OCELOT : Observation Centric Estimation and Learning for Outlook Trajectories

Direct forecasts from observations

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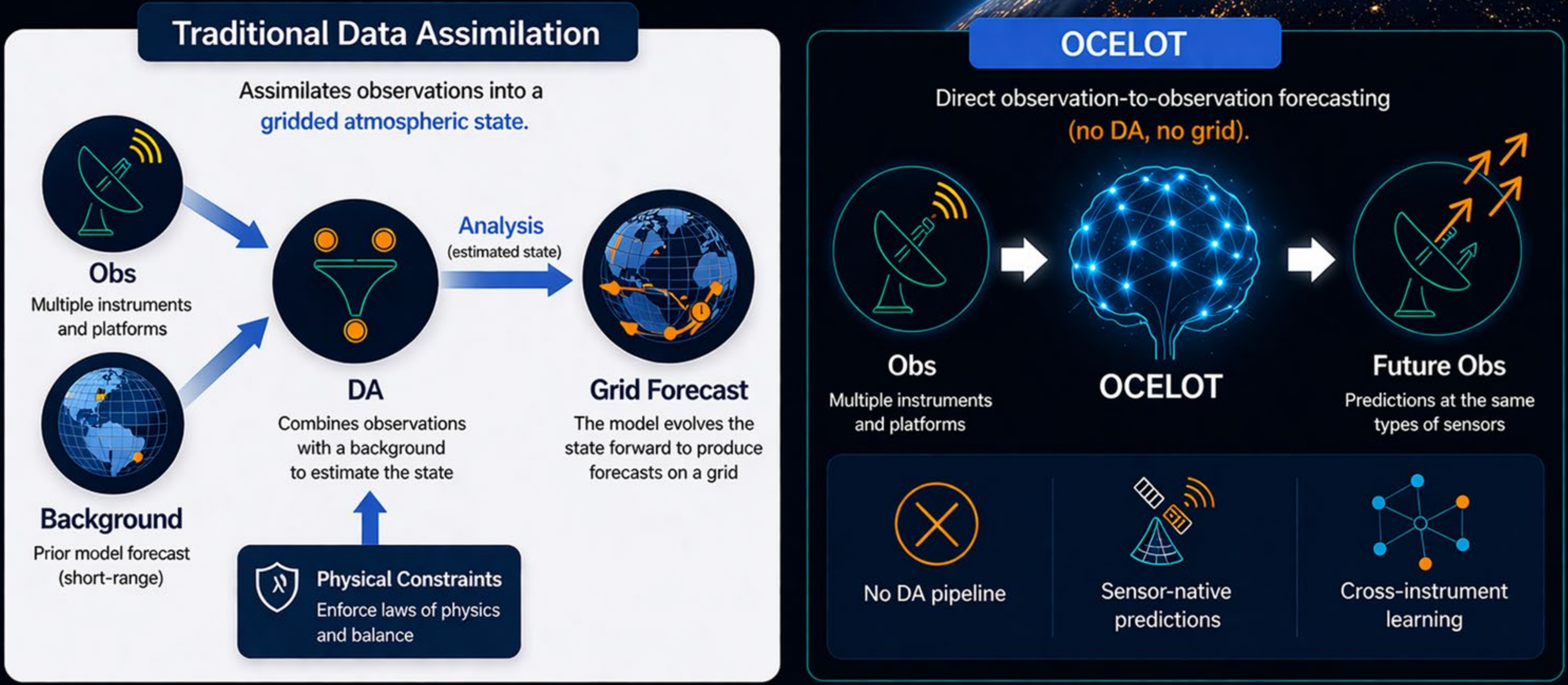
Forecasting Directly in Observation Space

OCELOT bypasses data assimilation to forecast directly from observations.



From Observations to a Learned Global State

Why Observation Space Is Hard

OCELOT is designed to embrace the complexity

CHALLENGES		OCELOT SOLUTIONS
Multi-instrument heterogeneity	→	Shared latent state
Irregular spatial sampling	→	Graph aggregation
Sensor-specific geometry	→	Geometry-aware decoding
Channel-dependent behavior	→	Per-channel modeling
Missing data / QC variability	→	Masking + robust loss
No natural grid	→	Mesh representation (no grid)

Each challenge is **built into the model design.**

OCELOT Architecture: From Observations to Forecasts

A modular system for multi-instrument forecasting

MESH OPTIONS

Icosahedral Mesh
(GraphCast-style)

Hierarchical Multi-Mesh
(U-Net-style)

Shared Global State
(Latent Mesh)

Encoder
Handles heterogeneity & irregular sampling

ENCODER OPTIONS

Graph Attention Network (GAT)
Map multi-instrument observations to the latent mesh

Interaction Network (GraphCast-style)
Learn physical interactions between instruments and locations

Satellites · Radiosondes · Aircraft · Surface

Instrument-specific modules preserve unique characteristics

Mesh Processor
Handles spatial structure (no grid)

OPTIONS FOR LEARNING GLOBAL DYNAMICS

Interaction Network
(GraphCast-style)

Sliding Window Transformer
(temporal)

Hybrid
(retrieved graph + attention)

Captures spatio-temporal patterns with global message passing

Decoder
Handles sensor geometry & prediction

DECODER OPTIONS

Graph Attention Network (GAT)
Decode latent mesh to observation space

Interaction Network (GraphCast-style)
Learn physical interactions for accurate predictions

CONDITIONED ON

Location (where)
Time (when)
Sensor (how)

Sensor-conditioned outputs
(e.g., scan angle, pressure level)

Key Idea: Flexible components. Shared latent space. Physics-aware by design. Tailored to both the data and the dynamics.

Heterogeneous Graph Representation

NODES

Mesh Nodes
Global latent state (shared mesh)

Input Observations
Multi-instrument observations

Target Query Nodes
Query locations for predictions

EDGES (MESSAGE PASSING)

obs → mesh
Local spatial encoding of observations

mesh ↔ mesh
Global propagation of information

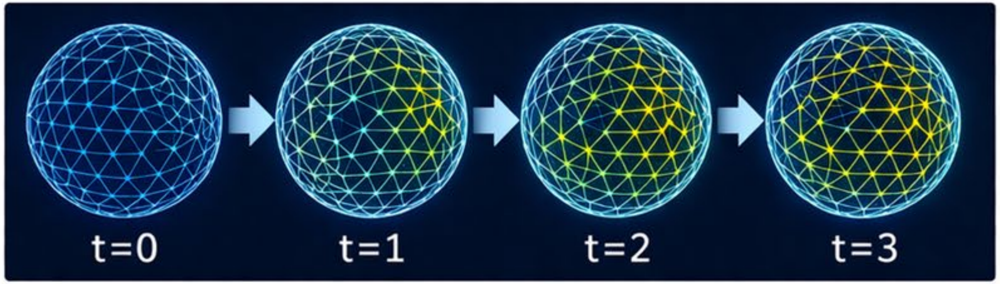
mesh → target
Query-based decoding for predictions

Temporal Modeling in Latent Space

Dynamics are learned in latent space—not in observation space

Mechanism

- Sliding-window transformer on mesh states
- Latent rollout across forecast steps
- Graph + attention for spatio-temporal mixing

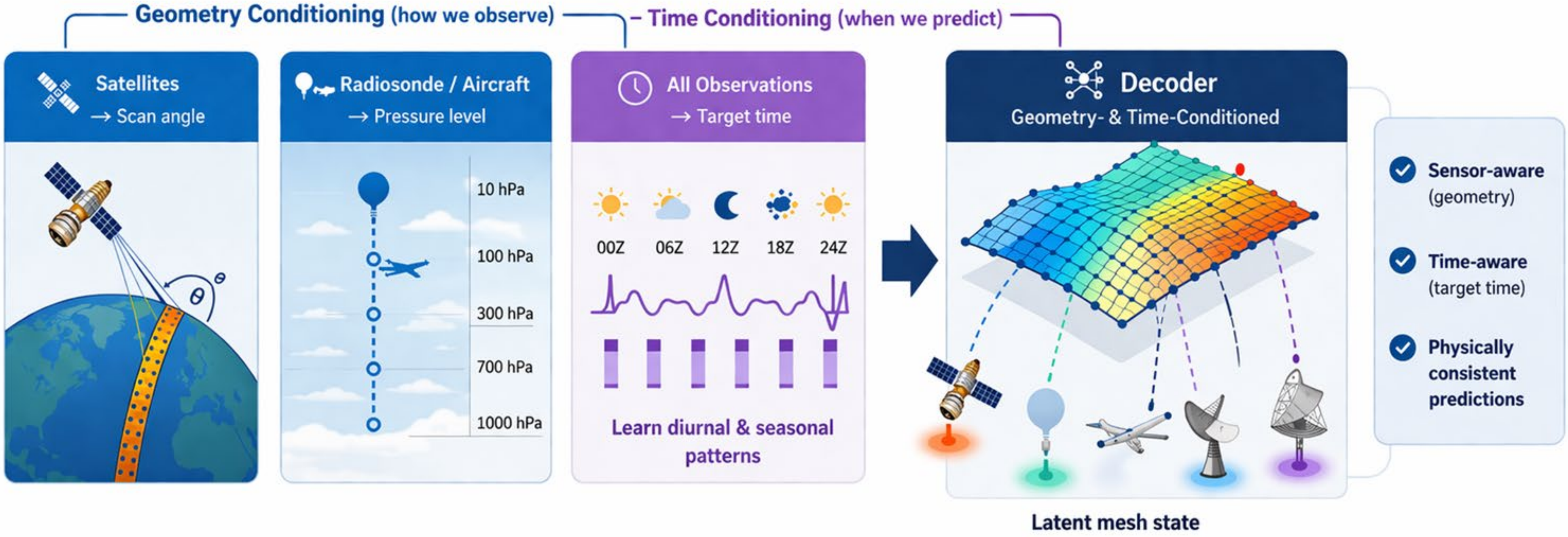


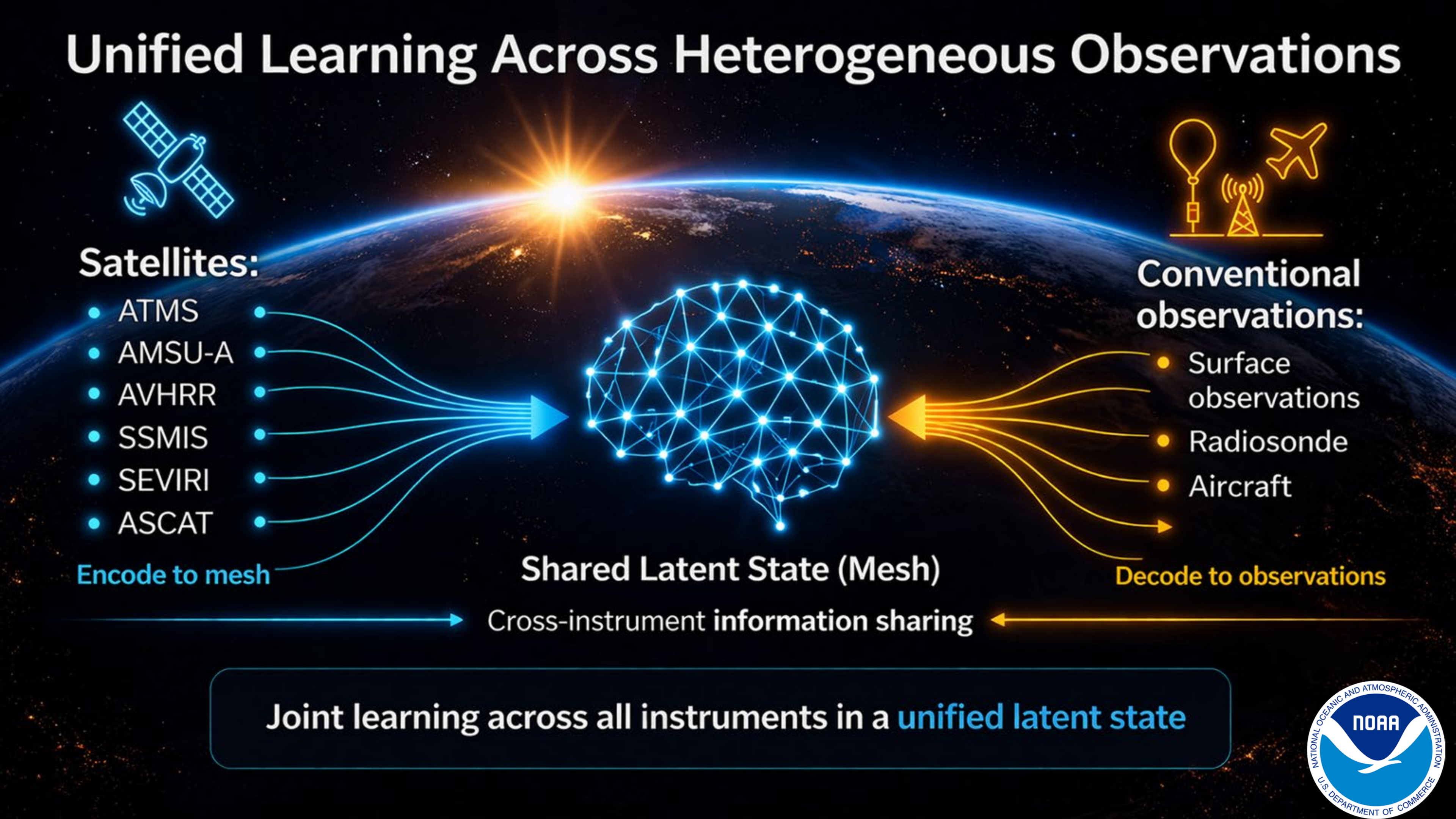
*Latent state evolving on a **fixed** mesh*

Enables stable multi-step forecasting without explicit physics models.

Geometry- and Time-Conditioned Decoding

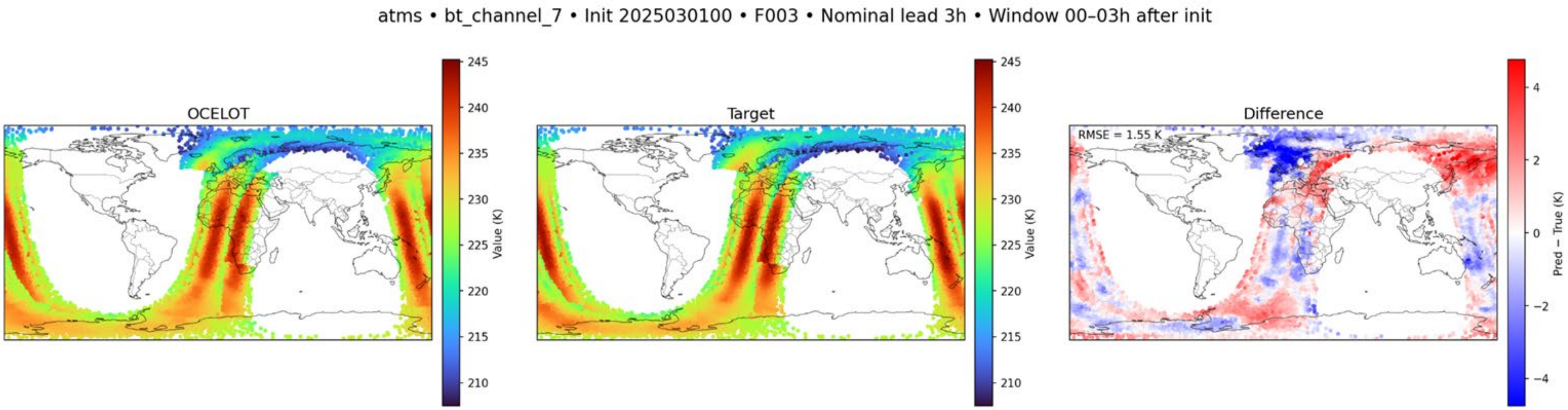
Making predictions that respect how, where, and when we observe




Unified Learning Across Heterogeneous Observations
Satellites:
ATMS
AMSU-A
AVHRR
SSMIS
SEVIRI
ASCAT
Encode to mesh
Conventional observations:
Surface observations
Radiosonde
Aircraft
Decode to observations
Shared Latent State (Mesh)
Cross-instrument information sharing
Joint learning across all instruments in a unified latent state
NOAA
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
U.S. DEPARTMENT OF COMMERCE

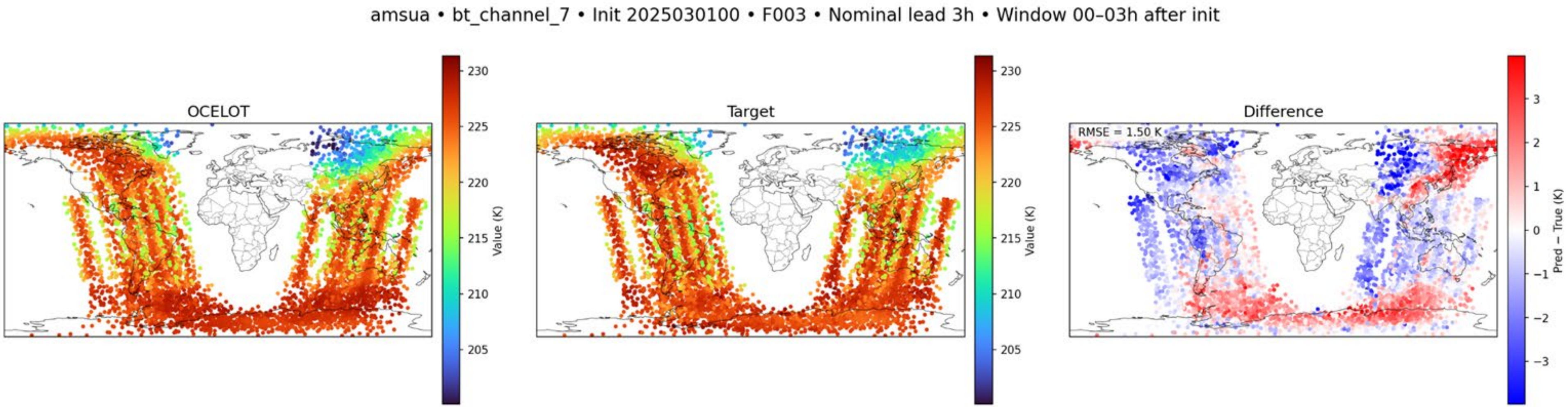
Example Satellite Results — ATMS

Channel 7 | lead 3 hour



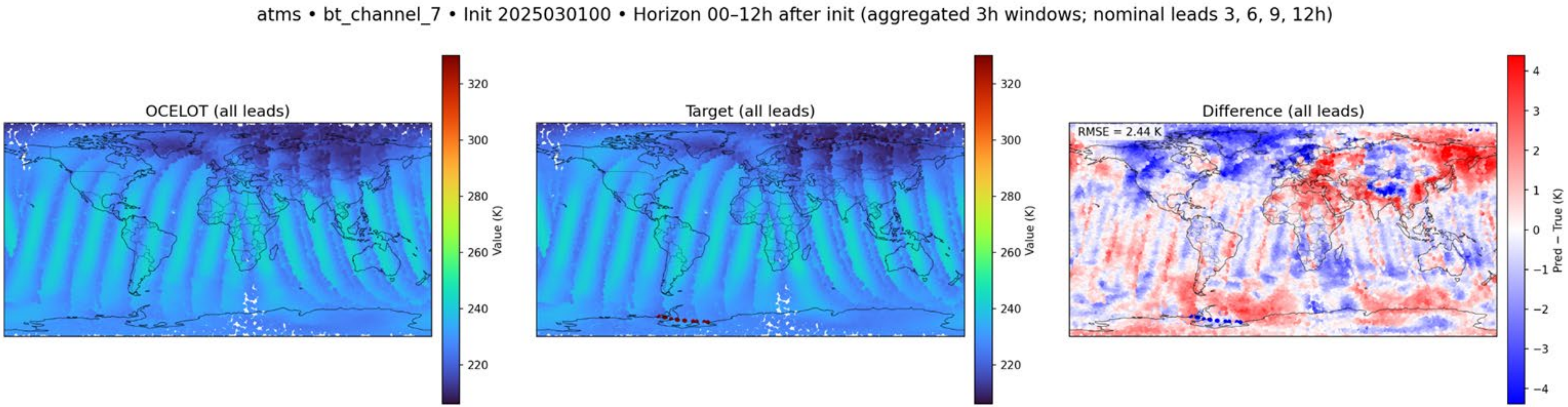
Example Satellite Results — AMSU-A

Channel 7 | lead 3 hour



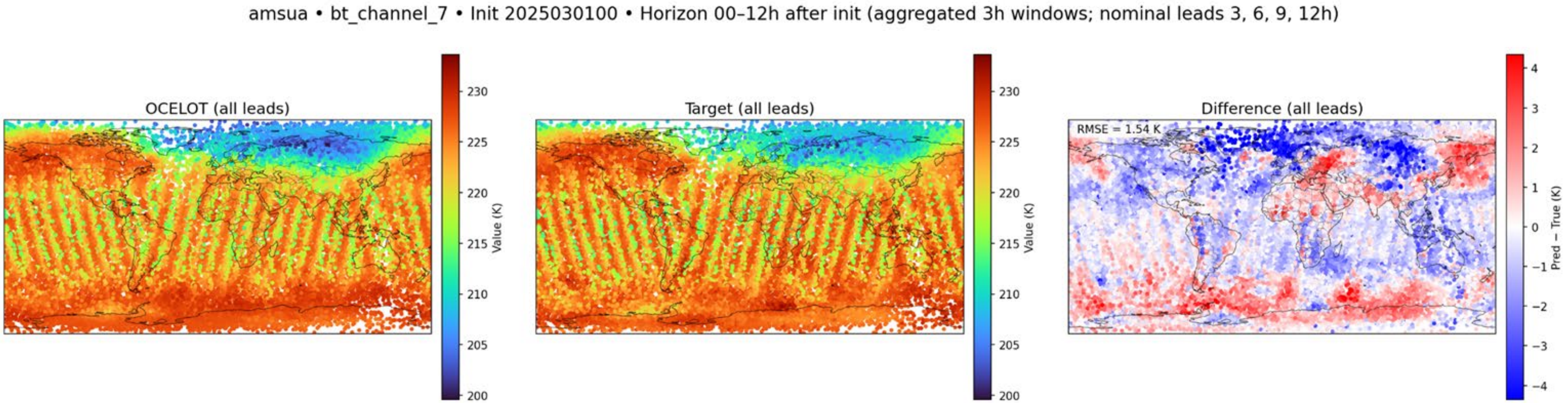
Multi-step Forecast— ATMS

Channel 7 | lead 12 hour

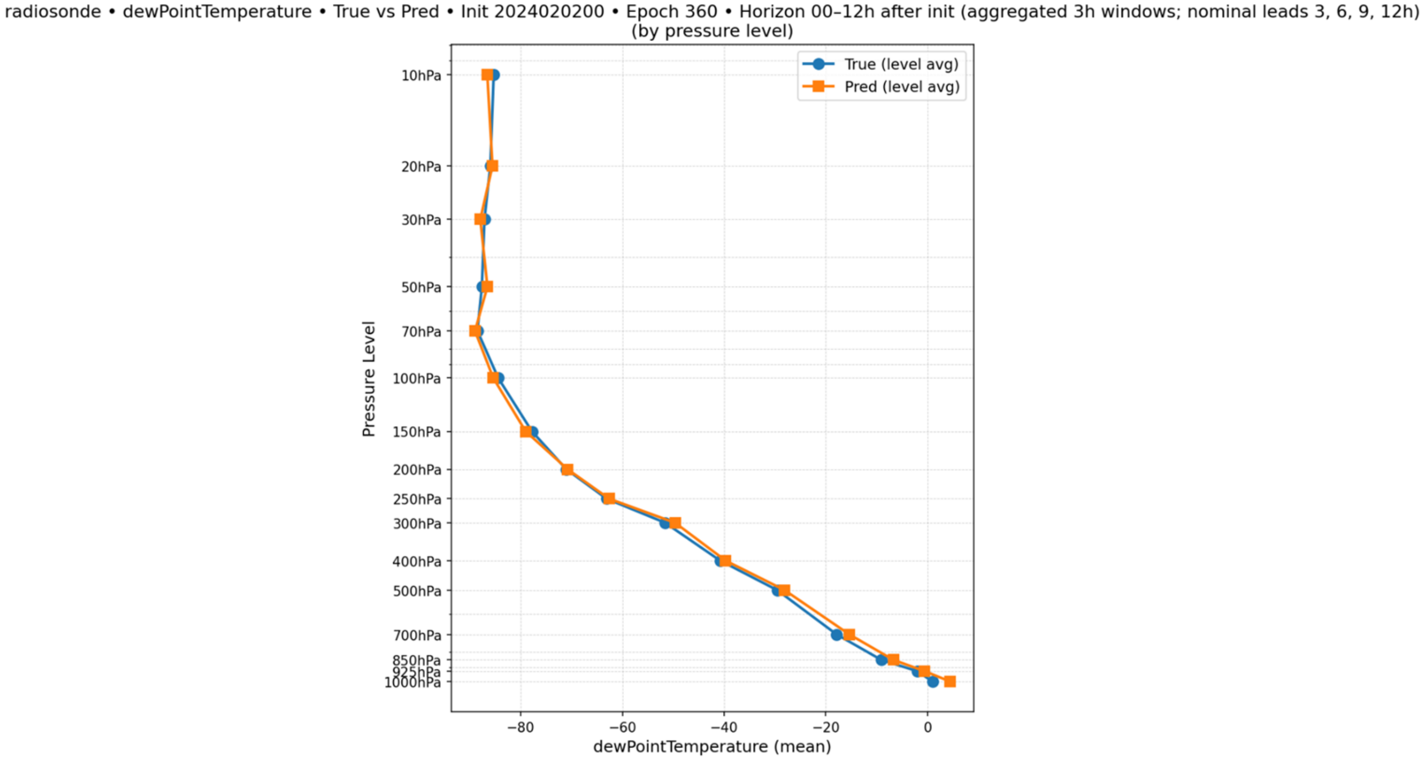


Multi-step Forecast— AMSU-A

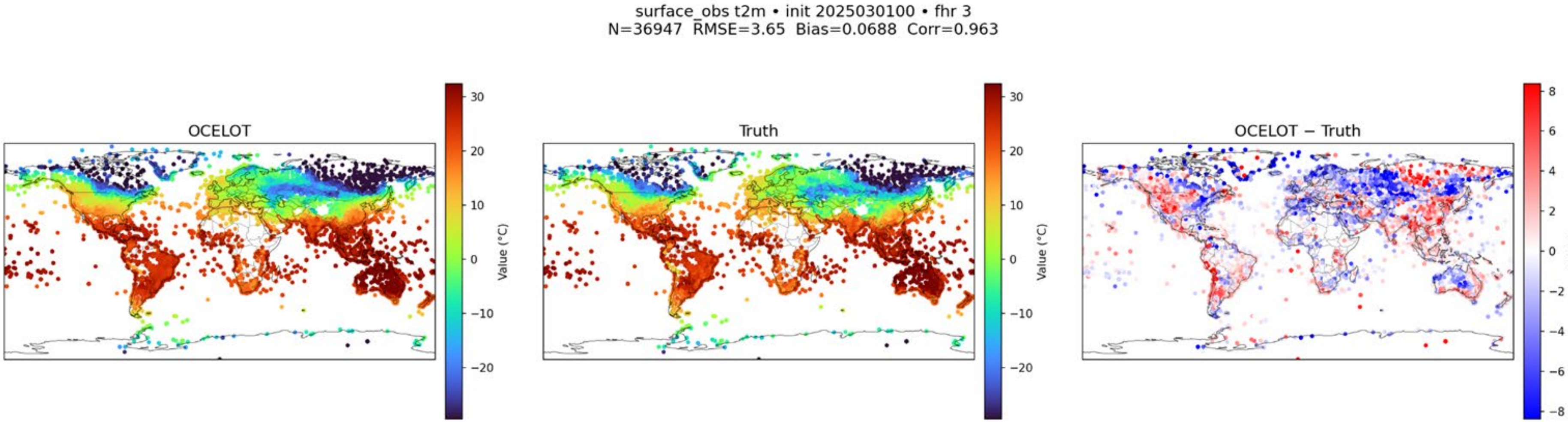
Channel 7 | lead 12 hour



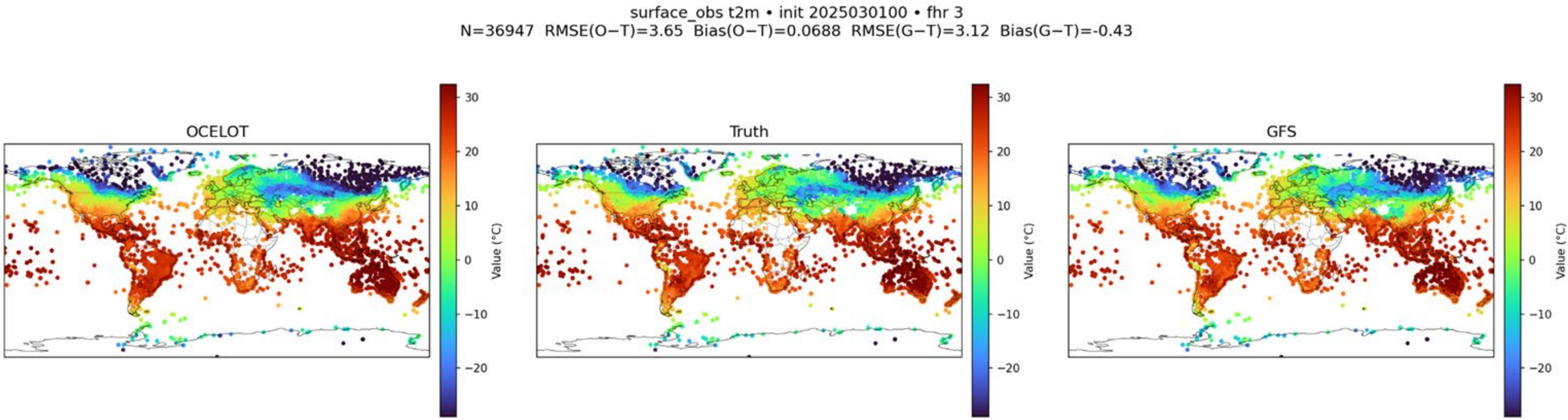
Example Conventional Results: Radiosonde Dew point temperature



Observation-Space Evaluation: OCELOT vs Truth

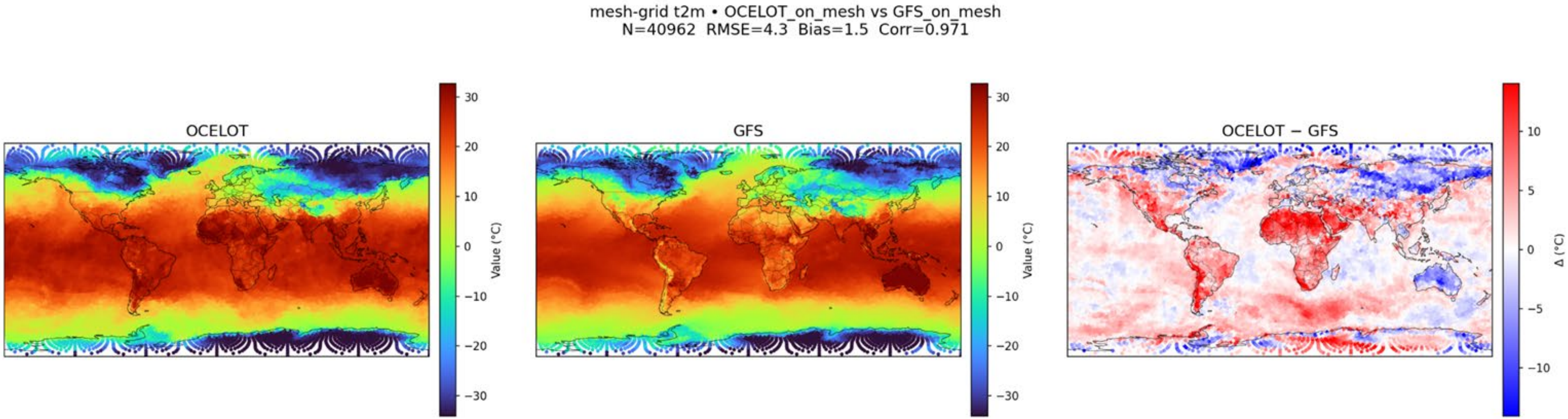


Observation-Space Evaluation: OCELOT vs Truth vs GFS



Comparison on Mesh (OCELOT vs GFS)

GFS interpolated to OCELOT mesh



AI-Based Forecast Sensitivity to Observations (FSOI)

What is FSOI?

Quantifies how each observation affects forecast error.

$FSOI(k)=\delta x(k)\cdot(g_a(k)+g_b(k))$

Computed via backpropagation (autograd), no explicit adjoint model

Where:

- $\delta x = xa - xb$ (innovation)
- g_a, g_b = gradients of forecast error
- Negative = **beneficial**
- Positive = **detrimental**

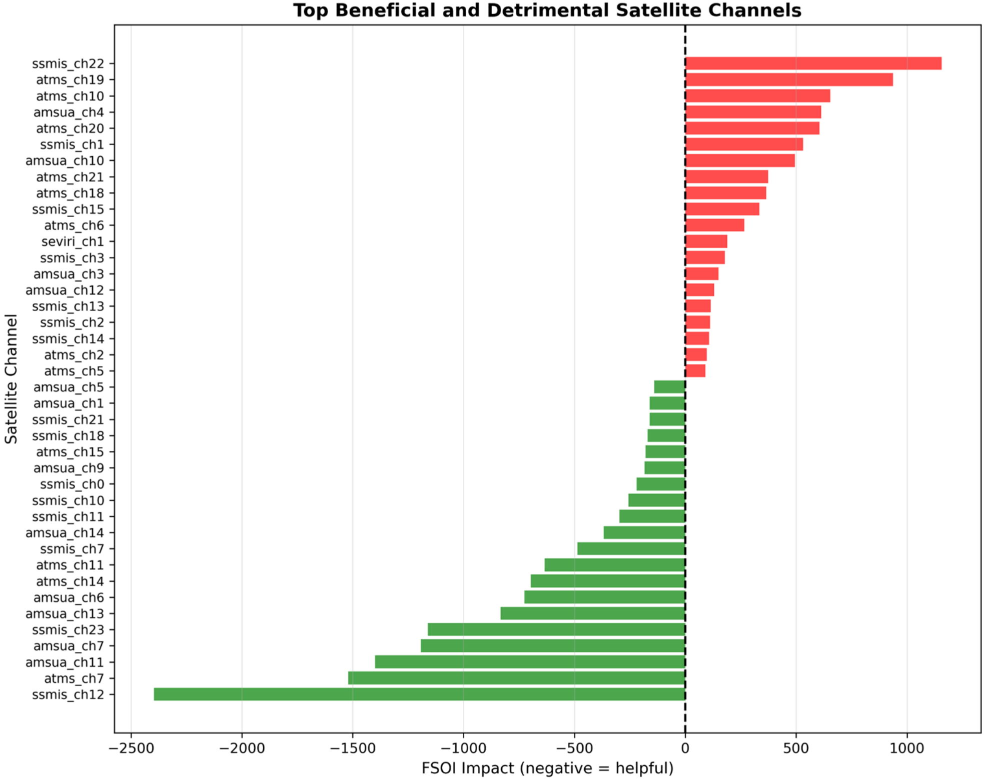
Top Beneficial & Detrimental Channels

Preliminary results — model still under development

Channel-Level Impact

Key Findings:

- Clear separation between beneficial and detrimental channels (consistent signal)
- Strong beneficial impacts from:
  - ATMS Ch7
  - AMSUA Ch11
  - SSMIS Ch12
- Some channels show consistent detrimental impact

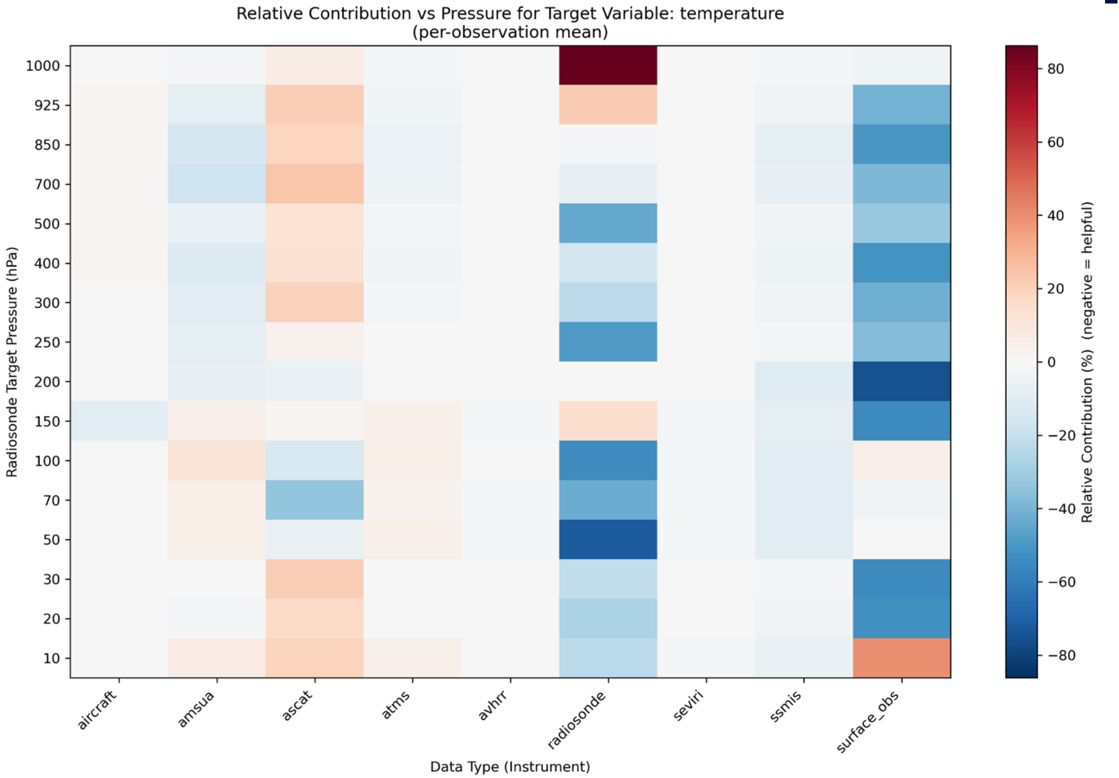


Pressure × Instrument Heatmap (Radiosonde Temperature Target)

Relative contribution (negative = beneficial)

Vertical Impact Structure

- **FSOI is not just telling us which observations matter — but where in the atmosphere they matter.**
- These patterns are still preliminary and will be validated further as the model matures.



Current Limitations

- Scaling to larger observation volumes remains a challenge
- Long-horizon stability still under study

Next steps

- Refine observation weighting (loss calibration + FSOI-guided tuning)
- Scale model capacity (model parallelism / tensor sharding)
- Extend to longer forecast horizons

Takeaway

OCELOT advances forecasting by learning **directly from the observations.**

Forecast directly
in observation space

Handle heterogeneous
sensors explicitly

Learn cross-instrument
relationships

Enable observation-impact
diagnostics

A complementary research pathway to strengthen **operational NWP.**

Questions?

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