



# Connecting Localized Geomagnetic Disturbances to the Solar Wind: A Survey of Model Architectures

Raman Mukundan<sup>1,2</sup>, Amy Keese<sup>1,2</sup>, José Marchezi<sup>2</sup>, Mike Coughlan<sup>1,2</sup>, Victor Pinto<sup>3</sup>, Don Hampton<sup>4</sup>

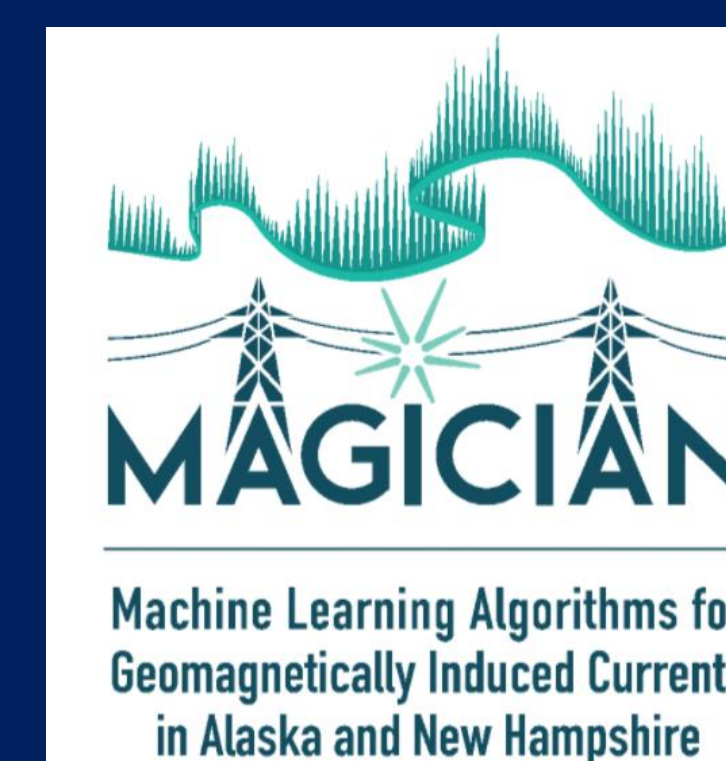
<sup>1</sup>Department of Physics and Astronomy, University of New Hampshire

<sup>2</sup>Institute for the Study of Earth, Oceans, and Space, University of New Hampshire

<sup>3</sup>Departamento de Física, Universidad de Santiago de Chile

<sup>4</sup>Geophysical Institute, University of Alaska Fairbanks  
AGU Fall Meeting 2024

SM21C-2703

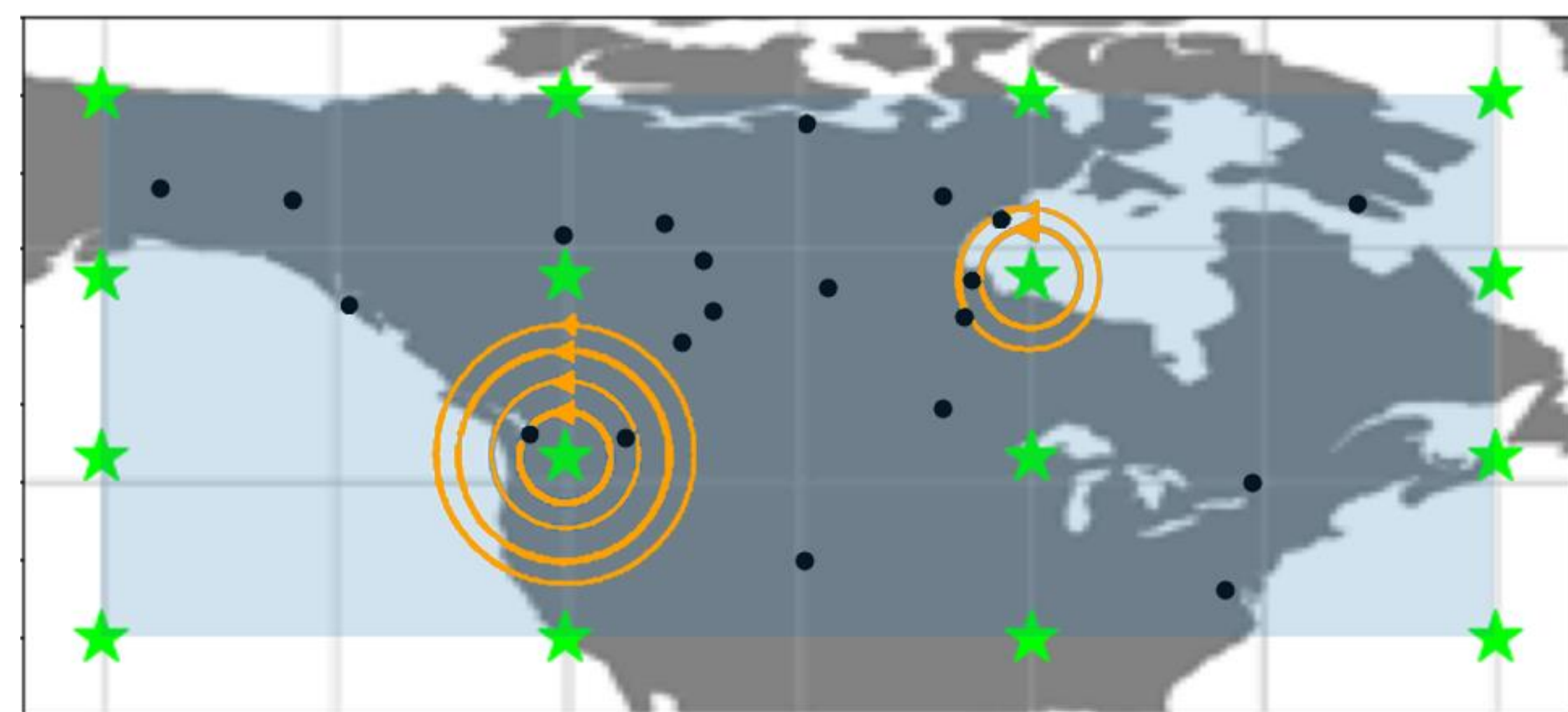


## Introduction

- ❖ The solar wind's interaction with the Earth's magnetic field can cause Geomagnetically Induced Currents (GICs), which are hazardous to power and communications infrastructure.
- ❖ Changes in the horizontal component of the ground magnetic field ( $dB_H$ ) or its time derivative are used as a proxy for GIC measurements.
- ❖ Our goal is to obtain a  $dB_H$  forecast at every point in a large region using the Spherical Elementary Current Systems interpolation technique.
- ❖ We model the physics that connect the solar wind to  $dB_H$  with a neural network and compare three different schemes for doing so. We seek either to predict Current System values or to predict the magnetic field disturbance directly.

## Mapping the Magnetic Field

- ❖ SuperMAG data from 24 North American stations with the best availability used to fit a grid of Spherical Elementary Current Systems, representing ionospheric currents.
- ❖ From these currents, we reconstruct 1-minute cadence  $dB_H$  values across the region during storm time in Solar Cycle 24 (2009-2019).
- ❖ Interpolations are validated by leaving each station out 1 by 1 and at comparing at that station's site.



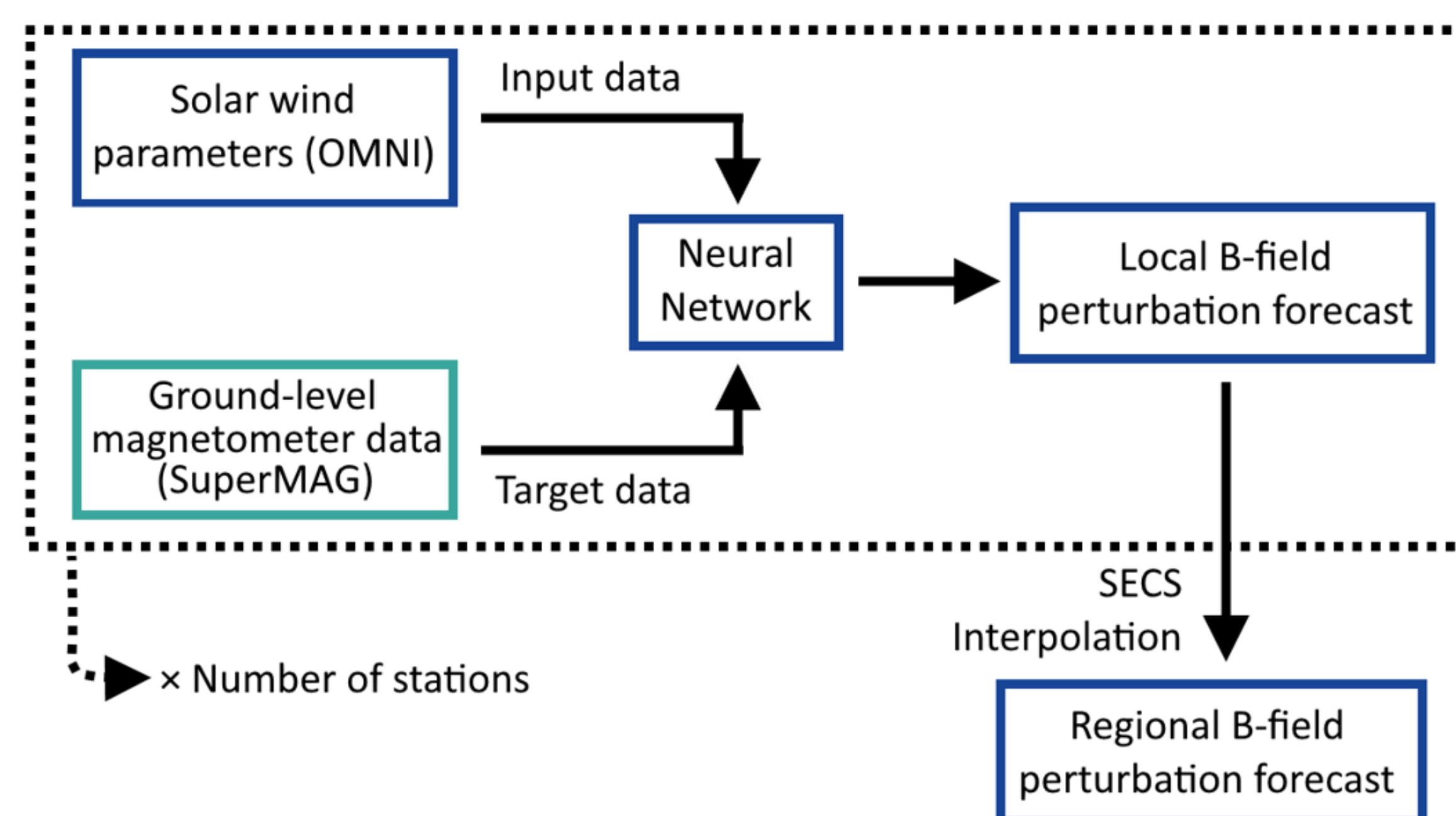
● = Magnetometer    ★ = Current System Pole  
 ← = Current Vector Field

## Acknowledgements and References

This work is supported by NSF EPSCoR T-2 Award 1920965 & NSF Award 2331527

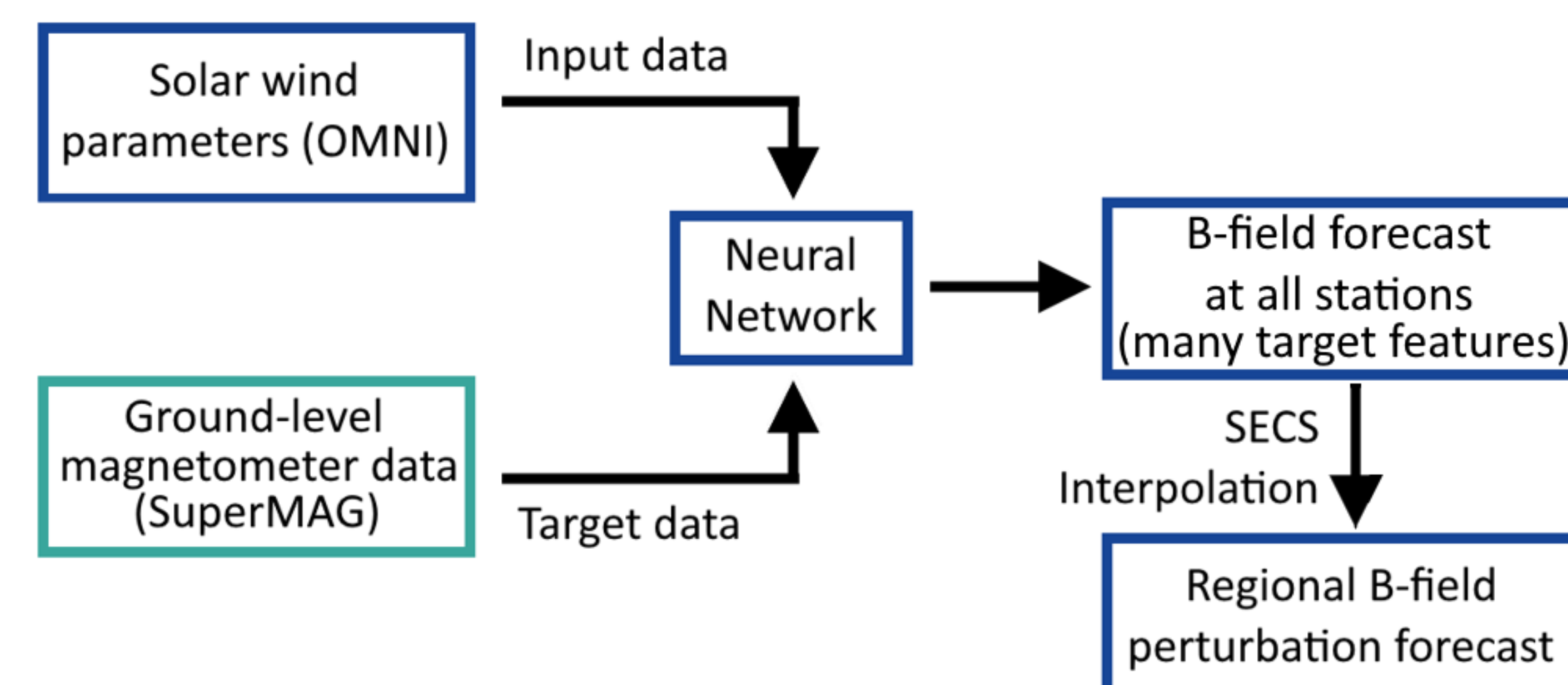
- ❖ Amm & Viljanen 1999. *Ionospheric disturbance magnetic field continuation from the ground to the ionosphere using spherical elementary current systems.*
- ❖ OMNIWeb data from [omniweb.gsfc.nasa.gov](http://omniweb.gsfc.nasa.gov)
- ❖ SuperMAG data obtained from [supermag.jhuapl.edu](http://supermag.jhuapl.edu)

## Magnetic Multi-Model Approach

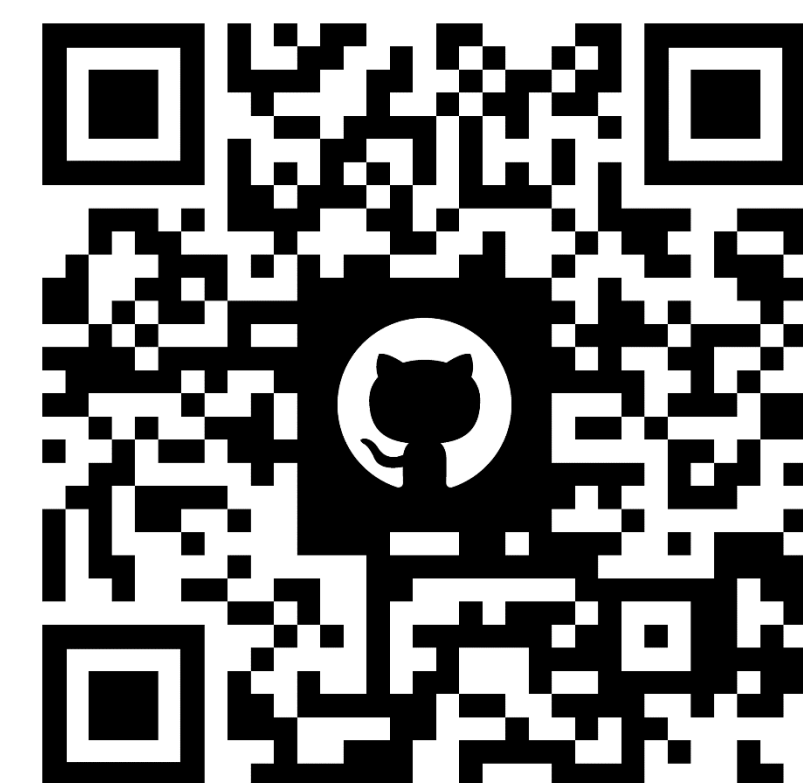


- ❖ Each of the 24 magnetometer stations has an associated convolutional neural network trained to predict only that station's measurements using 30-minute time history (similar to Pinto+ 2022; Coughlan+, 2023). Spatial interpolation is performed afterward.
- ❖ **Theoretical Advantage:** Each model has a relatively simple task, so each model needs to learn less information to maintain the same level of performance as the other approaches.

## Magnetic Multi-Target Approach



- ❖ A single convolutional neural network is trained to predict all magnetometers' measurements at once (24 target features). Spatial interpolation is performed afterward.
- ❖ **Theoretical Advantage:** Information is shared between many of the target features, so as the model learns to predict one feature, it will learn a little bit about how to predict the other features.
  - Test-set RMSE of this approach is better than the **Multi-Model** approach for every station (see bar chart)

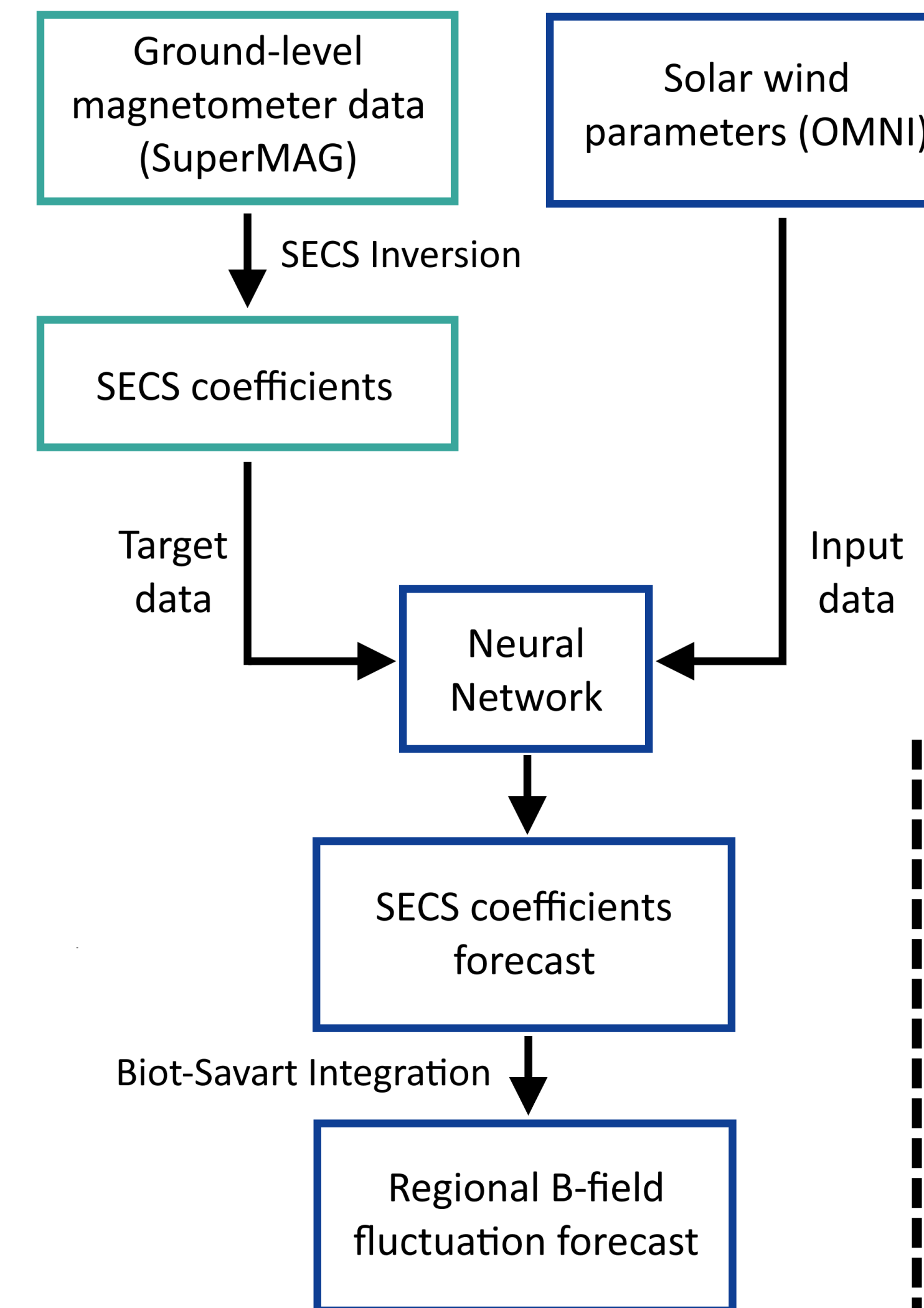


GitHub

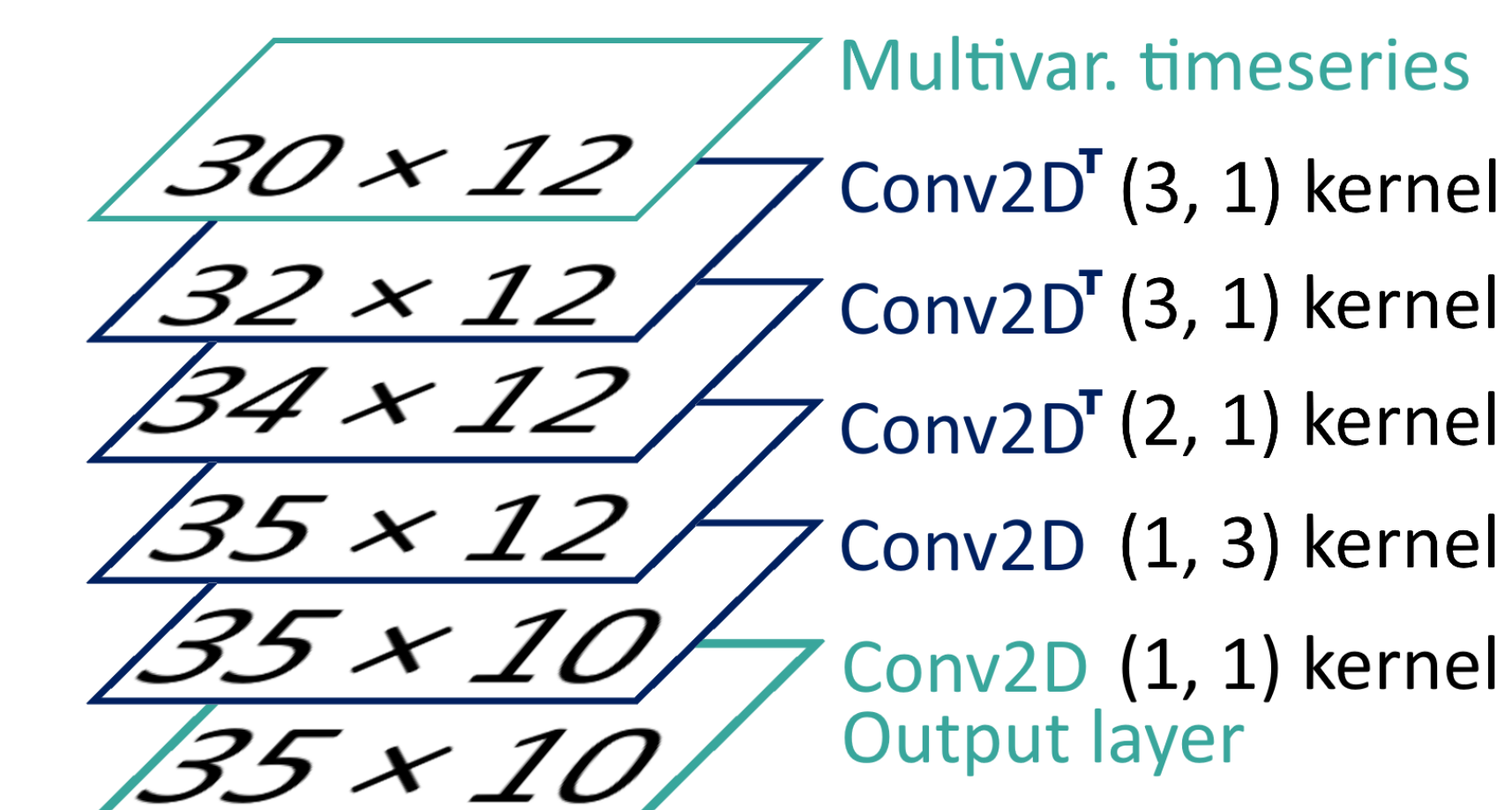


Website

## Currents Image-to-Image Approach



- ❖ Current System coefficients are predicted with a CNN to account for the relative locations of the 350 Current Systems.
- ❖ A sequence of convolutional and transpose-convolutional layers transforms a multivariate timeseries "image" into a grid of Current System coefficients.
- ❖ **Theoretical Advantage:** The ability of CNNs to account for spatial relationships is leveraged.



## Conclusions and Key Insights

- ❖ A multi-model approach to predict Current Systems is probably infeasible.
- ❖ Each magnetometer's data behave differently, so each model in the **Magnetic Multi-Model** approach should have its hyperparameters optimized separately. This was not done here because it is computationally expensive.
- ❖ Models with many output features (**Currents Image-to-Image** and **Magnetic Multi-Target**) perform much better with very low initial learning rates ( $\sim 10^{-9}$ ) with the Adam optimizer. This is because of the "spiky" nature of their associated loss landscapes.
- ❖ The best loss function for handling multiple target features is yet to be determined.
- ❖ Other architectures will be investigated, e.g. XGBoost or chained multi-target regression.

