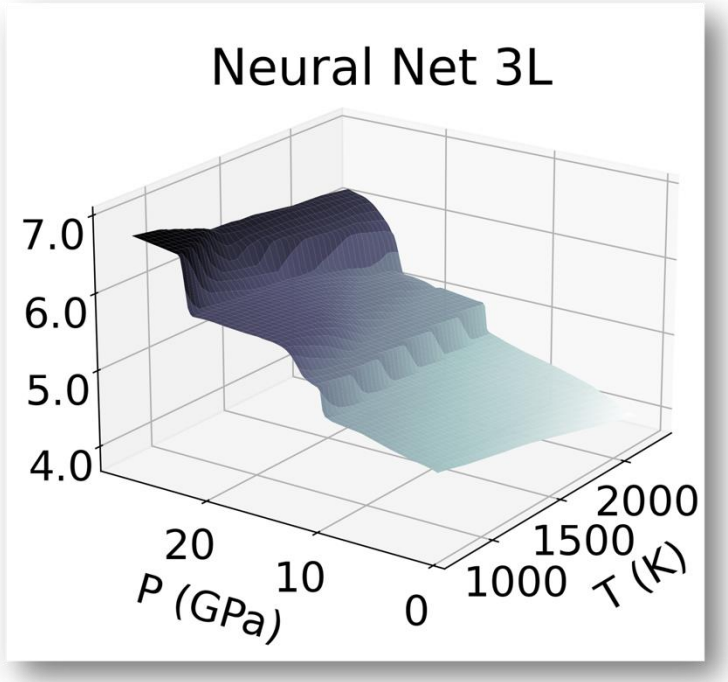
RocMLMs

Predicting Rock Properties through Machine Learning Models

Training Dataset



RocMLM Predictions



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[1]*Nestor Cerpa**

[1]*Andréa Tommasi**

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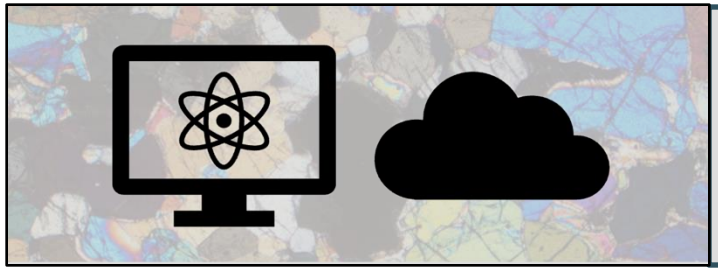
We developed RocMLMs to emulate dynamic phase changes in numerical simulations of mantle convection



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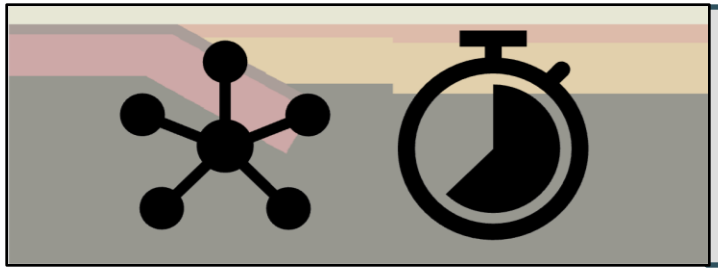
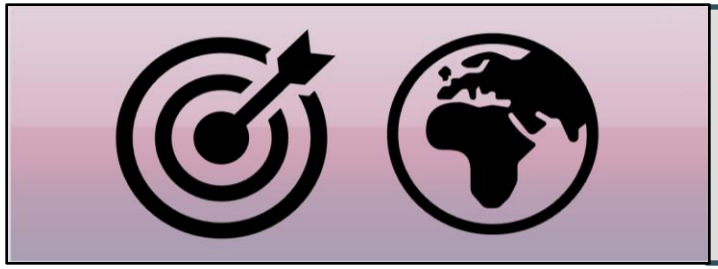
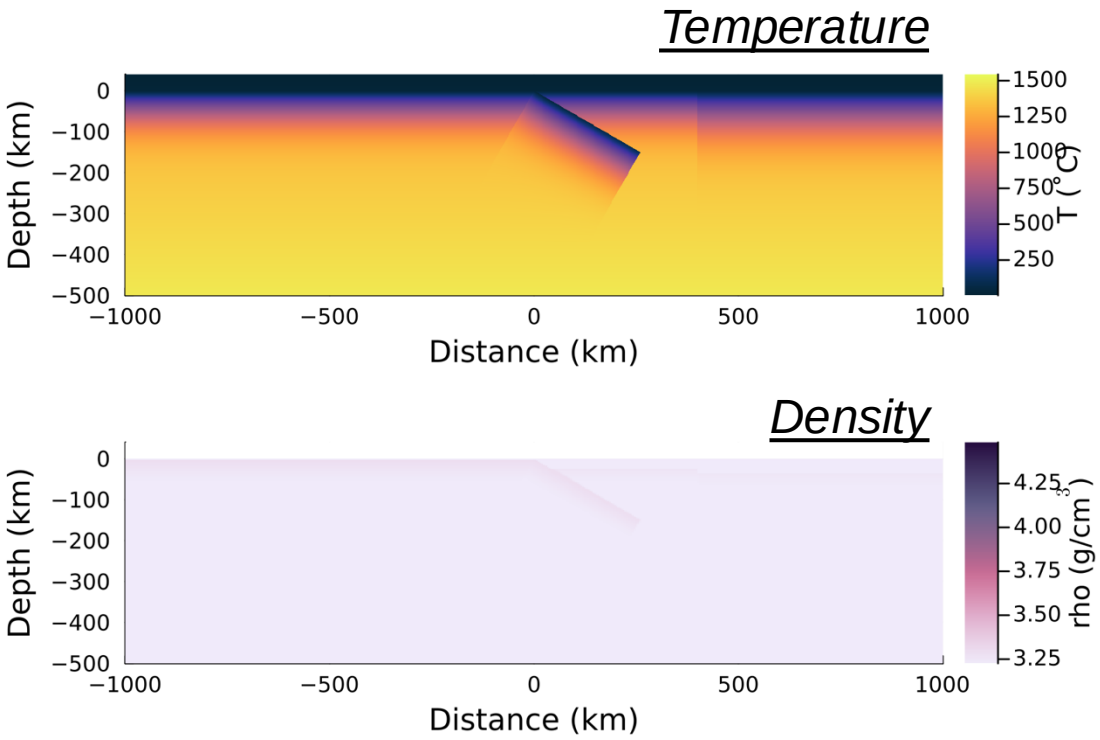


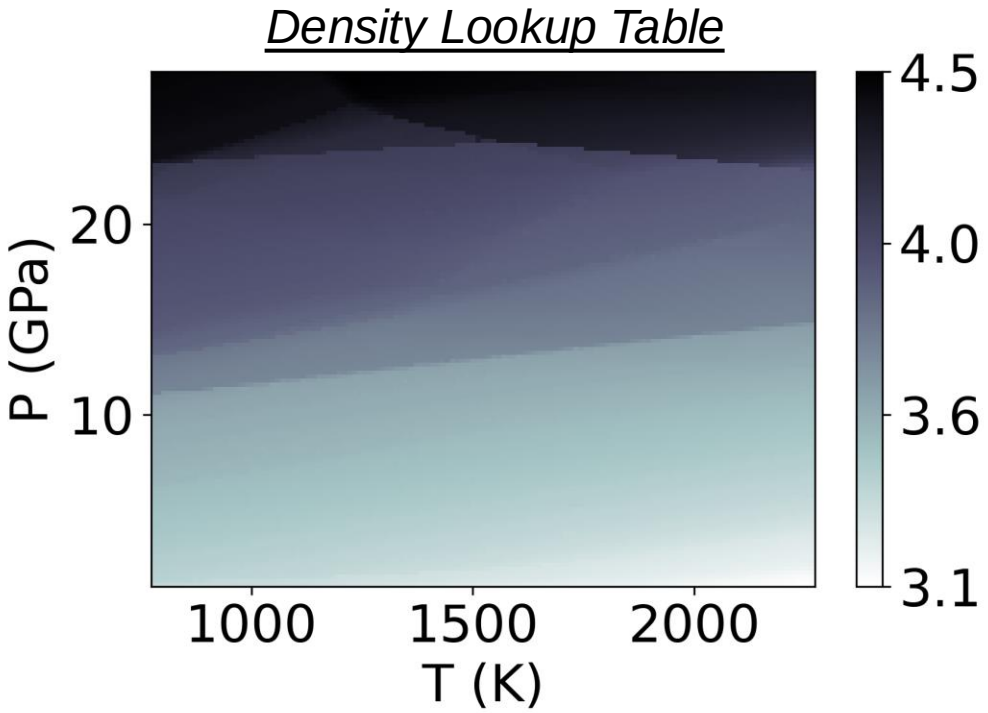
Performance



Accuracy

Lookup Tables are effective at implementing phase changes





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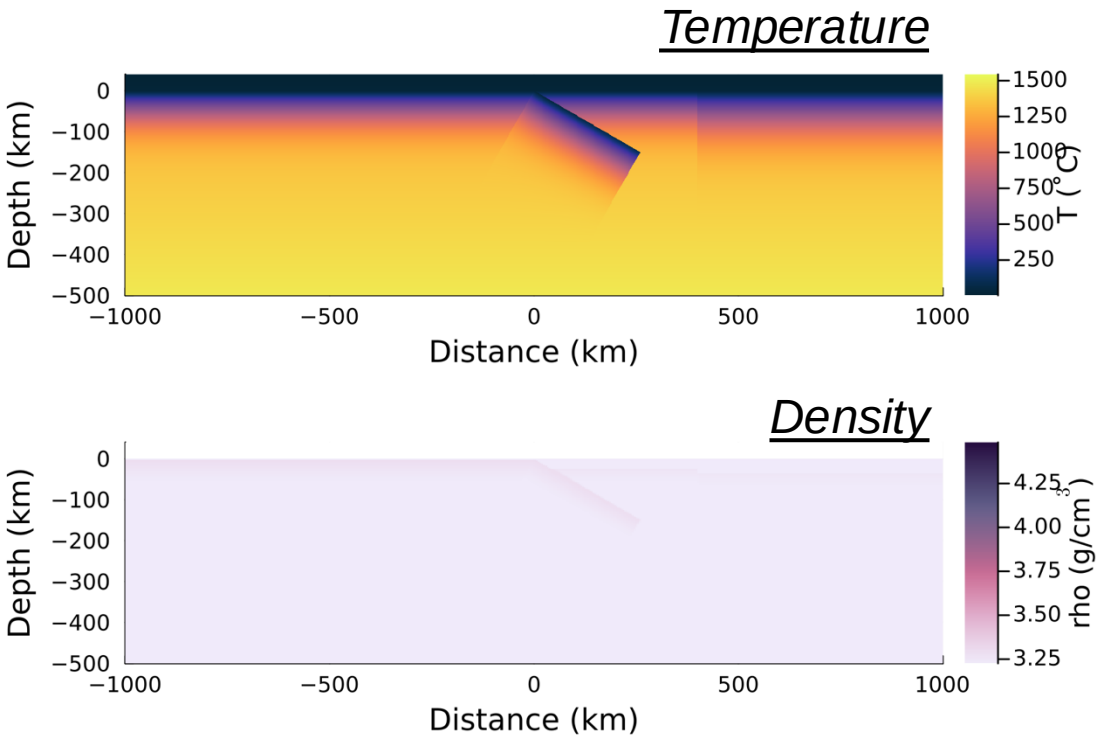

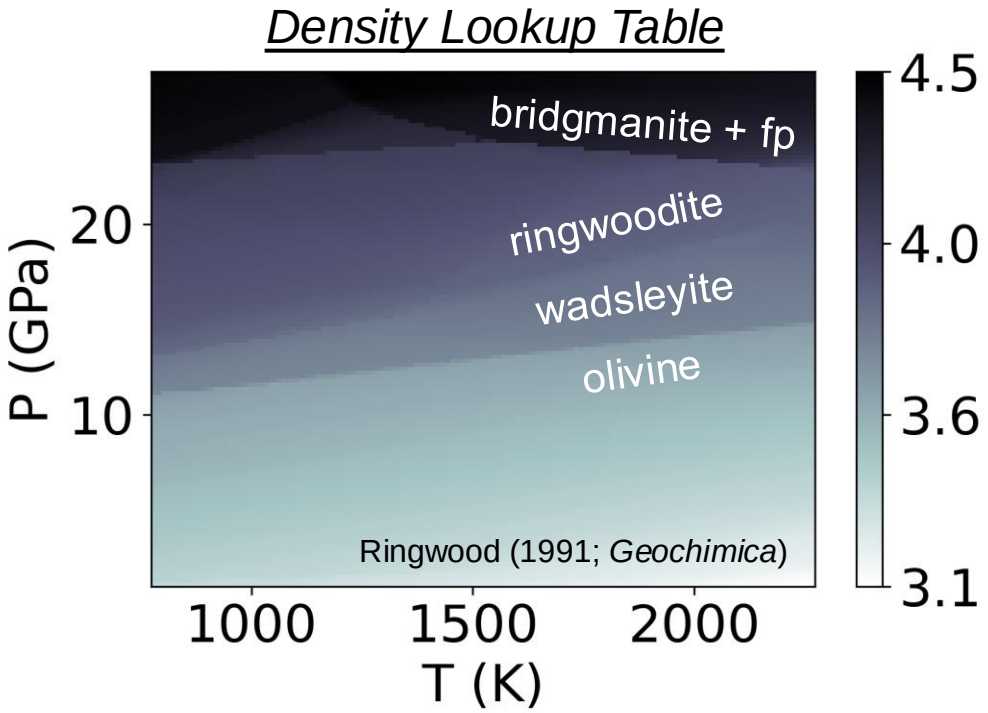

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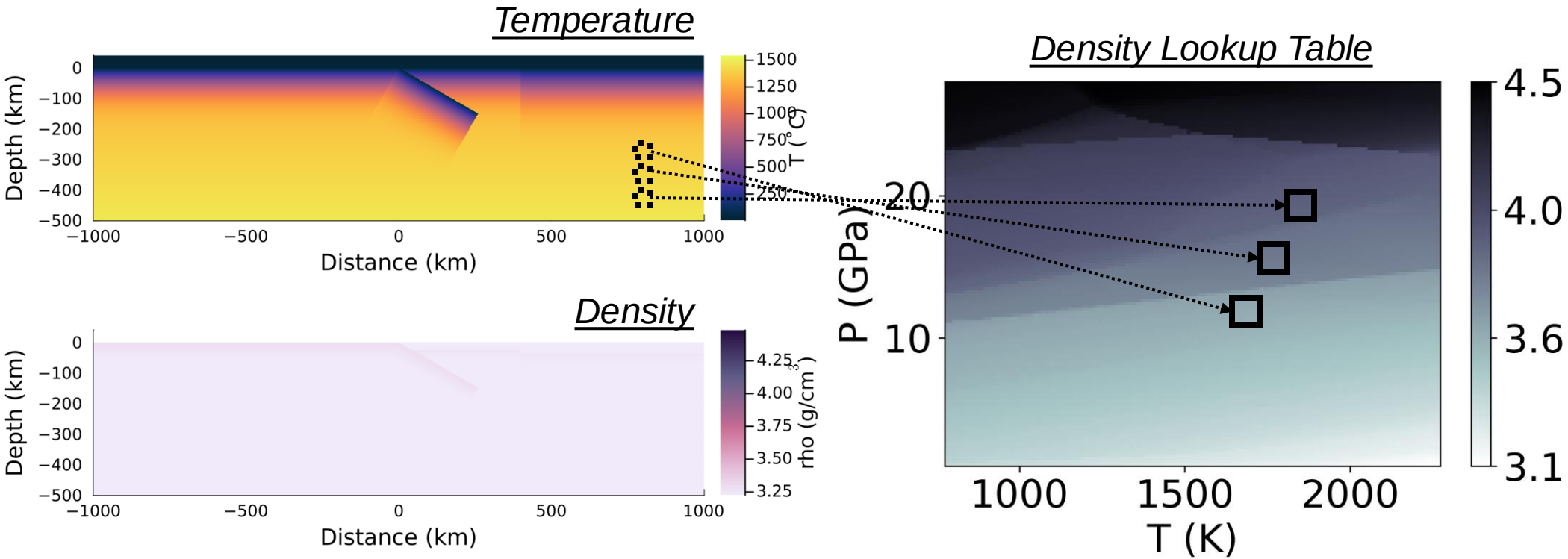

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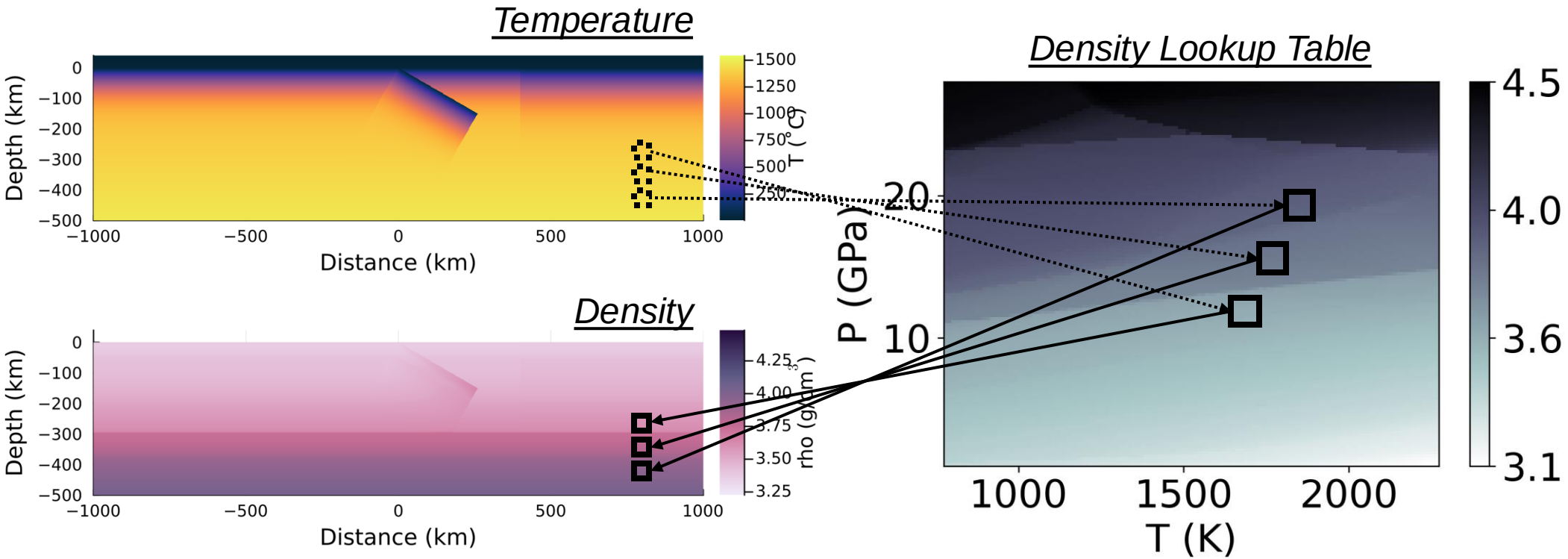
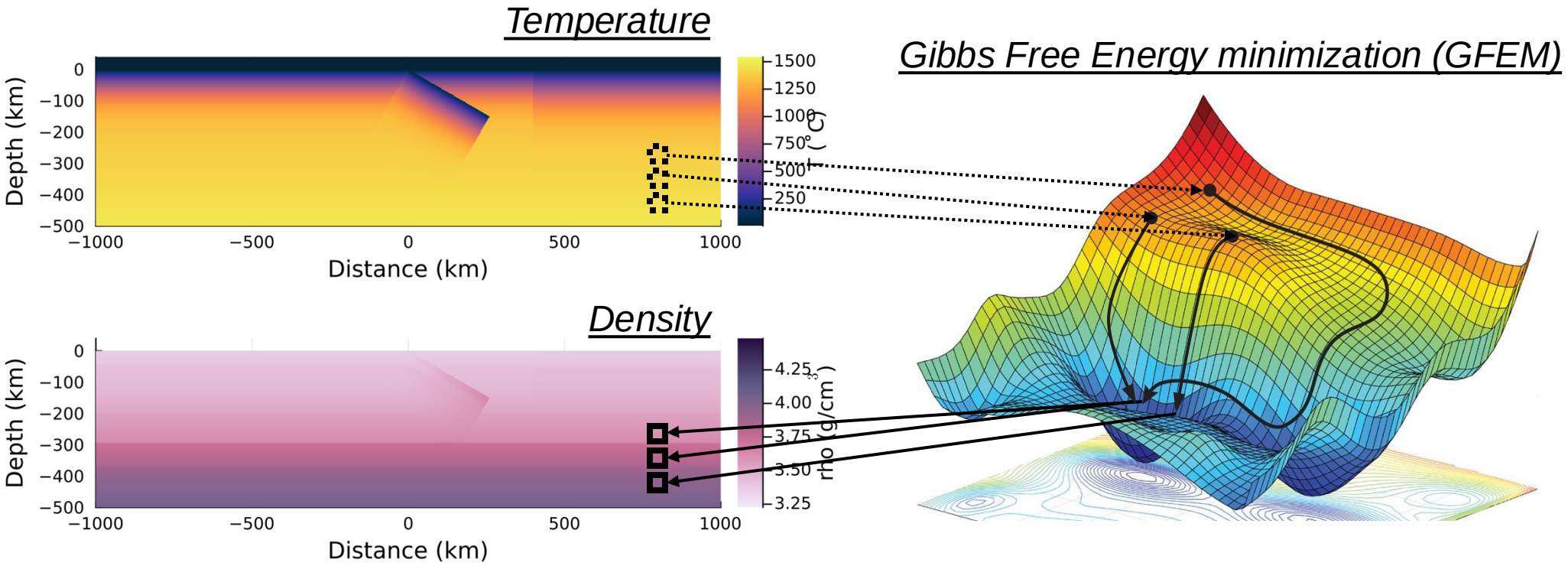


+ : *adds a degree of thermodynamic self-consistency*

– : *need Lookup Tables for each rock composition and rock property*

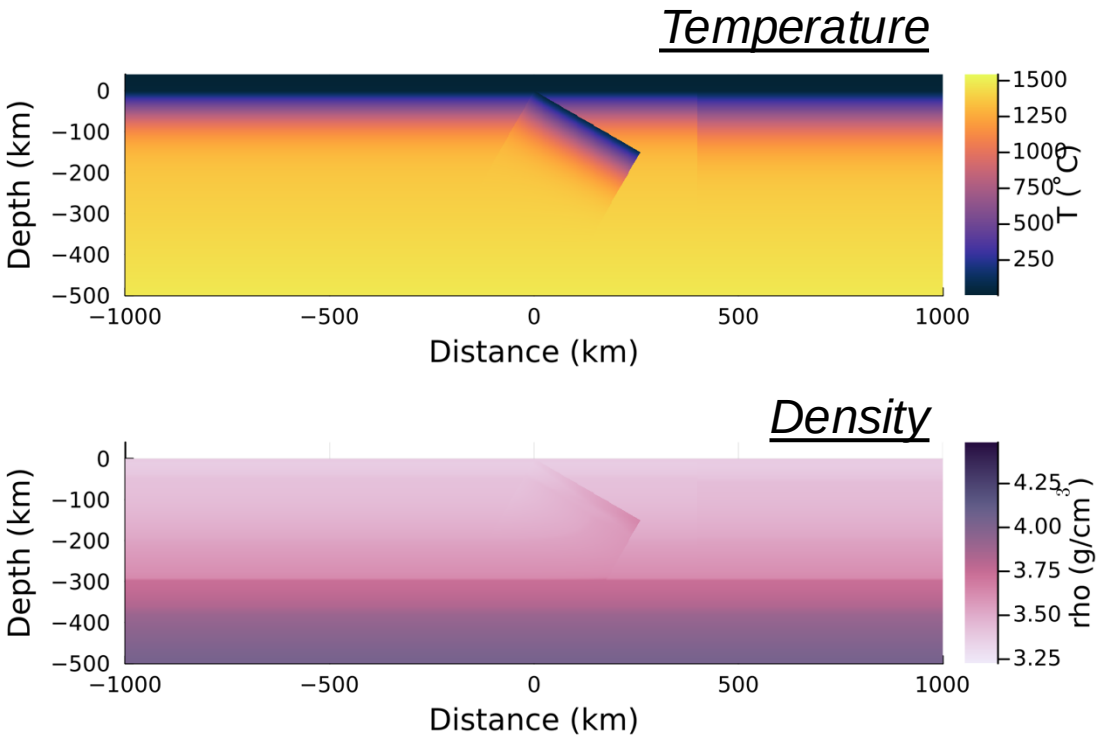
Phase equilibria modeling is more effective, but slow

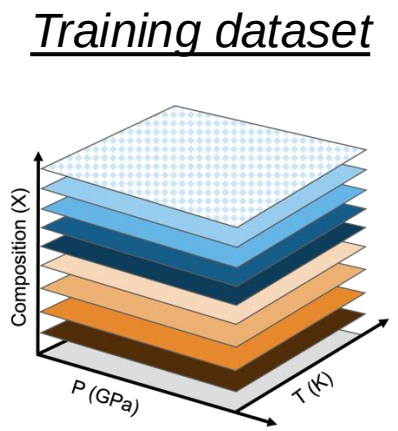


+ : *thermodynamically self-consistent, can handle changing compositions*

– : *computationally expensive to run (too slow for high-res simulations)*

Machine learning models (RocMLM) are effective and fast





Kerswell et al. (2024; submitted G3)

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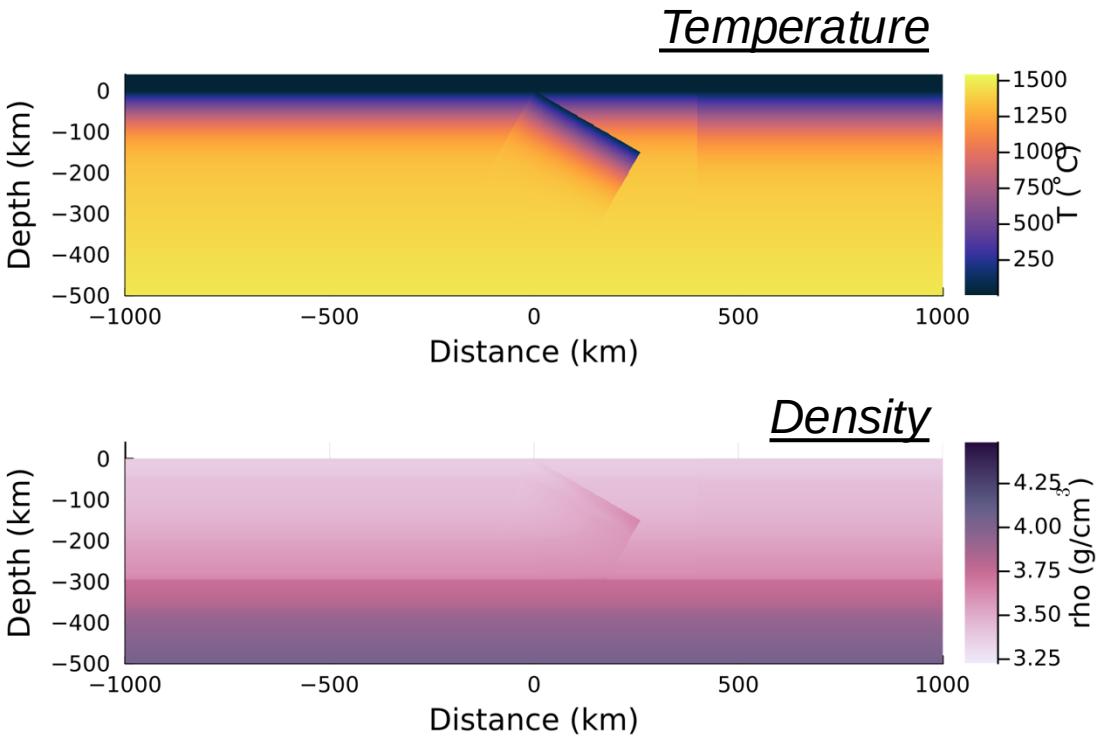

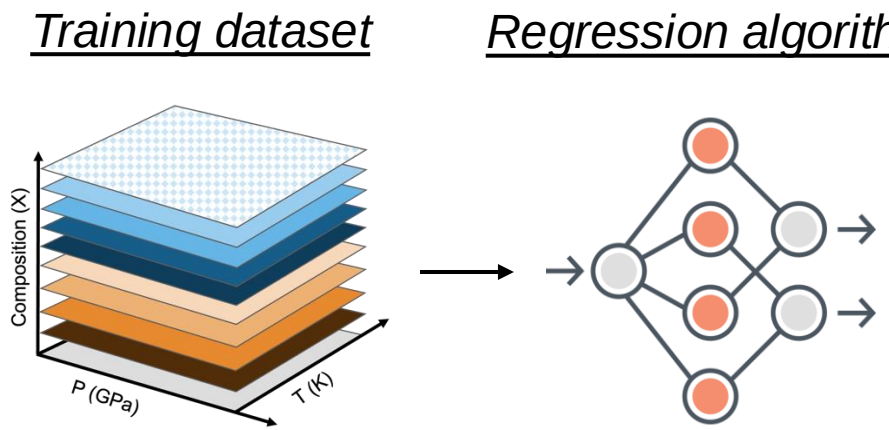

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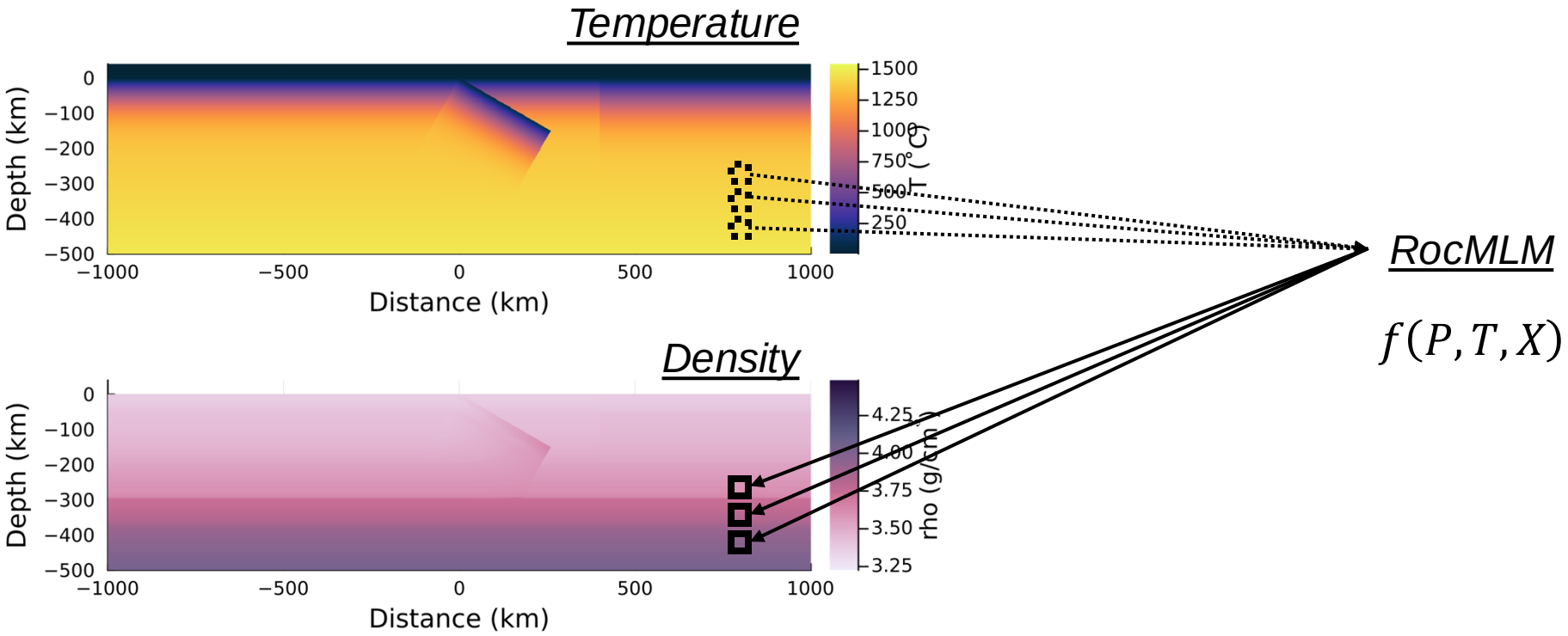
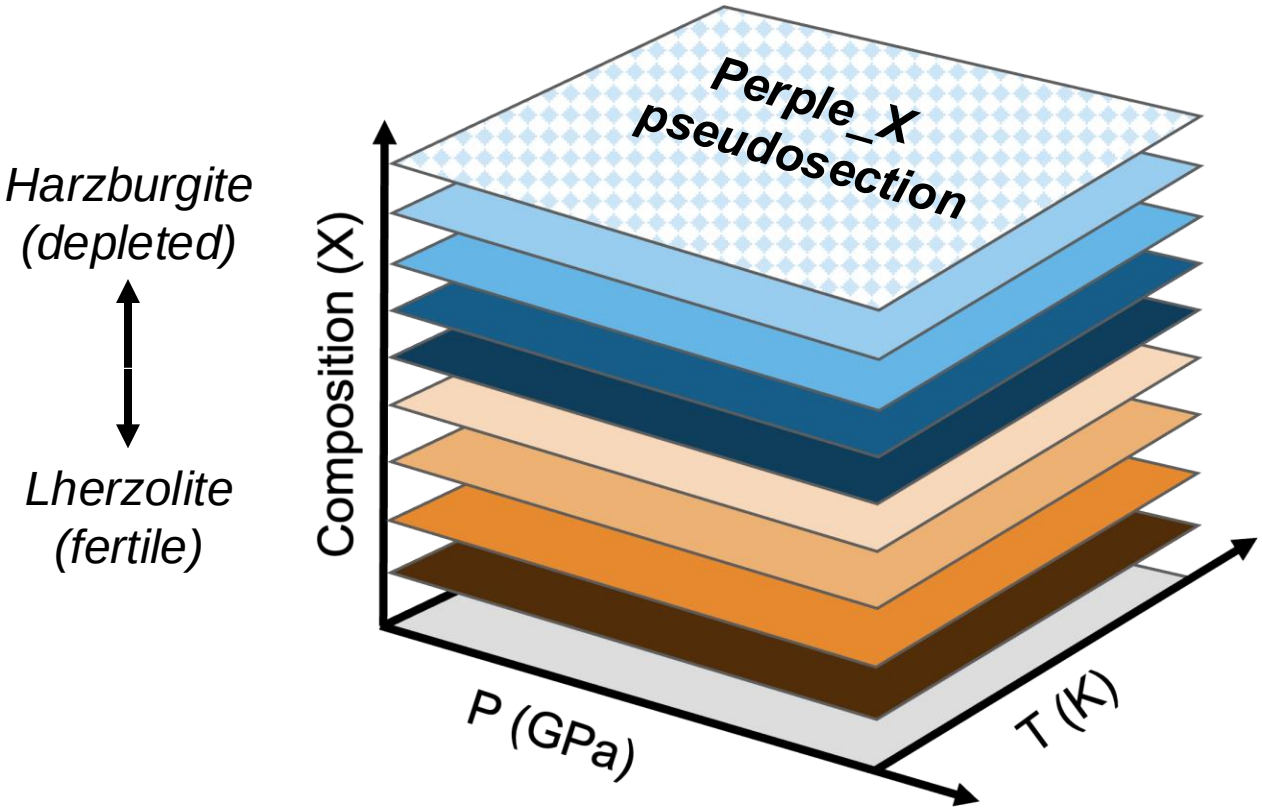


+ : *potentially much faster than Lookup Tables and GFEM*

– : *requires building and training on a large dataset*

Kerswell et al. (2024; submitted G3)

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



Kerswell et al. (2024; JGR:MLC)

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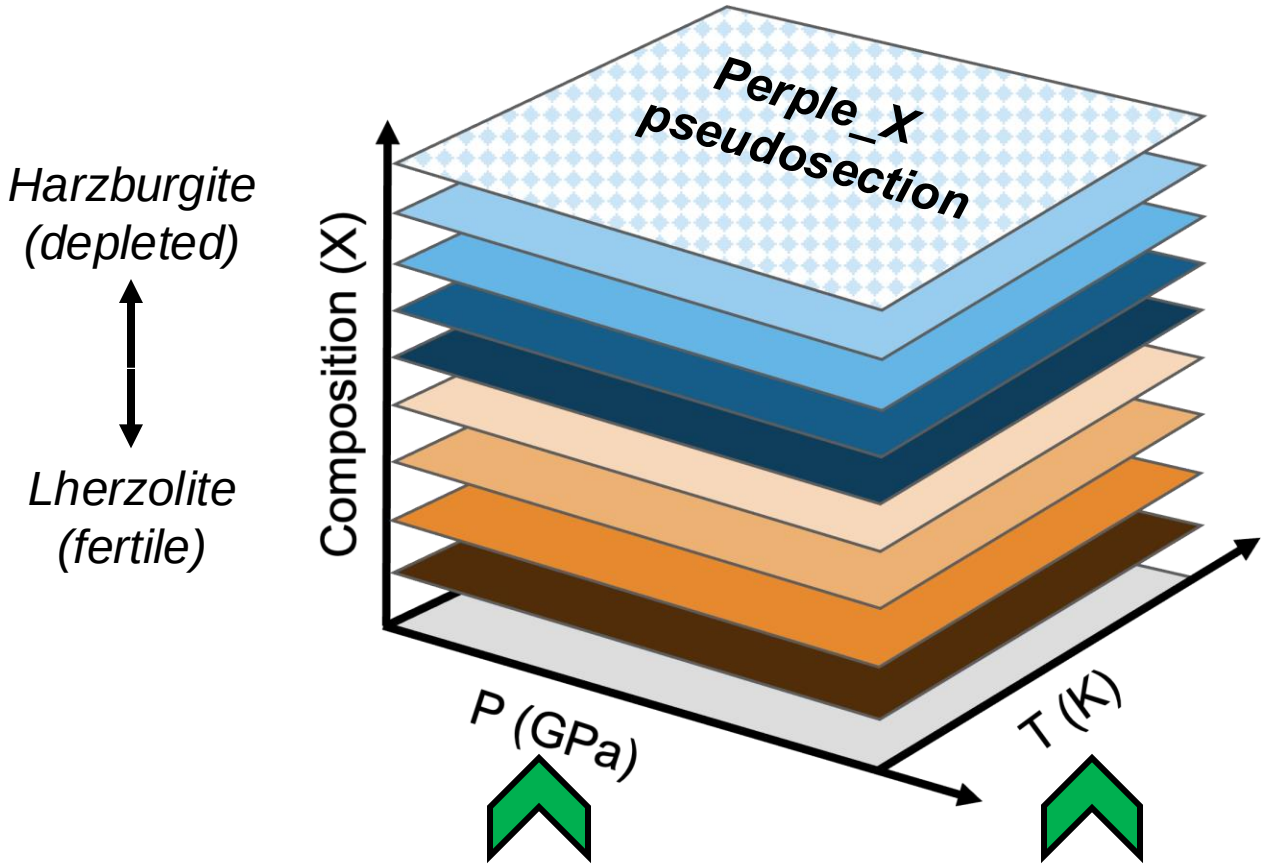


P : *1–28 GPa*

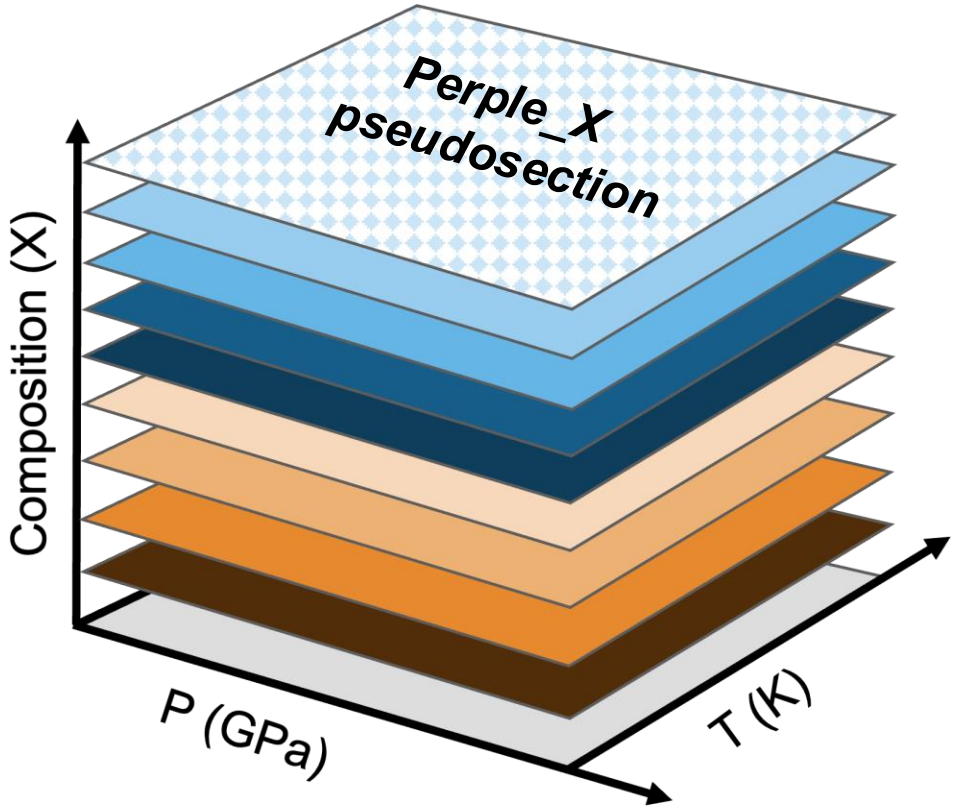
T : *773–2273 K*

Kerswell et al. (2024; JGR:MLC)

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

Harzburgite (depleted)

Lherzolite (fertile)



P : *1–28 GPa*

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

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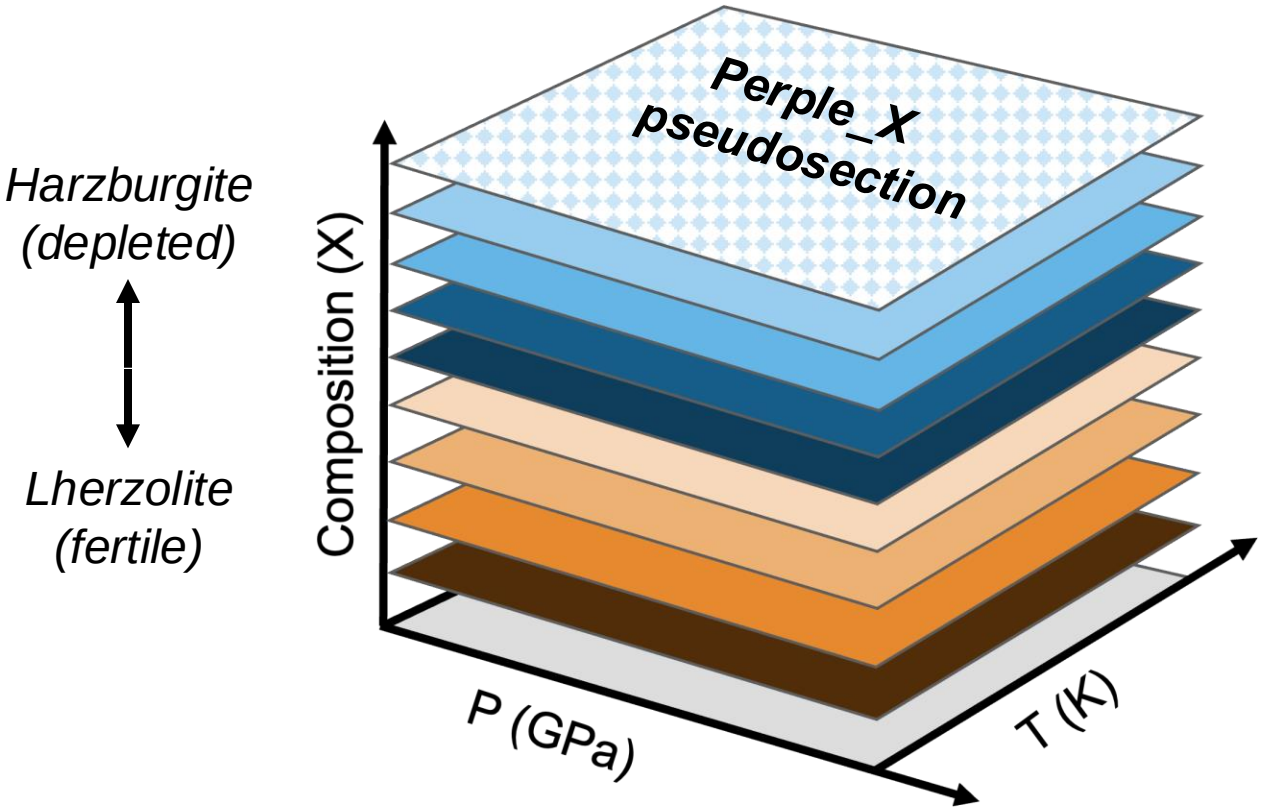


P : *1–28 GPa*

T : *773–2273 K*

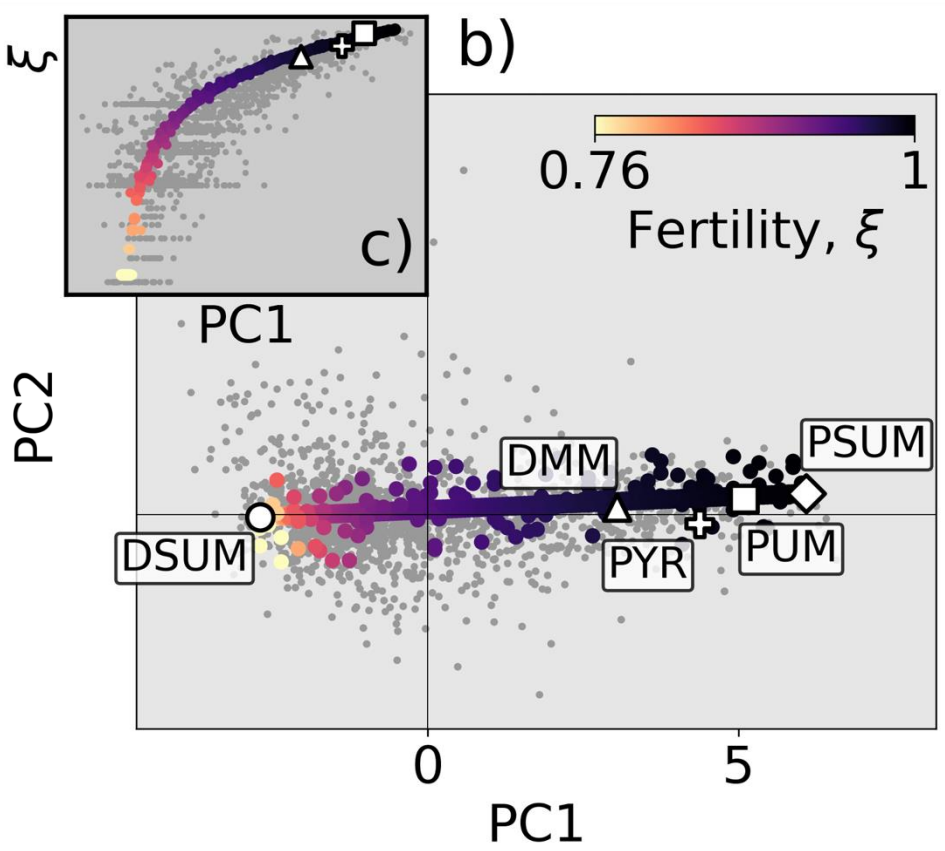
X : *[Na_2O-CaO-FeO-MgO-Al_2O_3-SiO_2]*

Dimensions : *2 + 6 = 8*

Need to reduce this !

Kerswell et al. (2024; JGR:MLC)

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



ξ Fertility Index parameter represents composition

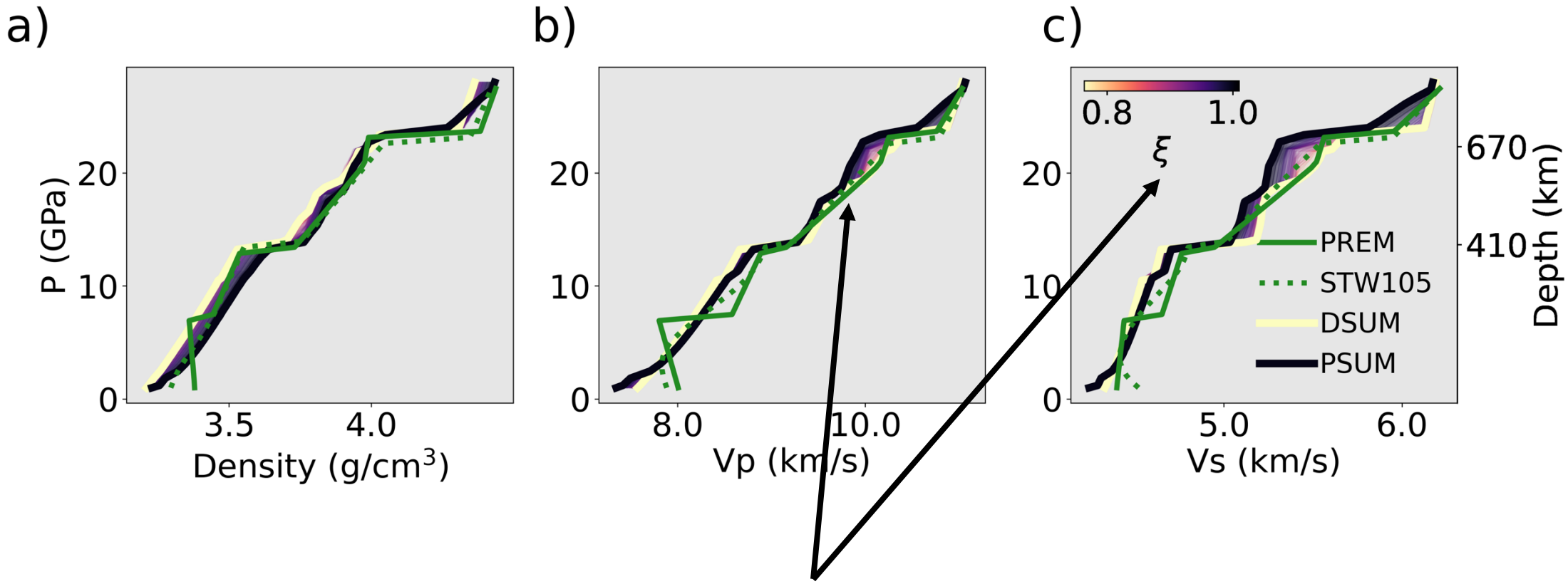
ξ : [Na_2O-CaO-FeO-MgO-Al_2O_3-SiO_2]

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

Shaw (1970; *Geochimica*)

Kerswell et al. (2024; JGR:MLC)

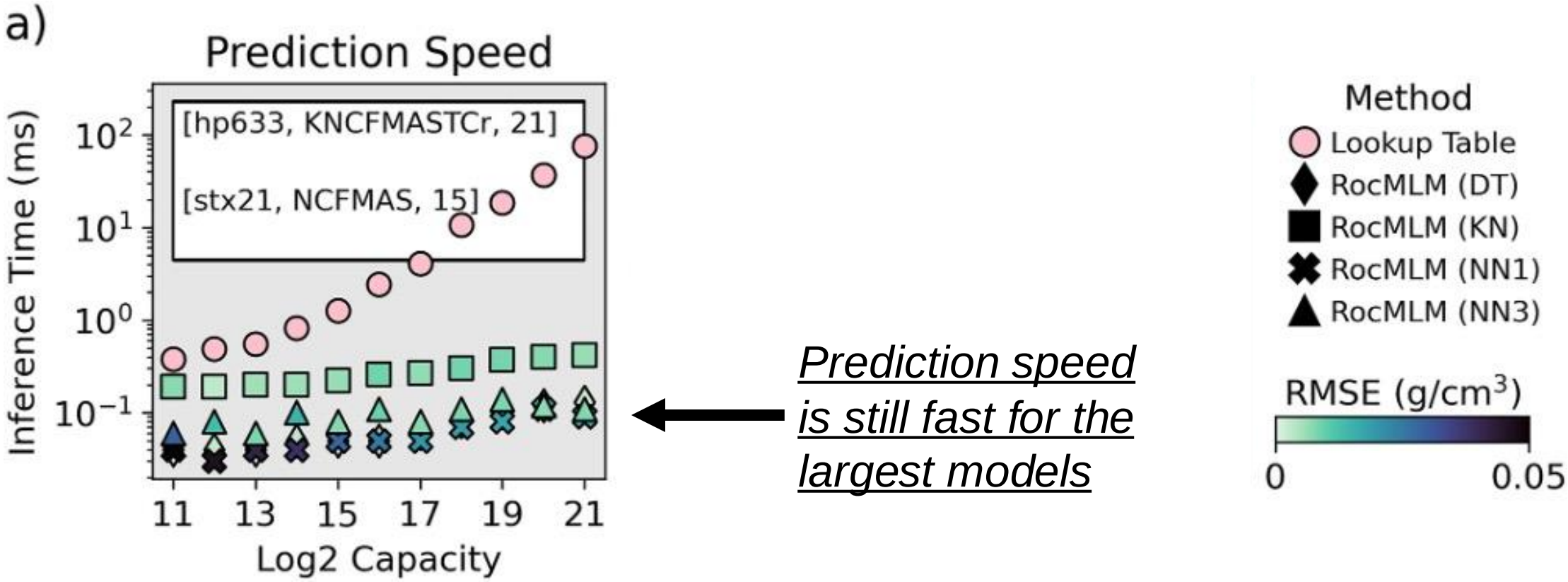
RocMLM training dataset contains 2^{21} (~2.1M) phase equilibria across an array of 128 mantle comp's from fertile → depleted



Training data are sensitive to mantle composition

Kerswell et al. (2024; JGR:MLC)

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

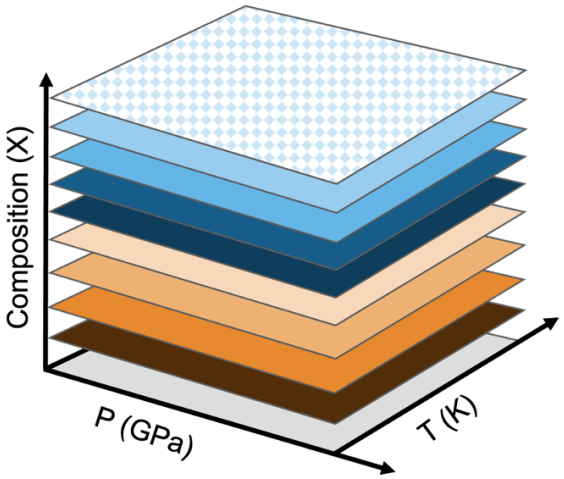


Prediction speed is still fast for the largest models

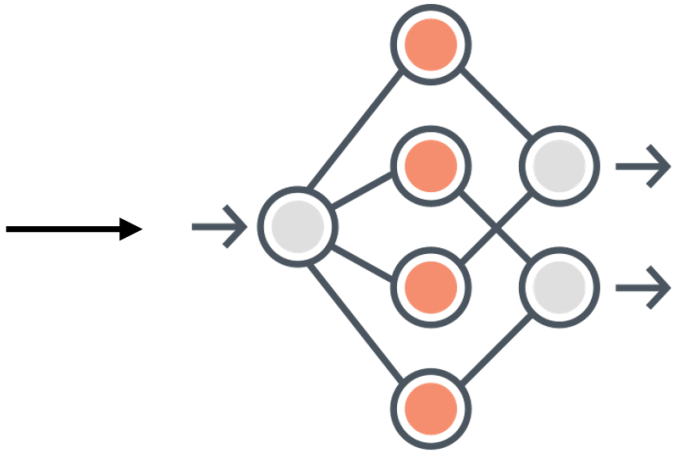
Kerswell et al. (2024; JGR:MLC)

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?

Kerswell et al. (2024; JGR:MLC)