Mars’ thermal evolution from machine-learning-based 1D surrogate modelling

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Agenda

- **Motivation** for using machine learning
- **Dataset** of Mars evolution simulations
- **Training results** from a neural network
- **Evolutions** of 1D temperature profiles using trained neural networks
- **Conclusion**

Motivation

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Motivation

Parameters

$\eta_{ref} \in [10^{19}, 10^{22}]$ Pa s

$\Lambda \in [1, 50]$

$T_{ini} \in [1600, 1800]$ K

E $\in [10^5, 5\text{x}10^5]$ J mol^{-1}

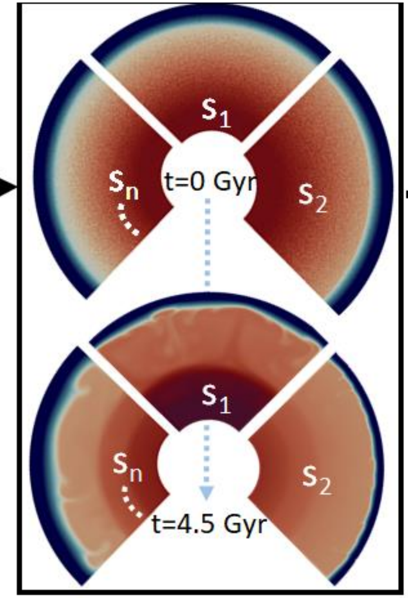
$V \in [4\text{x}10^{-6}, 10\text{x}10^{-6}]$ m^3 mol^{-1}

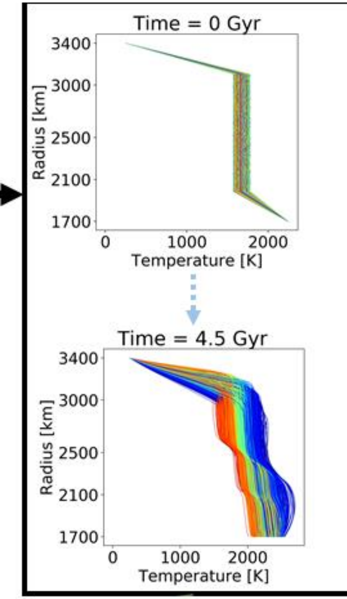
Convection models

$$\nabla' \cdot \boldsymbol{u}' = 0,$$

$$-\nabla' p' + \nabla' \cdot \left[\eta' \left(\nabla' \boldsymbol{u}' + (\nabla' \boldsymbol{u}')^{\mathrm{T}}\right)\right] + \left(Ra\, \alpha' T' - \sum_{l=1}^{3} Rb_l\, \Gamma_l\right) \boldsymbol{e}_r = 0,$$

$$\frac{DT'}{Dt'} - \nabla' \cdot (k' \nabla' T') - Di\, \alpha' (T' + T_0') u_r' - \frac{Di}{Ra} \Phi' - \sum_{l=1}^{3} Di \frac{Rb_l}{Ra} \frac{D\Gamma_l}{Dt} \gamma_l (T' + T_0') - \frac{Ra_Q}{Ra} = 0,$$





- Several parameters governing evolution are unknown
- Convection simulations are expensive
- Scaling laws are limited to low-dimensions

Motivation

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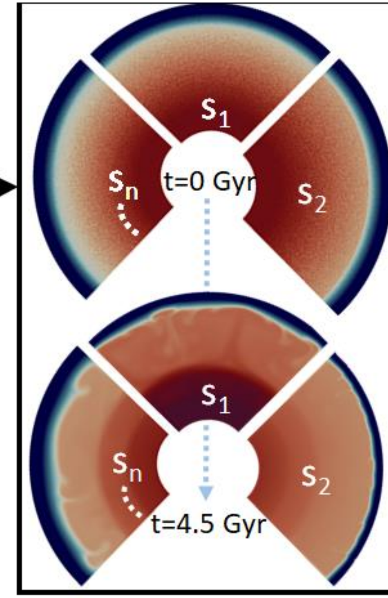

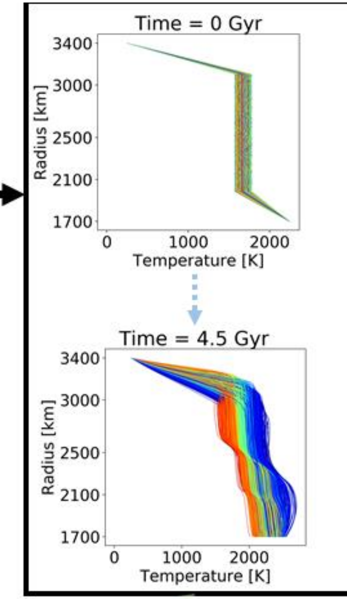

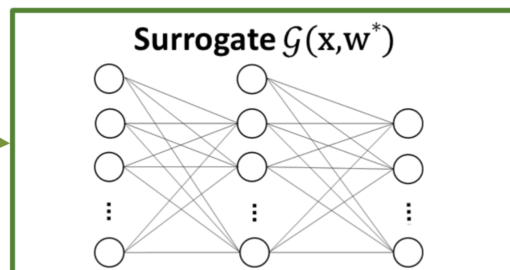

- Can a ML algorithm learn a higher-dimensional mapping?

Dataset

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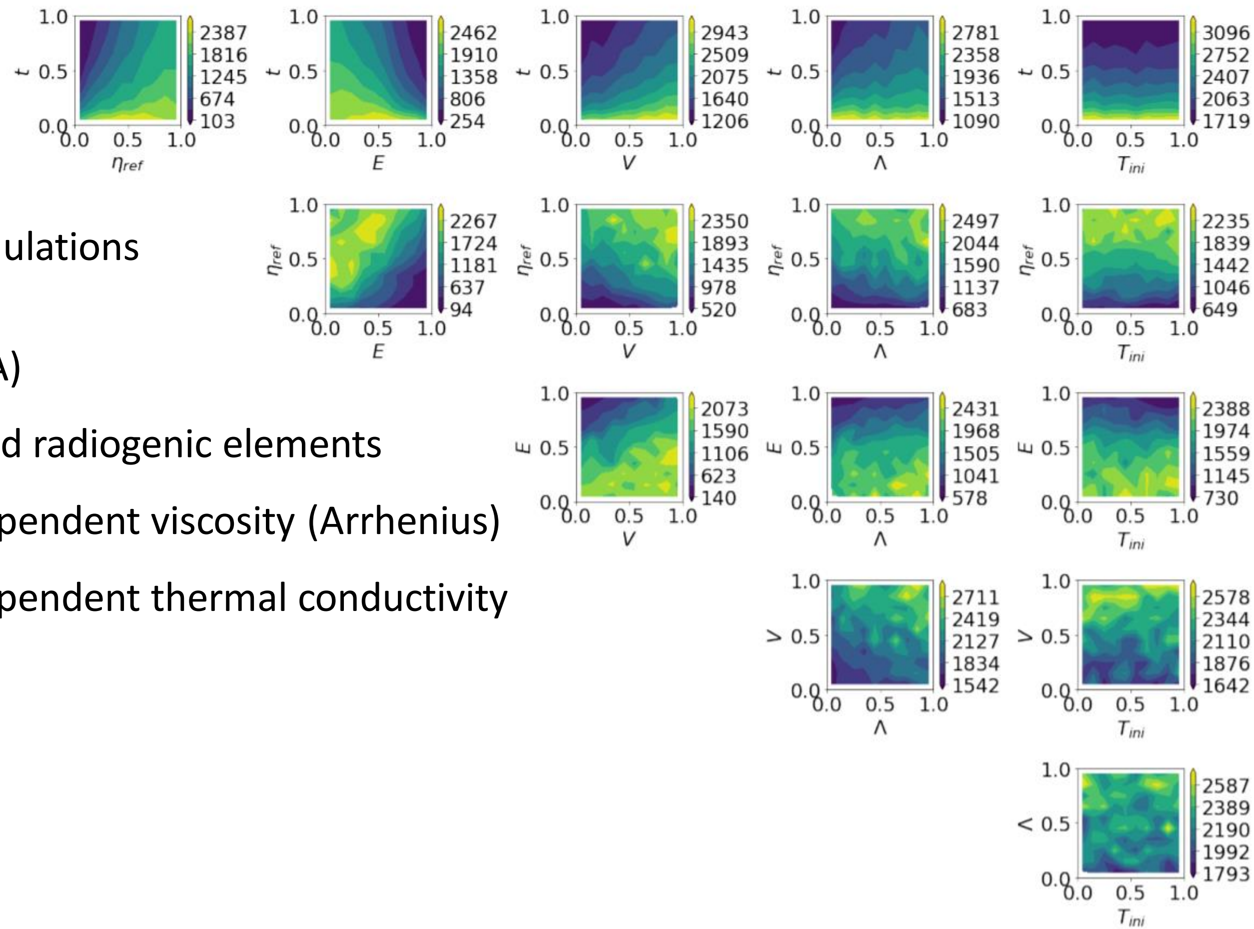
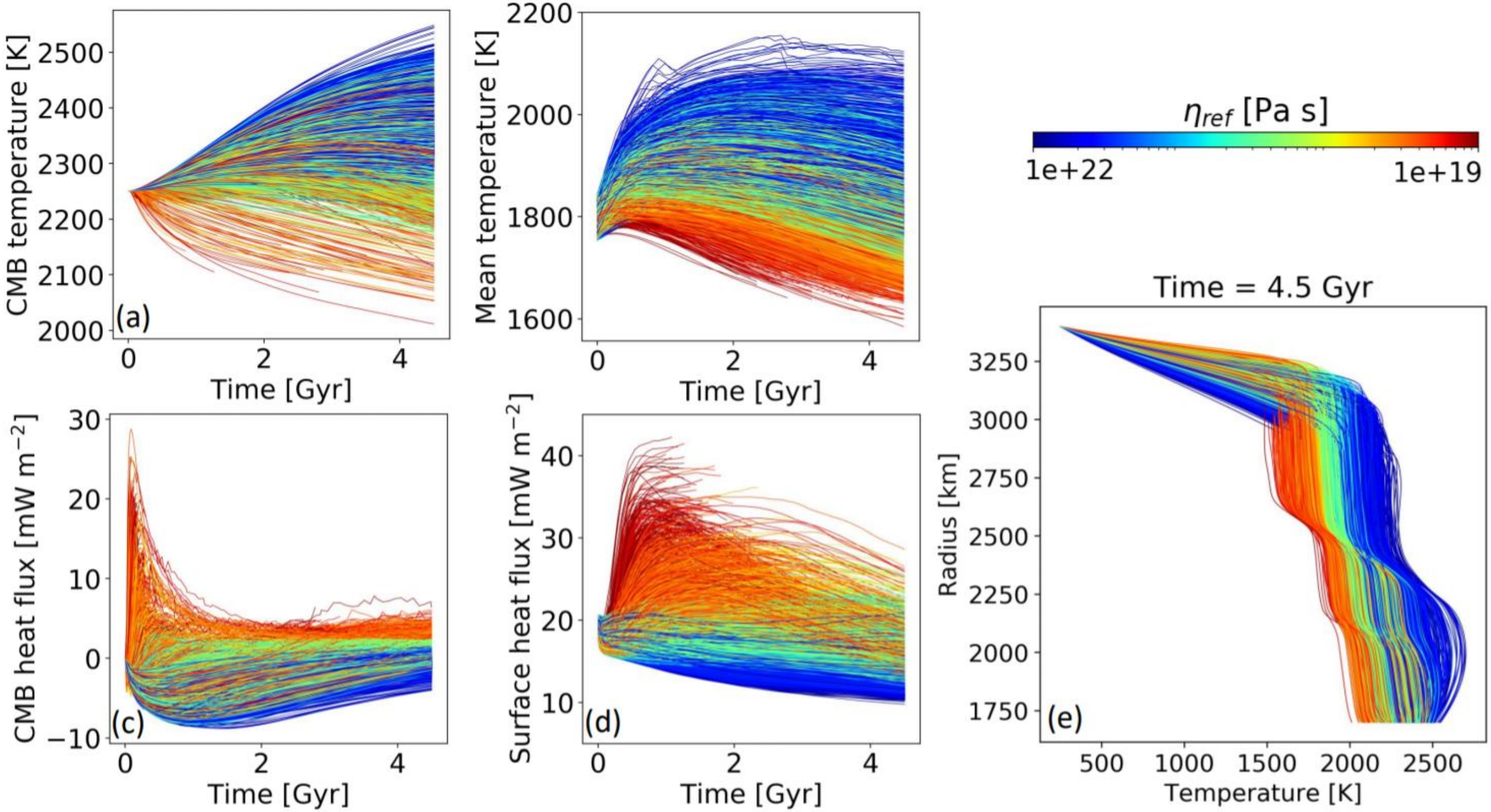
Dataset



Generated ~10,000 evolution simulations for Mars with:

- Compressible convection (EBA)
- Heat production from core and radiogenic elements
- Temperature and pressure dependent viscosity (Arrhenius)
- Temperature and pressure dependent thermal conductivity and thermal expansion
- Solid phase transitions
- Melting

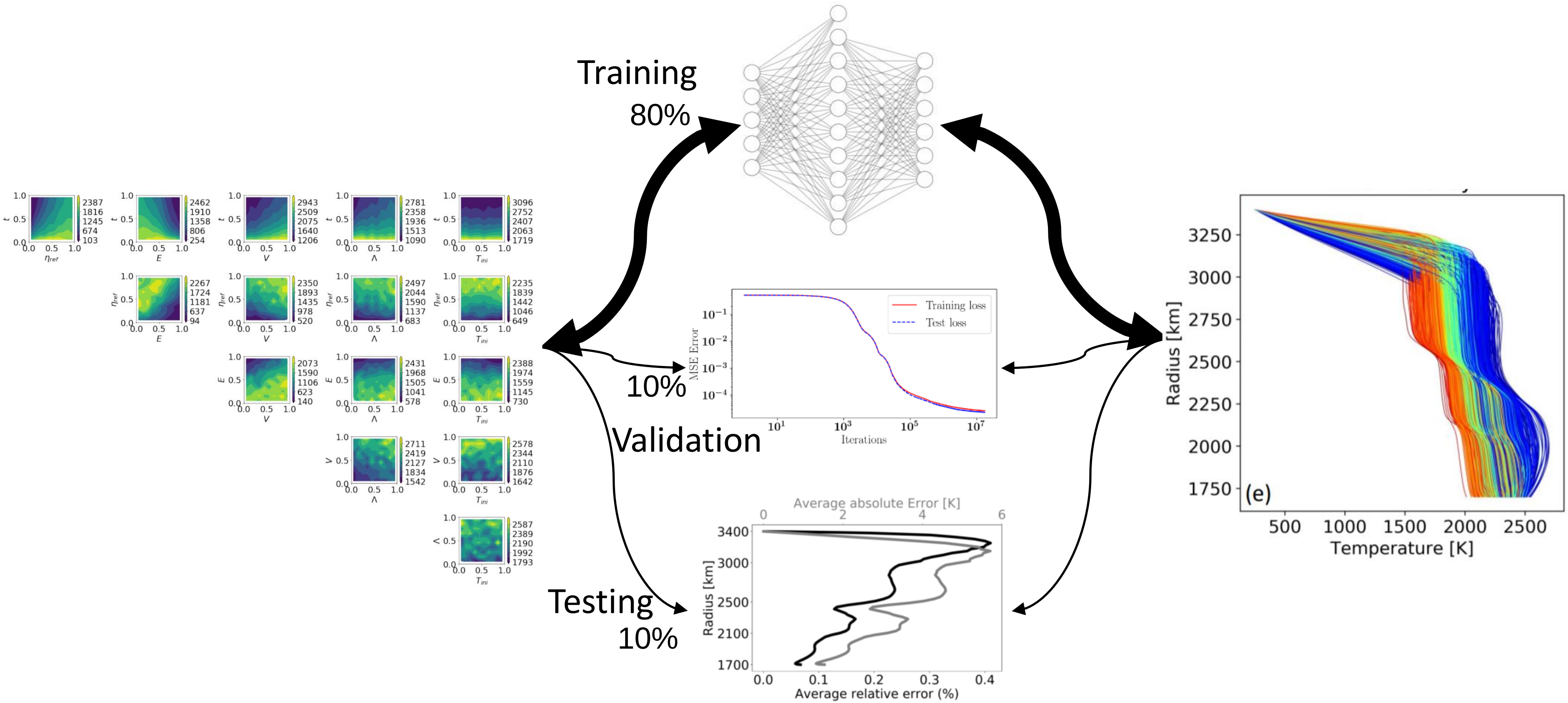
Dataset



CMB temperature [K]
2000
2100
2200
2300
2400
2500
(a)
Time [Gyr]
Mean temperature [K]
1600
1800
2000
2200
(b)
η_{ref} [Pa s]
1e+22
1e+19
CMB heat flux [mW m^{-2}]
−10
0
10
20
30
(c)
Surface heat flux [mW m^{-2}]
10
20
30
40
(d)
0
2
4
Time = 4.5 Gyr
Radius [km]
1750
2000
2250
2500
2750
3000
3250
(e)
500
1000
1500
2000
2500
Temperature [K]

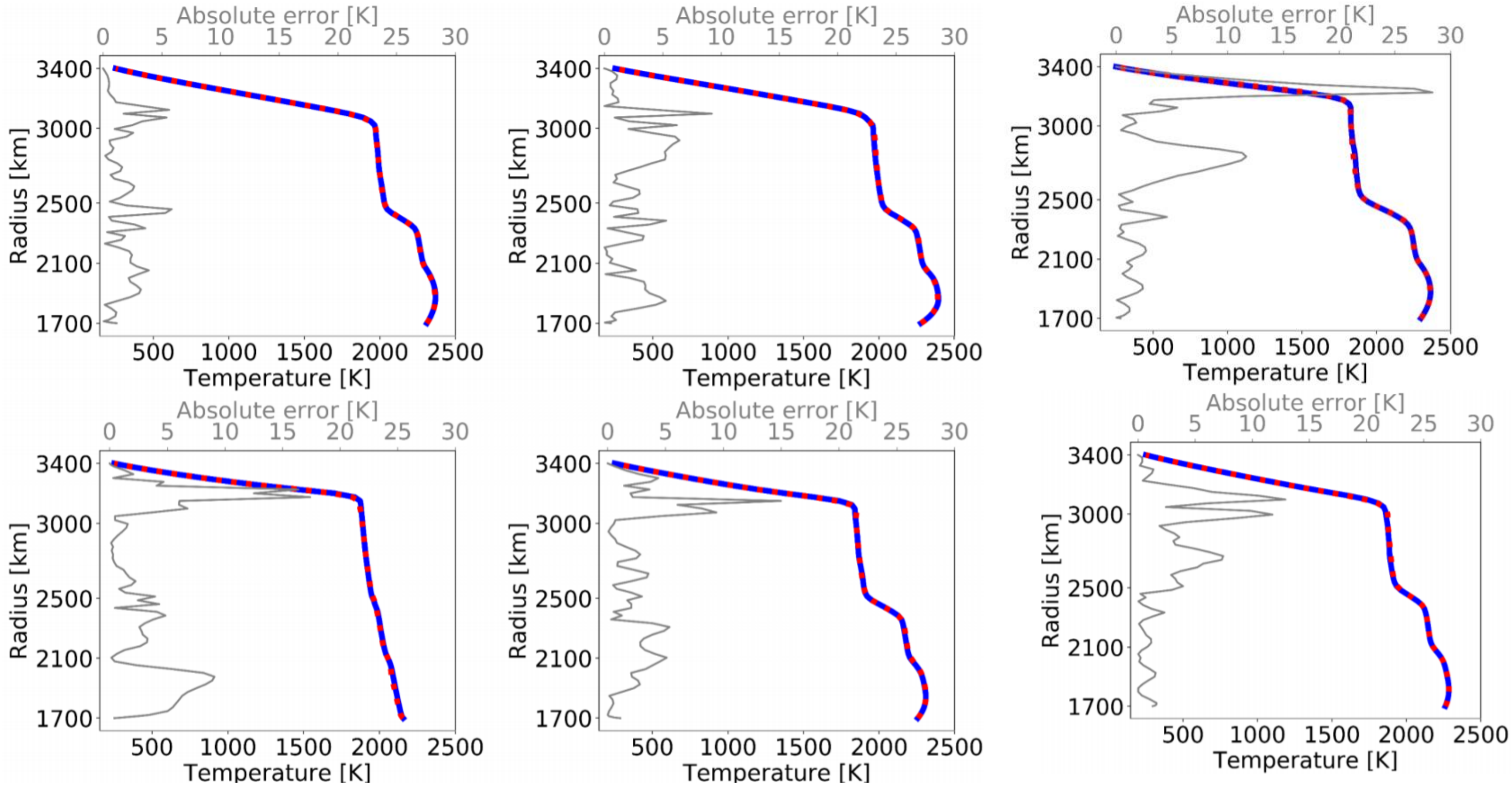
Training

Training


Training
80%
10%
Validation
Testing
10%
Training loss
Test loss
MSE Error
Iterations
Average absolute Error [K]
Radius [km]
Average relative error (%)
Temperature [K]
(e)

Training

Some randomly selected profiles from the test set



Evolution

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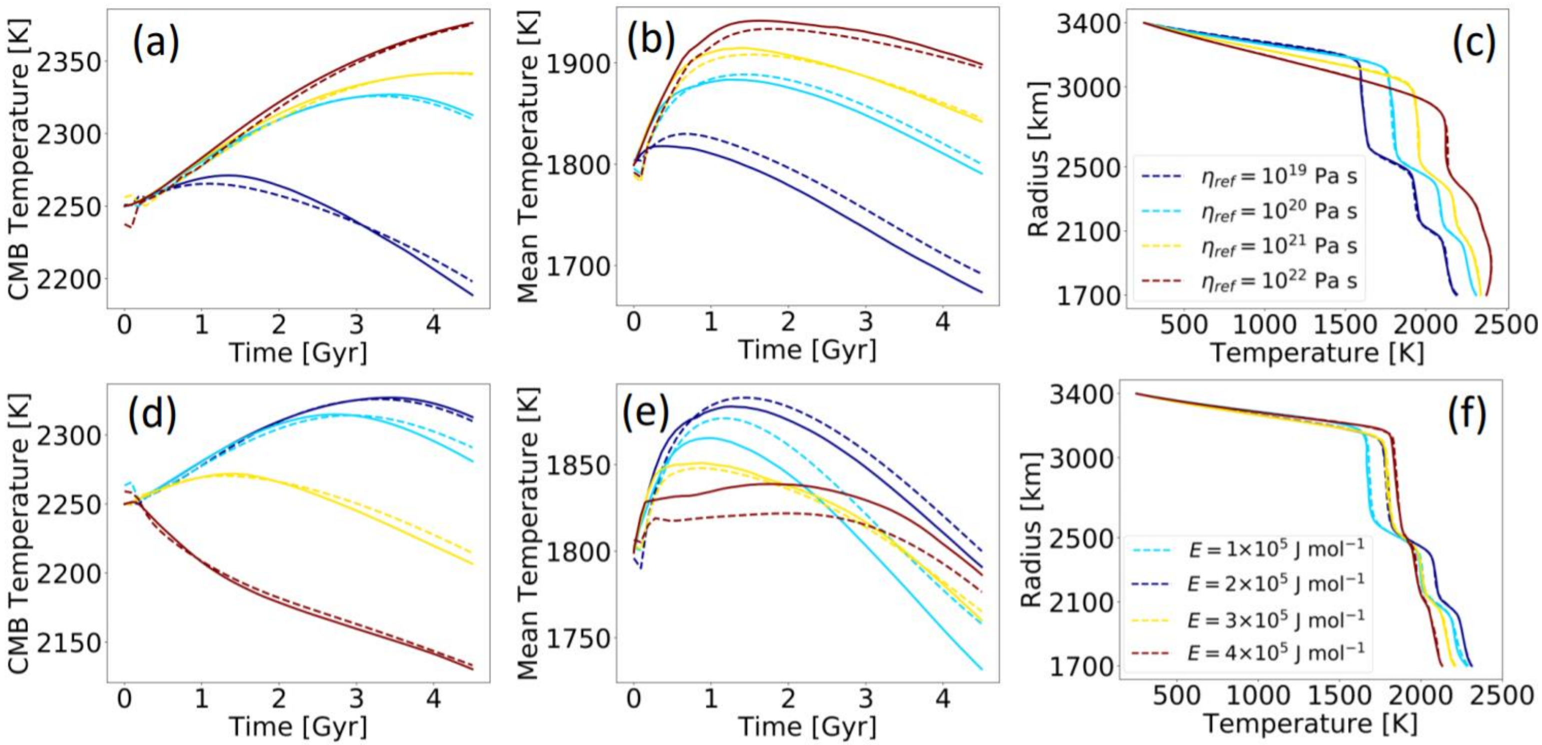
Evolution

The trained Neural Network can be used to generate evolutions



Conclusion

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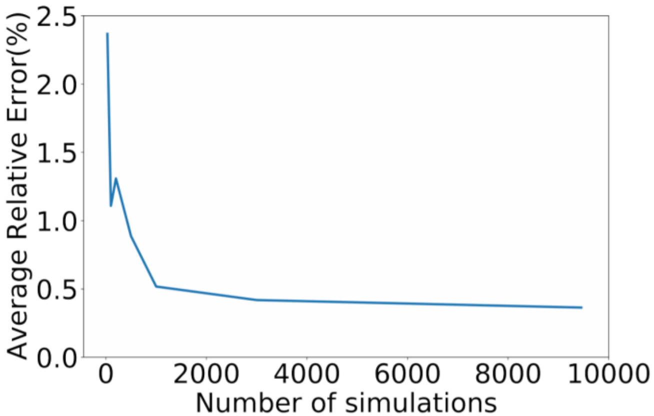
Conclusion

- Higher-dimensional ML algorithms can be leveraged for surrogate modelling in mantle convection.
- It is data-intensive, but effective.



- Future work: predict 2D temperature fields