Are observations all you need?

End-to-end forecasting from observations with **GraphDOP**

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ECMWF

Physics based NWP

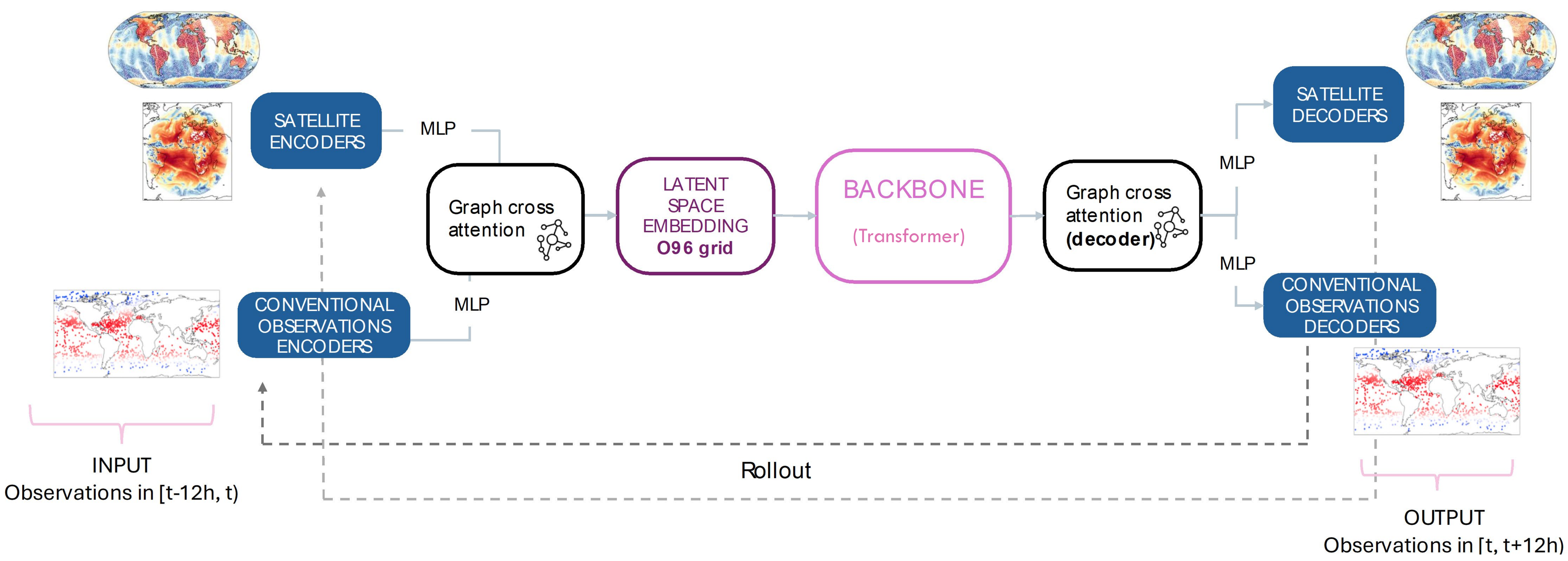
- Models have evolved to ever higher spatial resolution and levels of complexity (e.g. Destination Earth)
- Leads to challenges for Data Assimilation to provide initial conditions with sufficient detail and accuracy

Machine learned NWP

- Data-driven systems trained on NWP (re)analysis have demonstrated very accurate forecasts
- Will they one day hit a skill-ceiling limited by the training datasets?

Currently ML models cannot exist independently from the physics-based systems
Could we learn forecasts directly from observations?

GraphDOP is an end-to-end graph neural-network forecast system developed at ECMWF that is **trained and initialised exclusively from Earth System observations** with **no physics-based (re)analysis inputs** or feedbacks.
It learns the **correlations** between **observed quantities** (satellites) **and geophysical quantities** of interest (conventional observations), to form a coherent latent representation of Earth System state dynamics and physical processes.
It can then produce **gridded and global** forecasts.

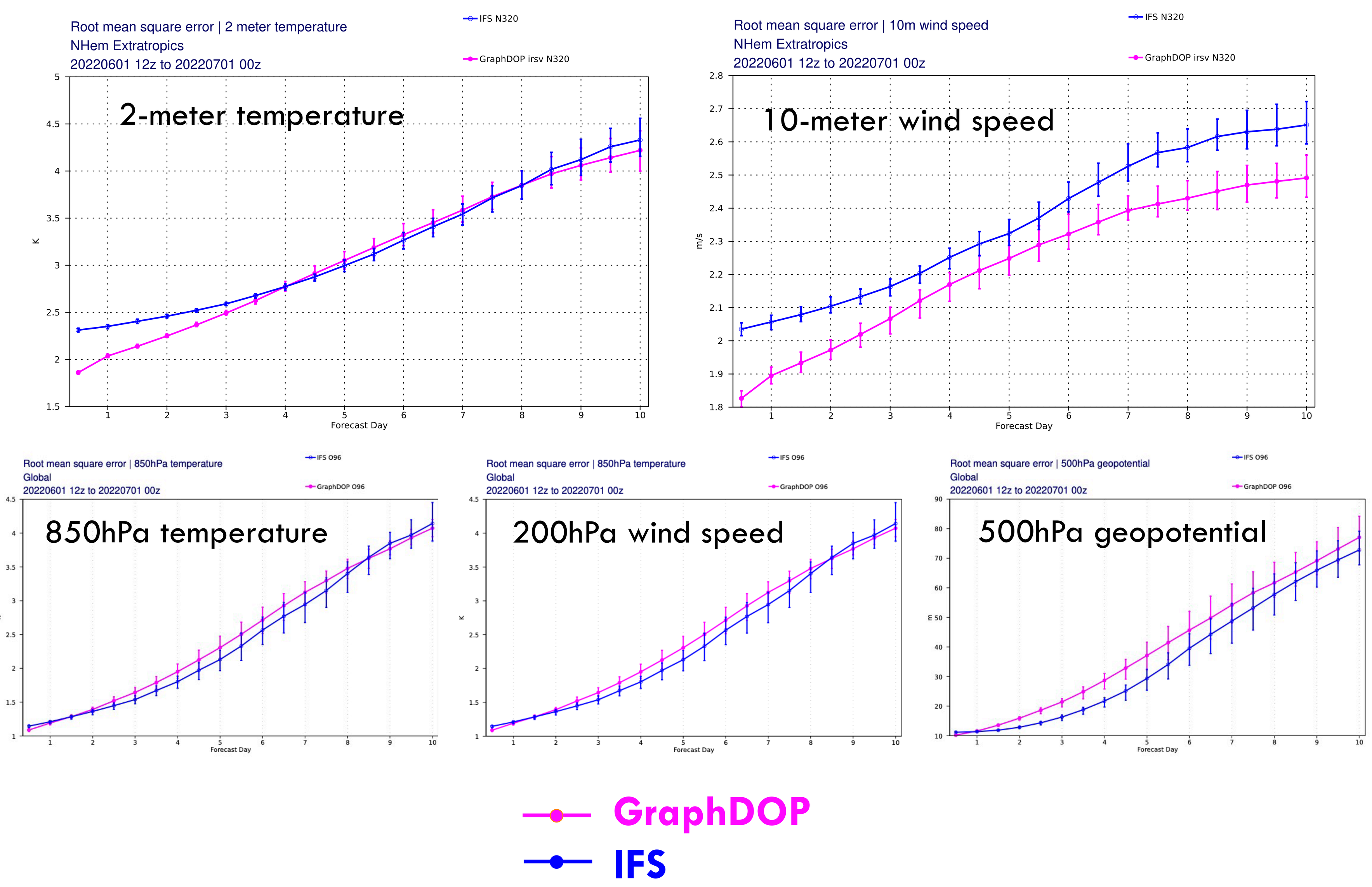


Encoder/decoder graphs project observations in a window onto and out of the latent space. Graphs are created **on the fly** to accommodate satellite observations

Processor is **a transformer** with **windowed attention** and is responsible for advancing the latent atmospheric state representation forward in time

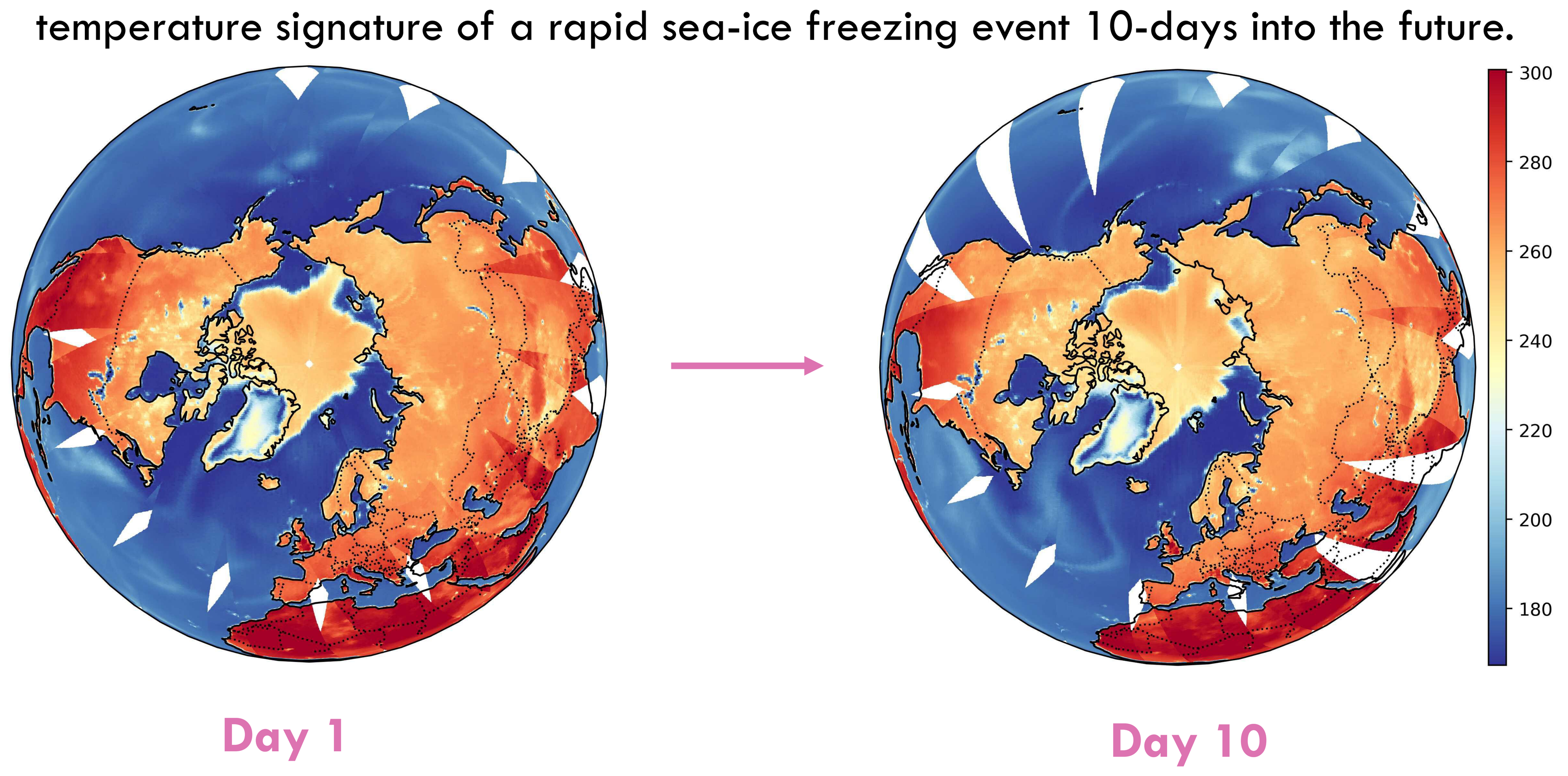
Evaluation of global forecasts

RMSE against observations



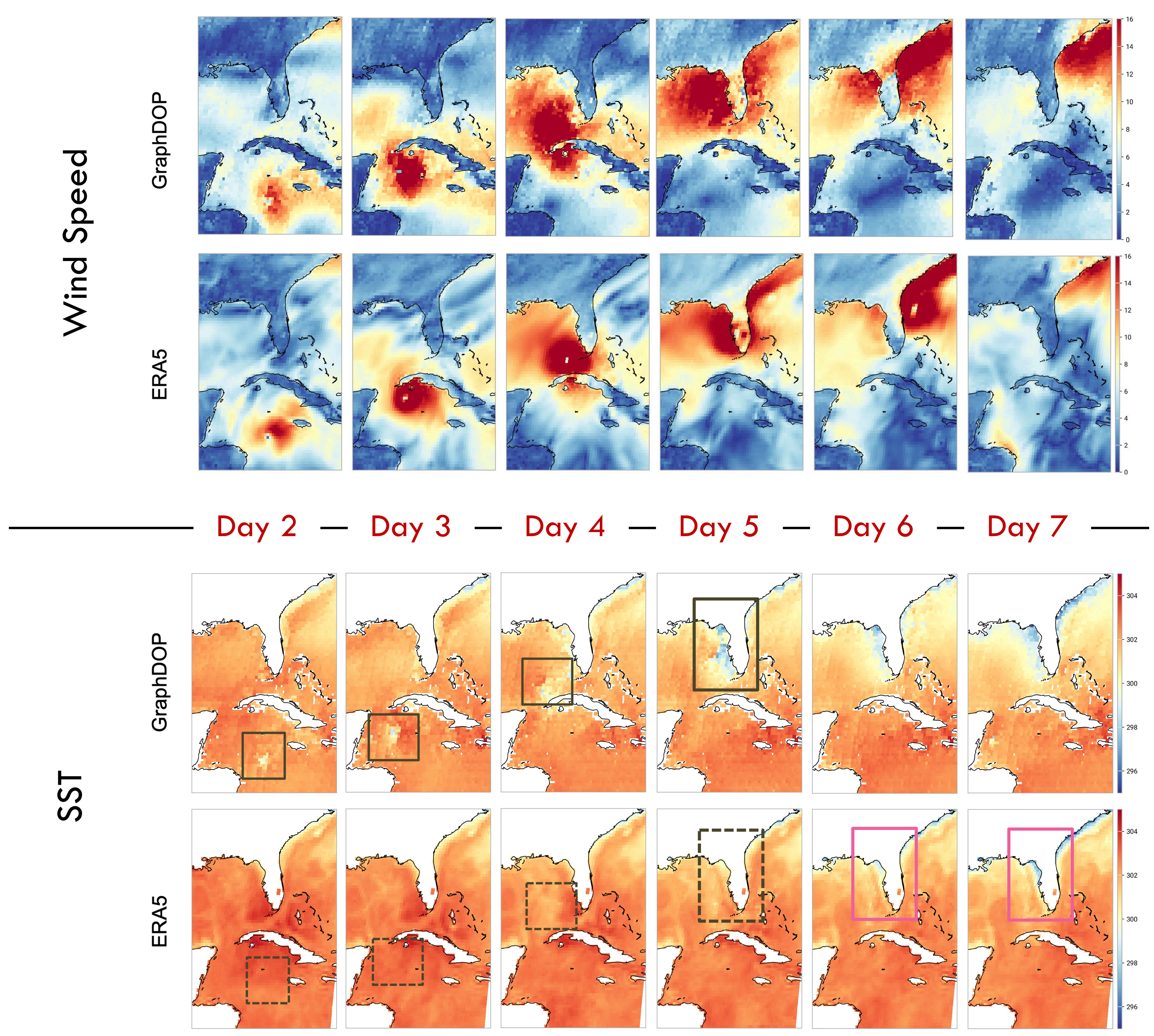
Forecasts of a late-season rapid freezing event

A GraphDOP forecast initialised on Oct 20, 2022, correctly forecasted the brightness temperature signature of a rapid sea-ice freezing event 10-days into the future.



Hurricane Ian forecasts

GraphDOP produces **consistent** forecasts across different Earth System Components. Here are shown the **wind speed** and **sea surface temperature** forecasts produced.



Read more on GraphDOP

Alexe, M., Boucher, E., Lean, P., Pinnington, E., Laloyaux, P., McNally, A. et al. (2024). **GraphDOP: Towards skilful data-driven medium-range weather forecasts learnt and initialised directly from observations.** *arXiv preprint arXiv:2412.15687*

Lean, P., Alexe, M., Boucher, E., Pinnington, E., Lang, S., Laloyaux, P., Bormann, N. McNally, A. (2025). **Learning from nature: insights into GraphDOP's representations of the Earth System**. *arXiv preprint arXiv:2508.18018*.

Boucher, E., Alexe, M., Lean, P., Pinnington, E., Lang, S., Laloyaux, P., Zampieri, L., De Rosnay, P., Bormann, N., McNally, A. (2025). **Learning Coupled Earth System Dynamics with GraphDOP.** *arXiv preprint arXiv:2510.20416*.

Laloyaux, P., Alexe, M., Boucher, E., Lean, P., Pinnington, E., Lang, S., Necker, T. McNally, A. (2025). **Using Data Assimilation Tools to Dissect GraphDOP**. *arXiv preprint arXiv:2510.27388*.