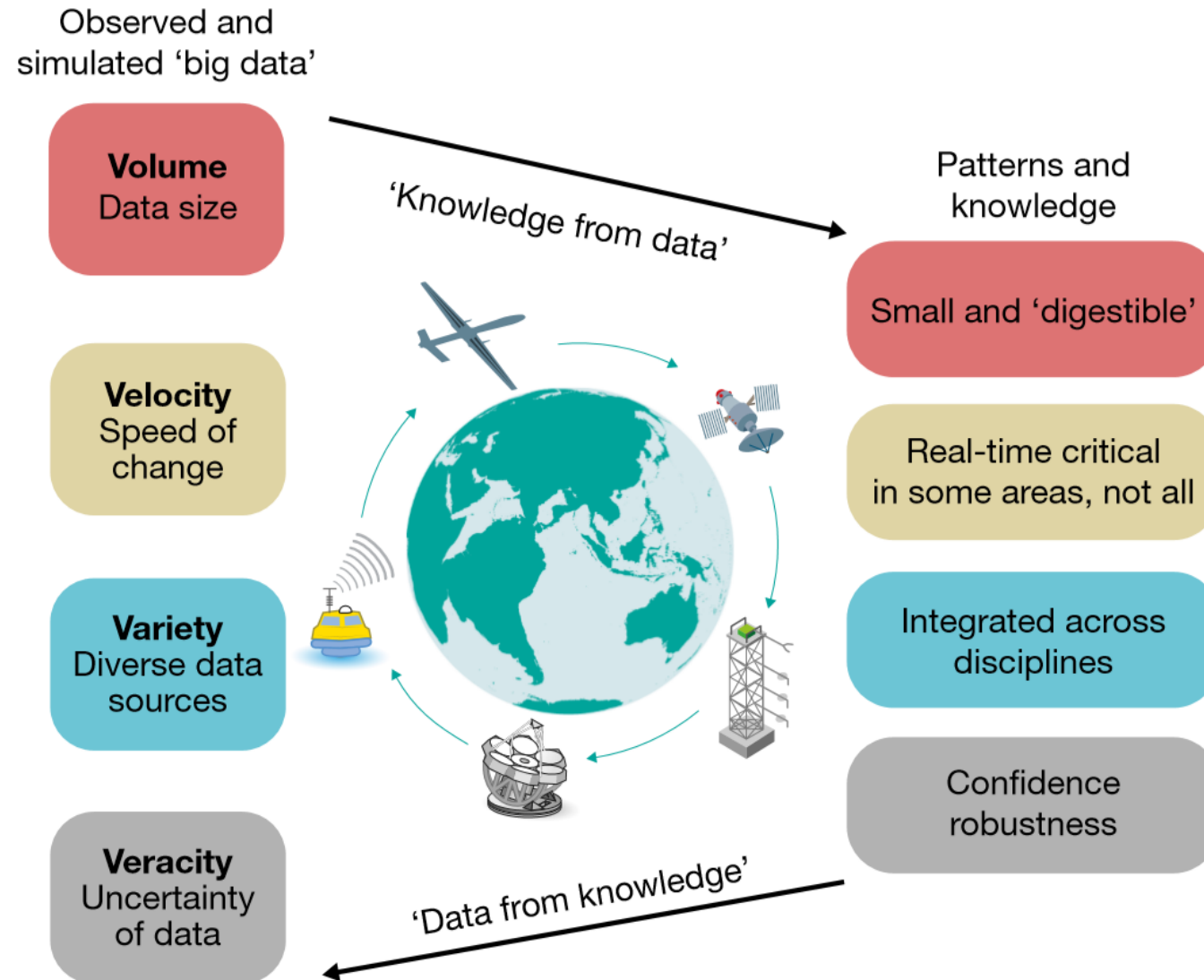


Deep learning and process understanding for data-driven Earth system science

Introduction



Big data challenges in the geoscientific context.

Introduction

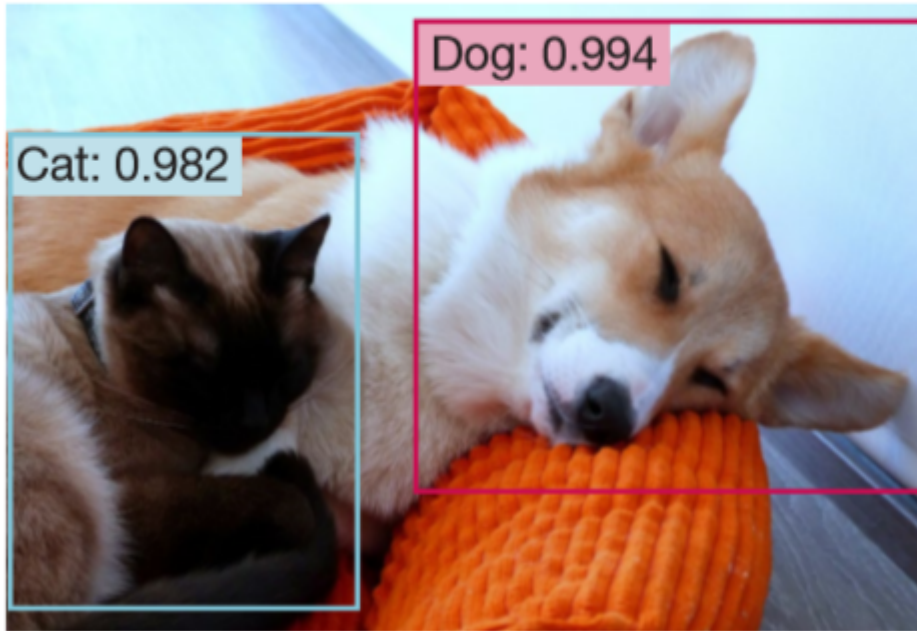
Two major tasks in the coming years:

- (1) extracting knowledge from the data deluge, and
- (2) deriving models that learn much more from data than traditional data assimilation approaches can, while still respecting our evolving understanding of nature's laws.

Background

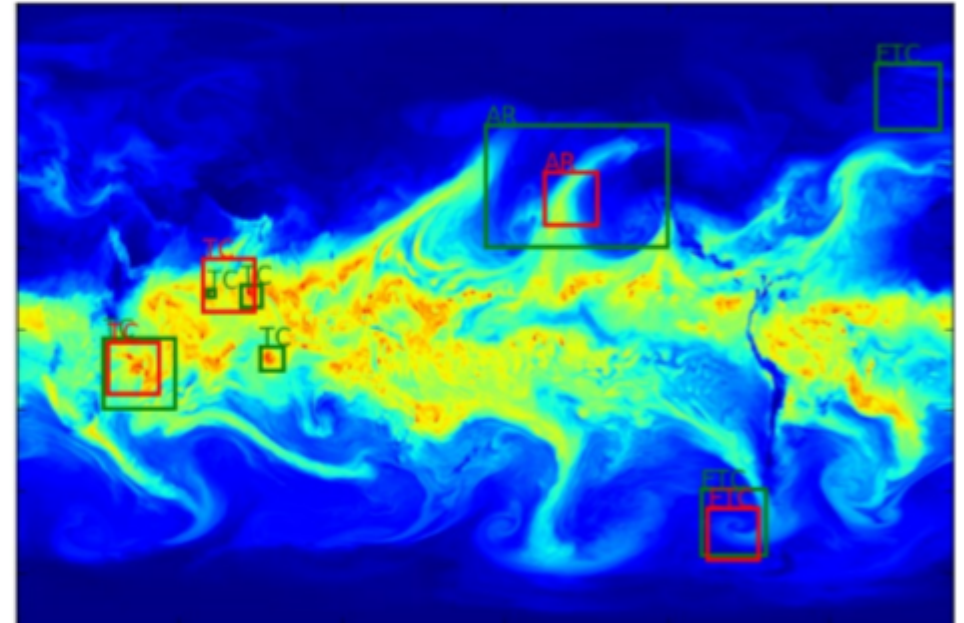
Machine learning tasks

a Object classification and localization



Earth science tasks

Pattern classification

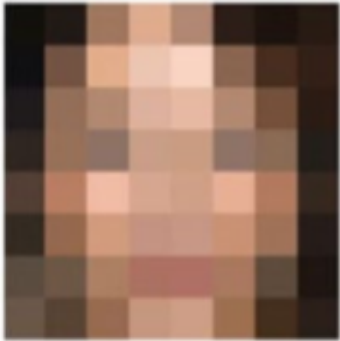


Background

b

Super-resolution and fusion

8×8
input



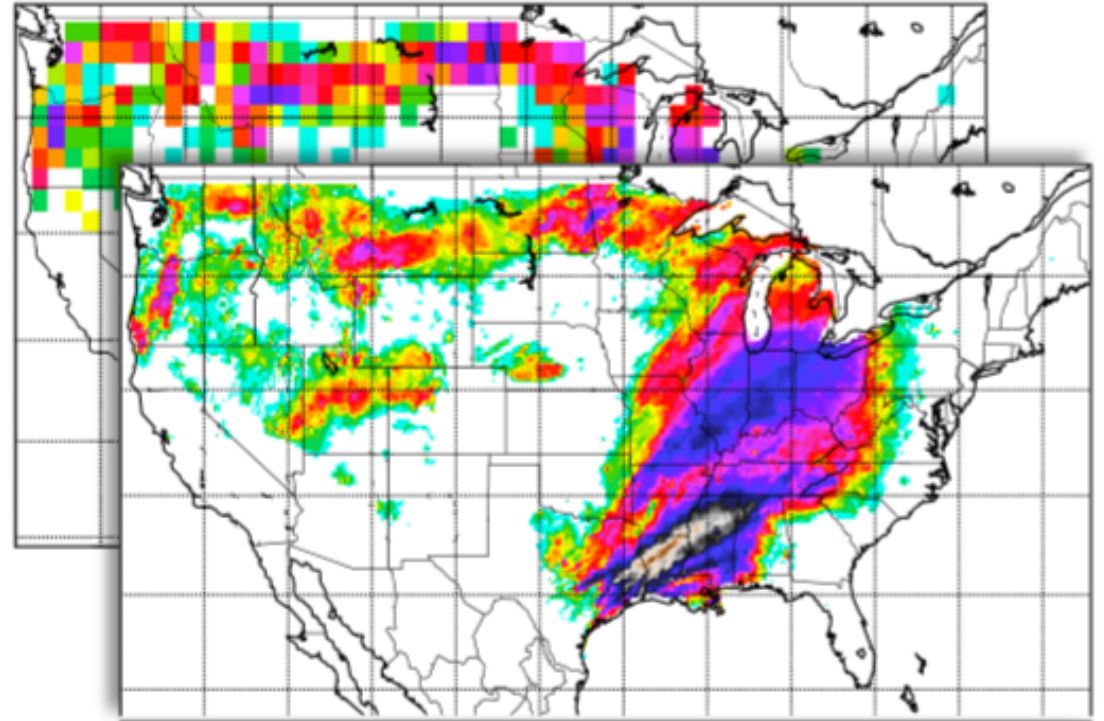
32×32
samples



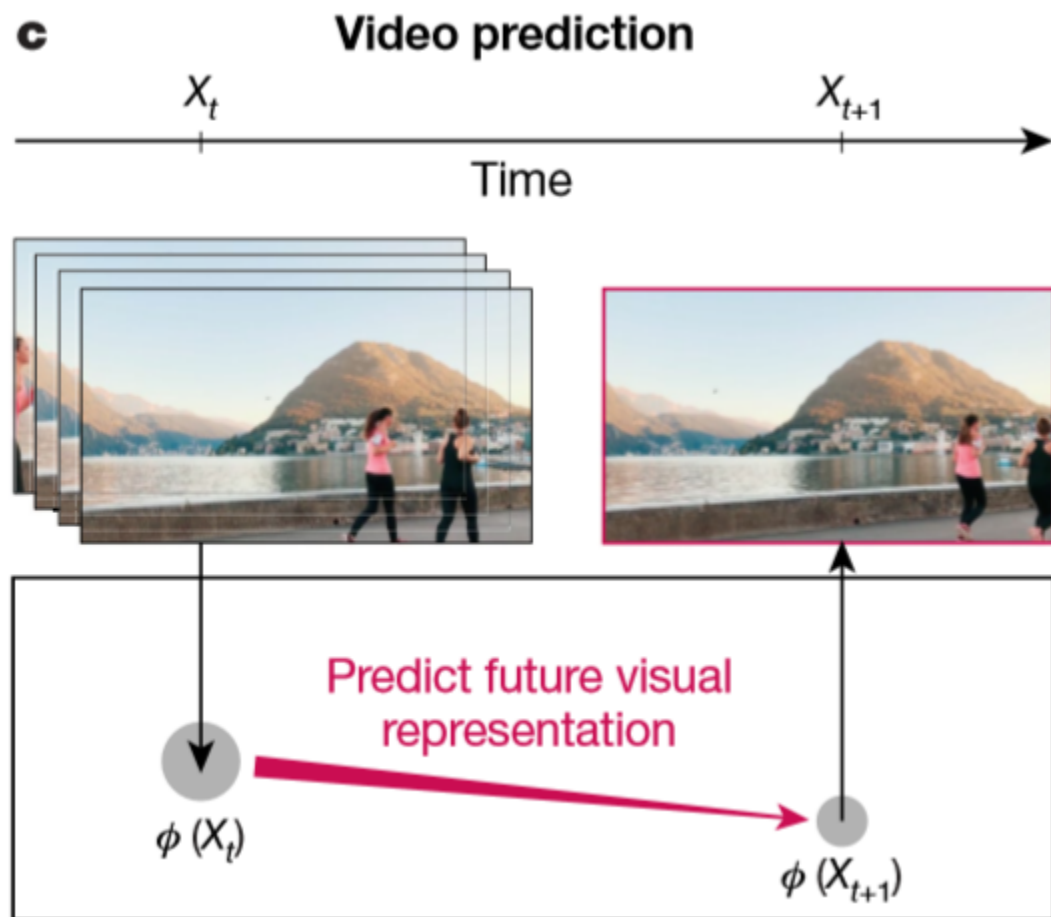
Ground
truth



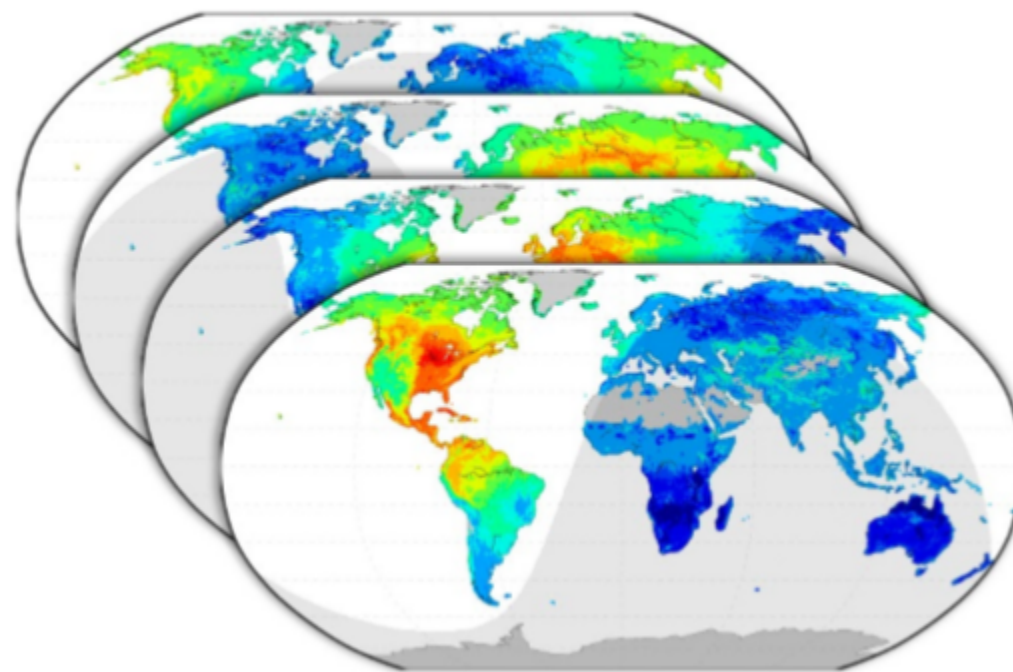
Statistical downscaling and blending



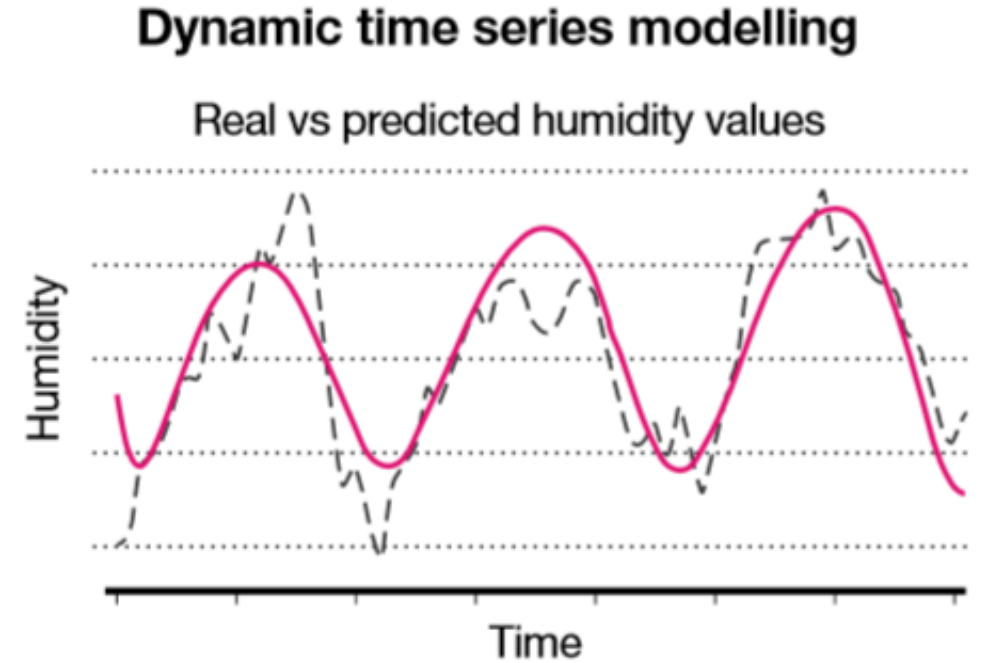
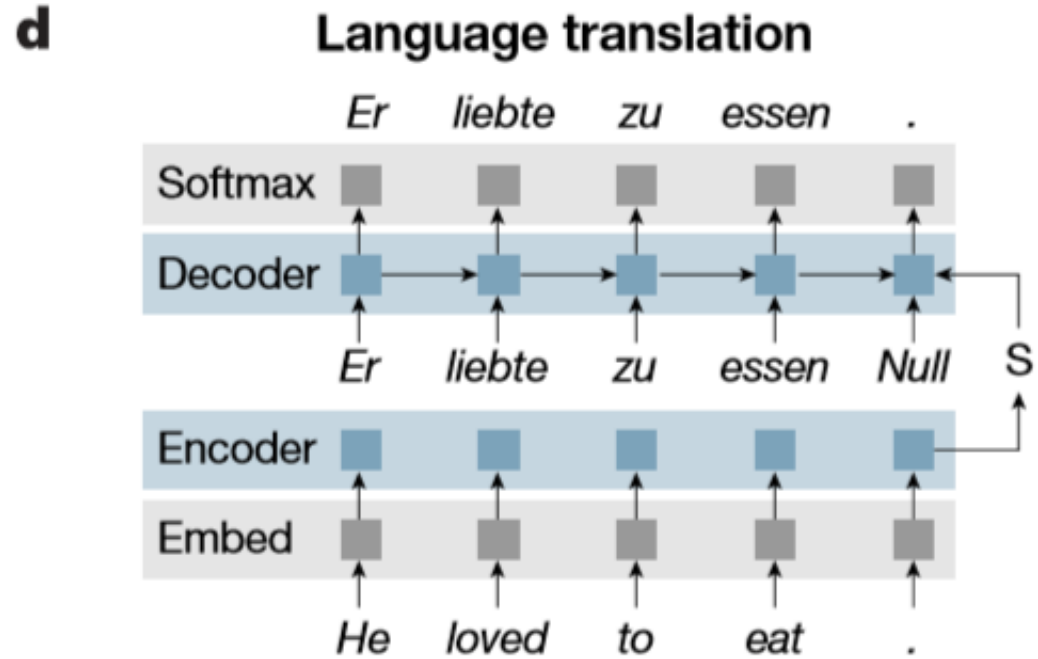
Background



Short-term forecasting



Background



DL challenges in Earth system science

Five major challenges and avenues:

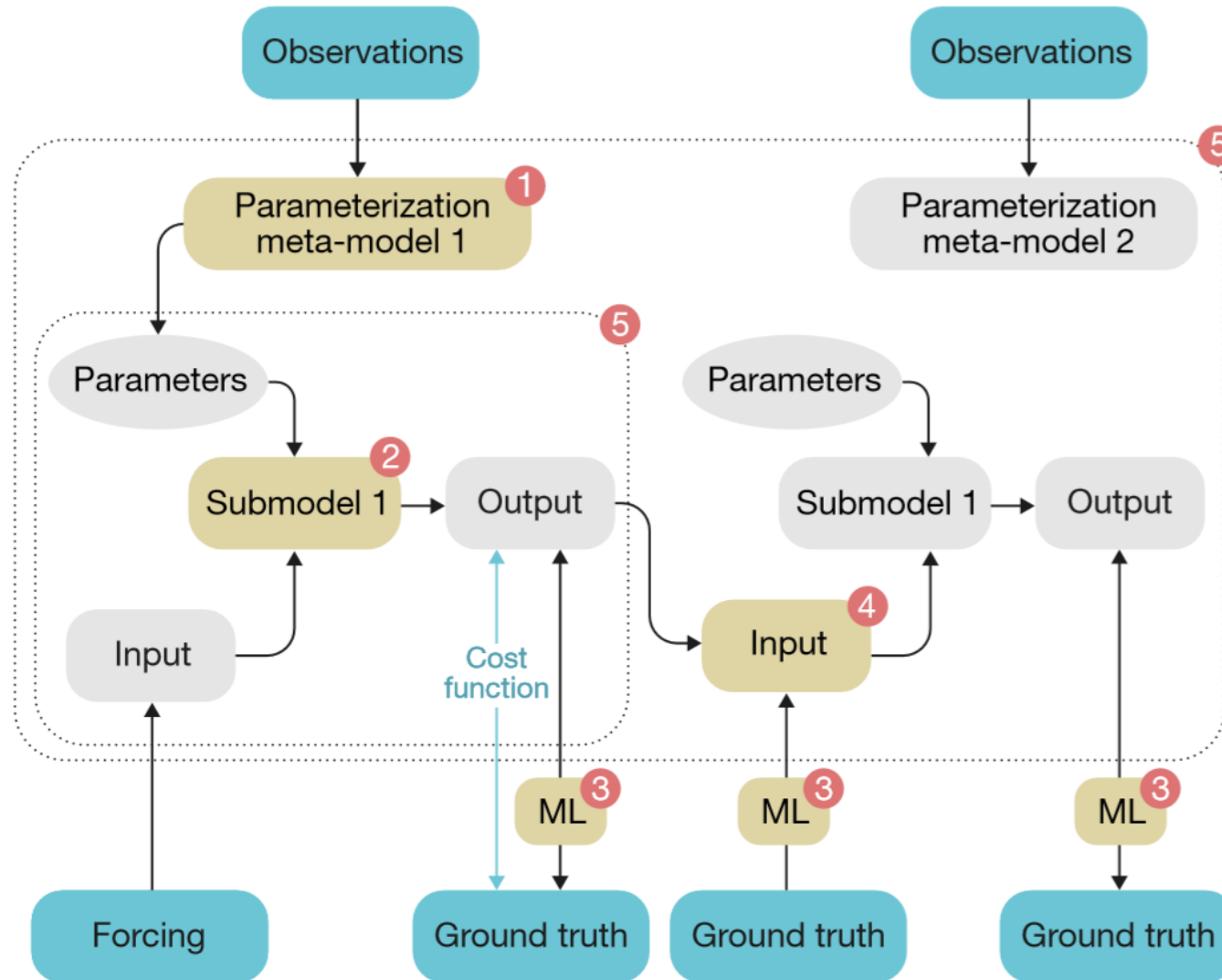
- (1) Interpretability
- (2) Physical consistency
- (3) Complex and uncertain data
- (4) Limited labels
- (5) Computational demand

Integration with physical modelling

Five points of potential synergy:

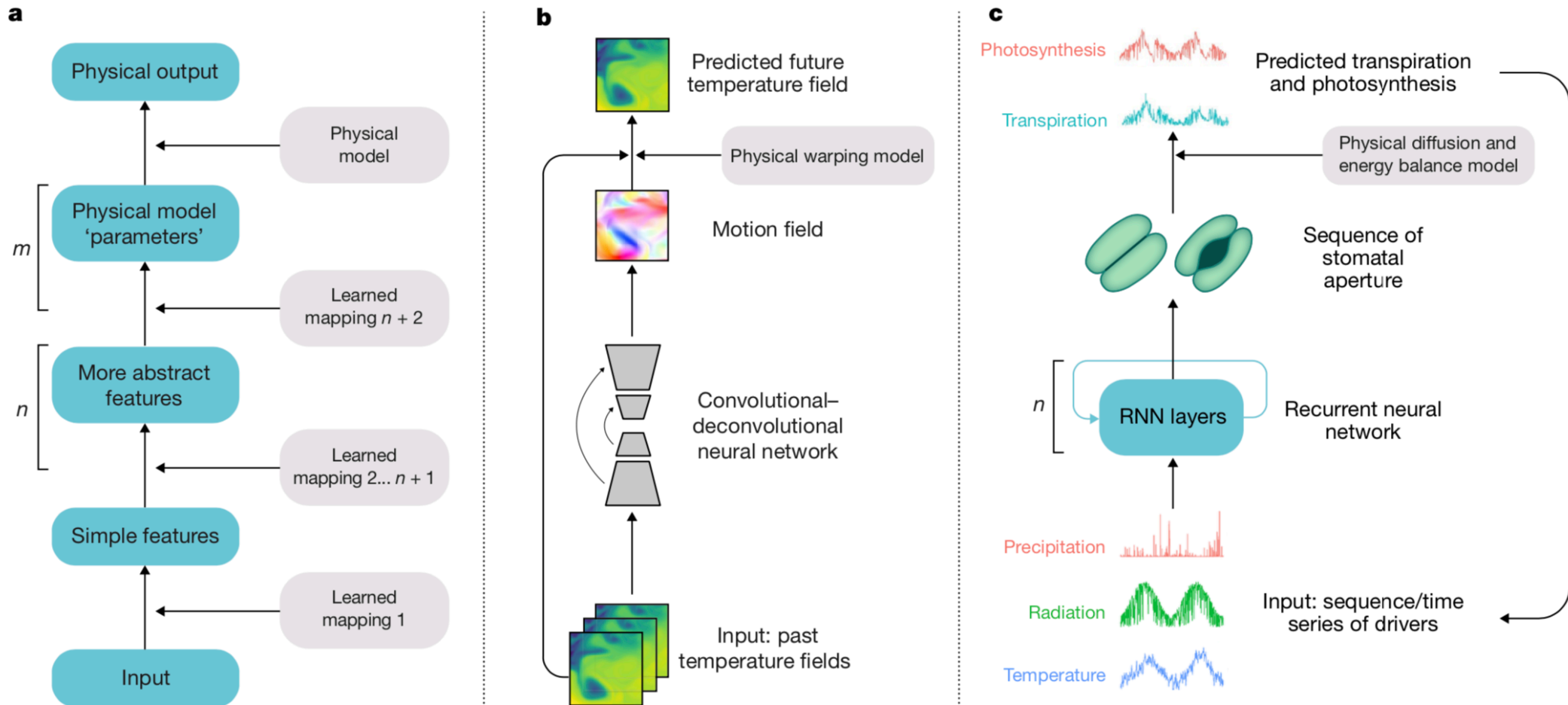
- (1) Improving parameterizations
- (2) Replacing a ‘physical’ sub-model with a machine learning model
- (3) Analysis of model–observation mismatch
- (4) Constraining submodels
- (5) Surrogate modelling or emulation

Integration with physical modelling



Linkages between physical models and machine learning.

Integration with physical modelling



Interpretation of hybrid modelling as deepening a deep learning architecture by adding one or several physical layers after the multilayer neural network to make the model more physically realistic.

Conclusion

- (1) Recognition of the particularities of the data
- (2) Plausibility and interpretability of inferences
- (3) Uncertainty estimation
- (4) Testing against complex physical models