

Reconstructing 4D Wind Fields from Radar Observations using Machine Learning

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MOTIVATION

The summer mesopause (80-90km) is home to multiple processes driving or reflecting global large scale circulations. A major characterizing quantity in this region is the turbulent dissipation rate, linked to gravity wave drag and other non-linear phenomena, which indicates how much energy is converted into turbulence (particularly relevant for the Lorentz energy cycle) opposed to secondary wave generation and mean-flow acceleration (relevant for global circulation). Due to the remoteness of the affected regions, direct

measurements are difficult and estimation of dissipation rates down to the relevant scales of kilometers so far require simplifications and approximations to accommodate sparse and incomplete data.

This work aims to combine state-of-the-art radar measurements with the machine learning approach HYPER to obtain full 4D km-scale wind fields as a basis for calculating robust estimates of turbulent dissipation rates and other governing statistics.

CONCLUSION

We propose a novel machine learning-based method for obtaining full 4D wind fields at km-scale in the summer mesopause based on line-of-sight measurements from a combination of radar systems under consideration of physics constraints.

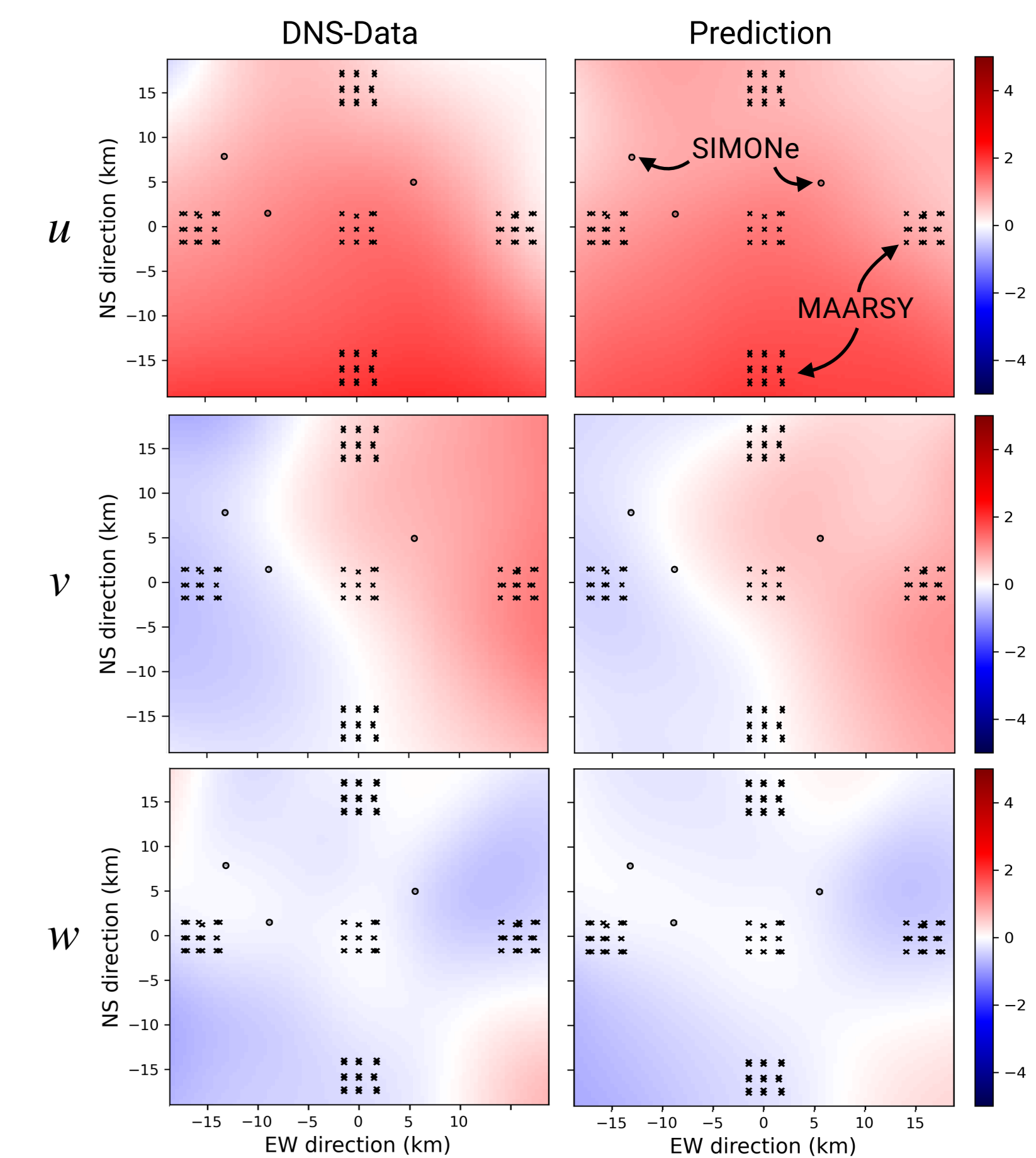
Validation on DNS simulations provide evidence for the high accuracy of the method and first tests on real data display confirm it's ability to predict high fidelity results, encouraging a followup application on an extensive one-month measuring campaign from June 2025.

VALIDATION USING VIRTUAL DNS RADAR

To ensure correctness of the algorithm we use a set of large-scale stratified turbulent DNS data with Mesosphere-like conditions [2] and virtual radar implementations of MAARSY and SIMONE systems.

Key Findings

- Combining data from different radar systems is key. MAARSY alone is not able to reproduce horizontal components, but adding SIMONE inputs provides sufficient guidance to fix horizontal winds, even with few, more sparsely distributed datapoints
- Gaps between beams with no data can be accurately inferred through physics constraints.



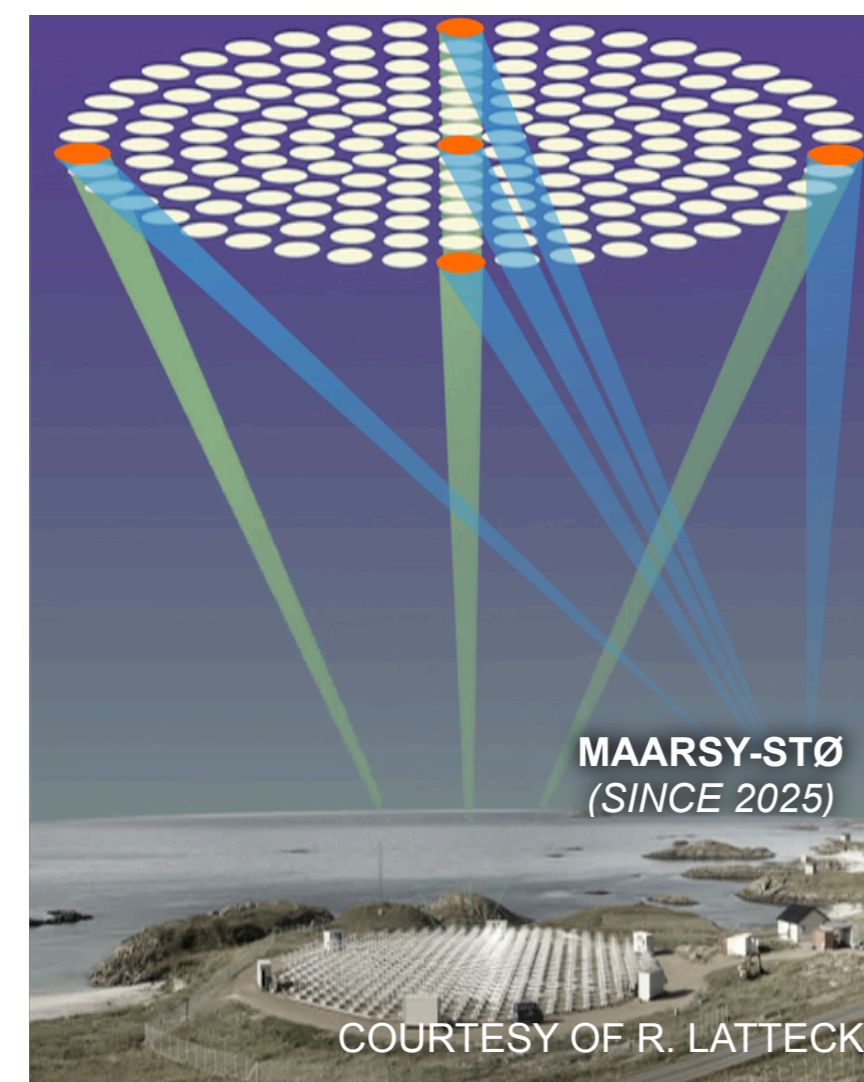
RADAR MEASUREMENTS OF THE MESOSPHERE

MAARSY RADAR SYSTEM

A radar array with 433 antennas in Andøya, Norway (69.3°N,16.0°E) and a secondary receiver in Stø (69.0°N,15.0°E) with a frequency of 53.5 MHz. Among other targets it can detect ice particles associated with polar mesospheric summer echoes.

Pros: High resolution coverage of vertical winds (~1-10km)

Cons: Suboptimal coverage of horizontal winds, small measuring domain (~40km width)

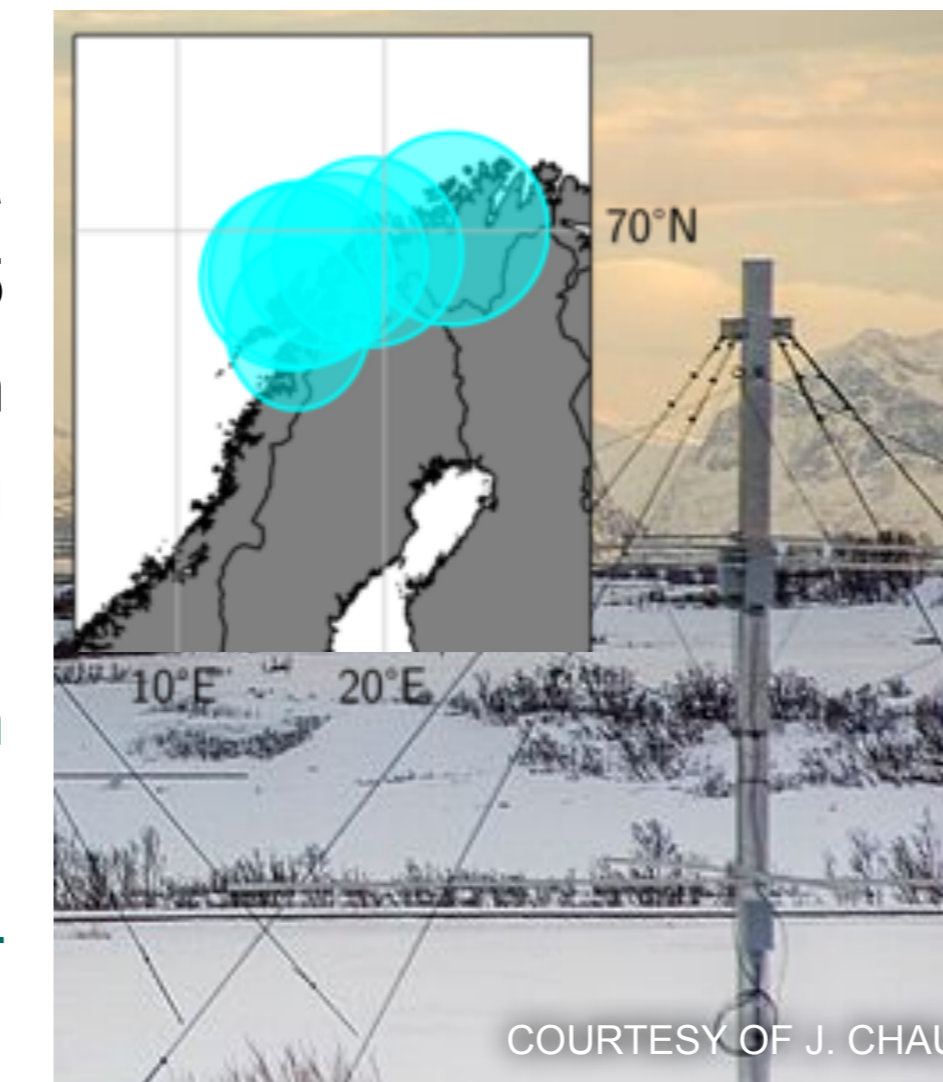


SIMONE RADAR NETWORK

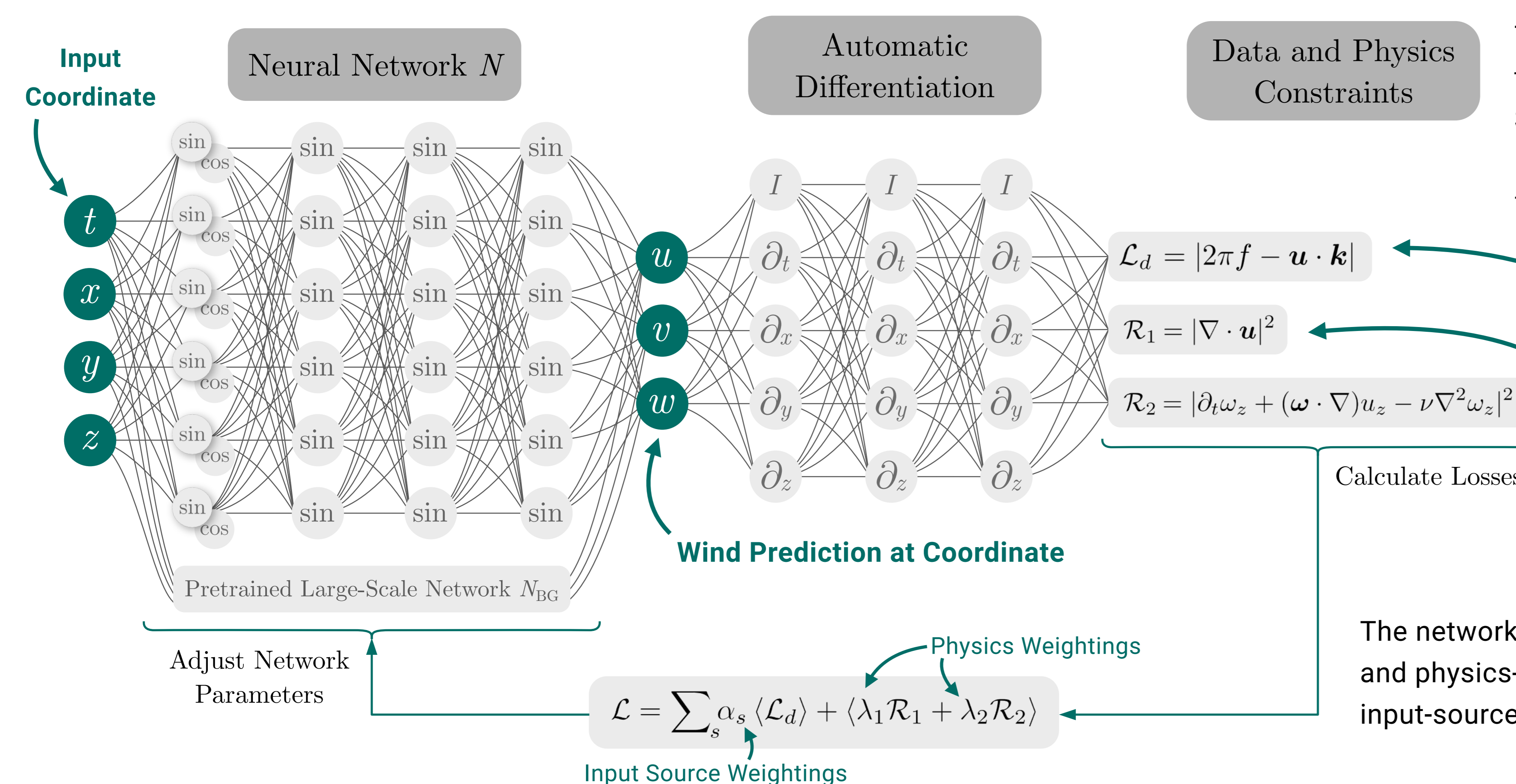
A multi-station radar network in Norway, covering a region of 400km diameter with a frequency of 32.55 MHz. It's main detection mechanism is observation of ionized plasma trails from tiny meteors entering the Mesosphere.

Pros: Good coverage of horizontal winds from multiple angles in a large area

Cons: Suboptimal coverage of vertical winds, lower resolution (~10-100km)



PREDICTING 4D WIND FIELDS - MACHINE LEARNING SETUP "HYPER"



To obtain complete 3D wind-vectors at km-scale from the varied line-of-sight measurements of MAARSY and SIMONE we employ a combination of neural networks to learn a smooth representation of the underlying wind fields in the given domain [1].

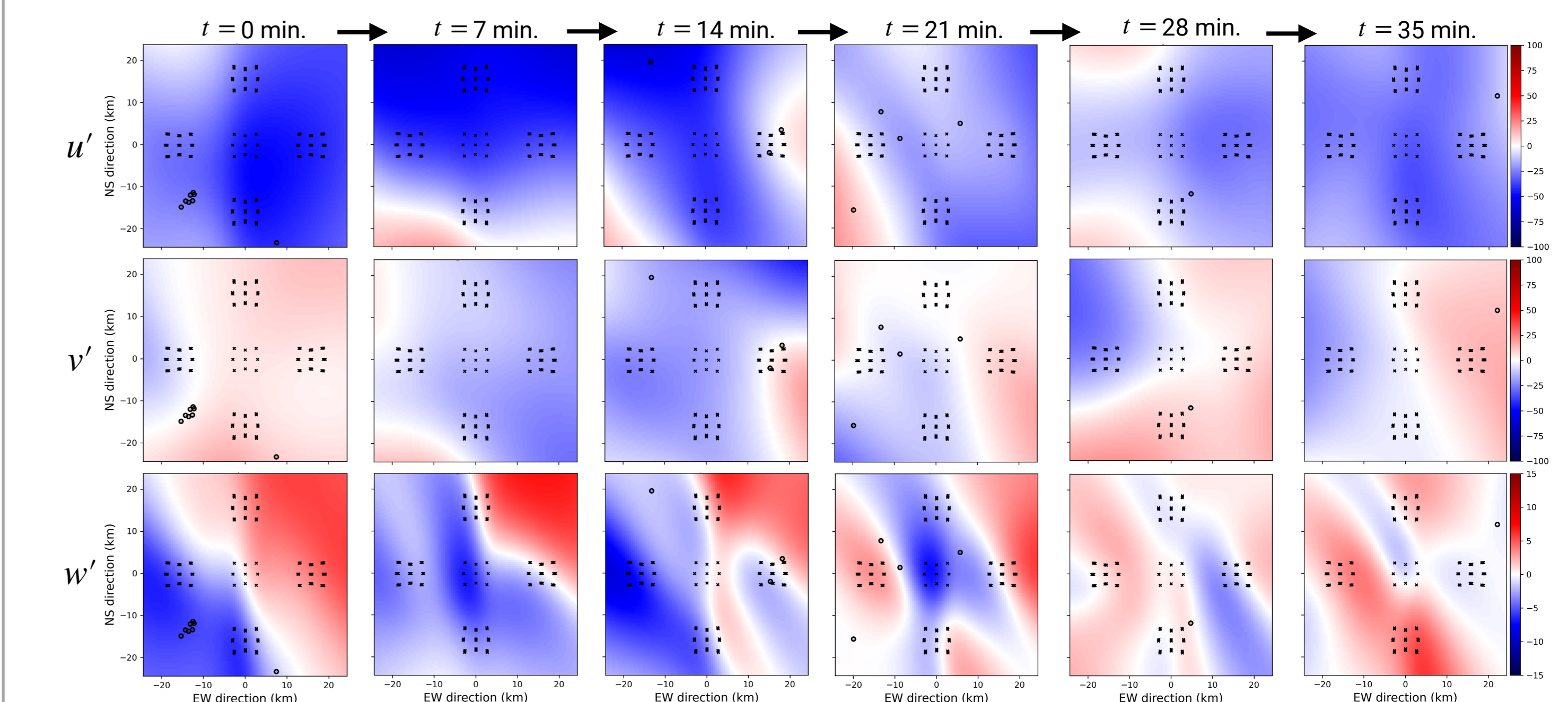
Training Objectives

- Match of radar-measured projected line-of-sight velocities given by doppler velocities and k-vector at the associated measurement points
- Adherence to physics constraints enforced in the entire prediction domain (not only at the individual measurement points). This allows to close the gaps between measurement points in a physically coherent way

The network is trained by minimizing the combined objective of data and physics-constraints with tuned weighting coefficient for different input-sources (i.e. different radars) and physics contributions.

APPLICATION ON REAL DATA

Using real measurements from MAARSY and SIMONE, the algorithm produces full 4D fields with km-scale resolution that are smooth, physically plausible and match the observations. The results naturally retain some limitations of the underlying data, namely horizontal coverage of about ~50km diameter and an effective horizontal resolution of ~1-10km. Given these constraints, the residual fields below show that the algorithm is able to predict high fidelity structures on small timescales in all components.



[1] Urco et al. (2024). JGR: Machine Learning and Computation
[2] Alexakis et al. (2024). Science

