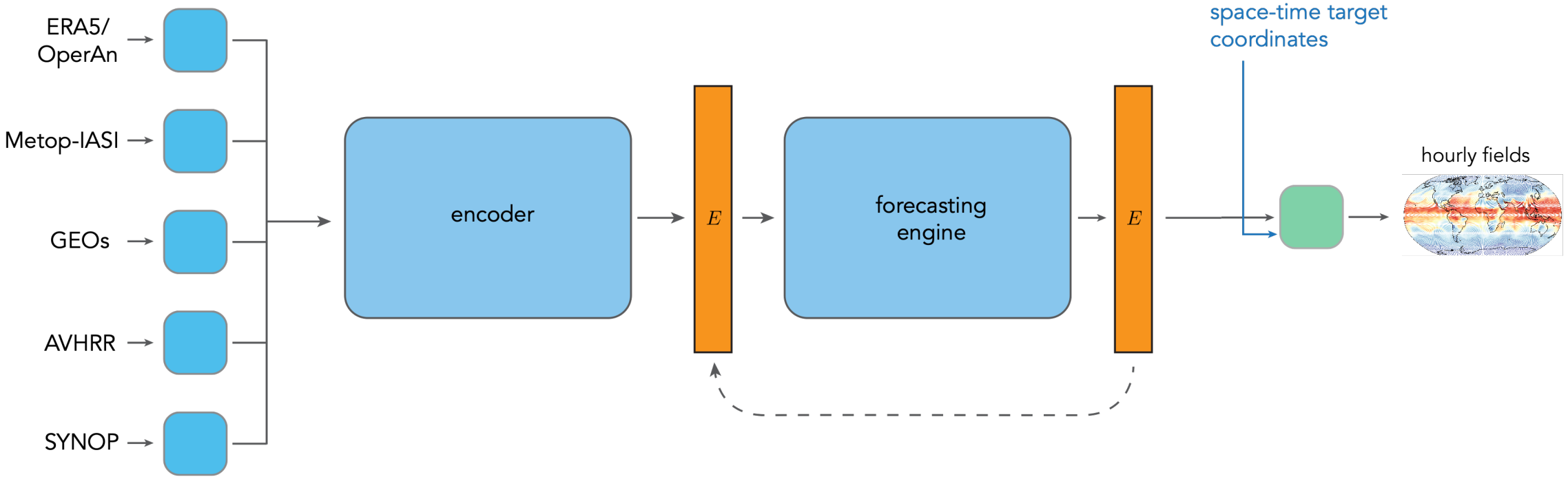
ECMWF

Weather Generator

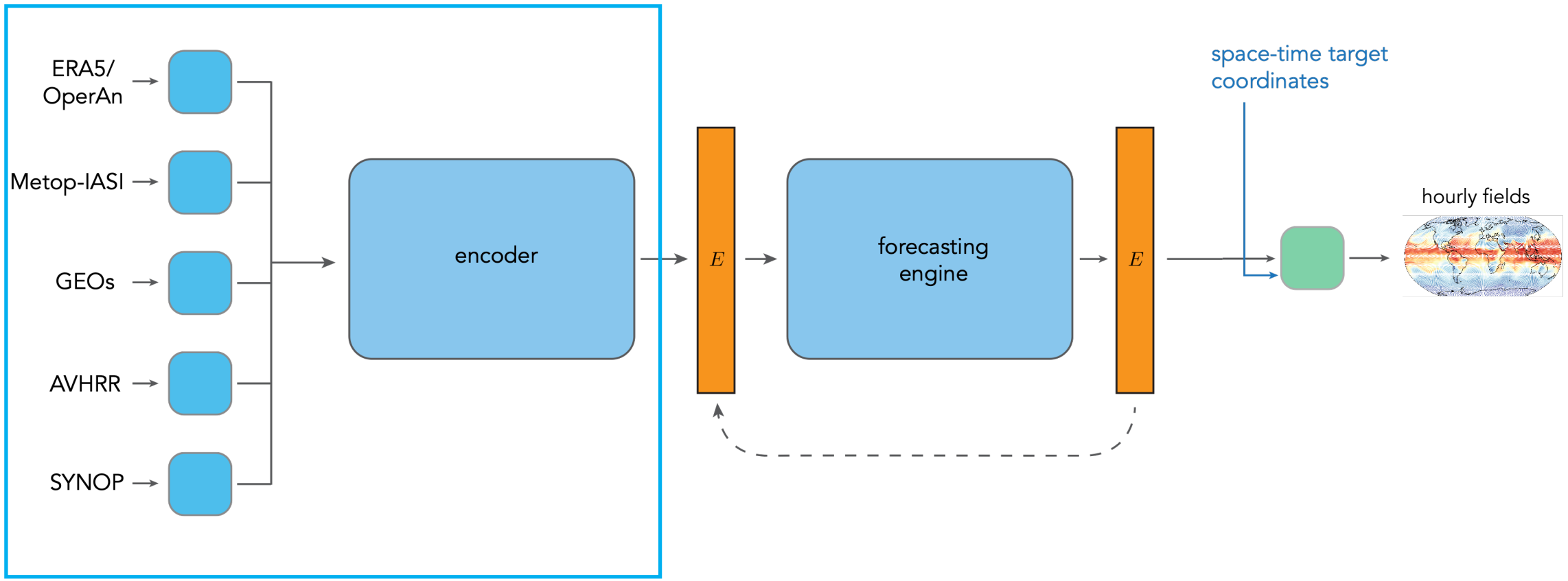
WeatherGenerator

Chistian Lessig, on behalf of the WeatherGenerator collaboration
christian.lessig@ecmwf.int

Overview

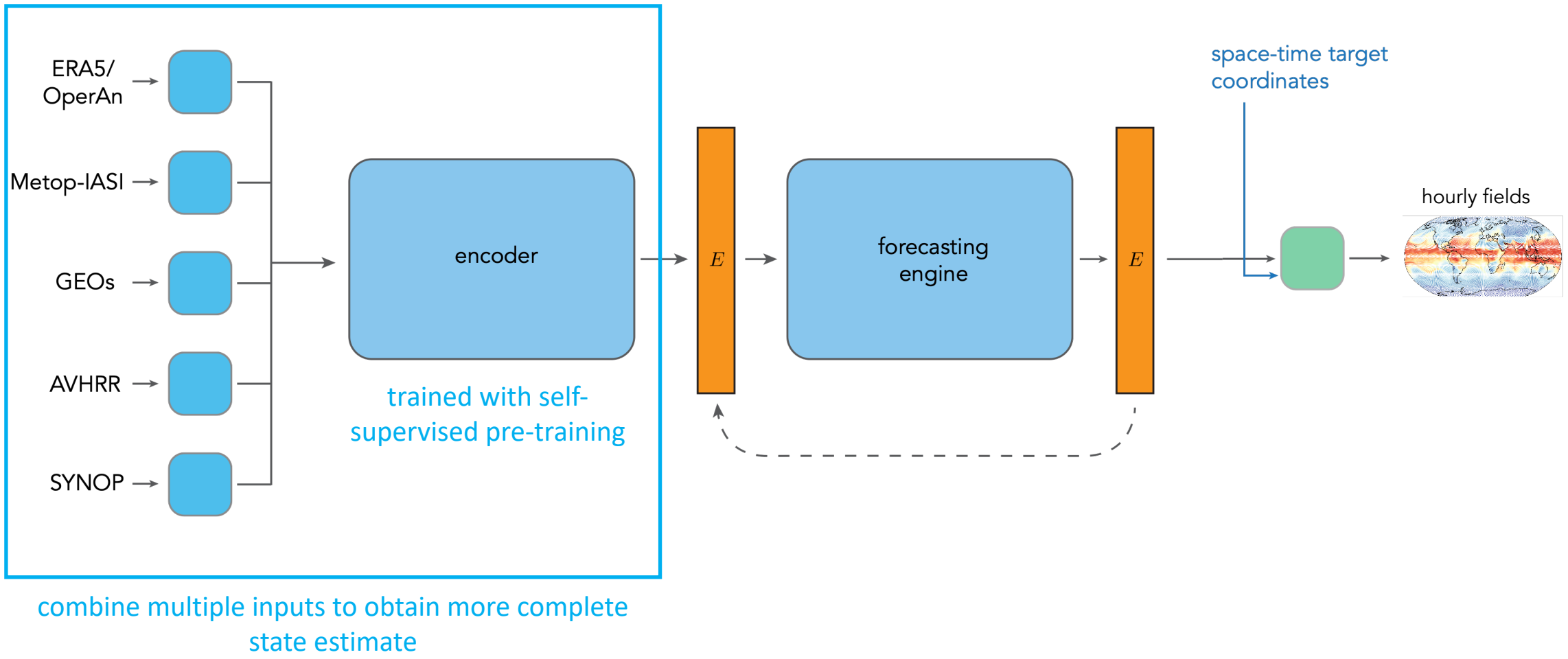

ERA5/
OperAn
Metop-IASI
GEOs
AVHRR
SYNOP
encoder
E
forecasting
engine
E
space-time target
coordinates
hourly fields

Overview

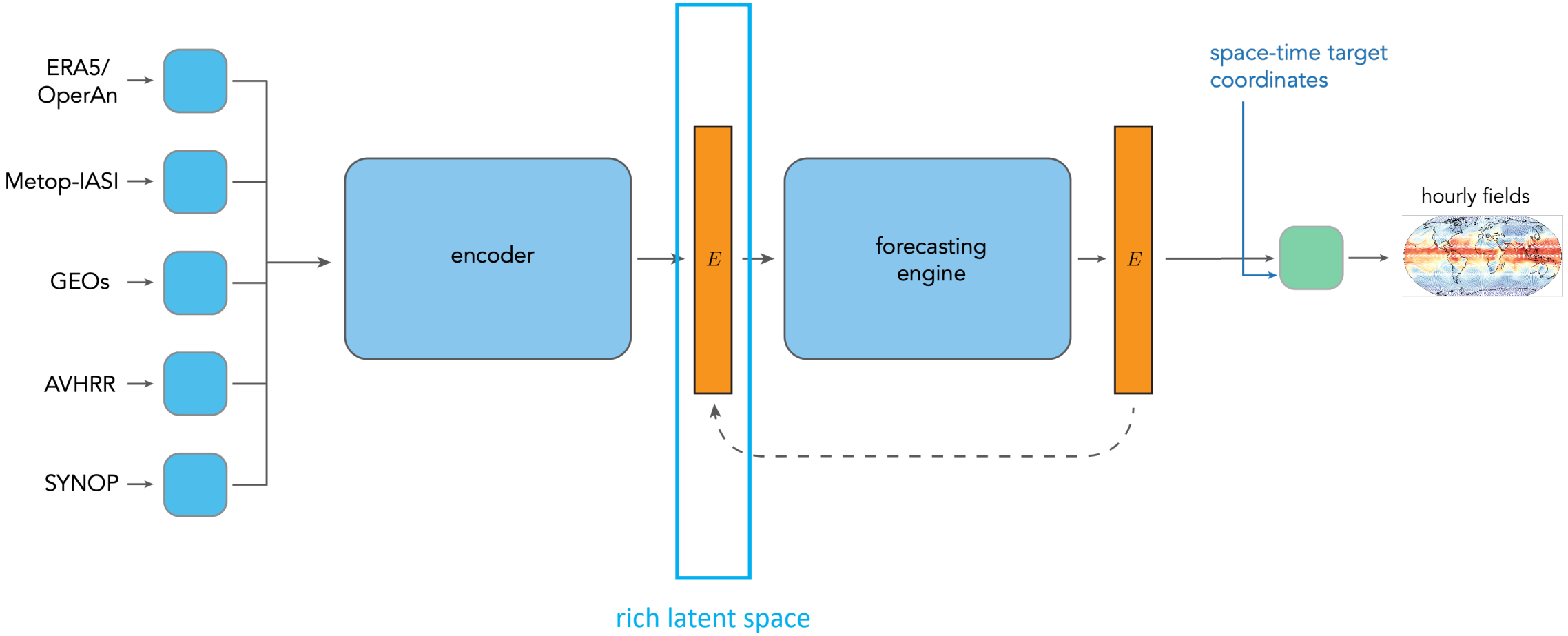


combine multiple inputs to obtain more complete state estimate

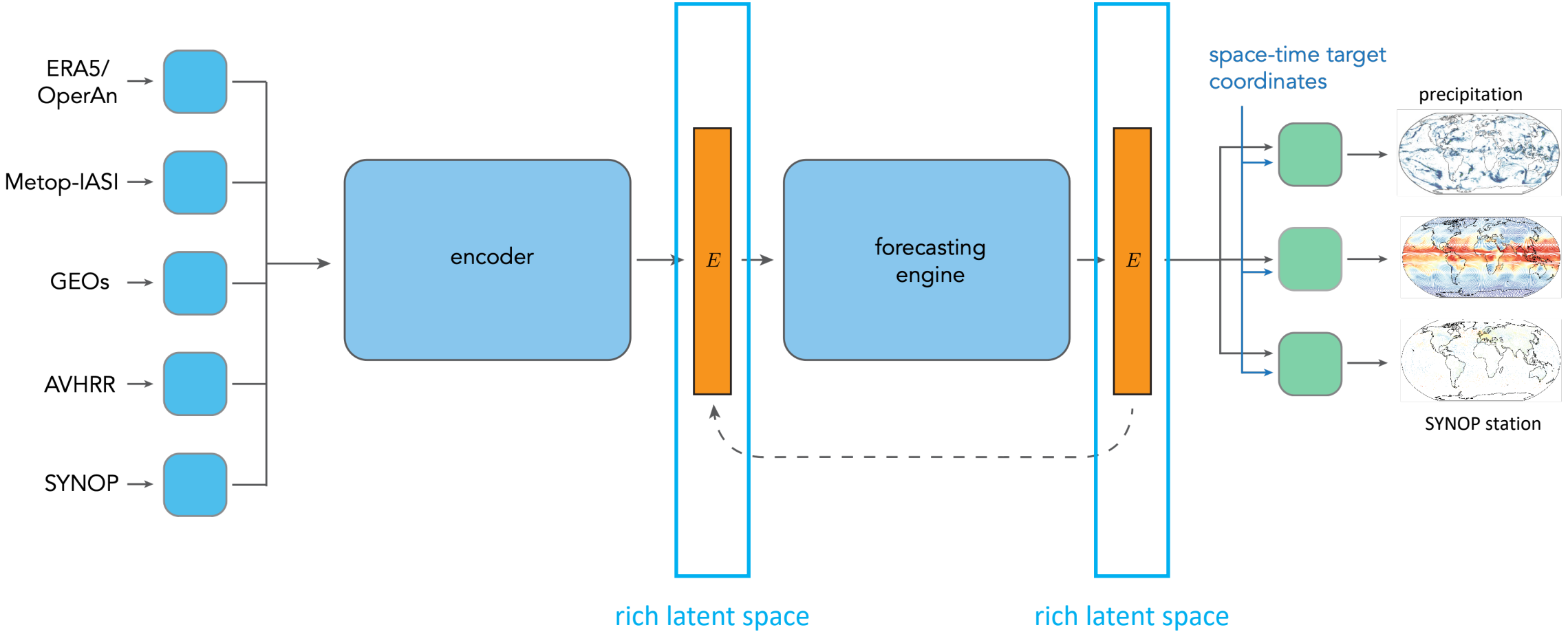
Overview


ERA5/
OperAn
Metop-IASI
GEOs
AVHRR
SYNOP
encoder
trained with self-supervised pre-training
E
forecasting engine
E
space-time target coordinates
hourly fields
combine multiple inputs to obtain more complete state estimate

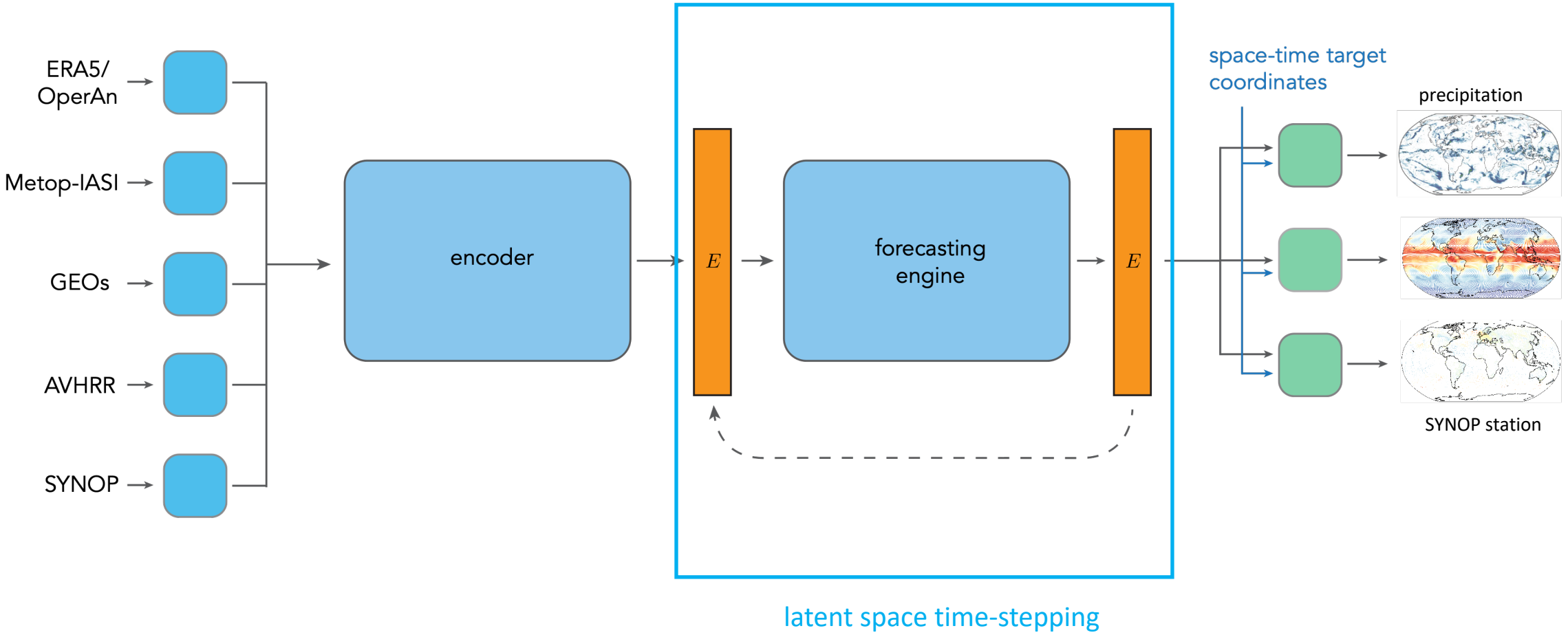
Overview


ERA5/
OperAn
Metop-IASI
GEOs
AVHRR
SYNOP
encoder
E
forecasting
engine
E
space-time target
coordinates
hourly fields
rich latent space

Overview

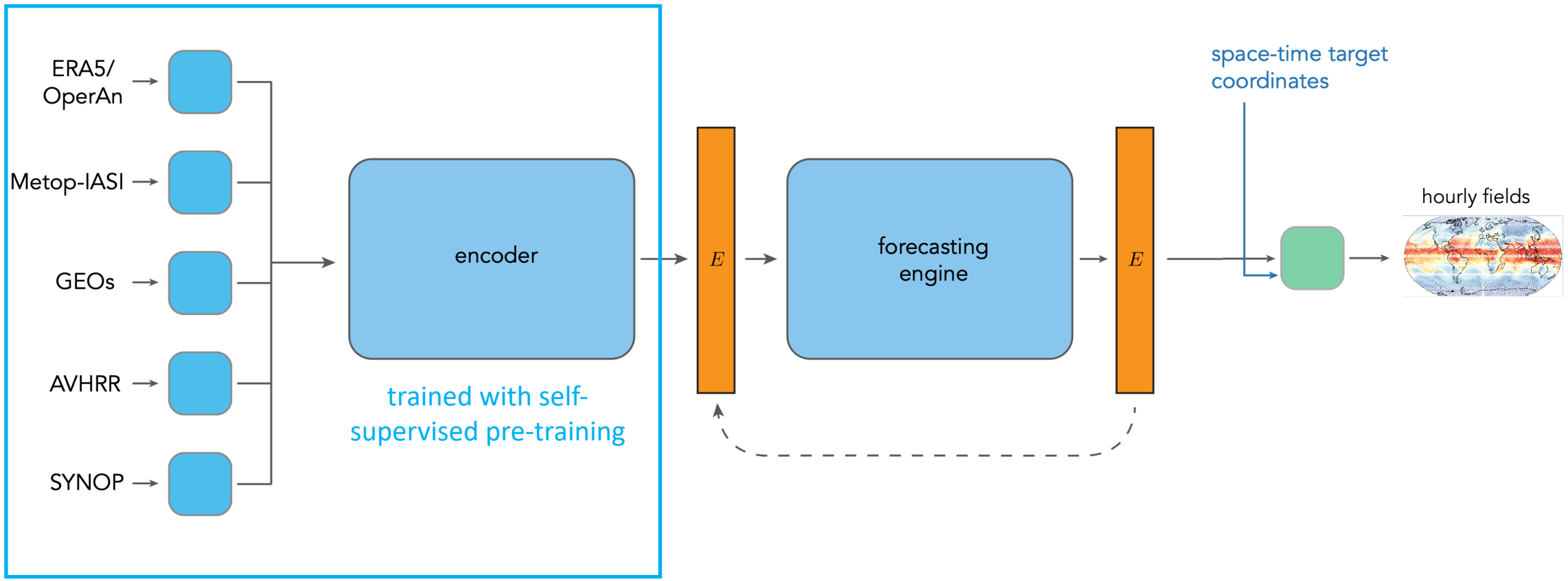

ERA5/
OperAn
Metop-IASI
GEOs
AVHRR
SYNOP
encoder
E
forecasting
engine
E
space-time target
coordinates
precipitation
SYNOP station
rich latent space
rich latent space

Overview


ERA5/
OperAn
Metop-IASI
GEOs
AVHRR
SYNOP
encoder
E
forecasting
engine
E
space-time target
coordinates
precipitation
SYNOP station
latent space time-stepping

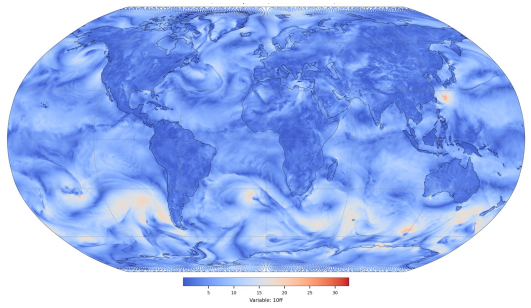
Multi-dataset input and pretraining

Multi-dataset input and pre-training

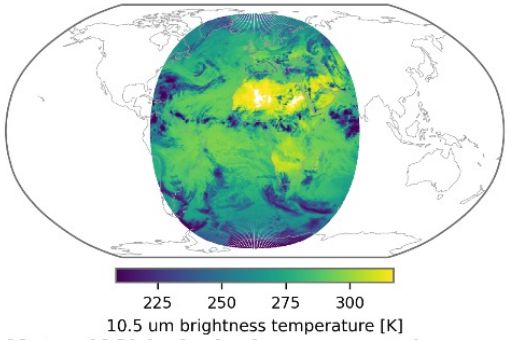


Multi-dataset input and pre-training

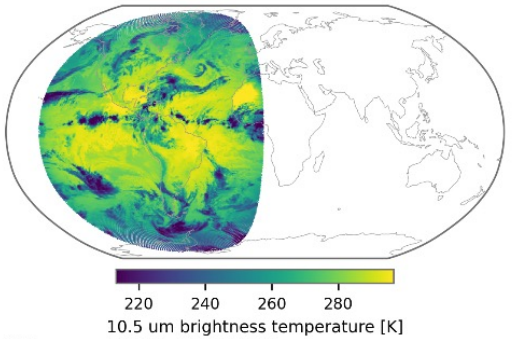
Operational Analysis



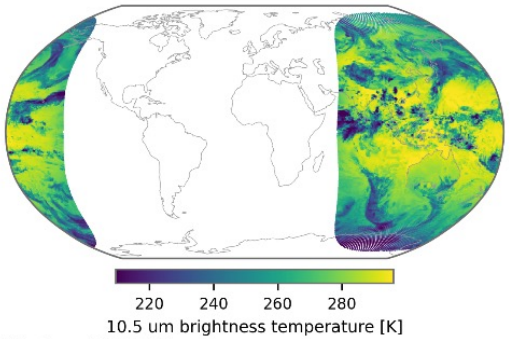
Meteosat SEVIRI (IR)
11 ch · 105k obs



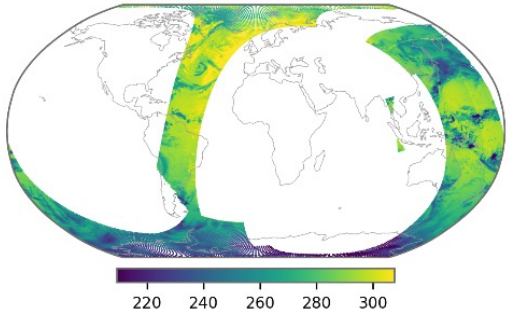
GOES-16 ABI (IR)
8 ch · 115k obs



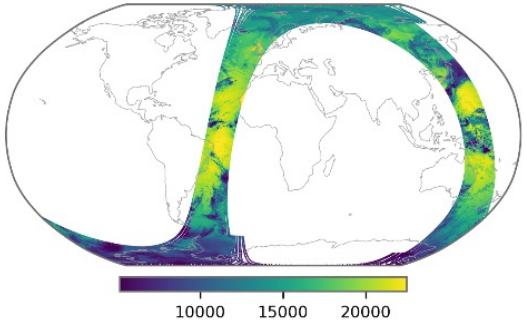
Himawari-8/9 AHI (IR)
8 ch · 112k obs



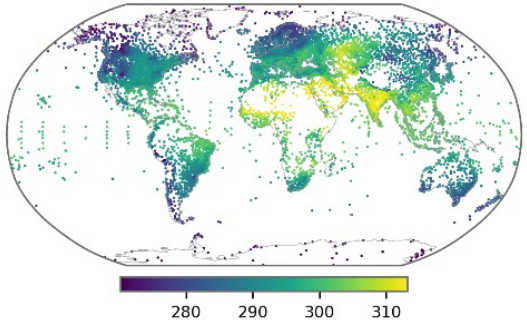
Metop AVHRR
5 ch · 115k obs



Metop IASI (principal components)
210 ch · 108k obs

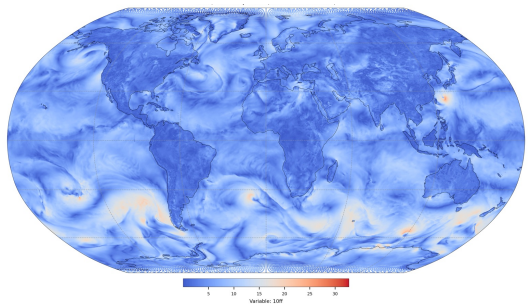


Surface (SYNOP / ship / buoy)
9 ch · 27k obs

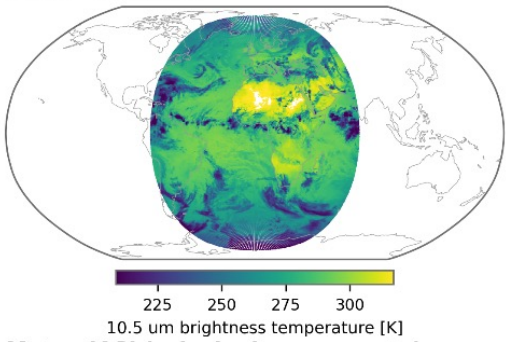


Multi-dataset input and pre-training

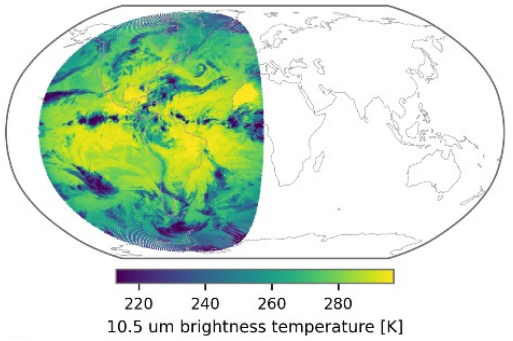
Operational Analysis



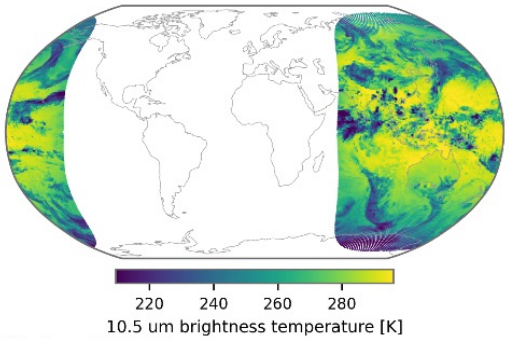
Meteosat SEVIRI (IR)
11 ch · 105k obs



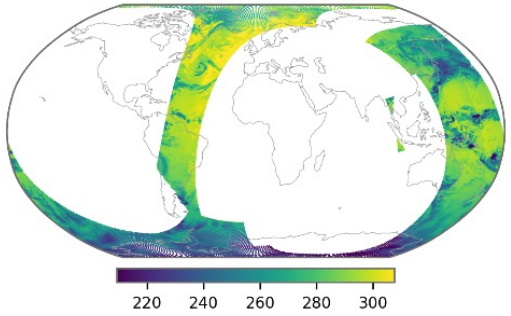
GOES-16 ABI (IR)
8 ch · 115k obs



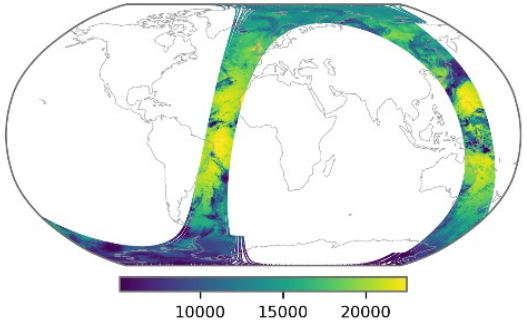
Himawari-8/9 AHI (IR)
8 ch · 112k obs



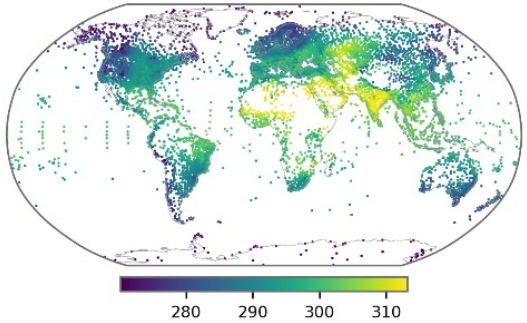
Metop AVHRR
5 ch · 115k obs



Metop IASI (principal components)
210 ch · 108k obs

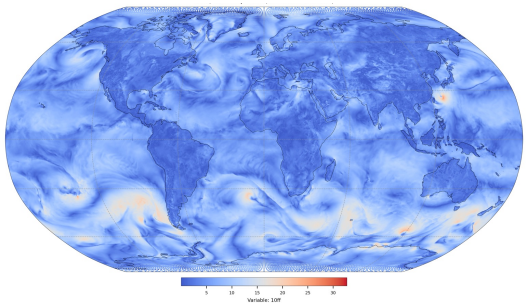


Surface (SYNOP / ship / buoy)
9 ch · 27k obs

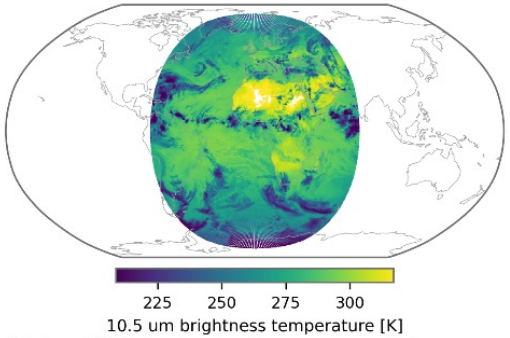


Multi-dataset input and pre-training

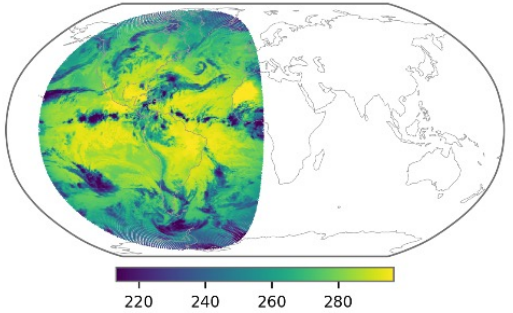
Operational Analysis



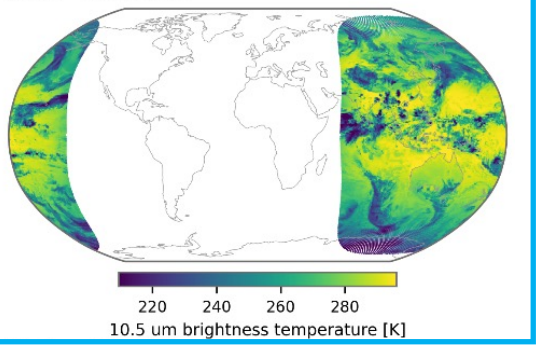
Meteosat SEVIRI (IR)
11 ch · 105k obs



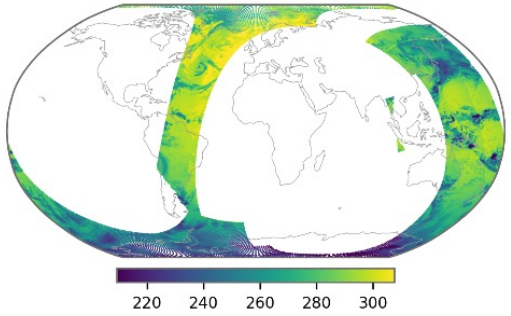
GOES-16 ABI (IR)
8 ch · 115k obs



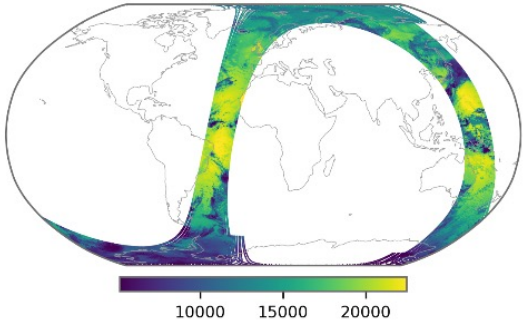
Himawari-8/9 AHI (IR)
8 ch · 112k obs



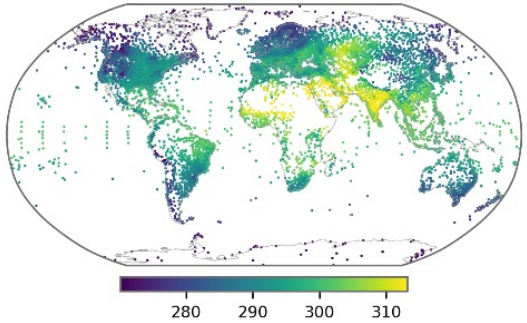
Metop AVHRR
5 ch · 115k obs



Metop IASI (principal components)
210 ch · 108k obs

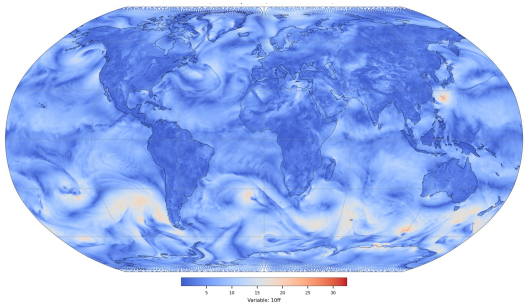


Surface (SYNOP / ship / buoy)
9 ch · 27k obs

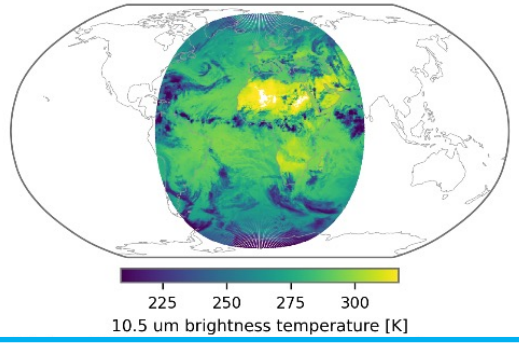


Multi-dataset input and pre-training

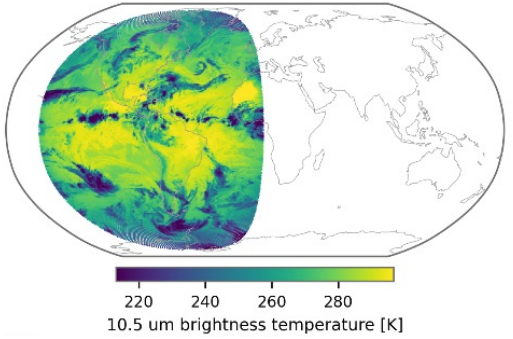
Operational Analysis



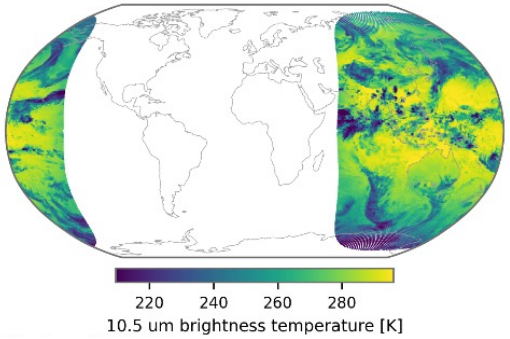
Meteosat SEVIRI (IR)
11 ch · 105k obs



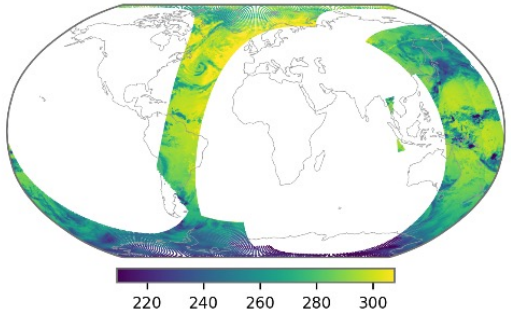
GOES-16 ABI (IR)
8 ch · 115k obs



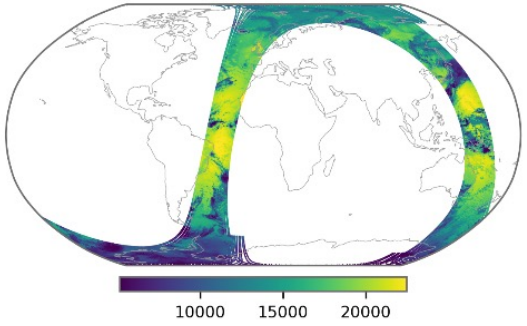
Himawari-8/9 AHI (IR)
8 ch · 112k obs



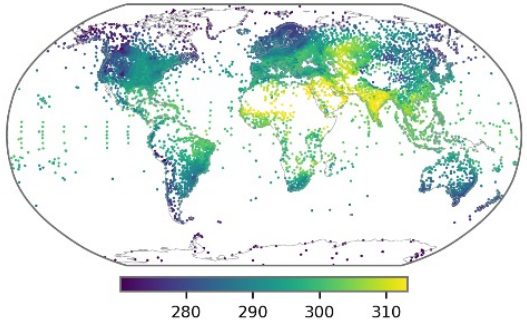
Metop AVHRR
5 ch · 115k obs



Metop IASI (principal components)
210 ch · 108k obs

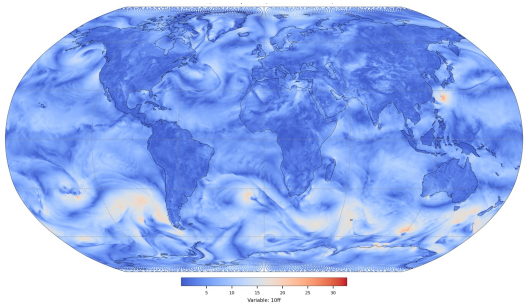


Surface (SYNOP / ship / buoy)
9 ch · 27k obs

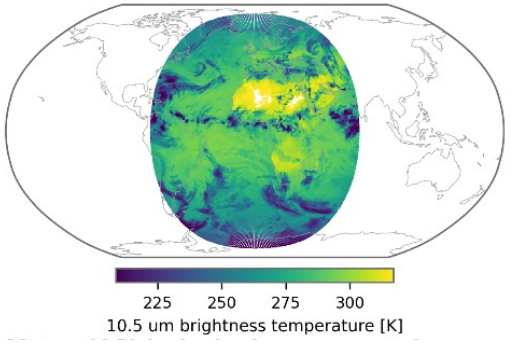


Multi-dataset input and pre-training

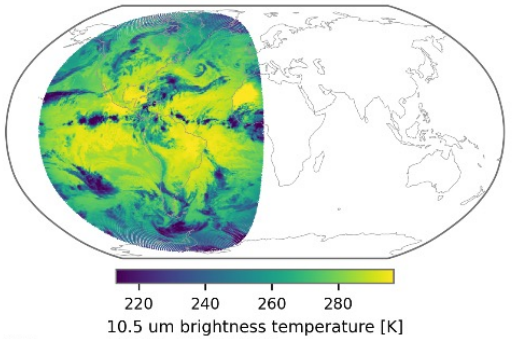
Operational Analysis



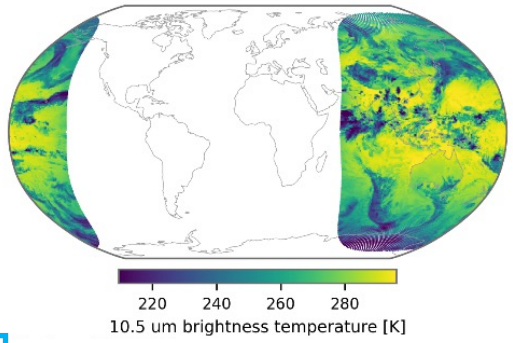
Meteosat SEVIRI (IR)
11 ch · 105k obs



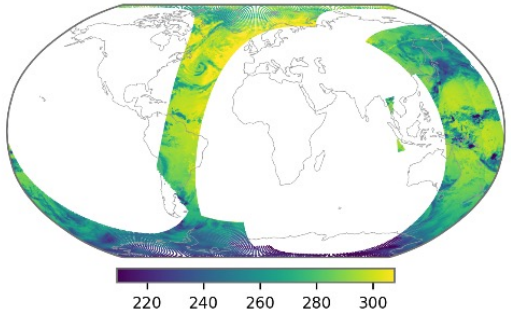
GOES-16 ABI (IR)
8 ch · 115k obs



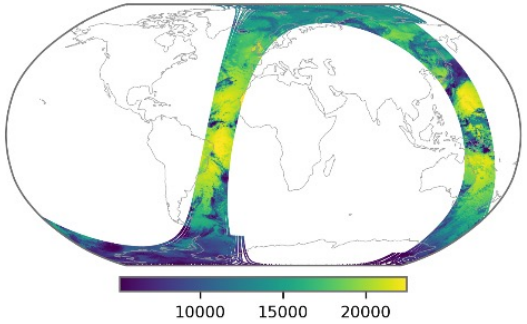
Himawari-8/9 AHI (IR)
8 ch · 112k obs



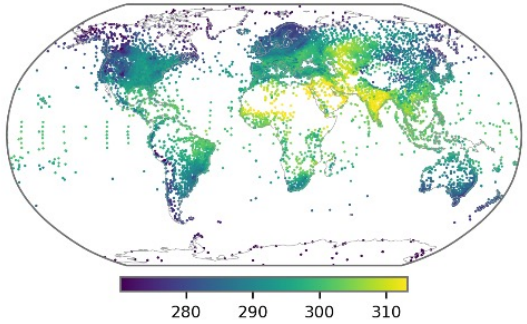
Metop AVHRR
5 ch · 115k obs



Metop IASI (principal components)
210 ch · 108k obs



Surface (SYNOP / ship / buoy)
9 ch · 27k obs

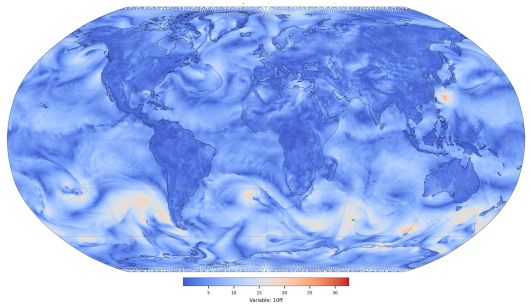


Multi-dataset input and pre-training

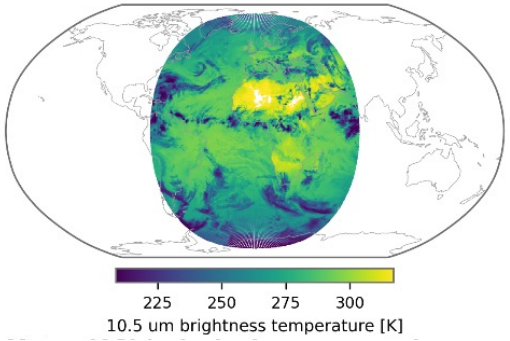
6-hourly

1-hourly

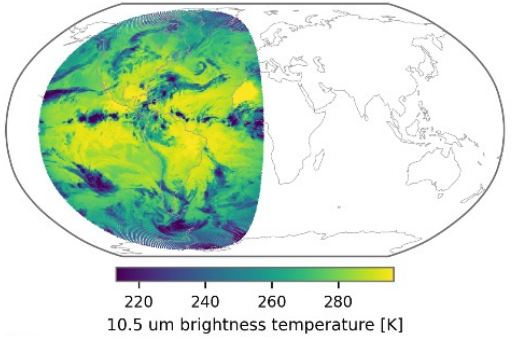
Operational Analysis



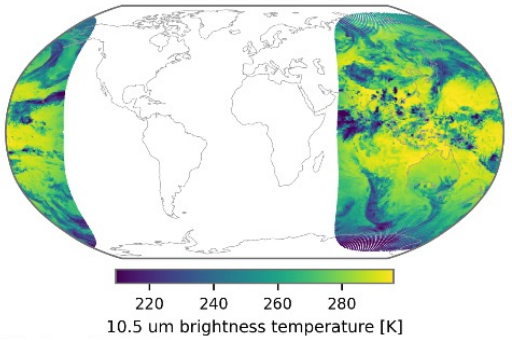
Meteosat SEVIRI (IR)
11 ch · 105k obs



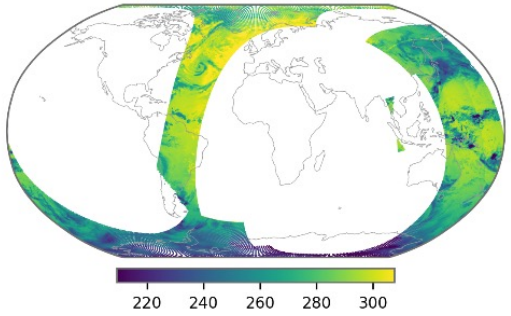
GOES-16 ABI (IR)
8 ch · 115k obs



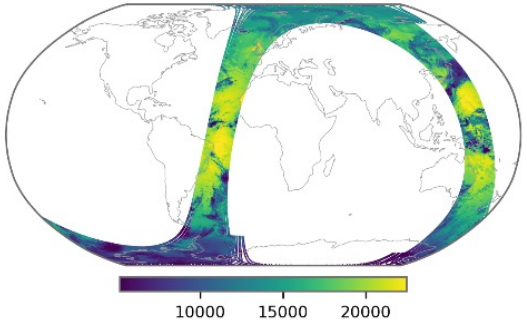
Himawari-8/9 AHI (IR)
8 ch · 112k obs



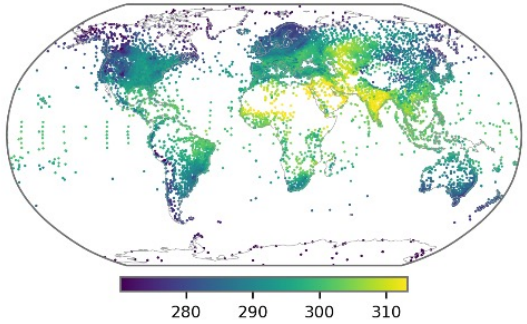
Metop AVHRR
5 ch · 115k obs



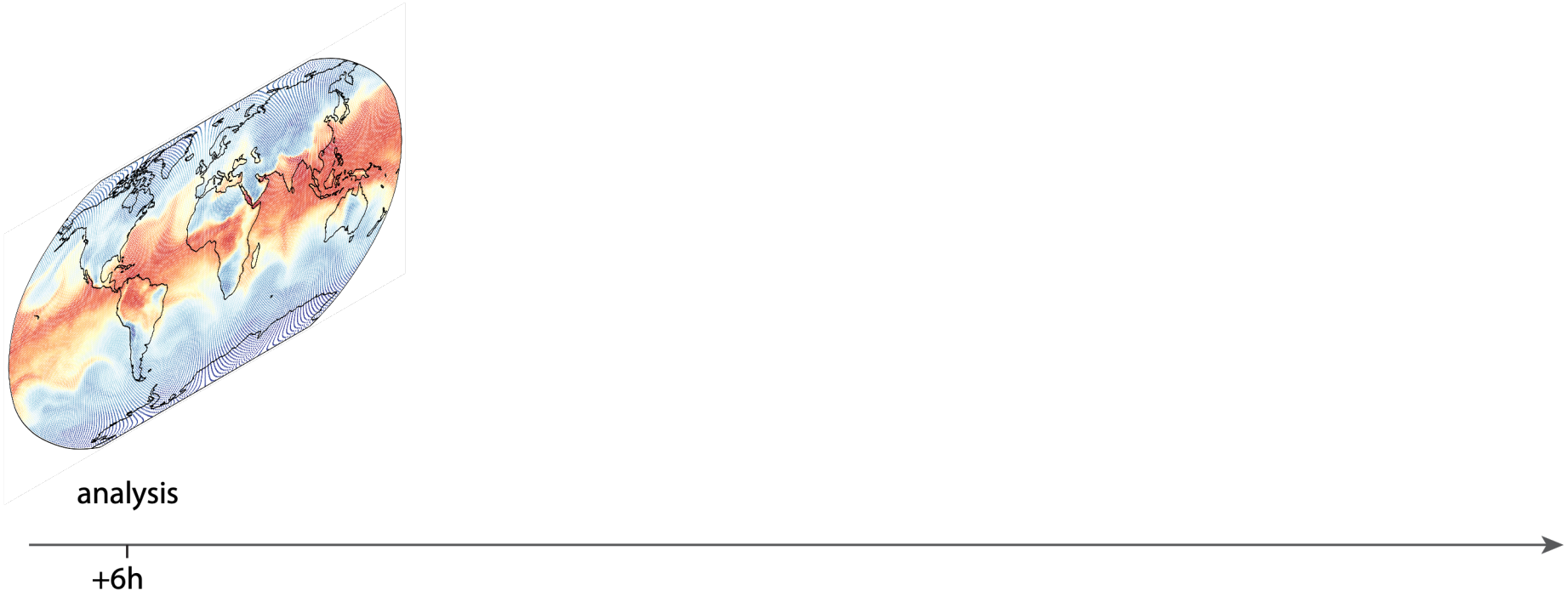
Metop IASI (principal components)
210 ch · 108k obs



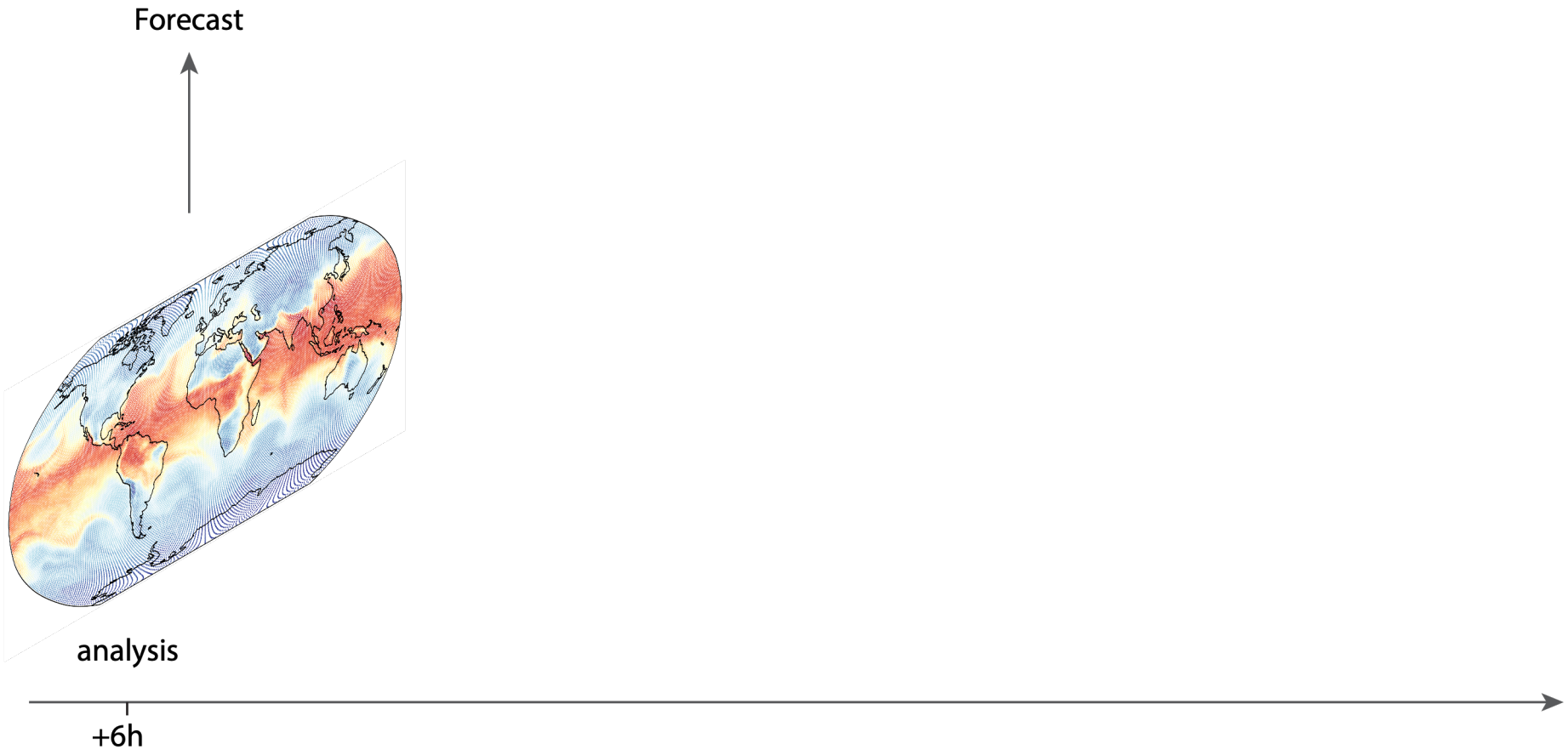
Surface (SYNOP / ship / buoy)
9 ch · 27k obs



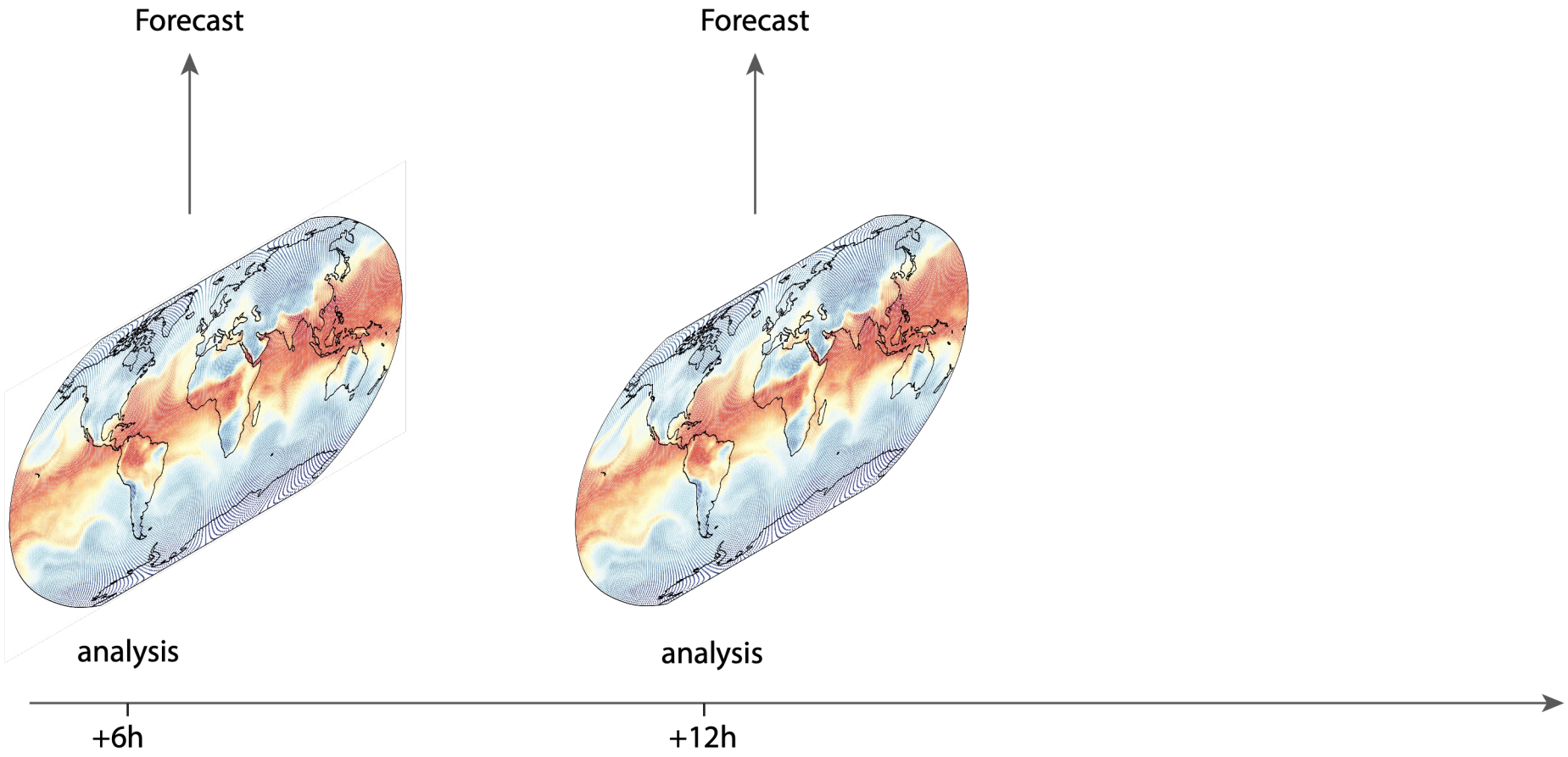
Multi-dataset input and pre-training



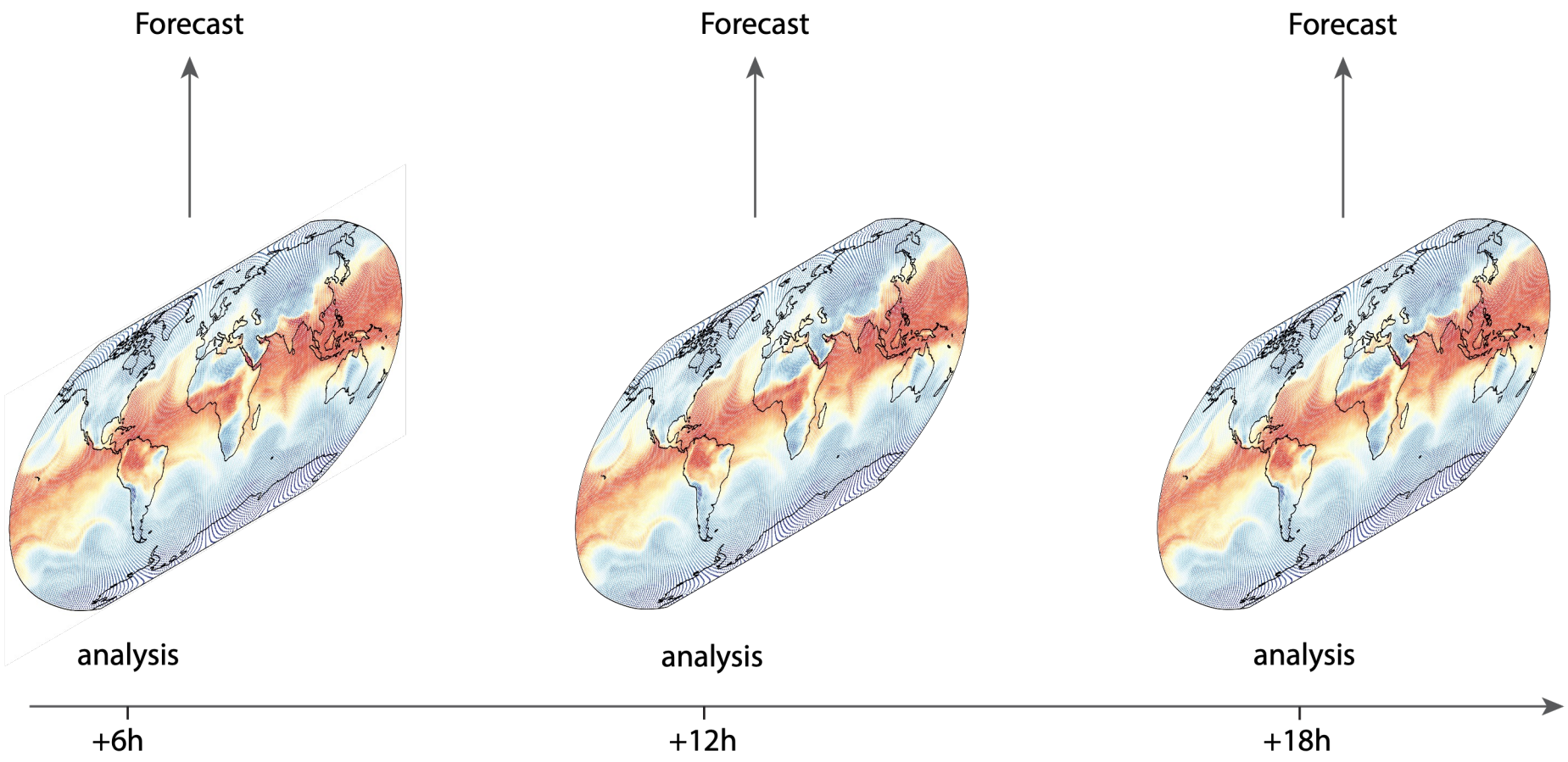
Multi-dataset input and pre-training



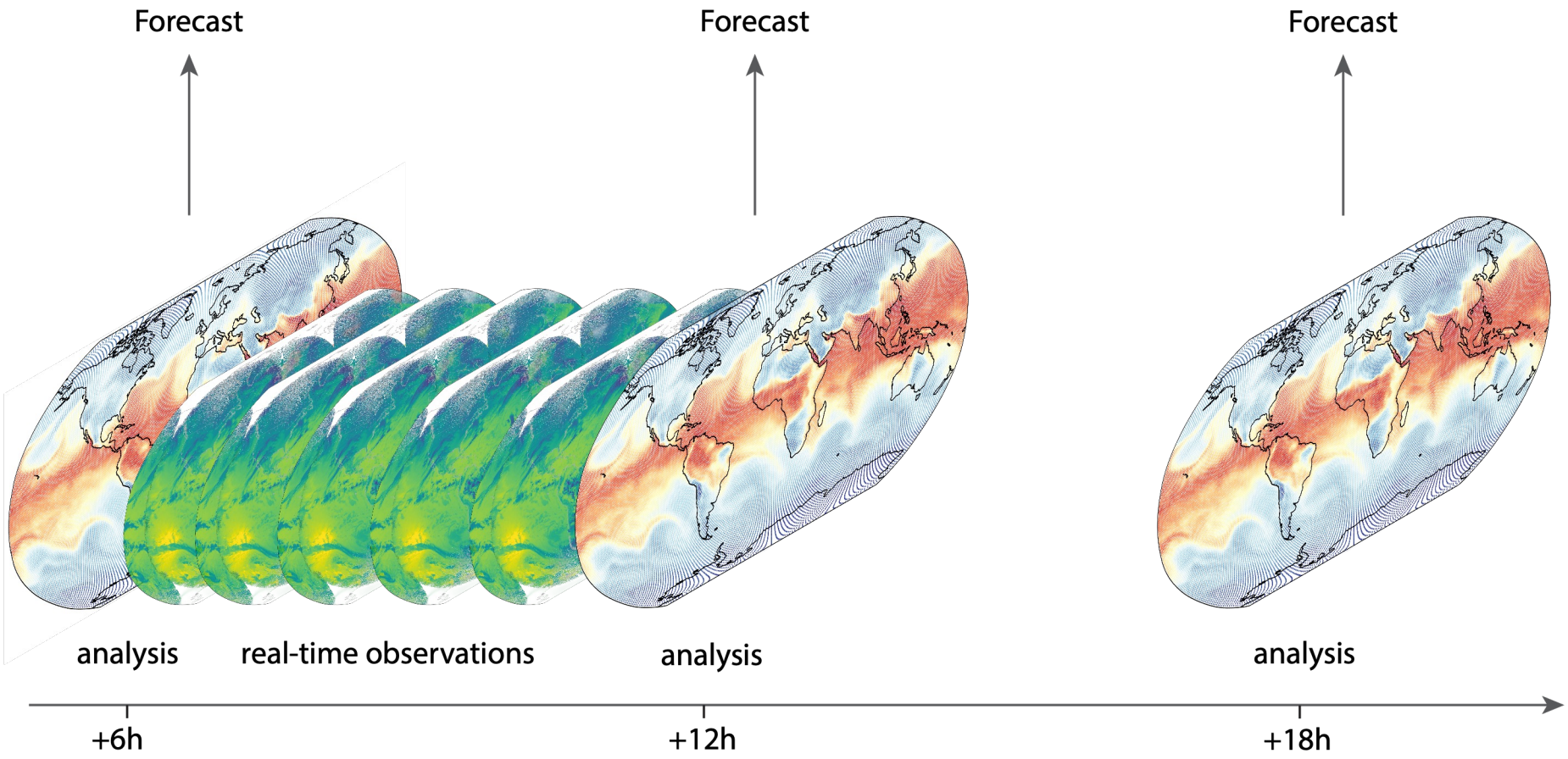
Multi-dataset input and pre-training



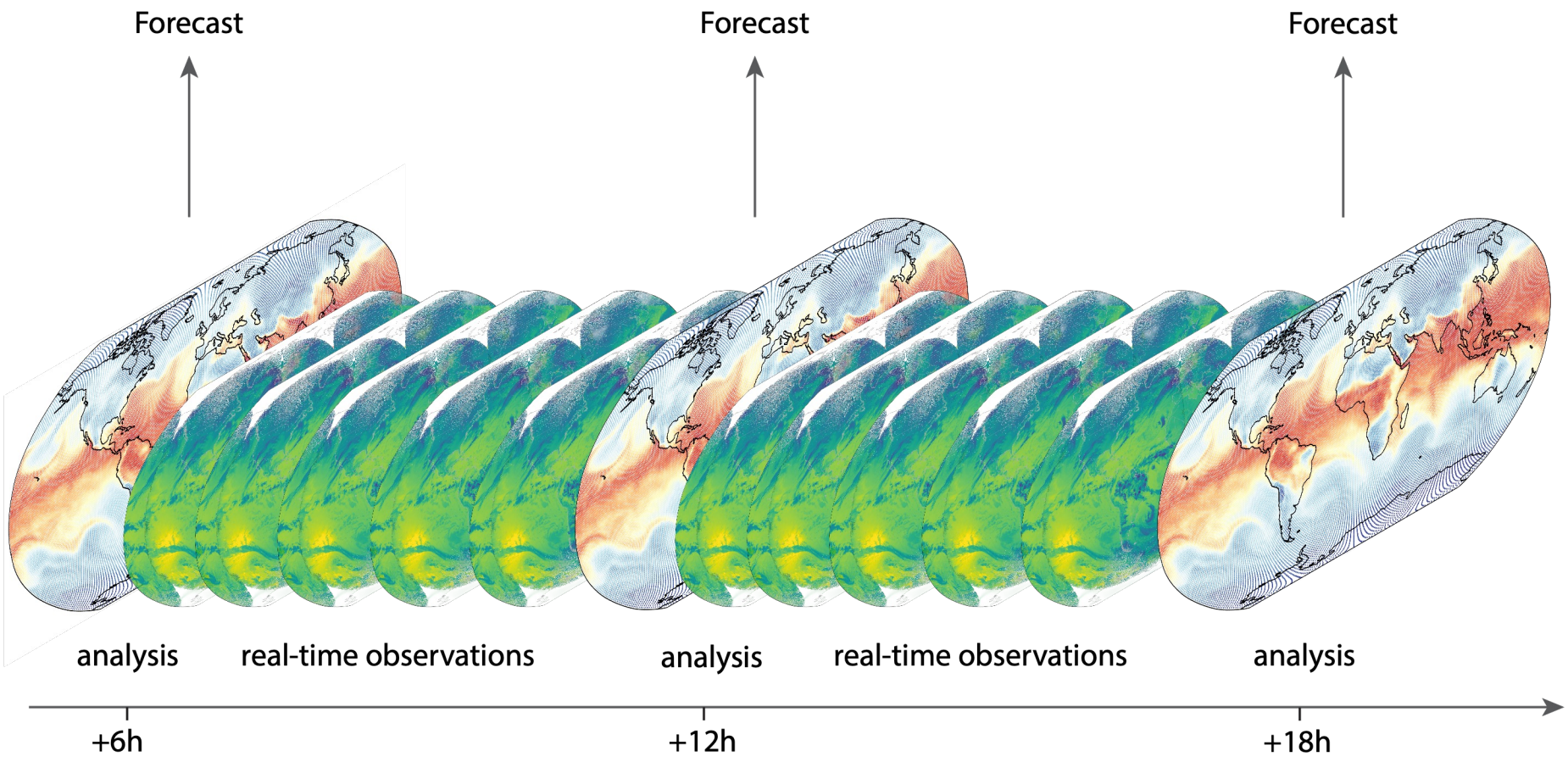
Multi-dataset input and pre-training



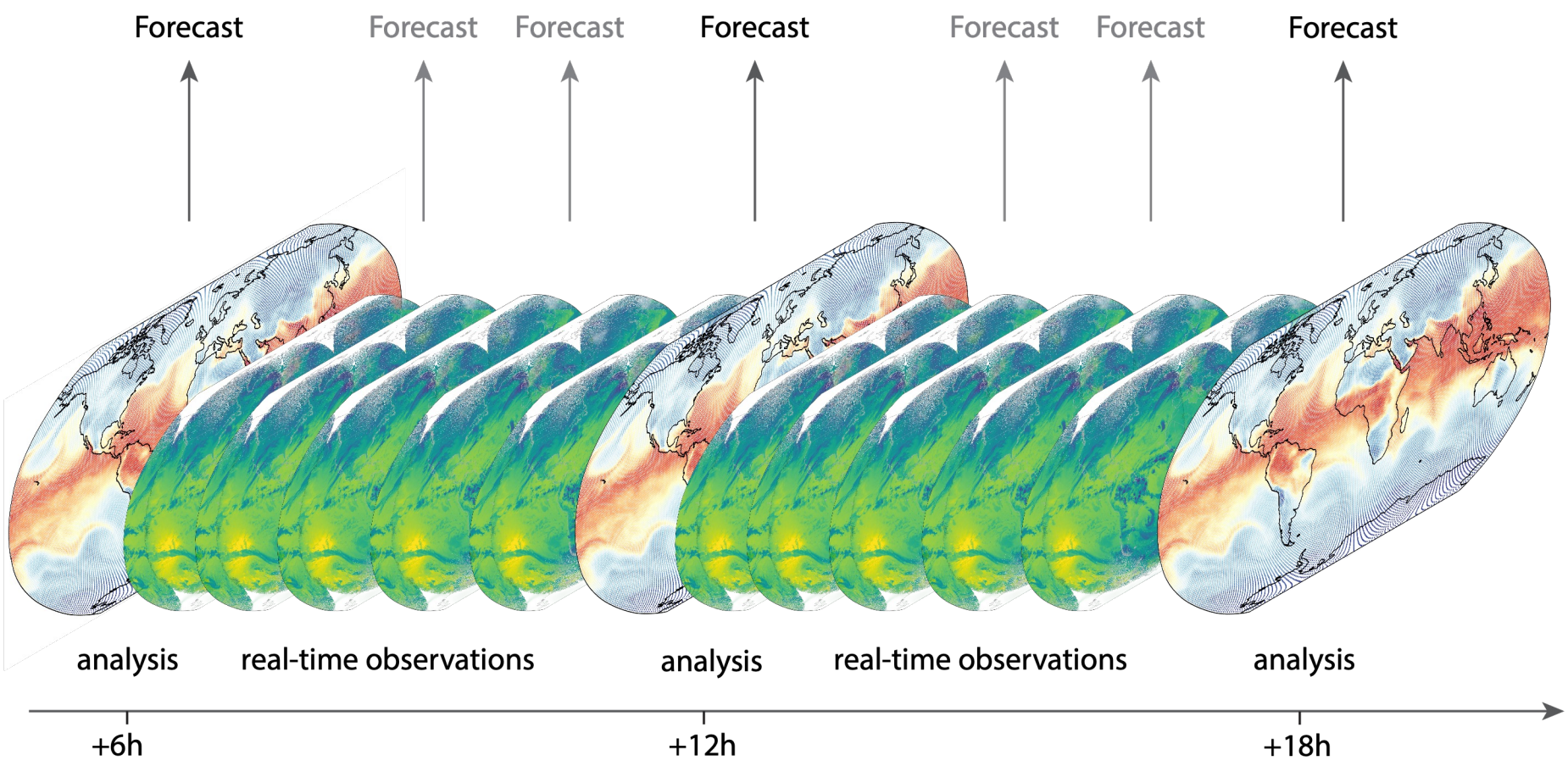
Multi-dataset input and pre-training



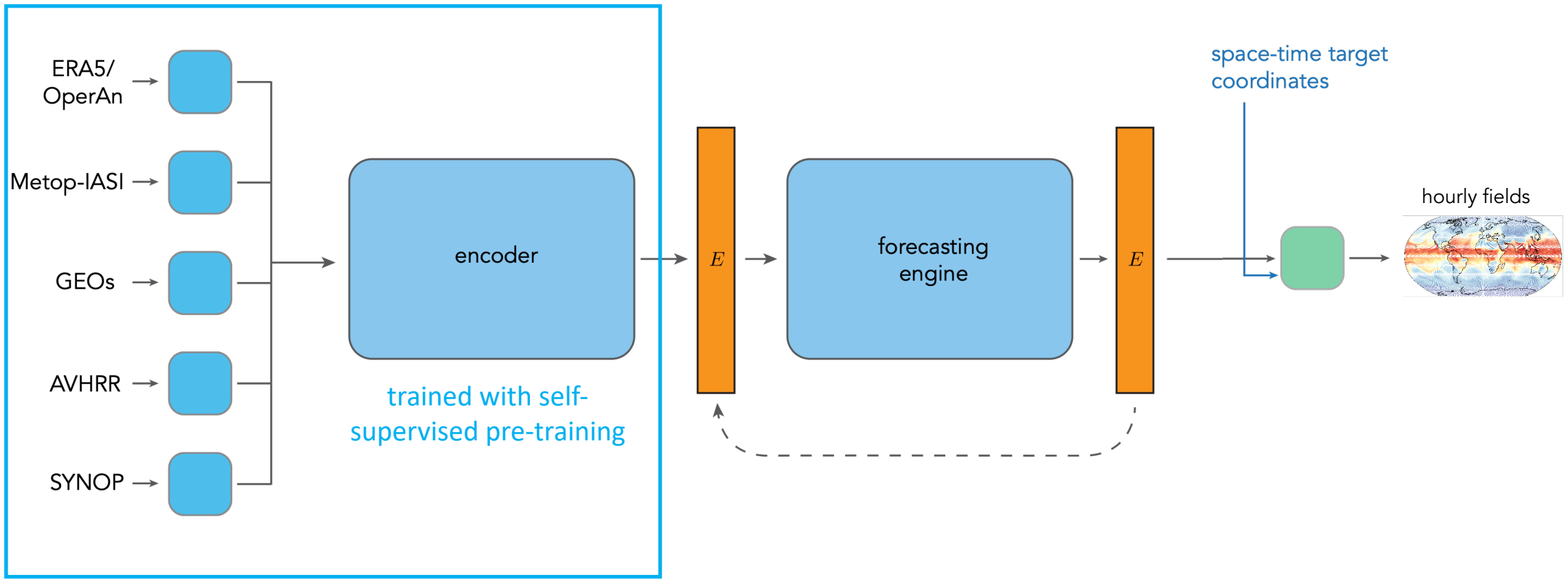
Multi-dataset input and pre-training



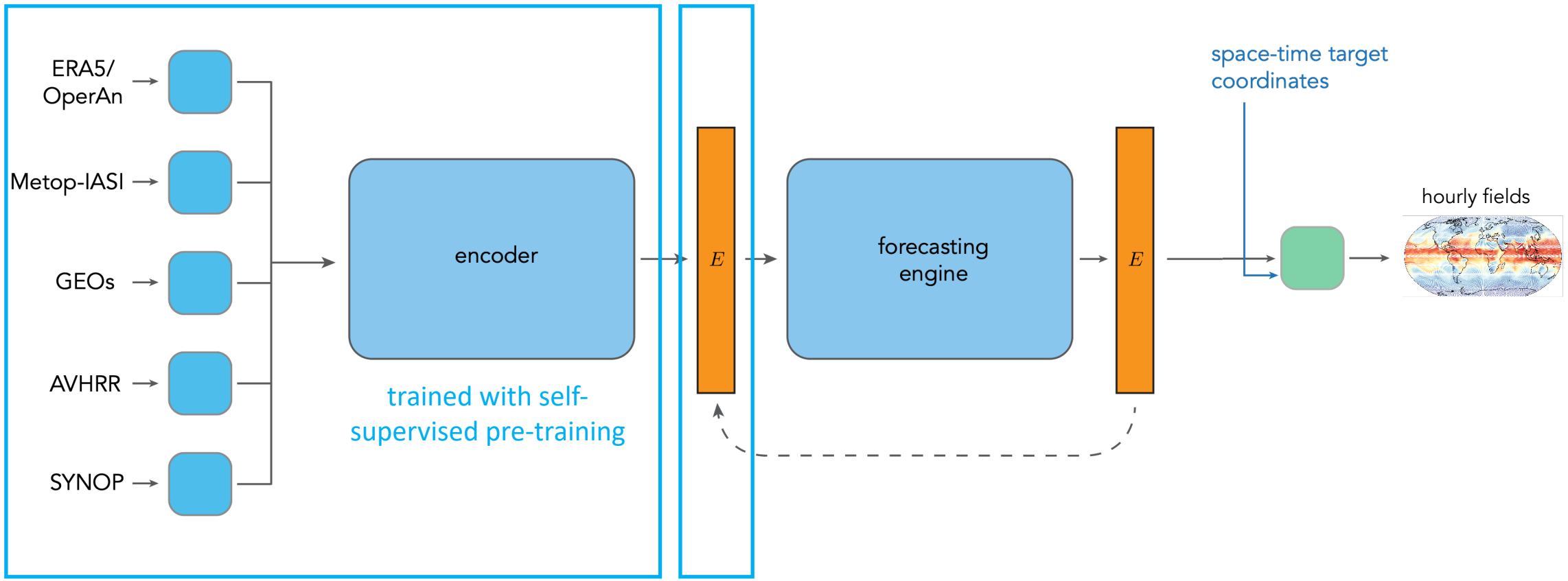
Multi-dataset input and pre-training



Multi-dataset input and pre-training

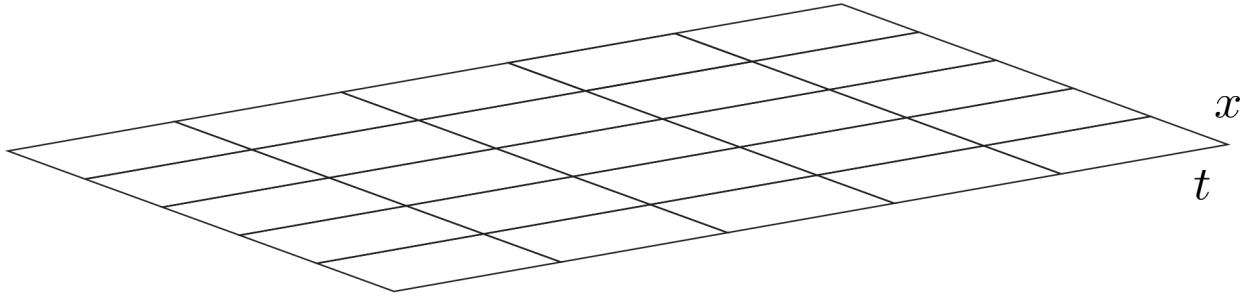


Multi-dataset input and pre-training

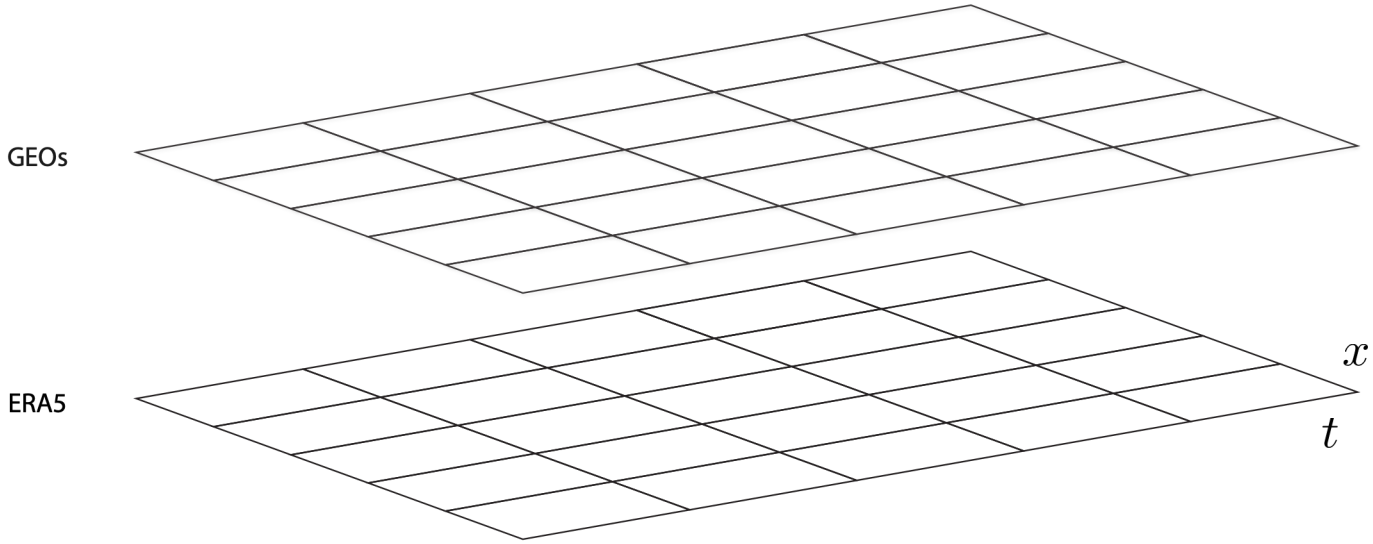


Multi-dataset input and pre-training

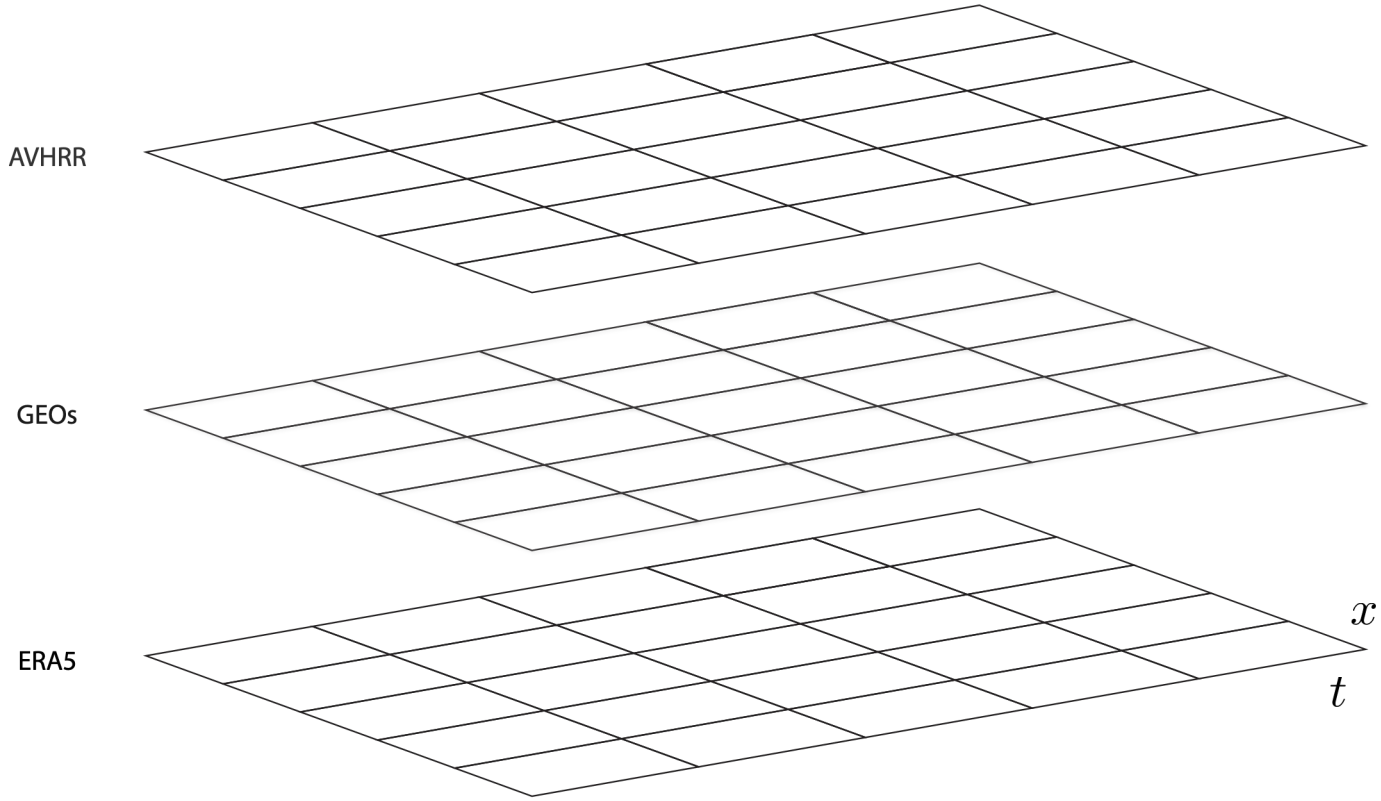
ERA5



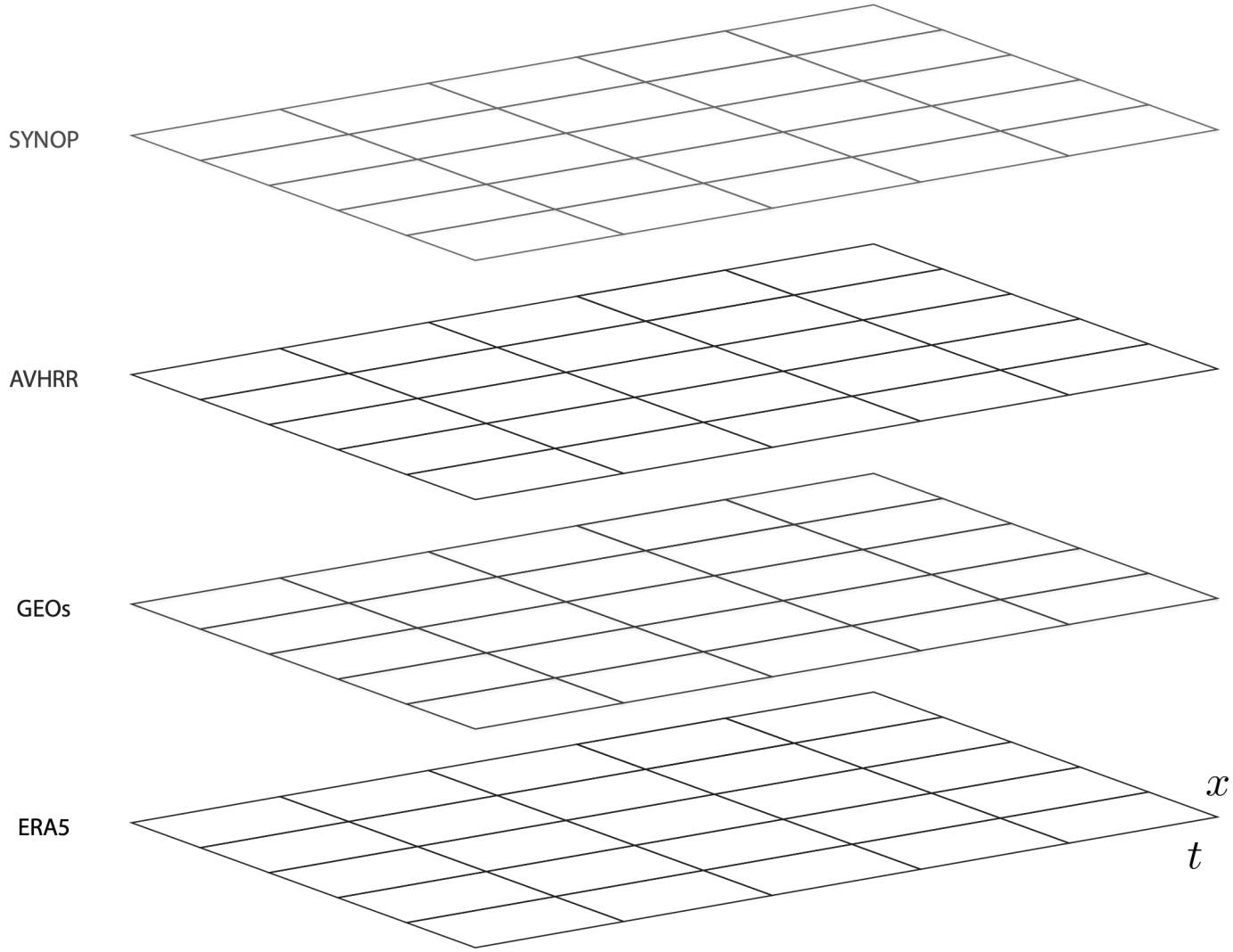
Multi-dataset input and pre-training



Multi-dataset input and pre-training

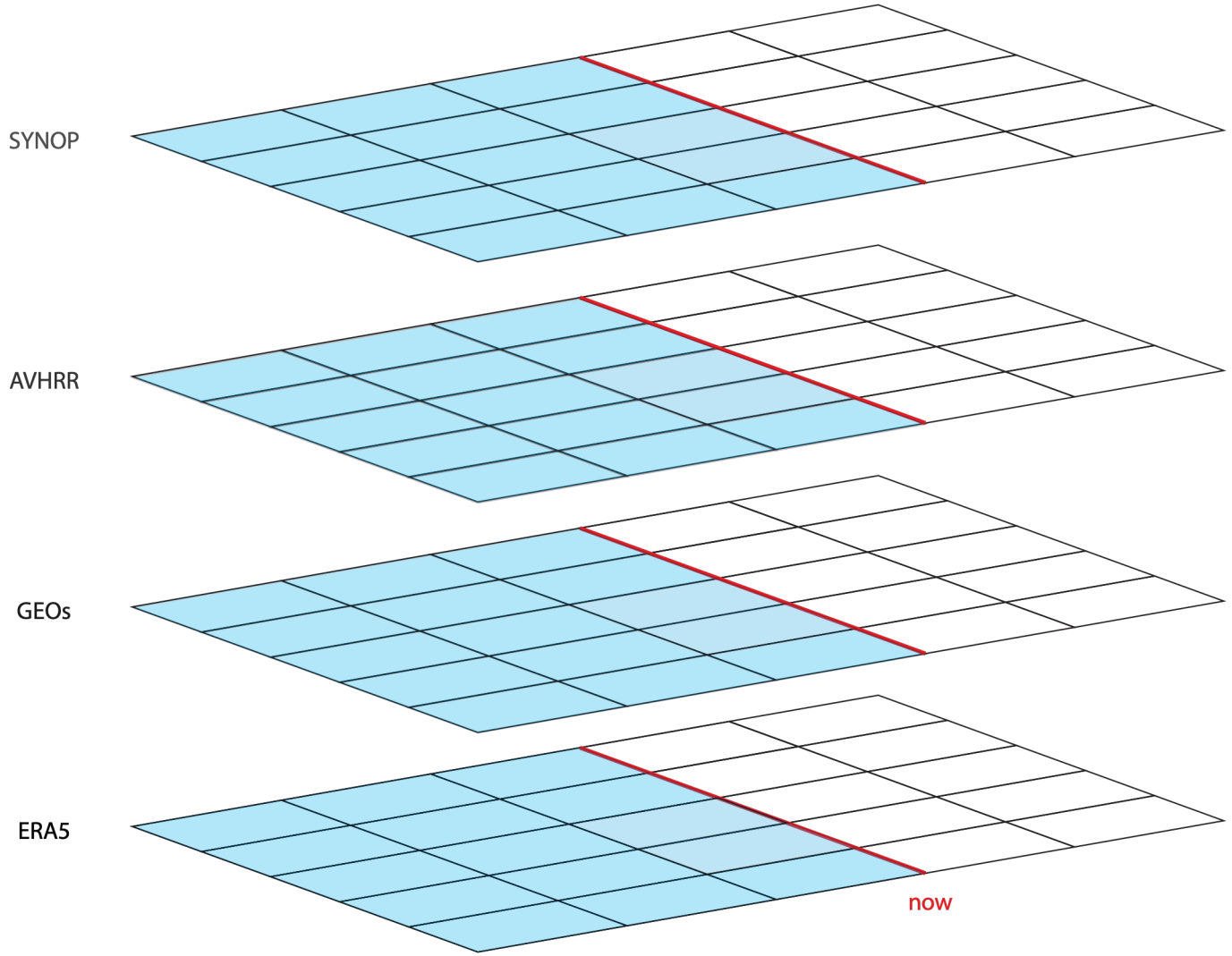


Multi-dataset input and pre-training



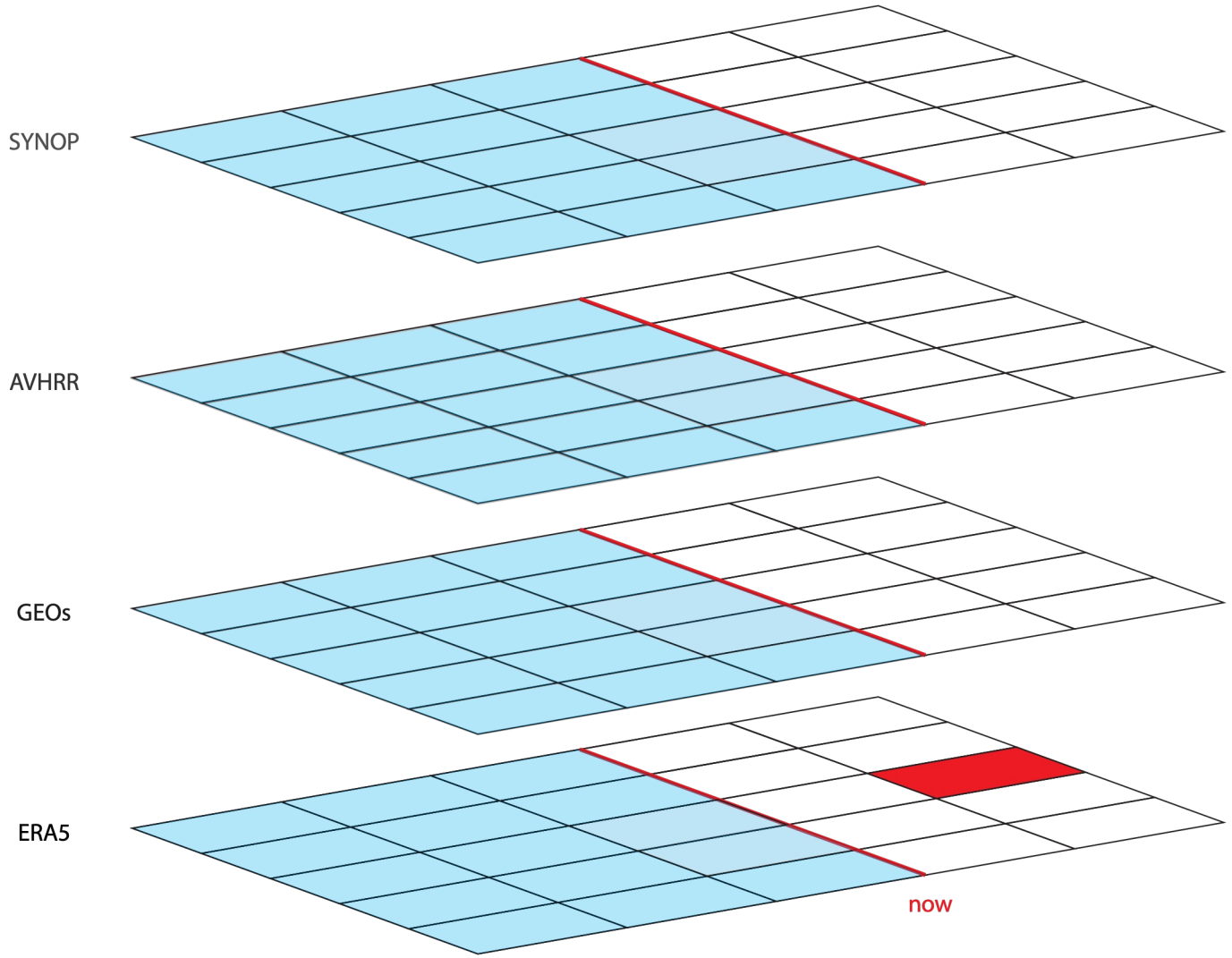
Multi-dataset input and pre-training

Training objective:
forecasting



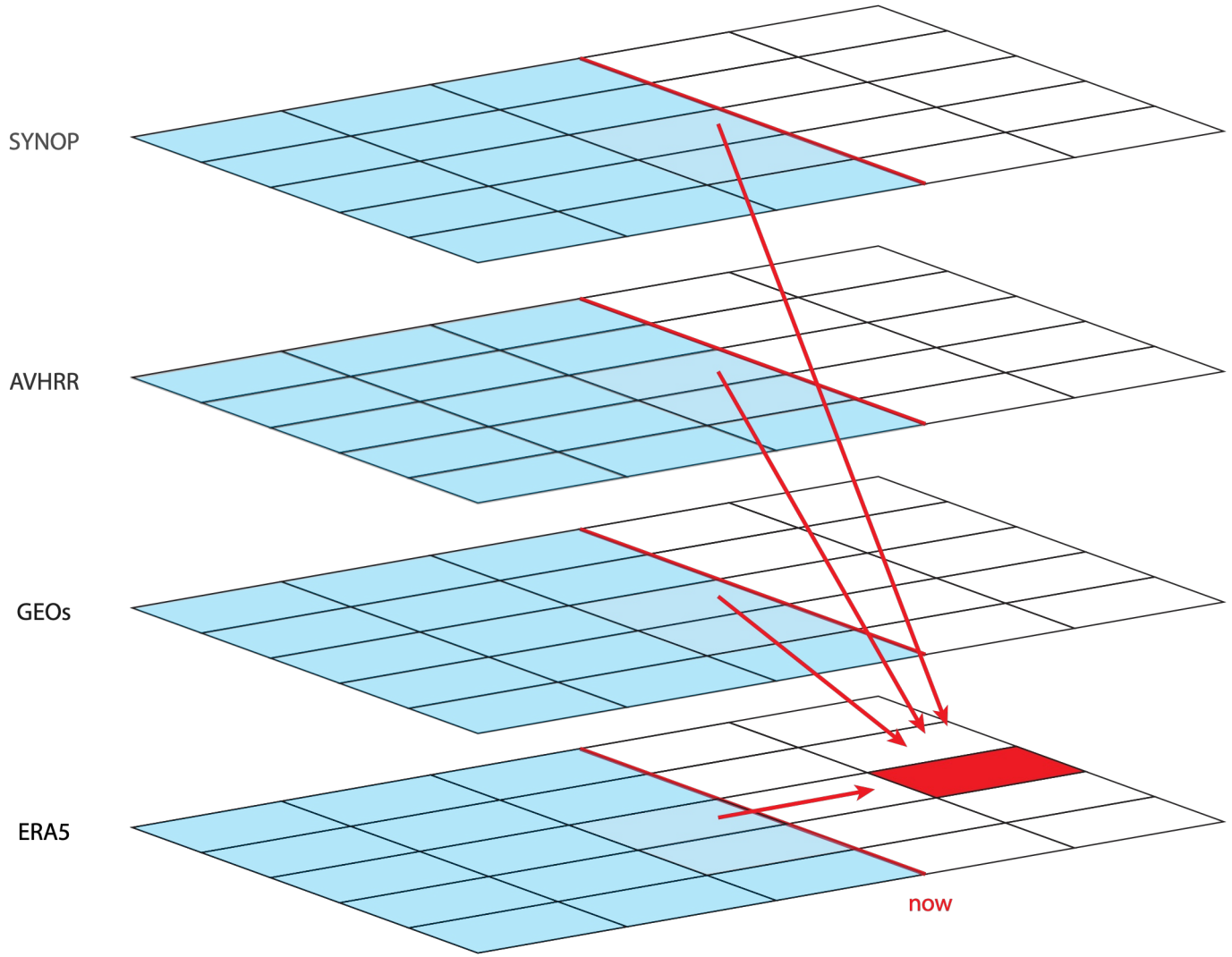
Multi-dataset input and pre-training

Training objective:
forecasting



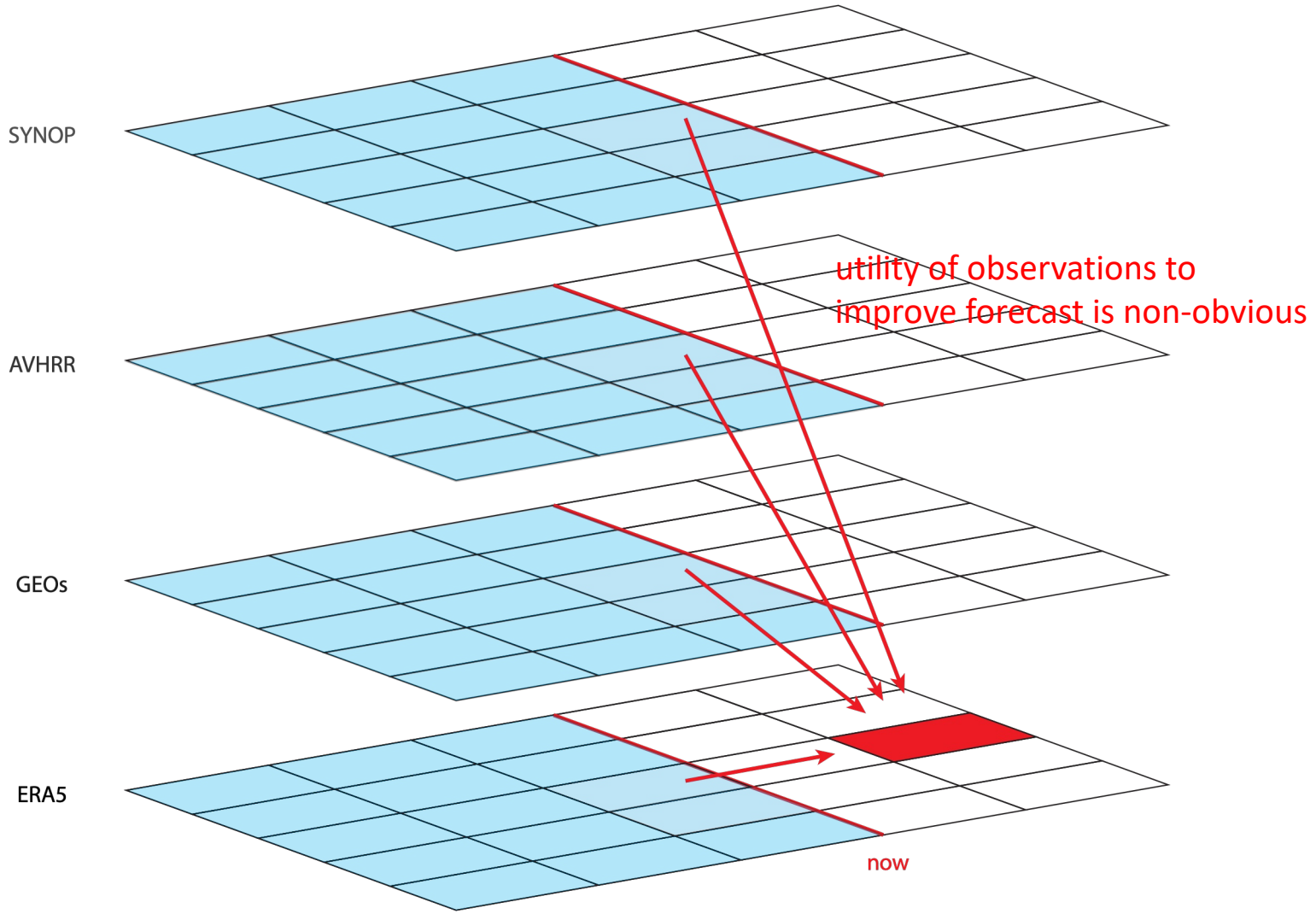
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forecasting



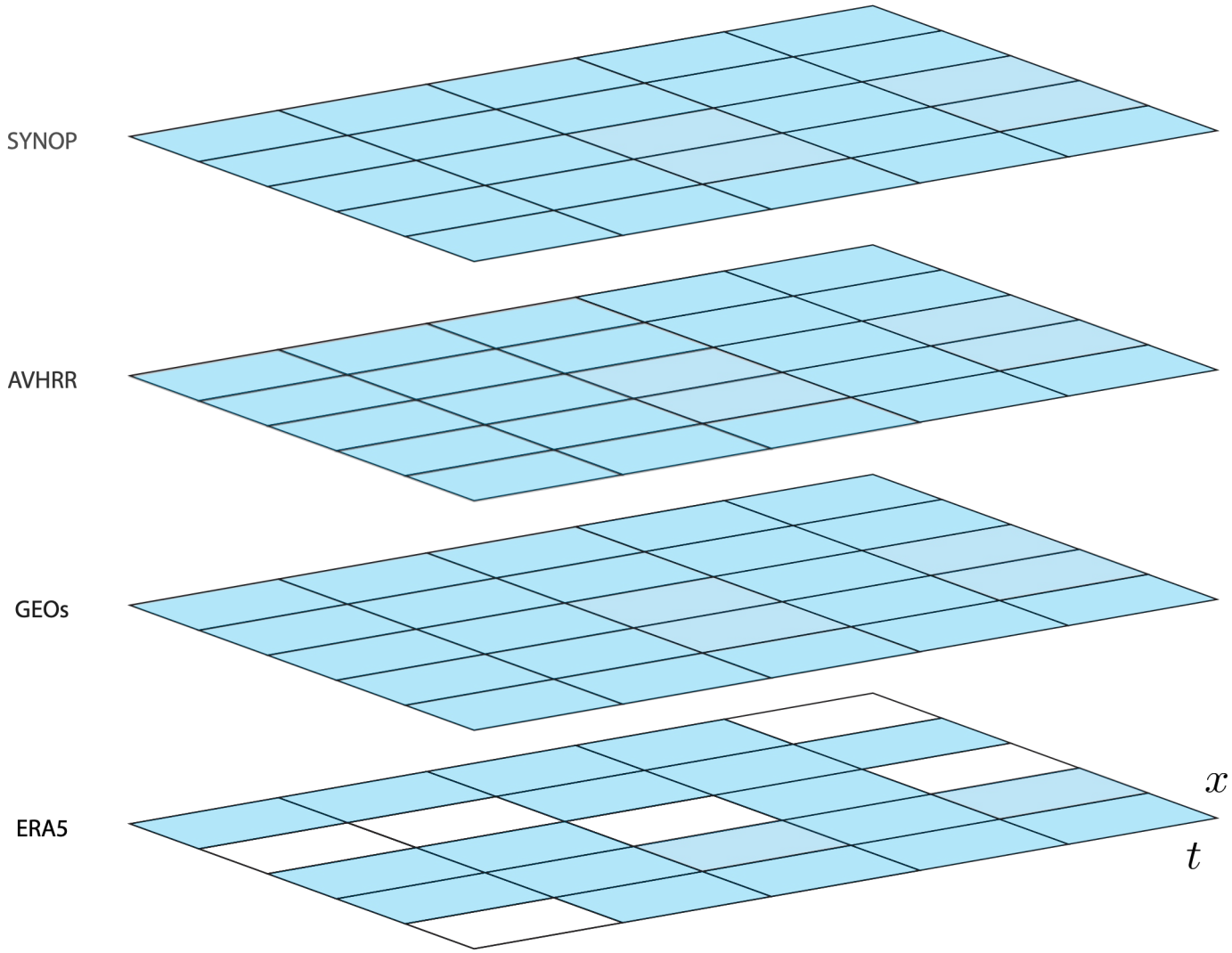
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forecasting



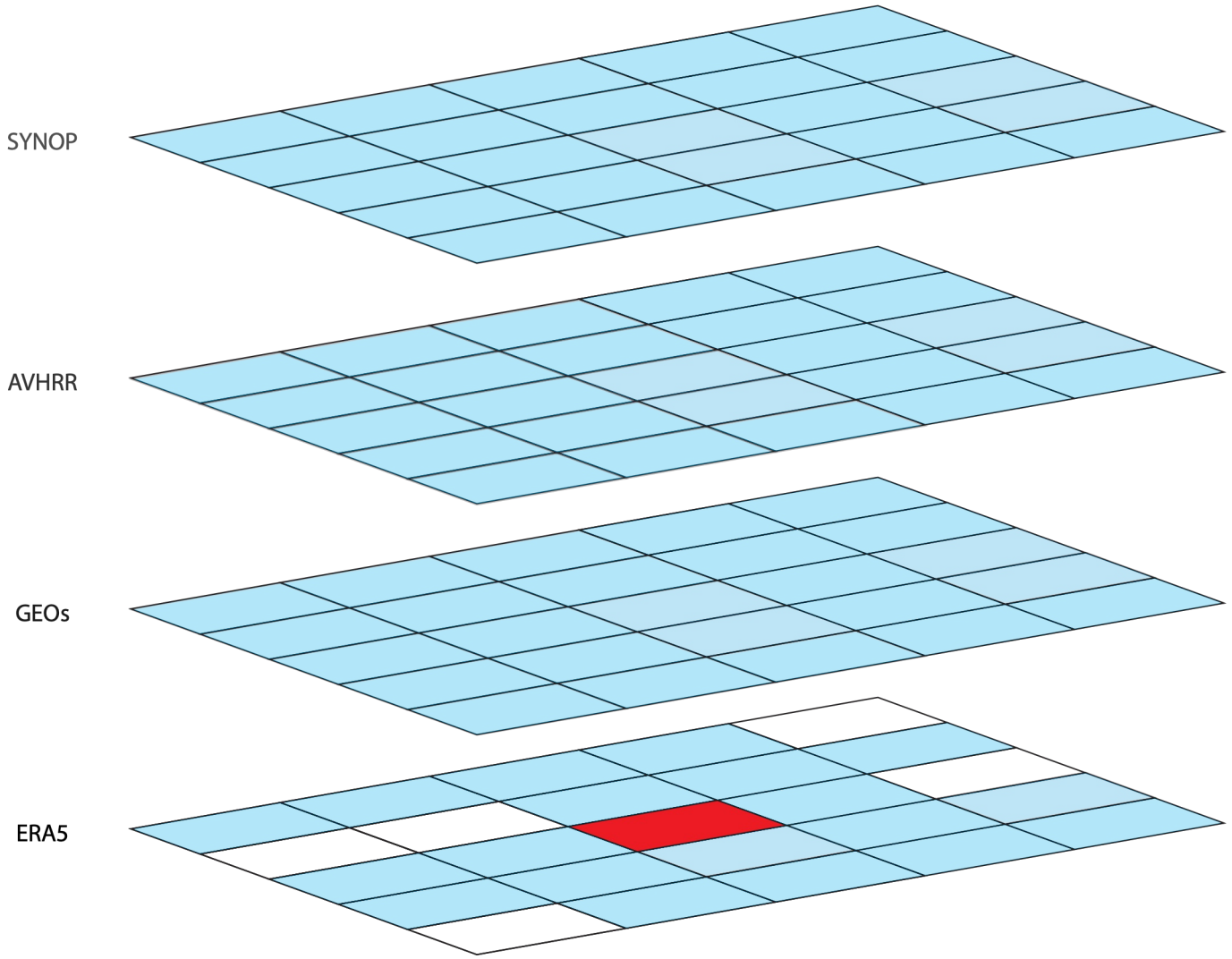
Multi-dataset input and pre-training

Training objective:
masked token modeling



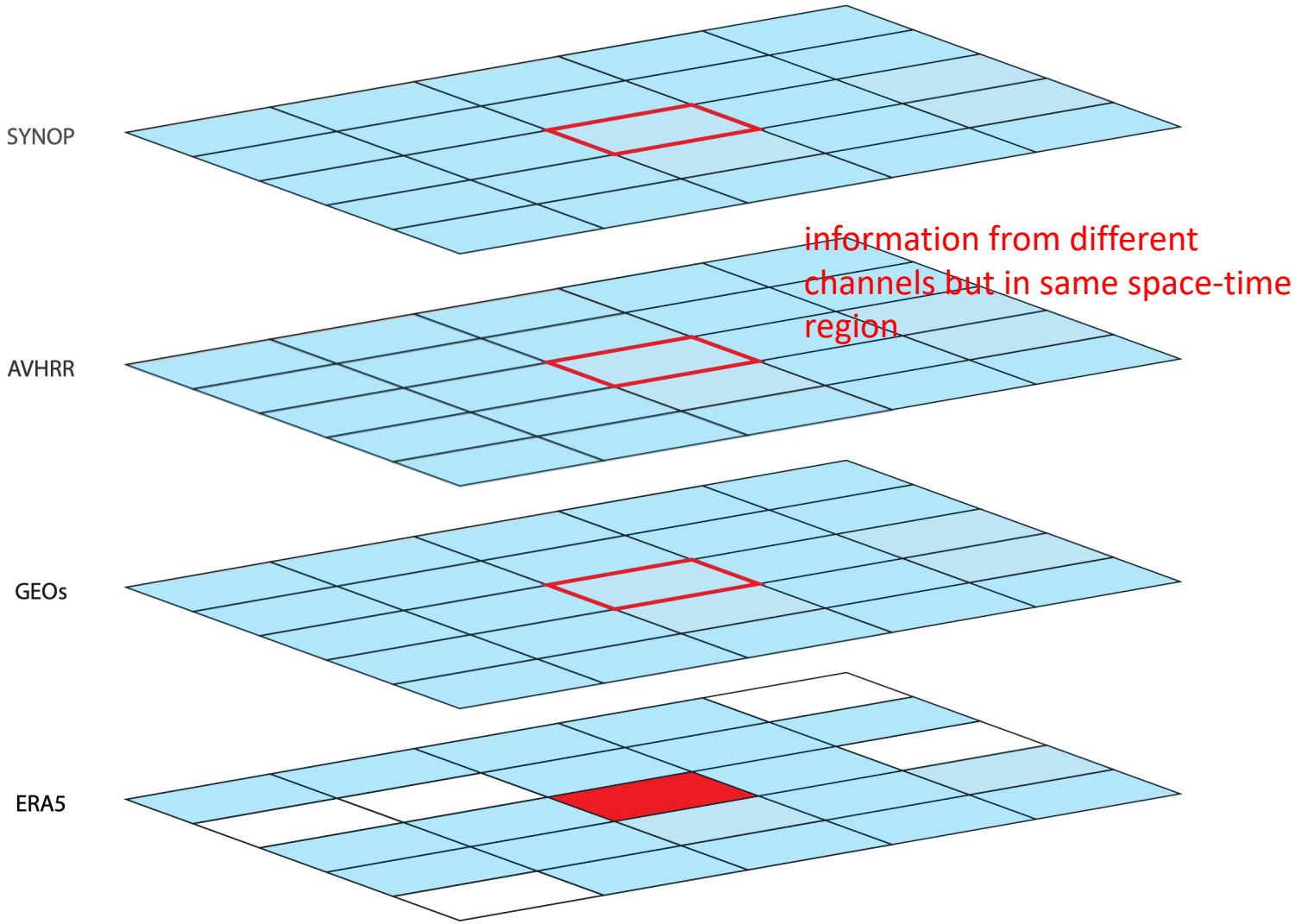
Multi-dataset input and pre-training

Training objective:
masked token modeling



Multi-dataset input and pre-training

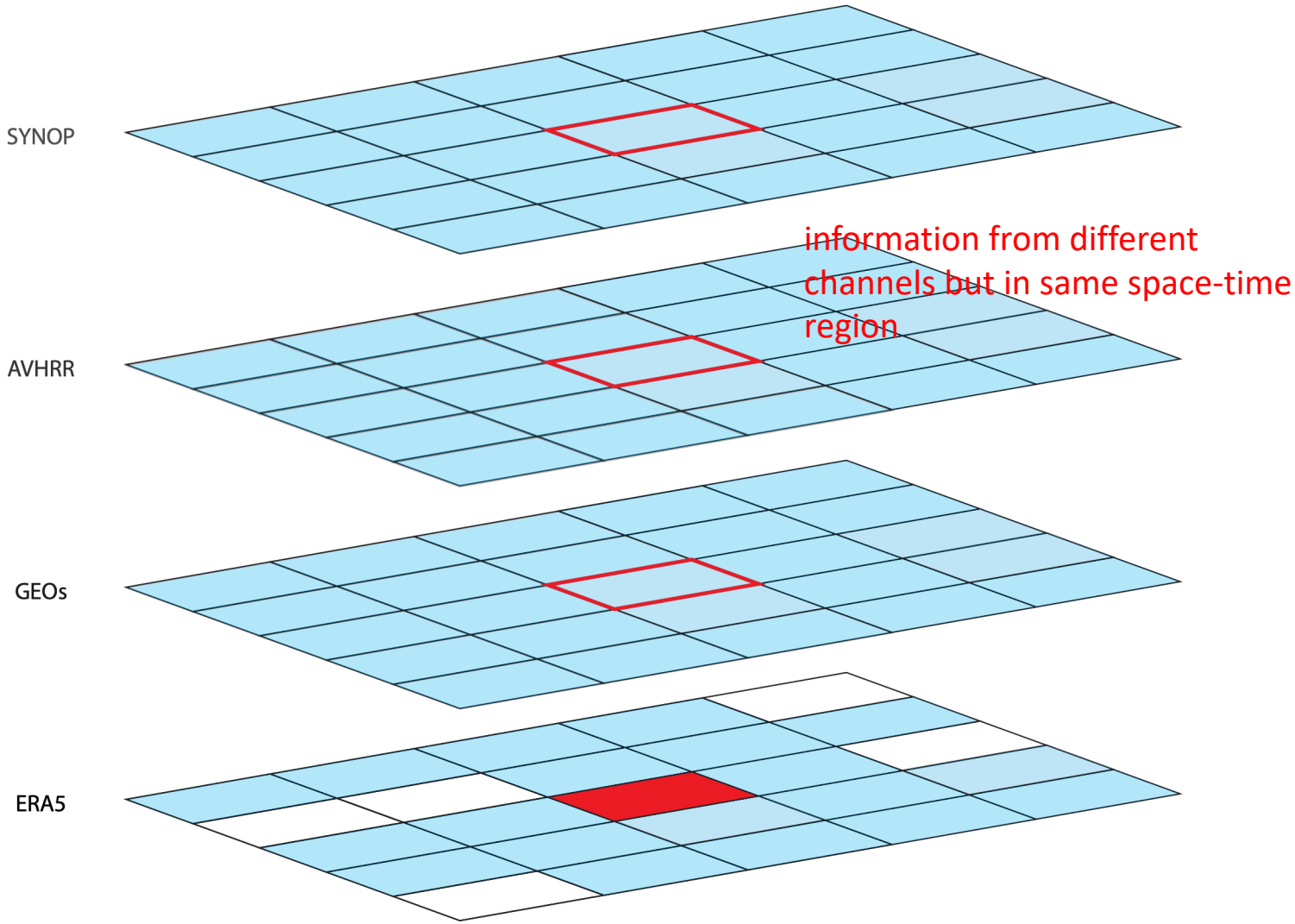
Training objective:
masked token modeling



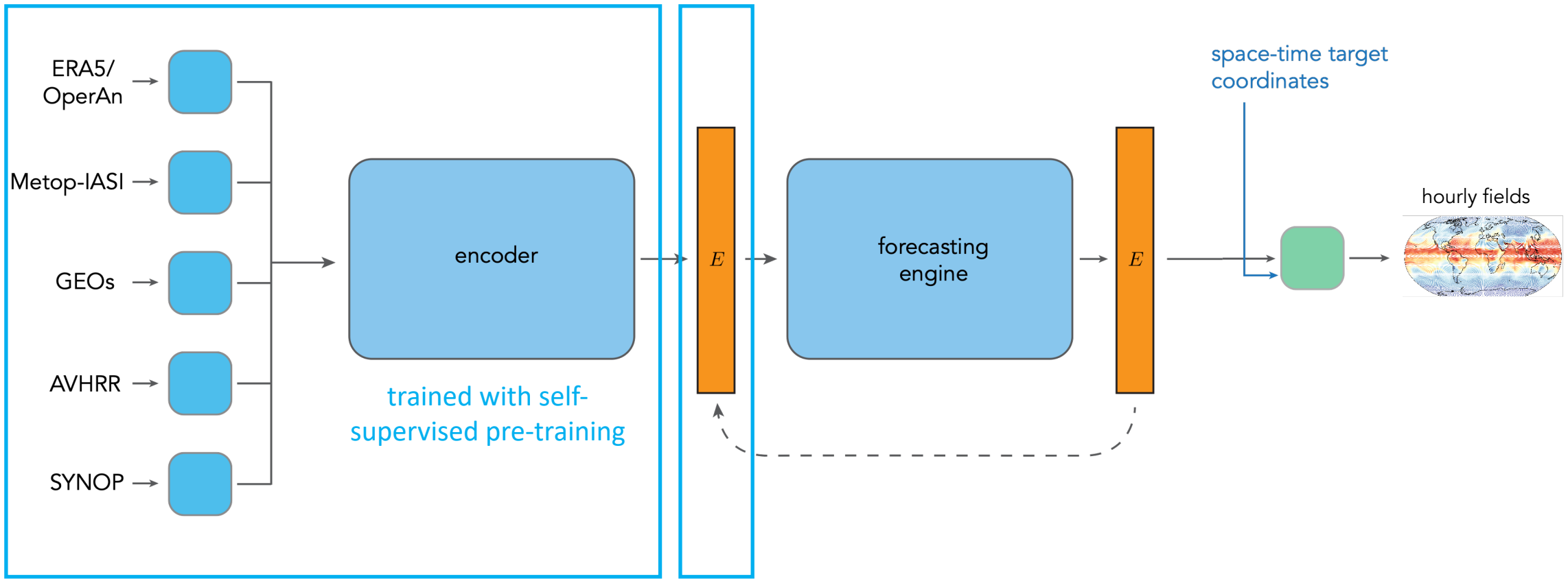
Multi-dataset input and pre-training

Training objective:
masked token modeling

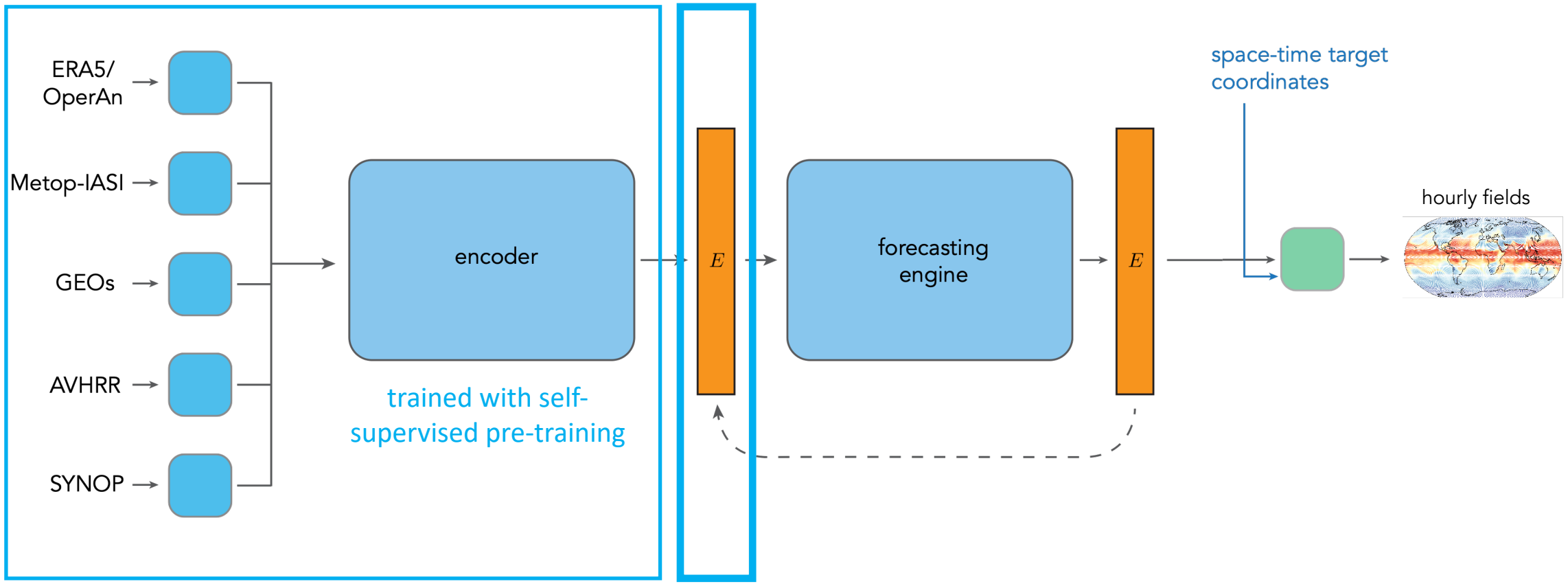
Ensure that training encourages model to use all available data



Multi-dataset input and pre-training



Multi-dataset input and pre-training

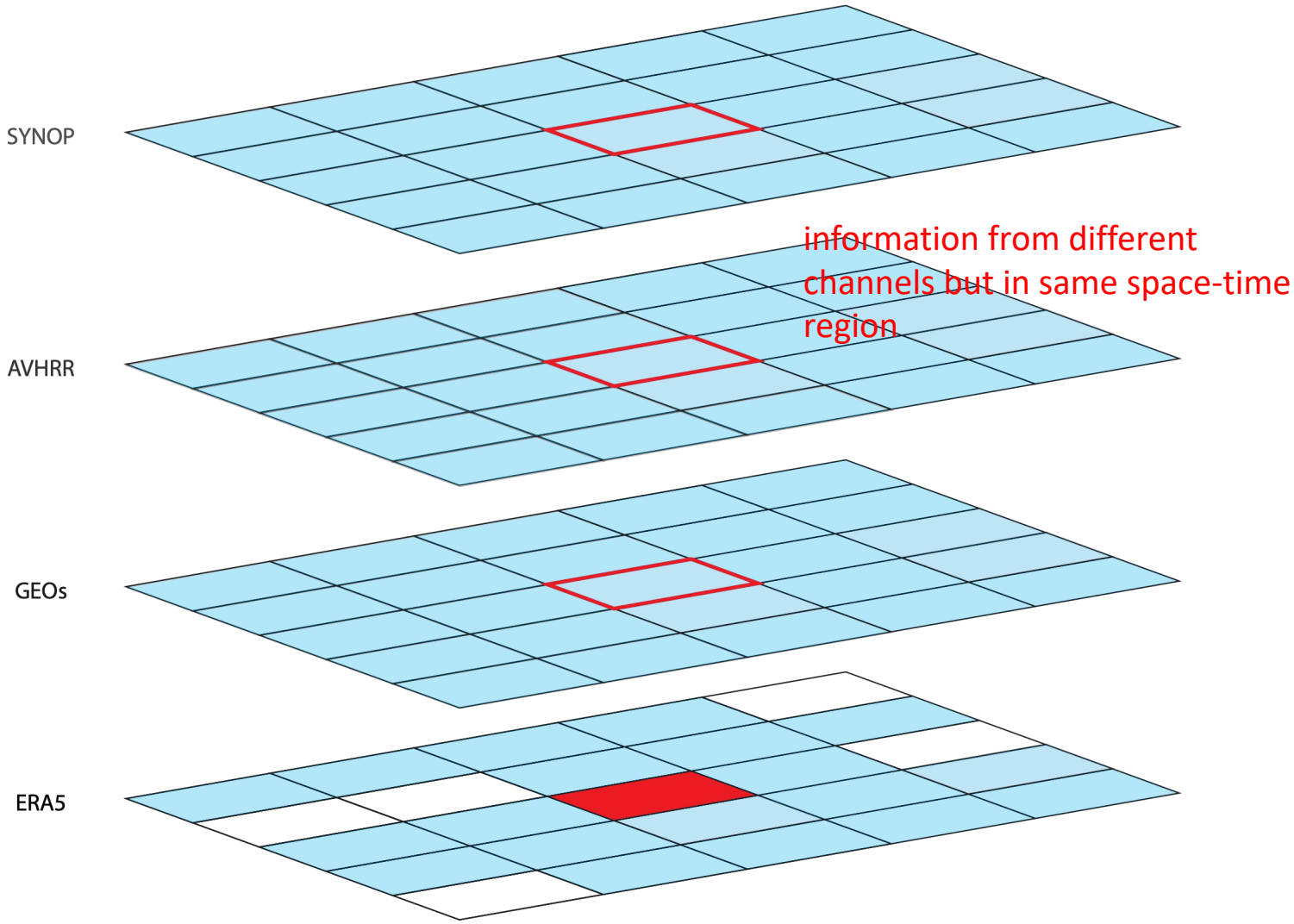


Multi-dataset input and pre-training

Training objective:
masked token modeling

Ensure that training encourages model to use all available data

Compute loss in latent space to explicit control its structure

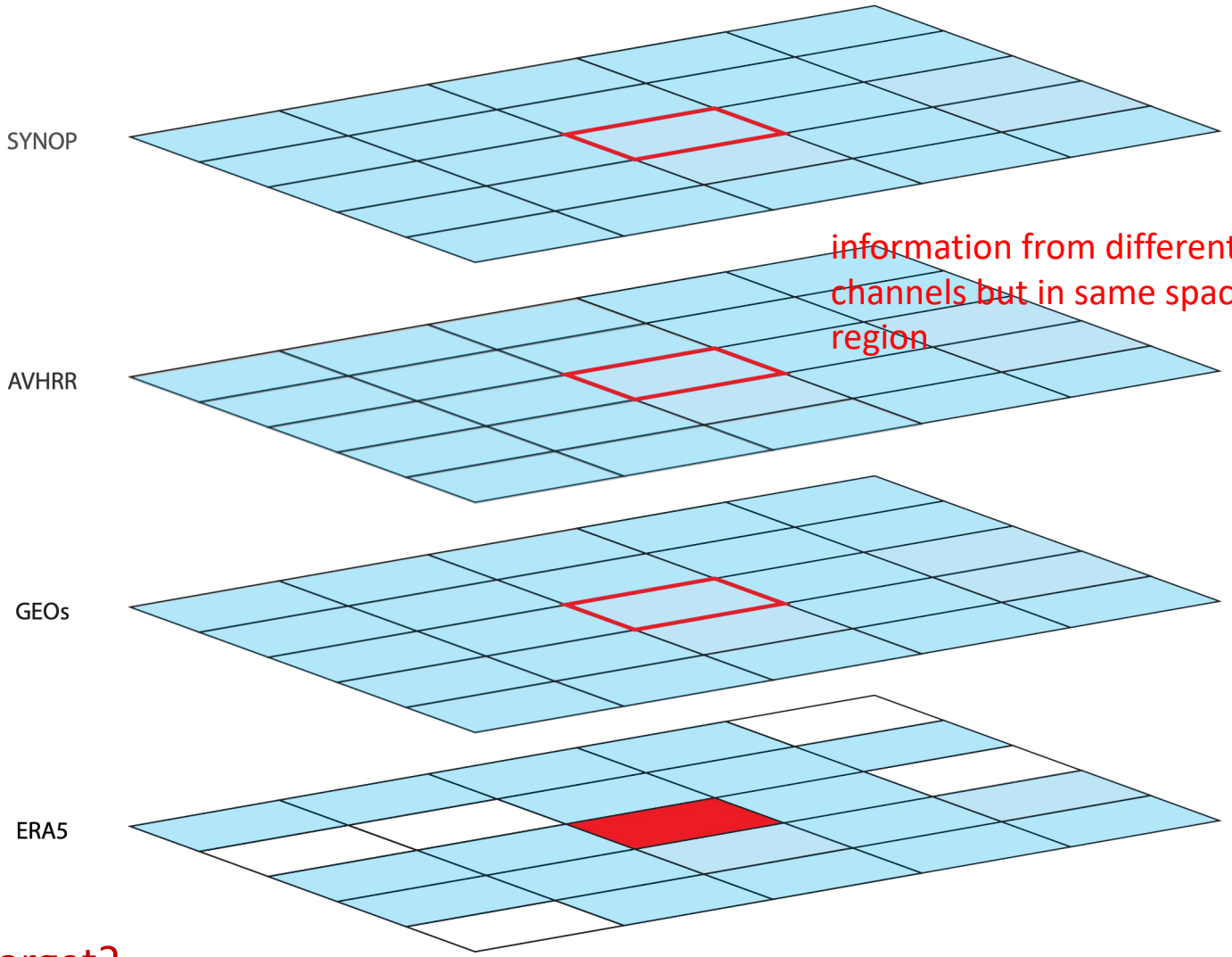


Multi-dataset input and pre-training

Training objective:
masked token modeling

Ensure that training encourages model to use all available data

Compute loss in latent space to explicit control its structure

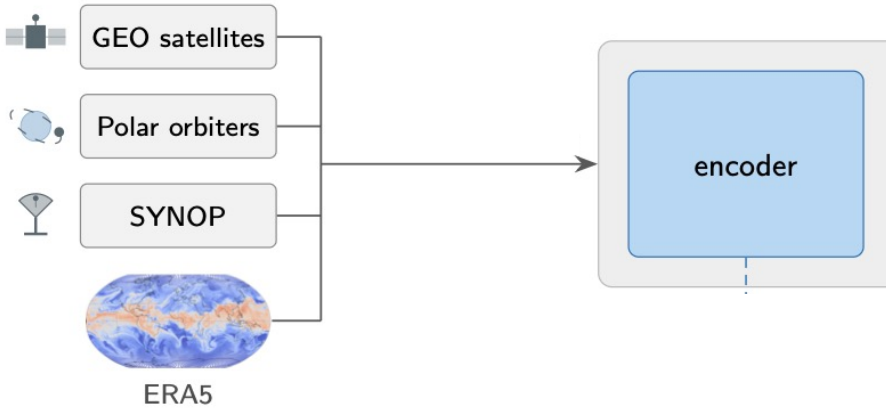


information from different channels but in same space-time region

What is training target?

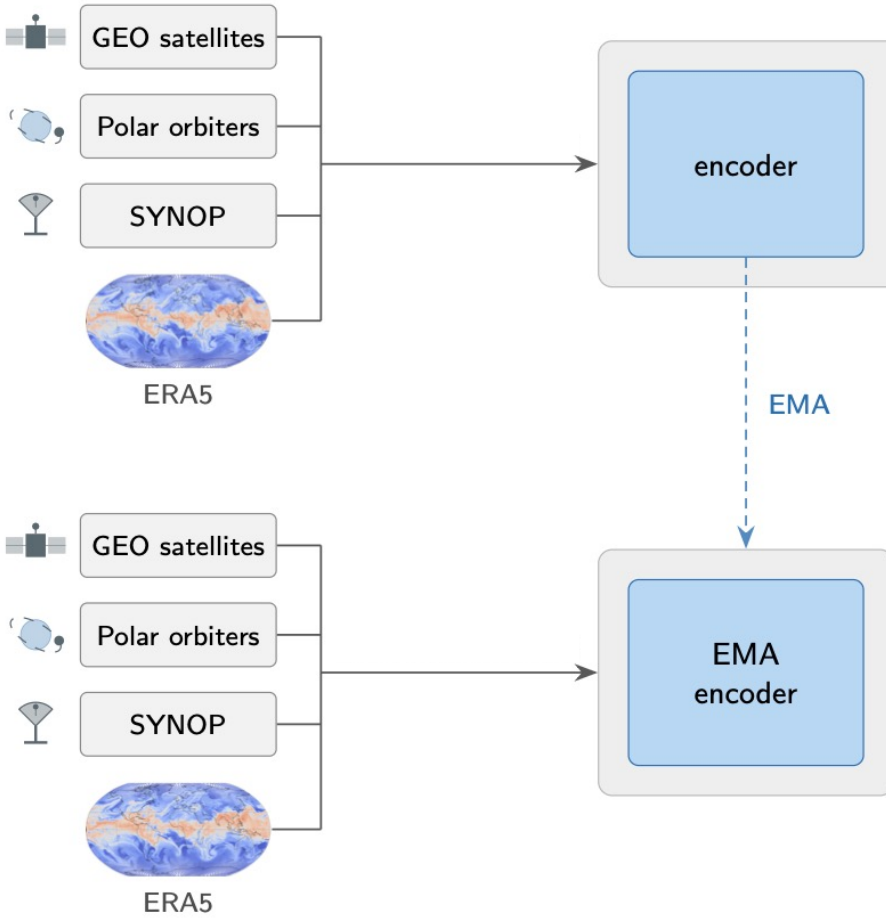
Multi-dataset input and pre-training

JEPA: Joint Embedding Predictive Architecture



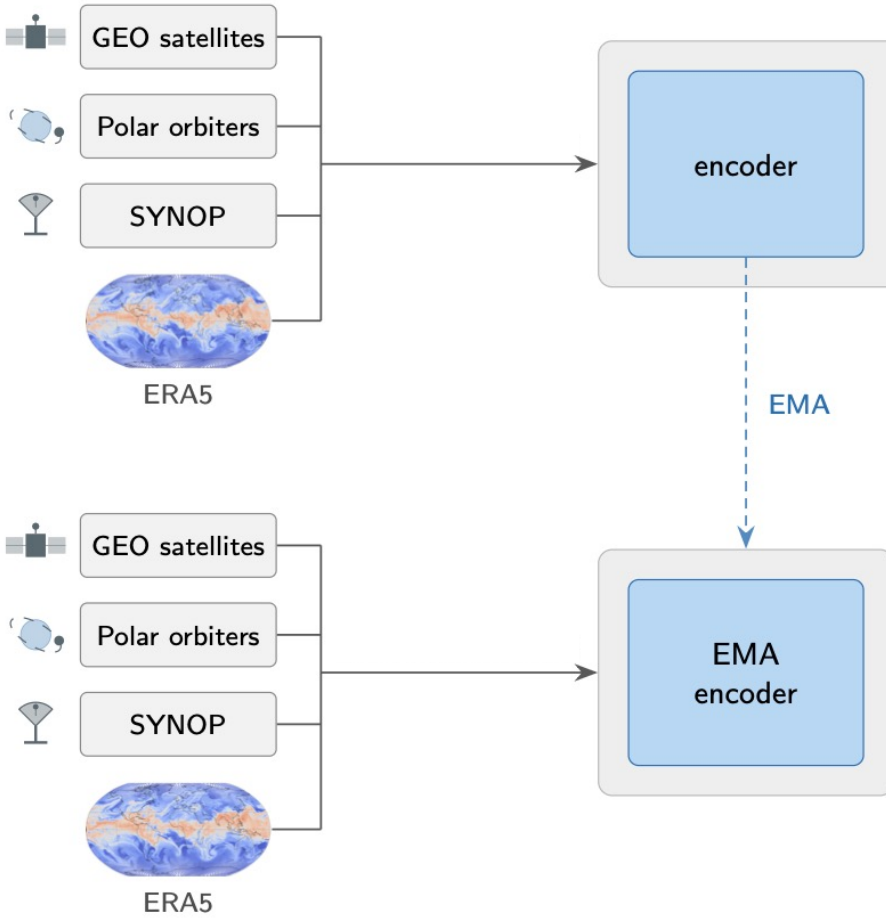
Multi-dataset input and pre-training

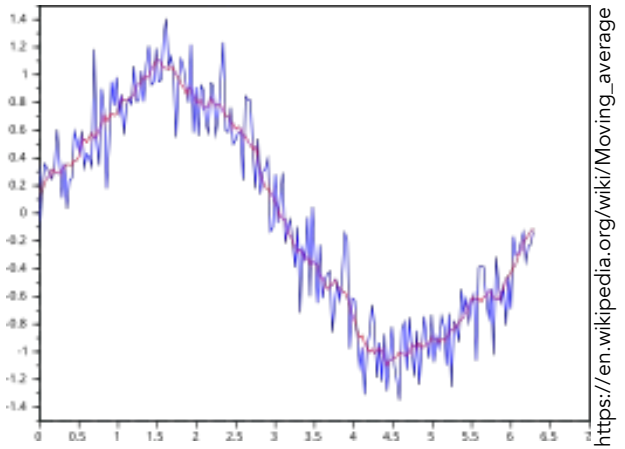
JEPA: Joint Embedding Predictive Architecture



Multi-dataset input and pre-training

JEPA: Joint Embedding Predictive Architecture

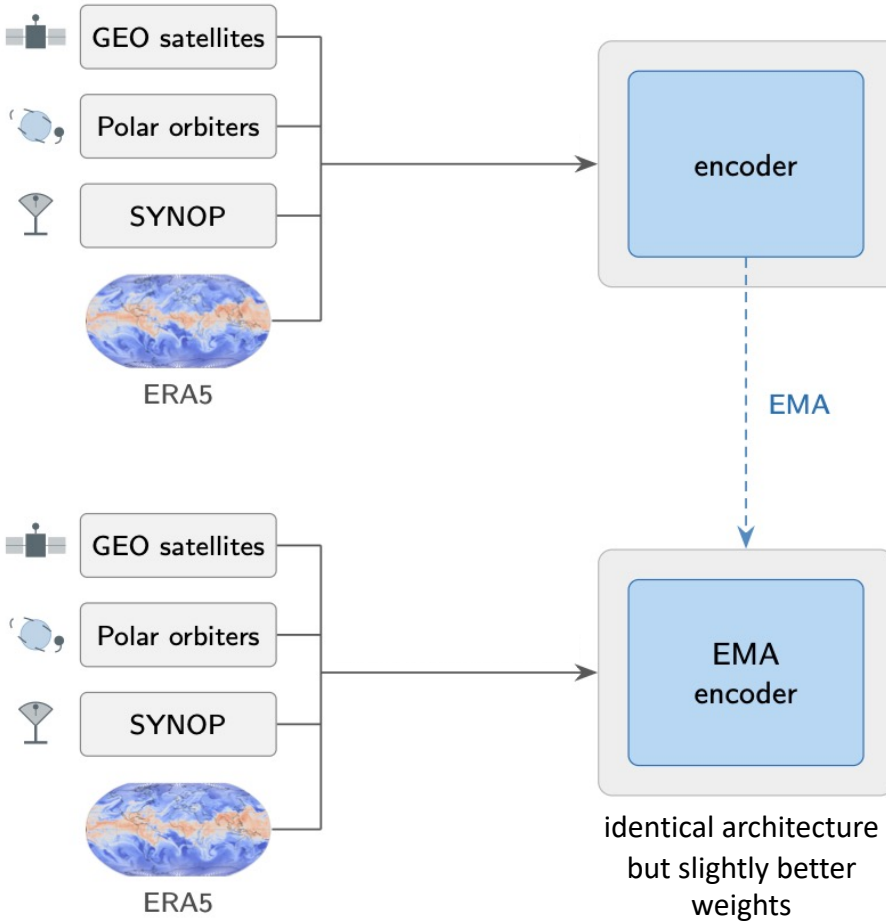


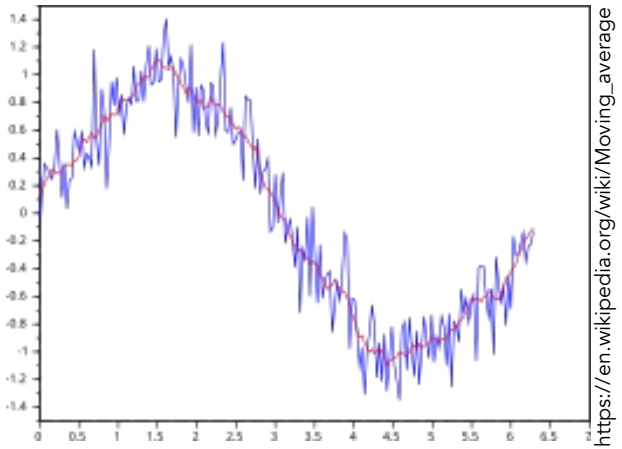


https://en.wikipedia.org/wiki/Moving_average

Multi-dataset input and pre-training

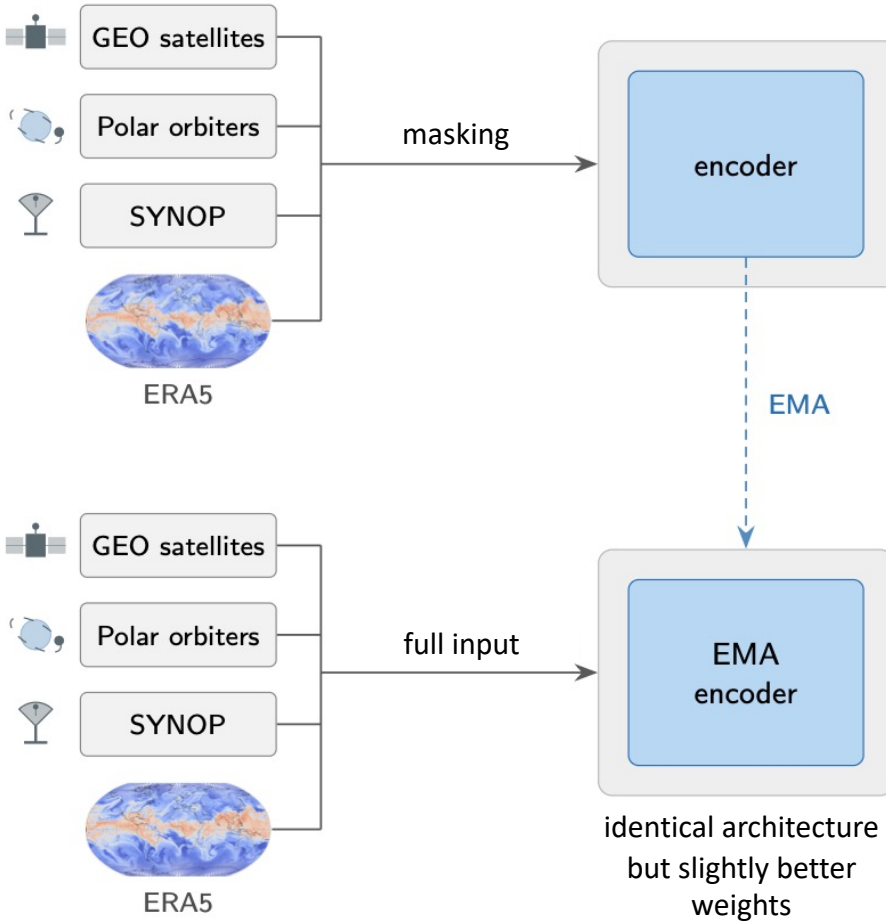
JEPA: Joint Embedding Predictive Architecture

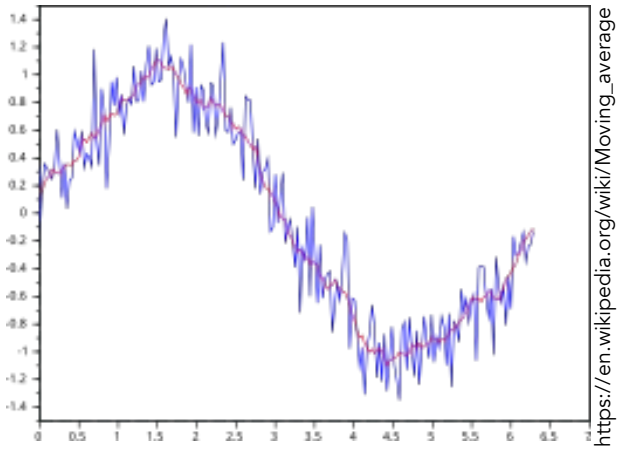




Multi-dataset input and pre-training

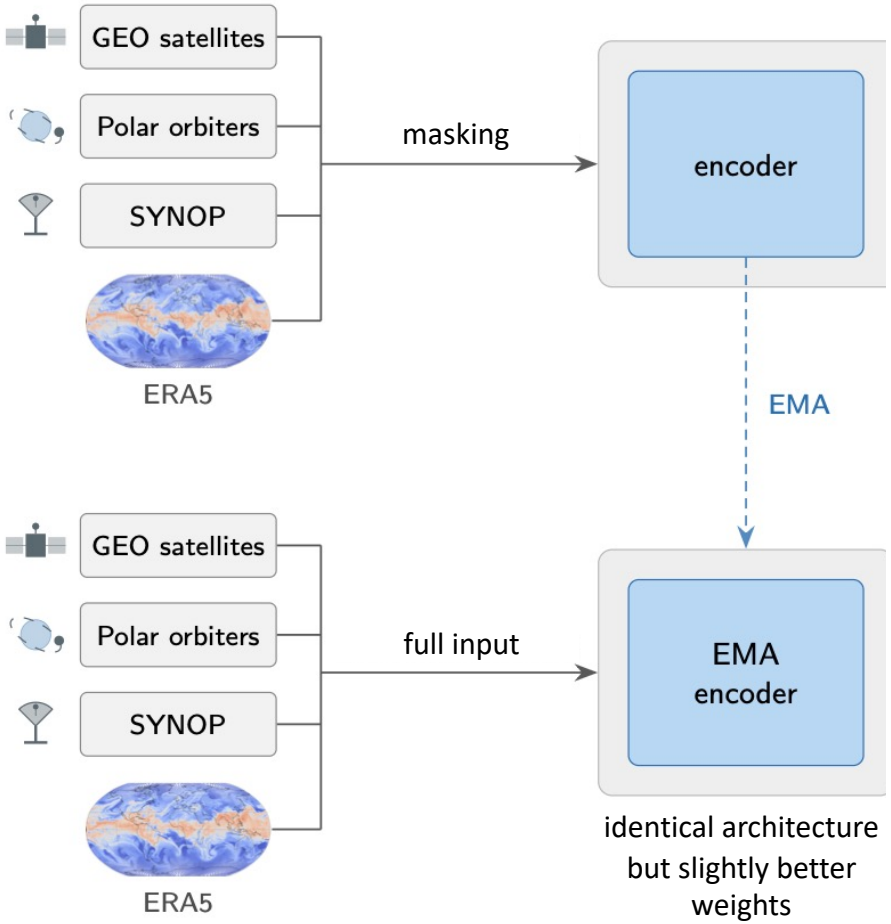
JEPA: Joint Embedding Predictive Architecture

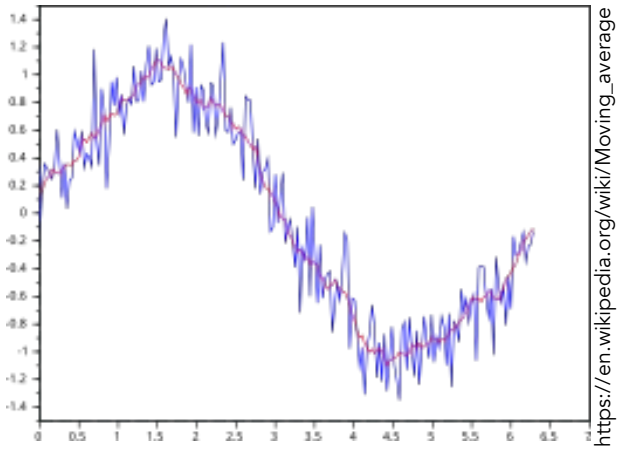




Multi-dataset input and pre-training

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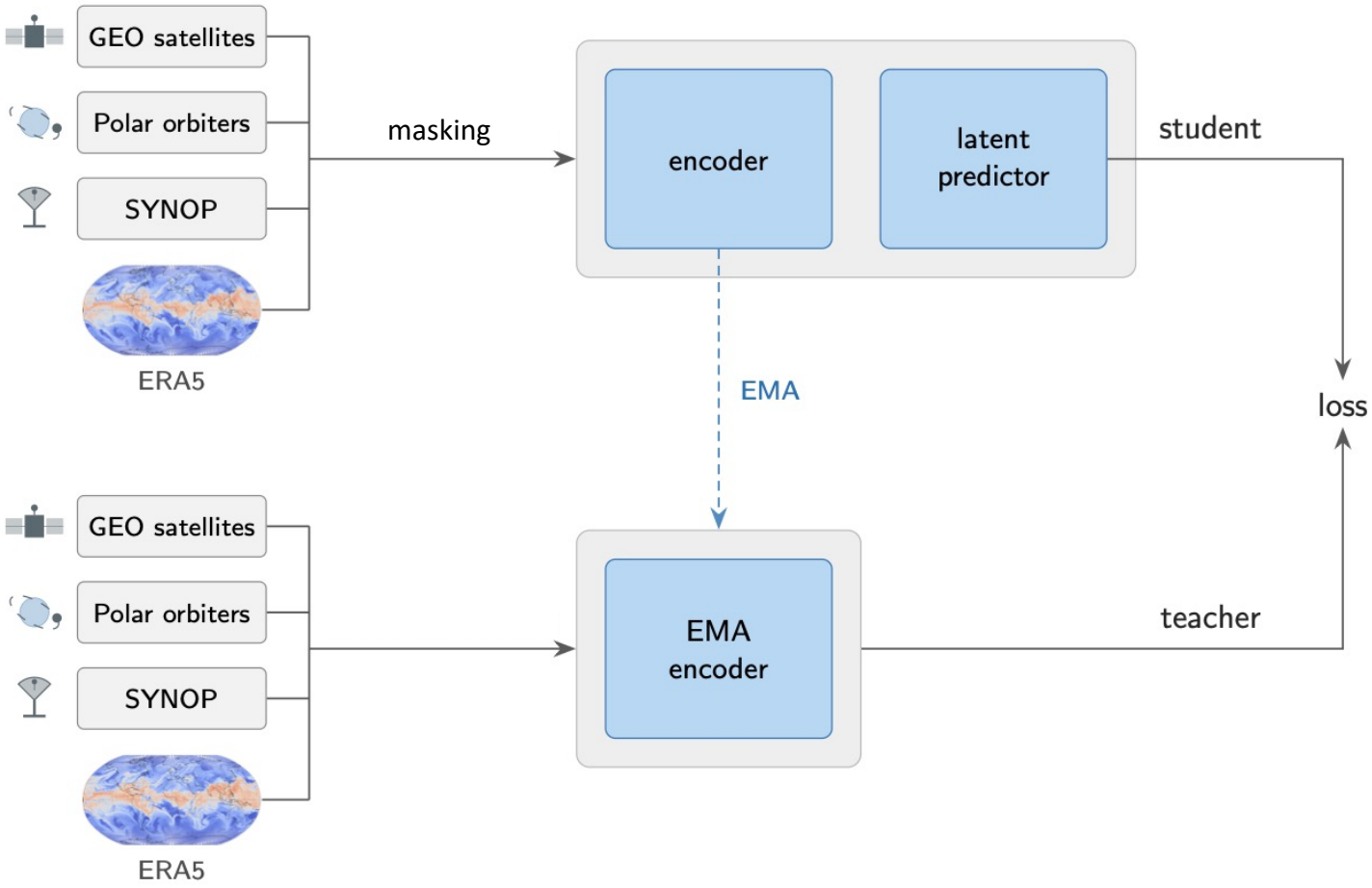




asymmetry ensures latents provide suitable training target

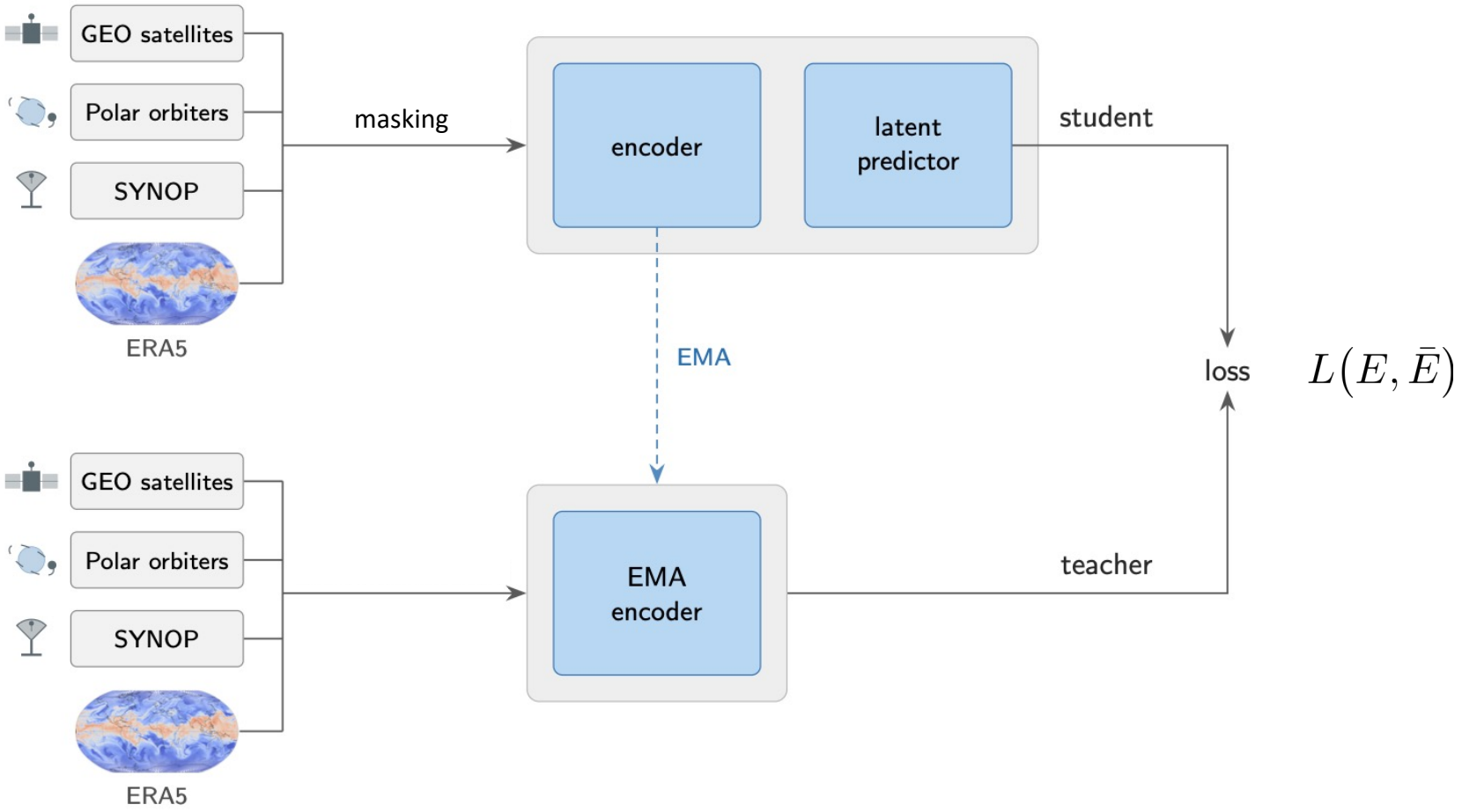
Multi-dataset input and pre-training

JEPA: Joint Embedding Predictive Architecture



Multi-dataset input and pre-training

JEPA: Joint Embedding Predictive Architecture

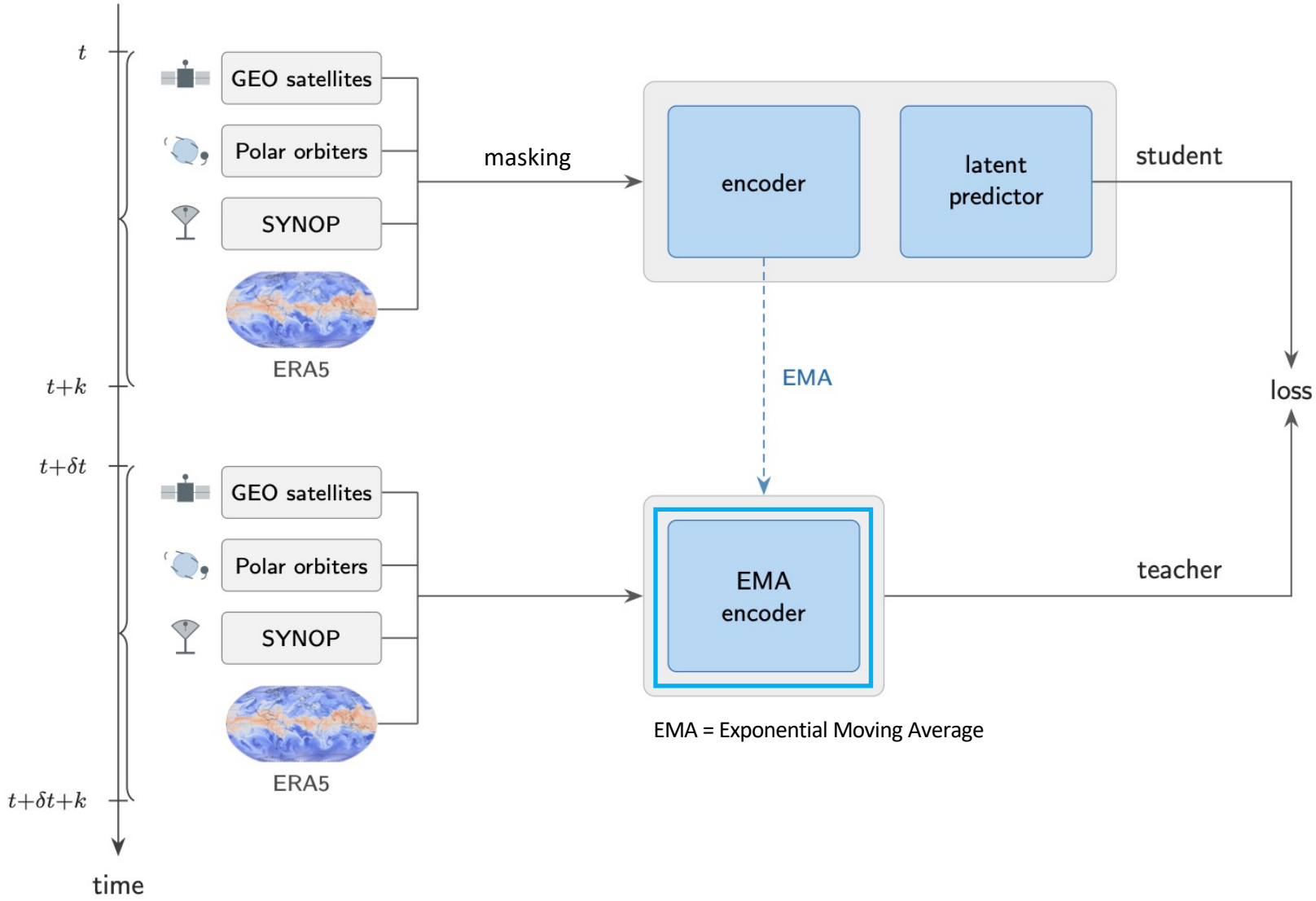


Multi-dataset input and pre-training

JEPA: Joint Embedding Predictive Architecture

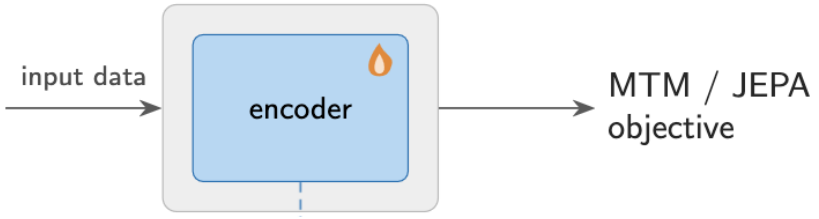
Spatial JEPA: $\delta t = 0$

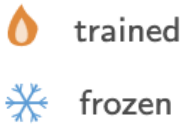
Temporal JEPA: $\delta t = k$



Multi-dataset input and pre-training

I. JEPA pretraining

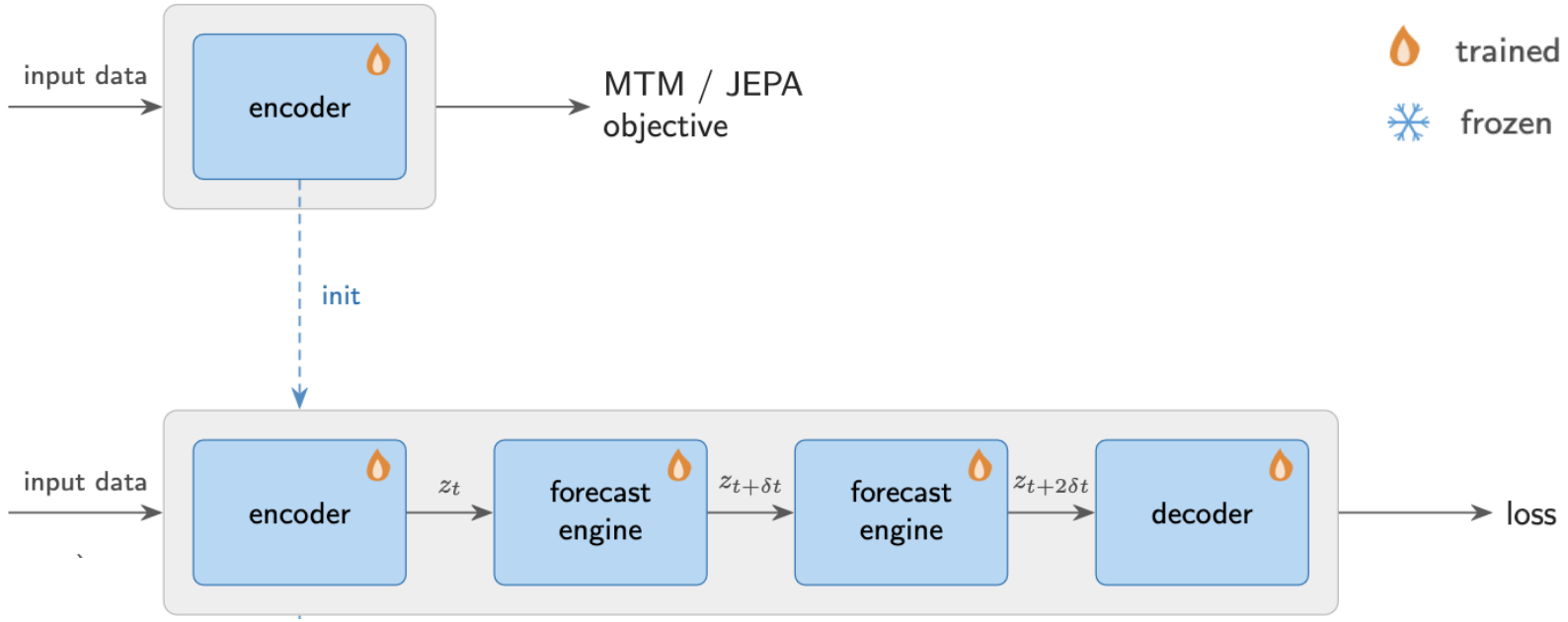




Multi-dataset input and pre-training

I. JEPA pretraining

II. 2-step forecast finetuning

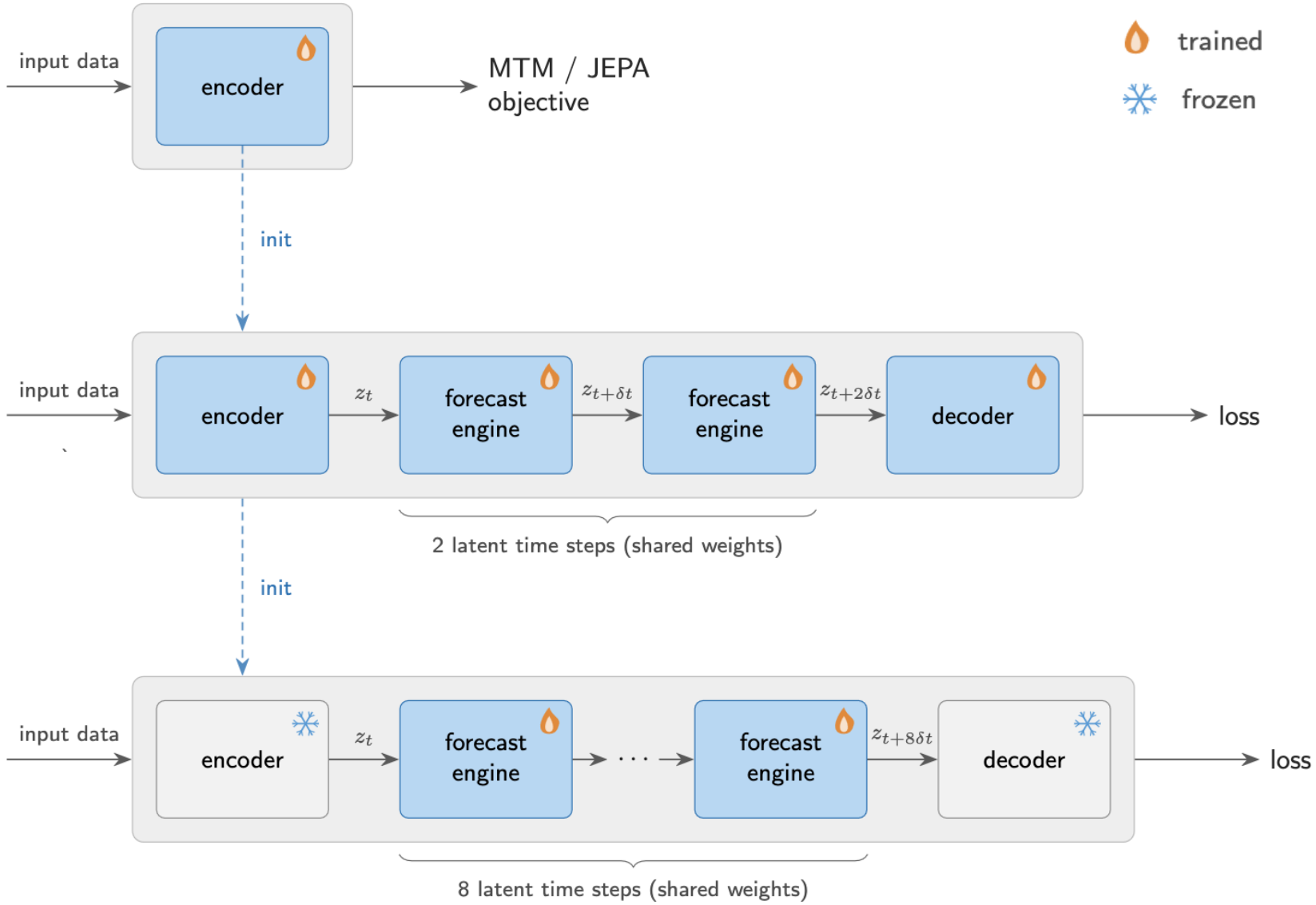


Multi-dataset input and pre-training

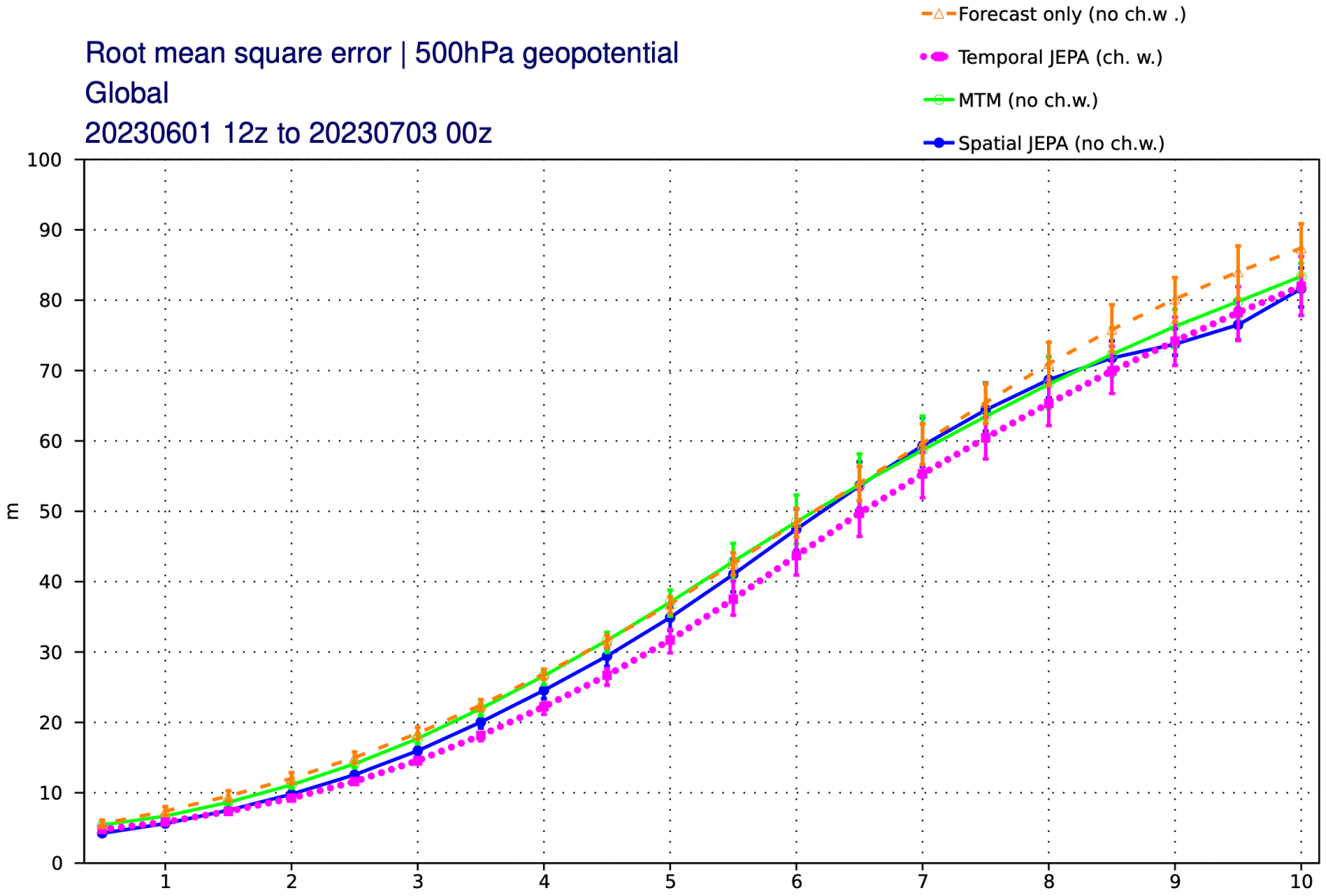
I. JEPA pretraining

II. 2-step forecast finetuning

III. 8-step forecast finetuning



Results: comparison of pretraining



Results: benefit of observations

Bias specific humidity (q) at 300 hPa for 12h forecast

Results: benefit of observations

Bias specific humidity (q) at 300 hPa

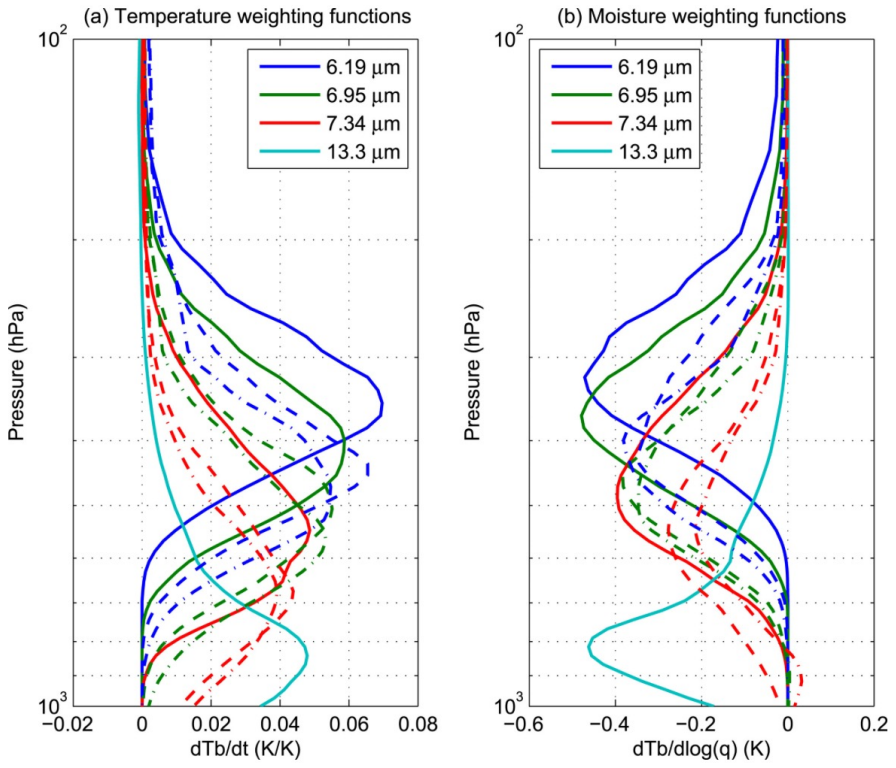


Figure 1 Open in figure viewer | PowerPoint

(a) The temperature and (b) water vapor weighting functions (Jacobian functions) of selected Advanced Baseline Imager (ABI) bands. The solid lines represent typical tropical profiles, dashed lines represent typical midlatitude winter profiles, and the dash-dotted lines represent typical subarctic winter profiles.

Results: benefit of observations

Bias specific humidity (q) at 300 hPa

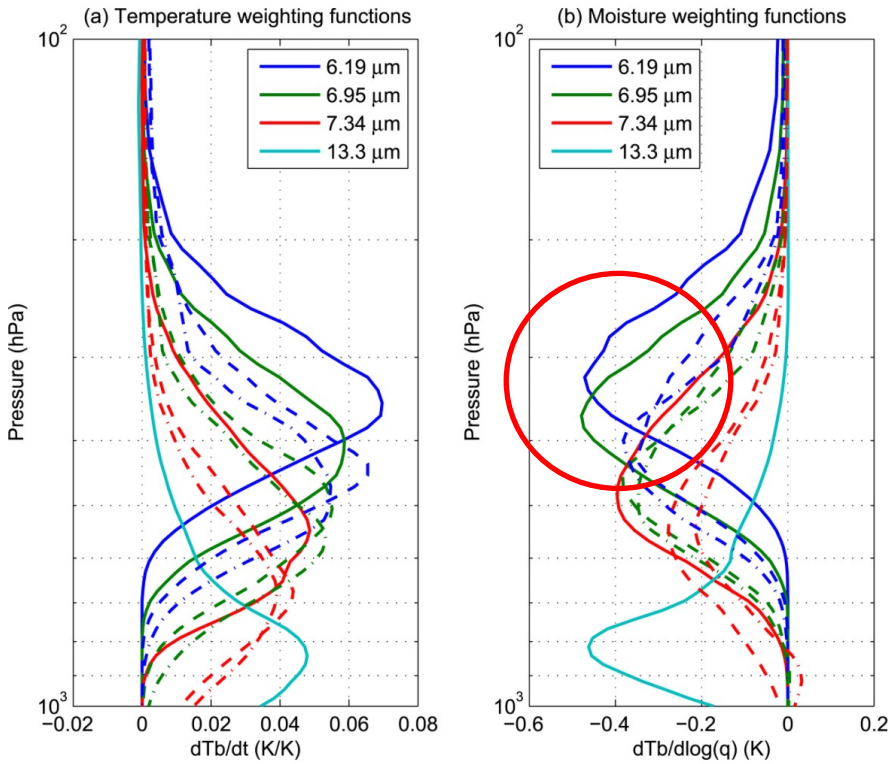


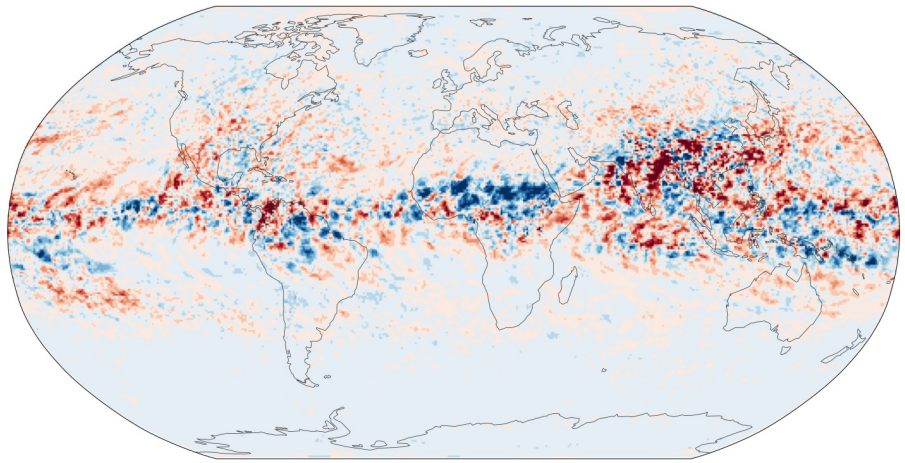
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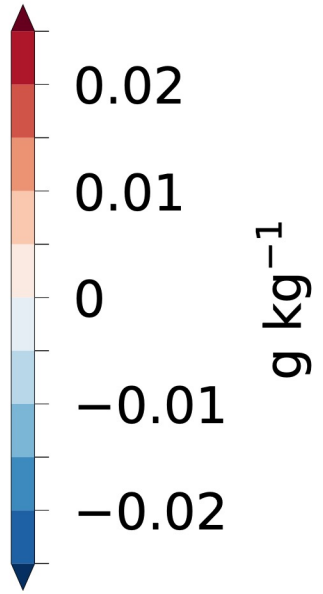
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Results: benefit of observations

Bias specific humidity (q) at 300 hPa for 12h forecast

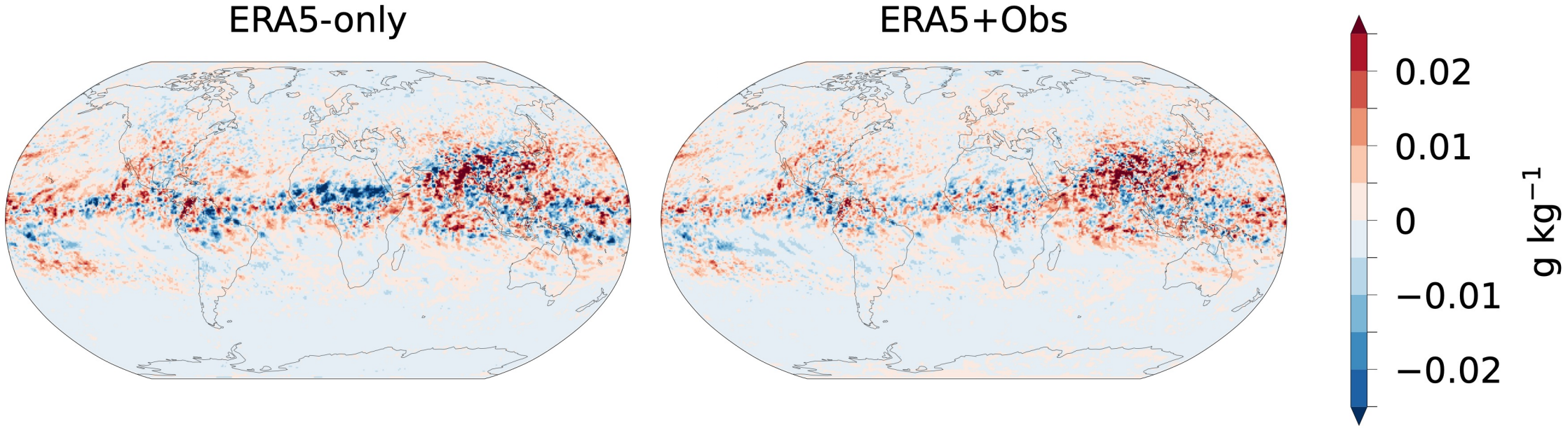
ERA5-only



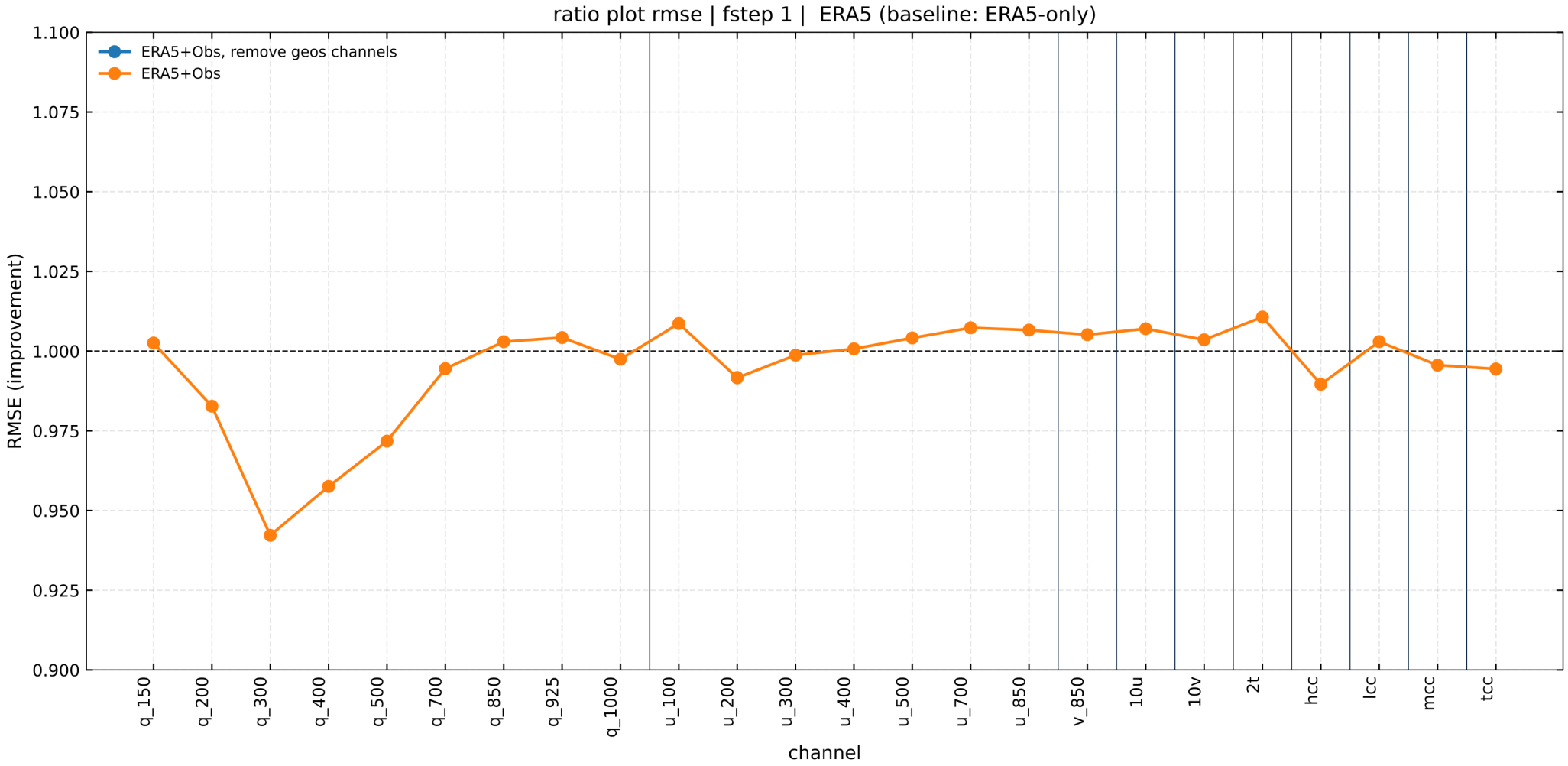


Results: benefit of observations

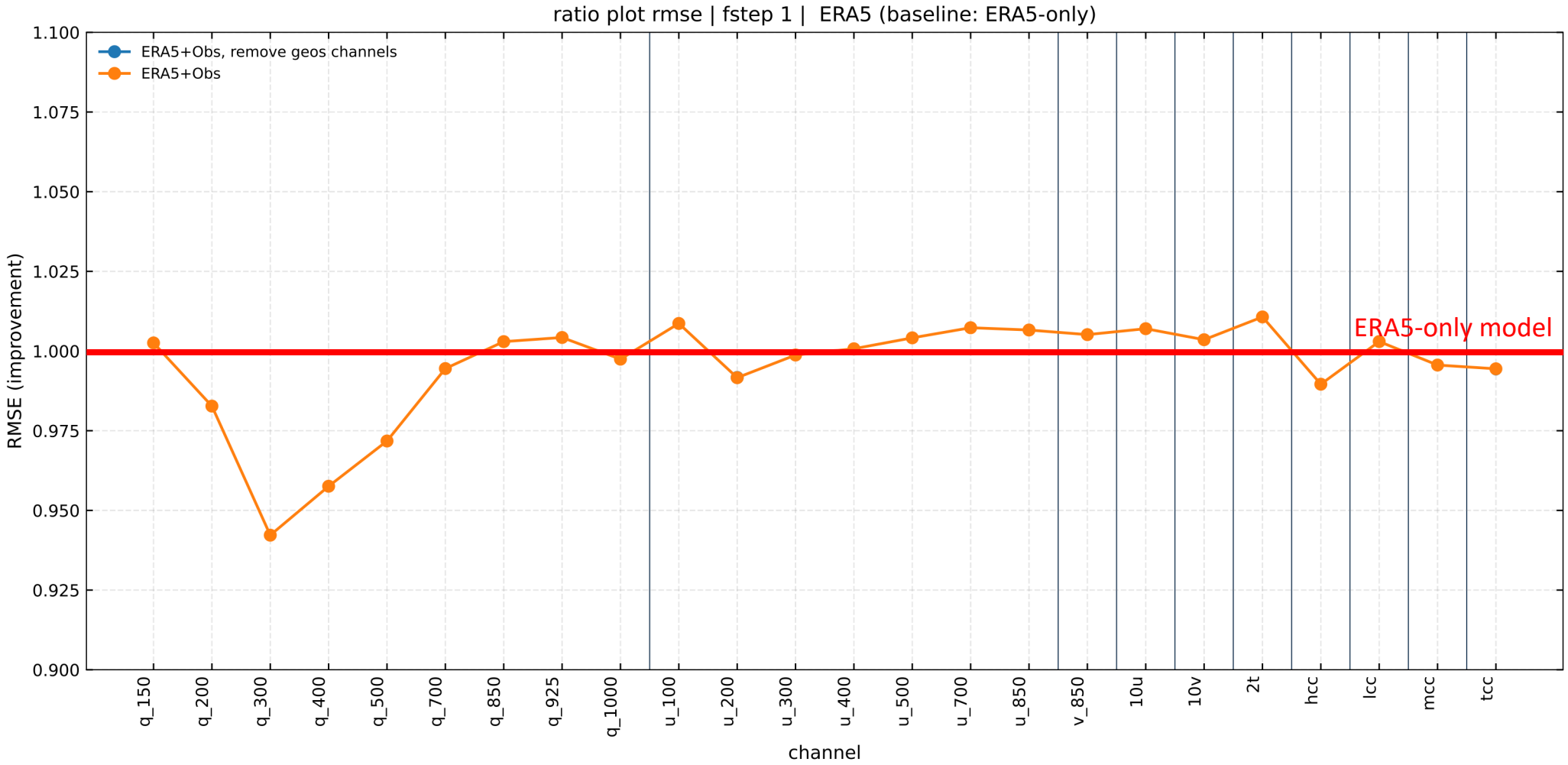
Bias specific humidity (q) at 300 hPa for 12h forecast



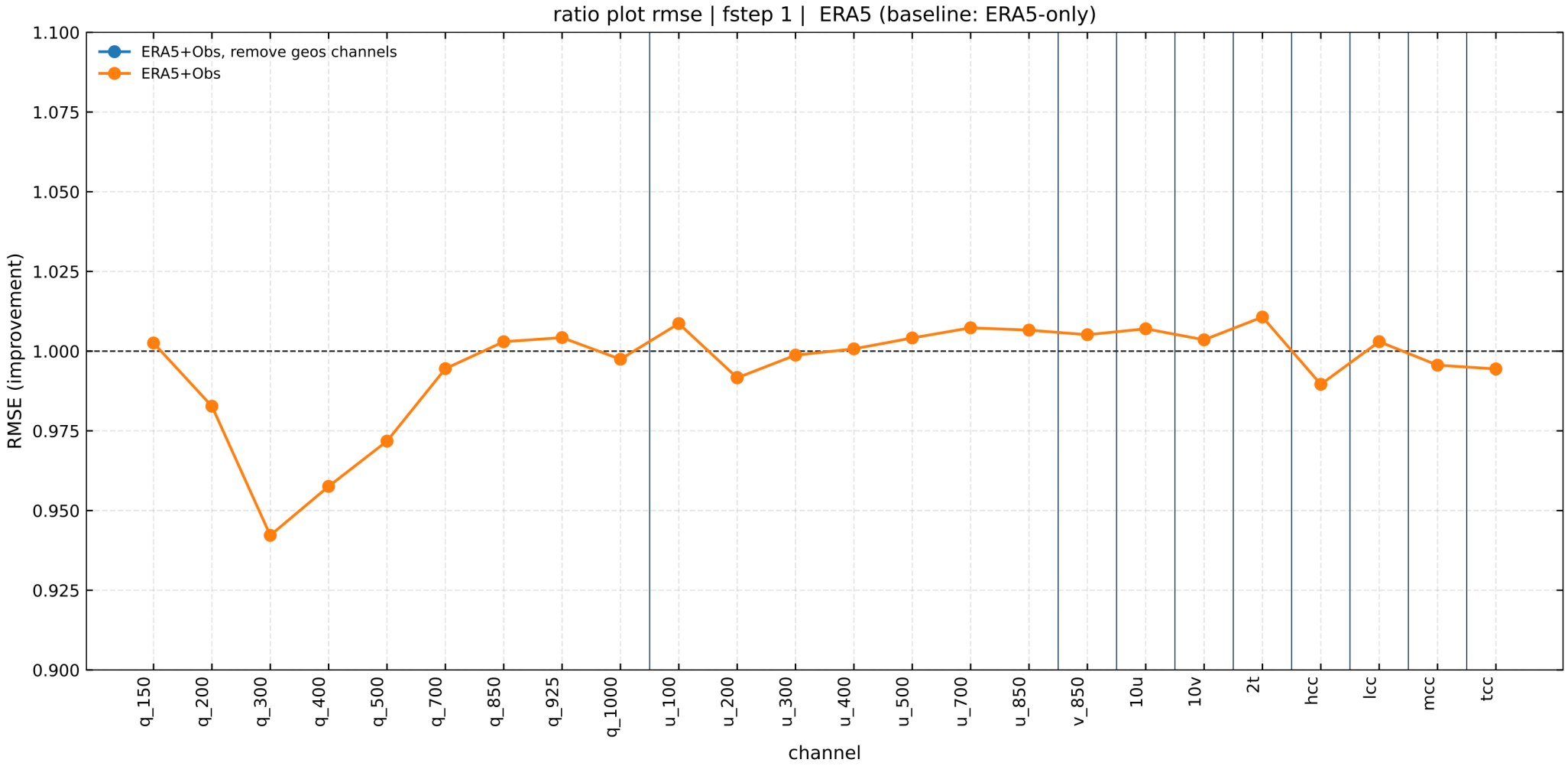
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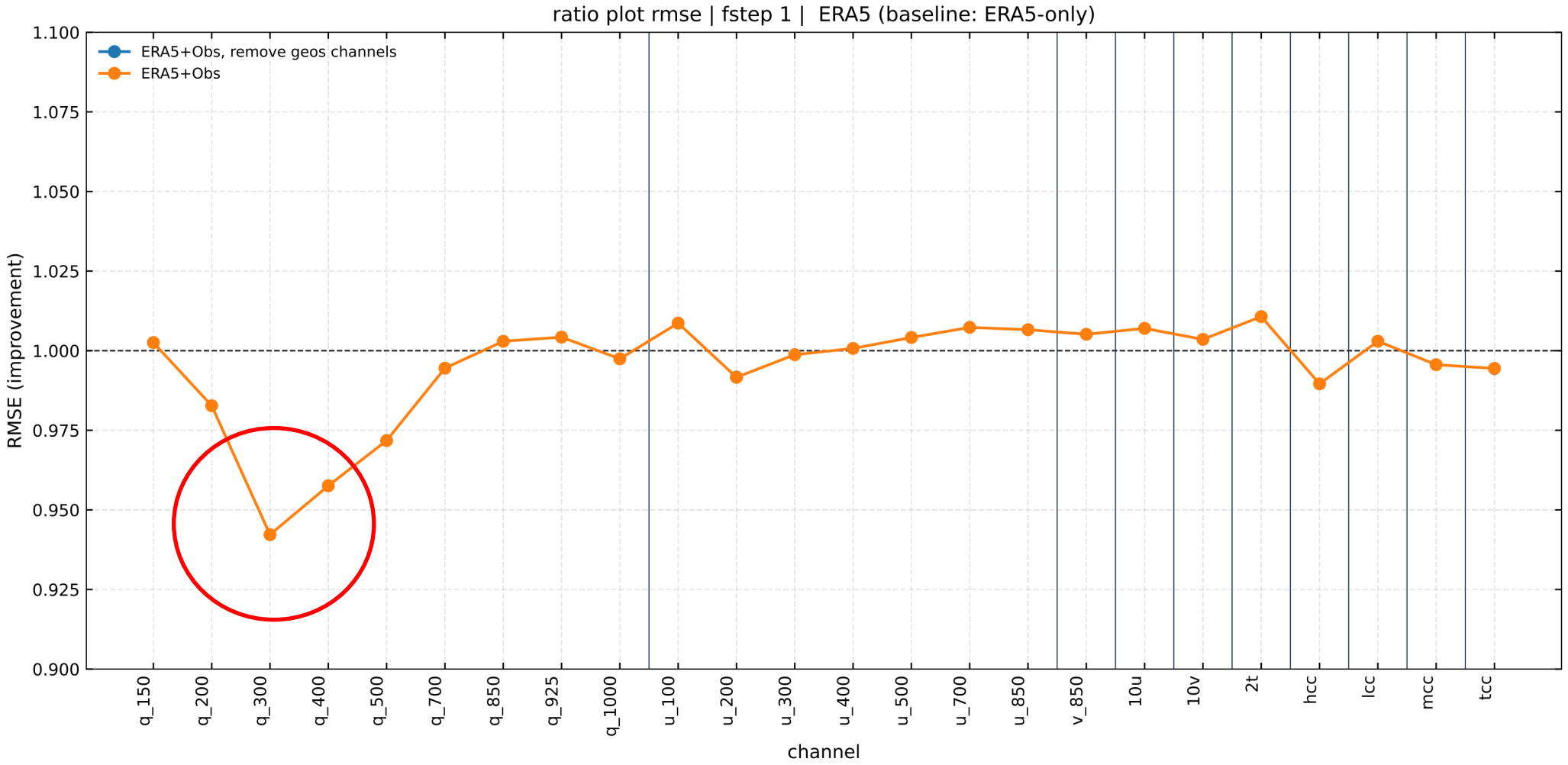
Results: benefit of observations



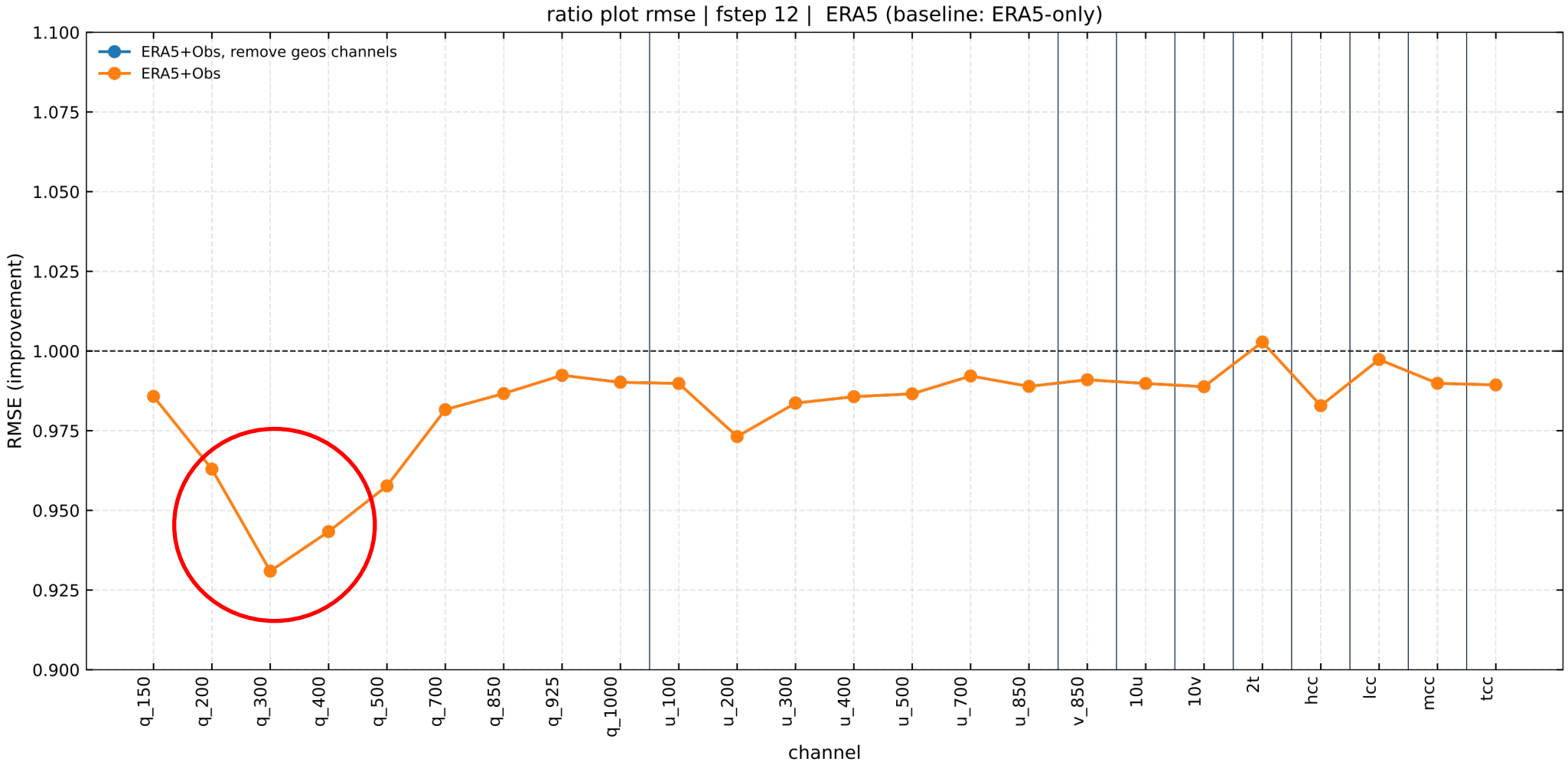
Results: benefit of observations



Results: benefit of observations



Results: benefit of observations



Results: benefit of observations

Channel sensitivities for GEOs

- Sensitivities depend strongly on the state of the atmosphere and in particular cloudiness

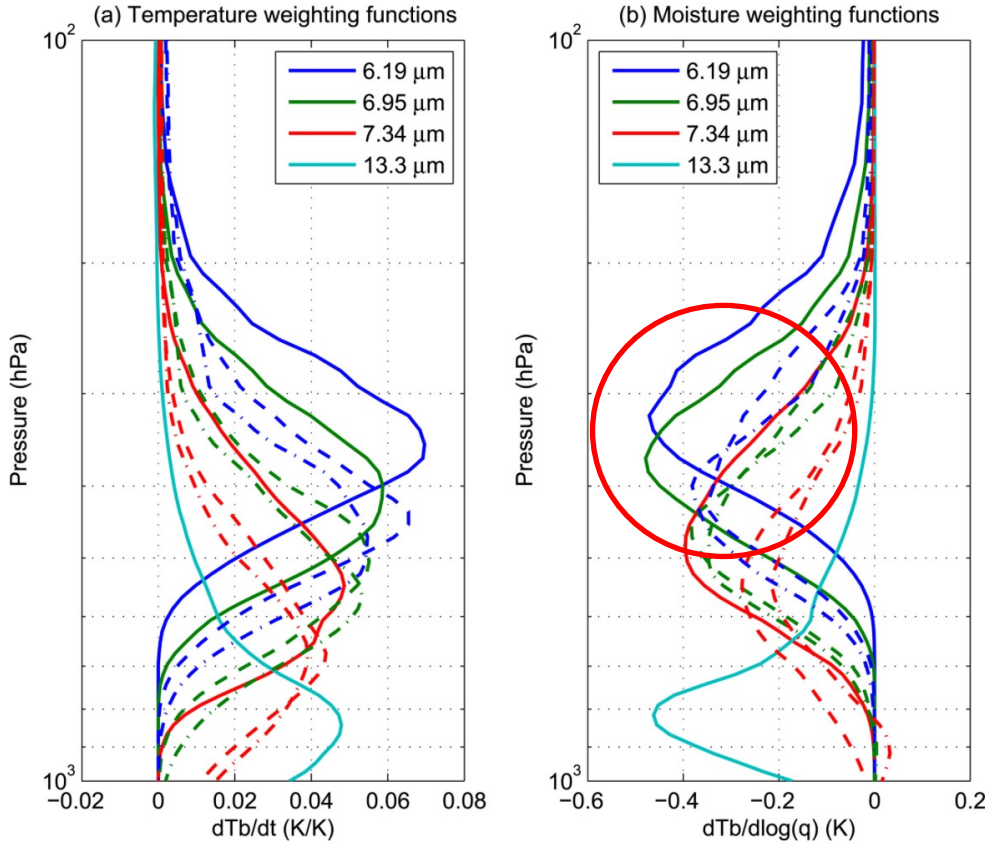
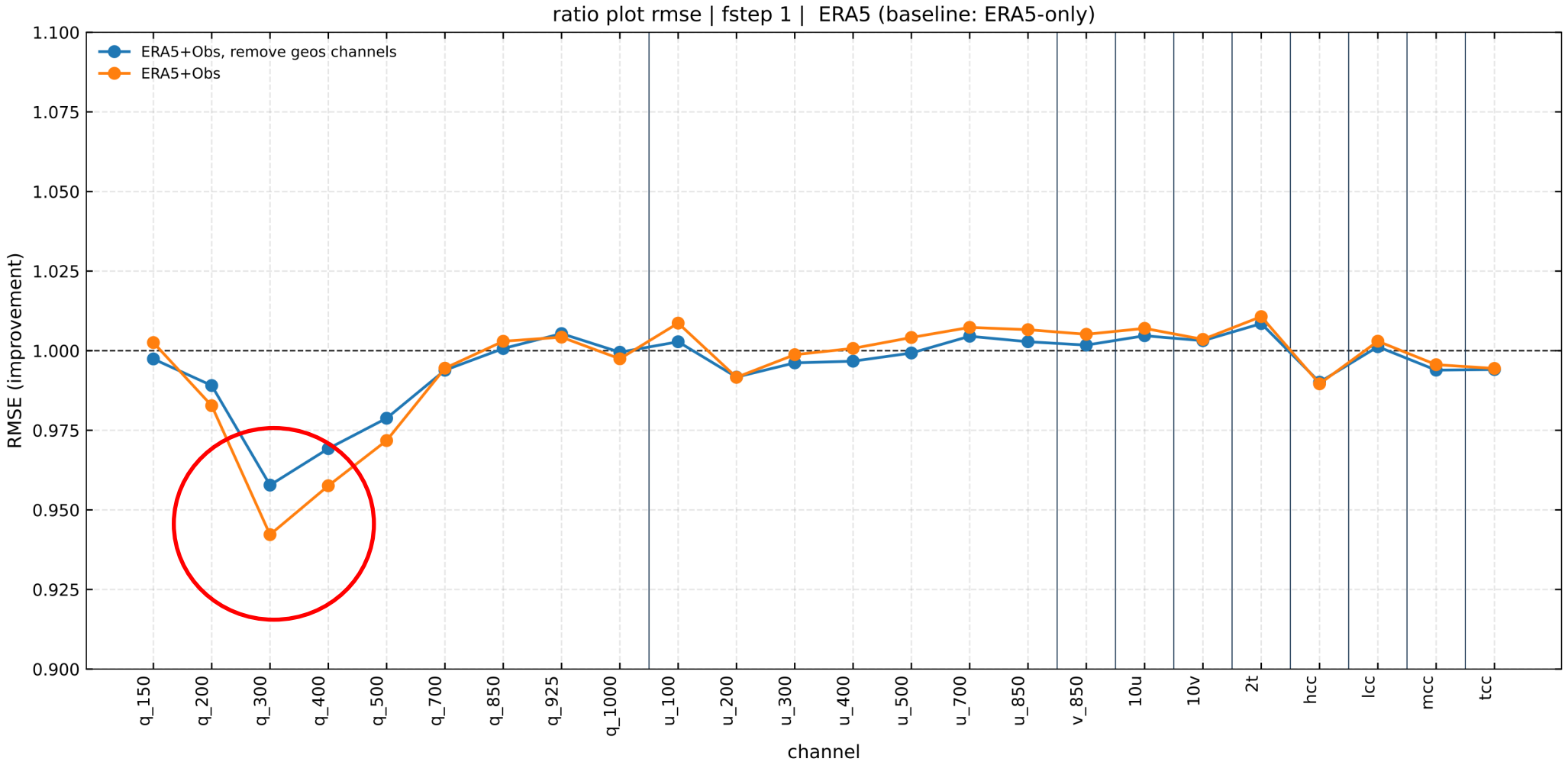


Figure 1 Open in figure viewer | PowerPoint

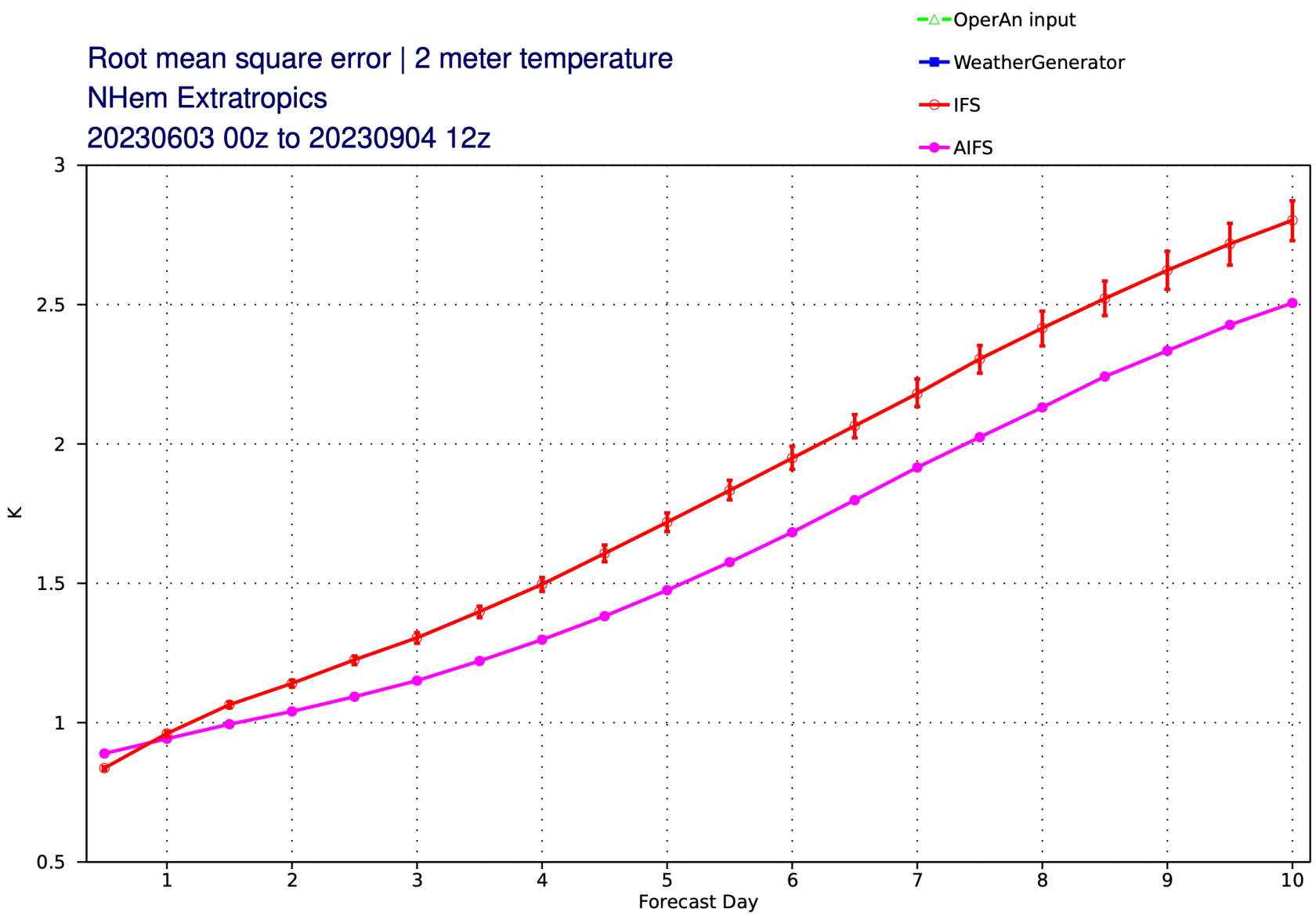
(a) The temperature and (b) water vapor weighting functions (Jacobian functions) of selected Advanced Baseline Imager (ABI) bands. The solid lines represent typical tropical profiles, dashed lines represent typical midlatitude winter profiles, and the dash-dotted lines represent typical subarctic winter profiles.

Results: benefit of observations

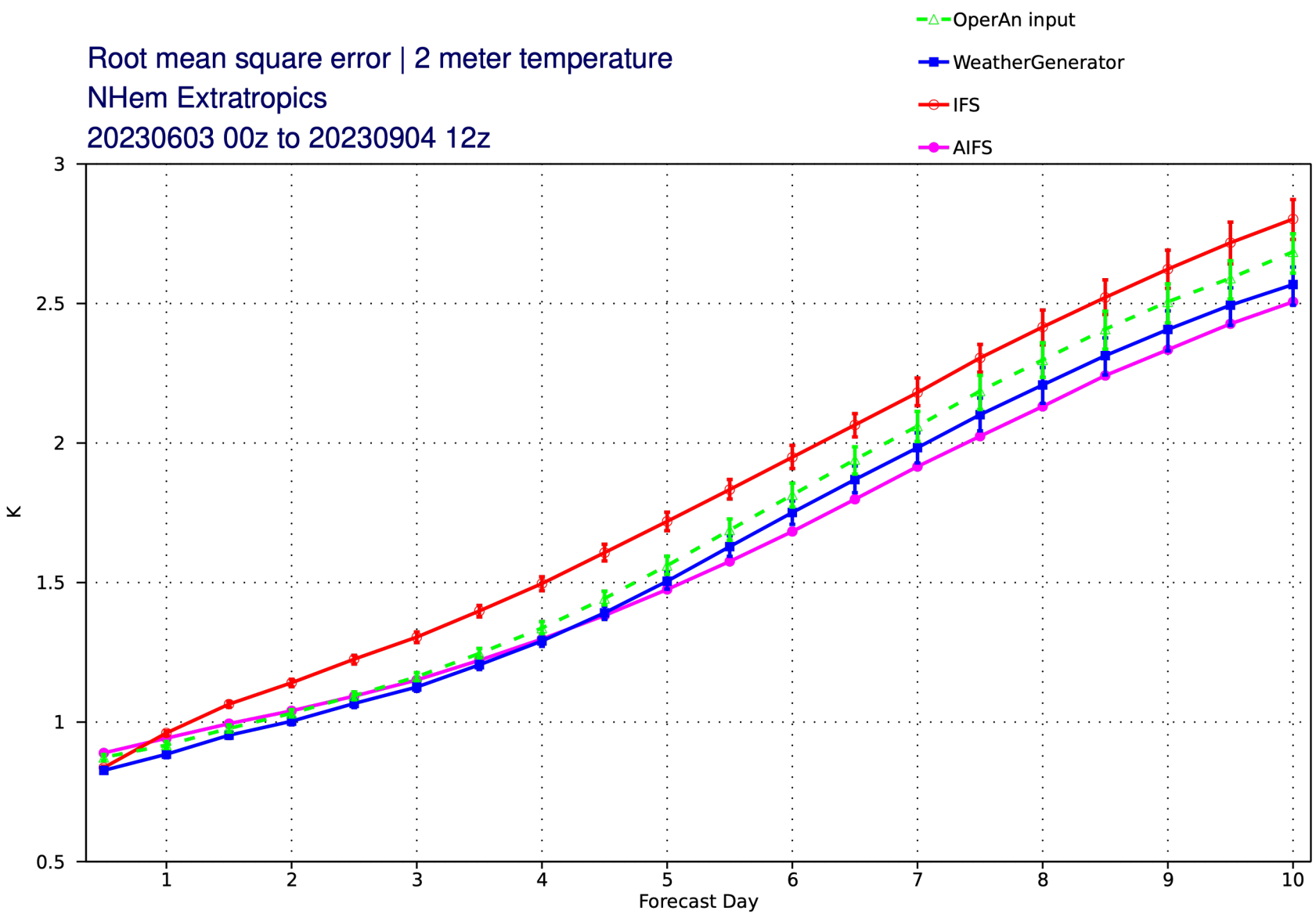


Results

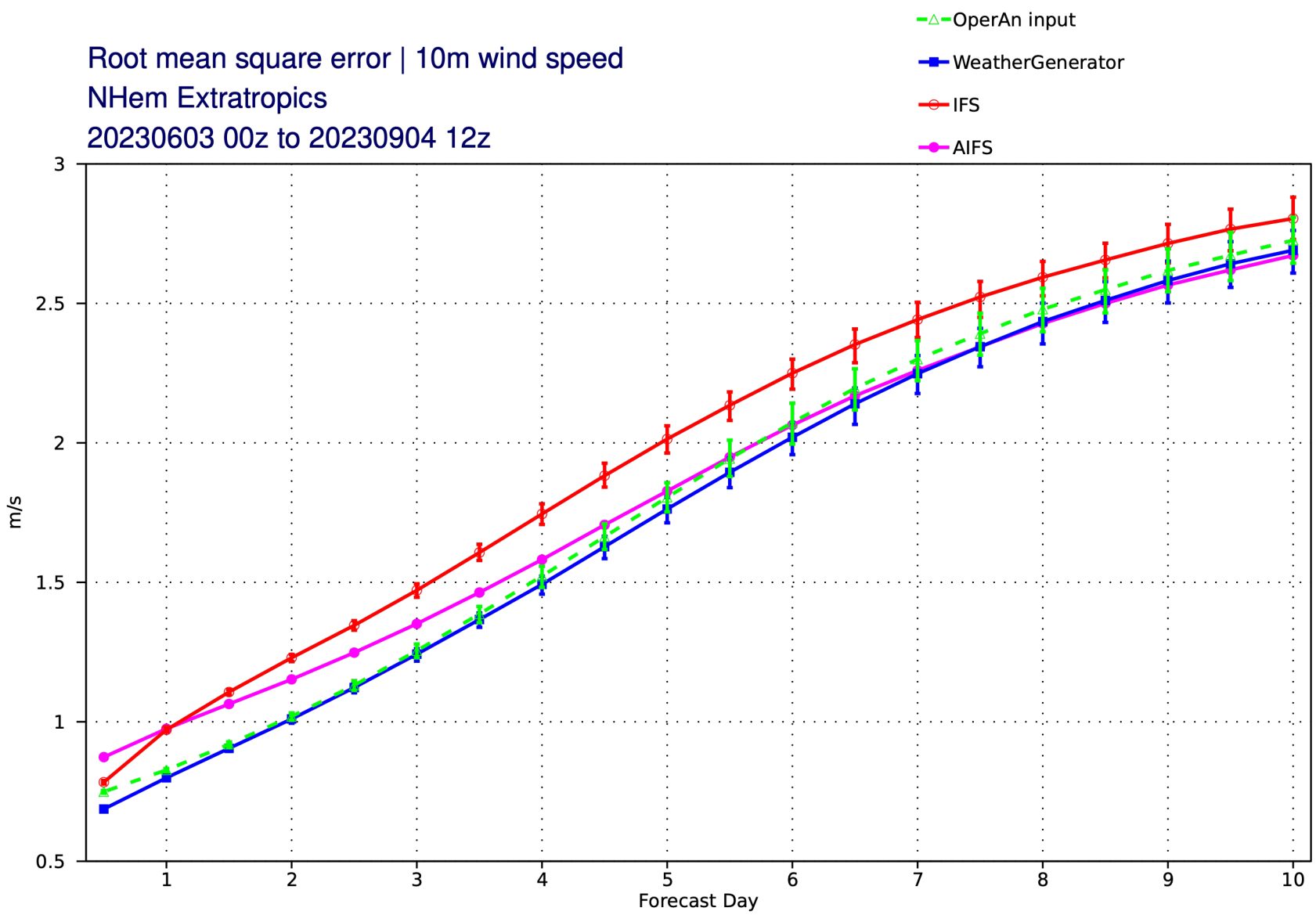
Results


Root mean square error | 2 meter temperature
NHem Extratropics
20230603 00z to 20230904 12z
OperAn input
WeatherGenerator
IFS
AIFS
K
Forecast Day
0.5
1
1.5
2
2.5
3
1
2
3
4
5
6
7
8
9
10

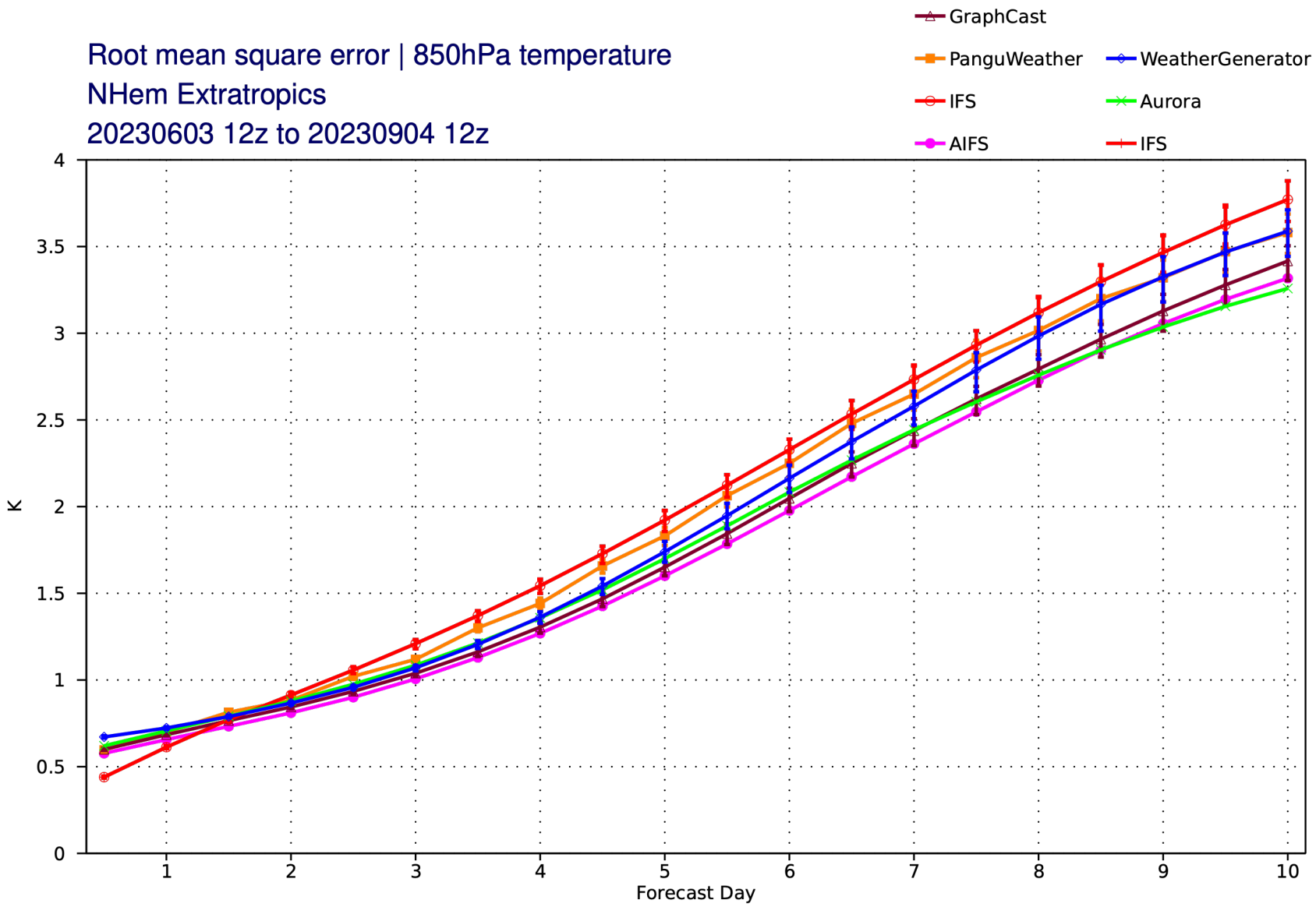
Results


Root mean square error | 2 meter temperature
NHem Extratropics
20230603 00z to 20230904 12z
OperAn input
WeatherGenerator
IFS
AIFS
K
Forecast Day
0.5
1
1.5
2
2.5
3
1
2
3
4
5
6
7
8
9
10

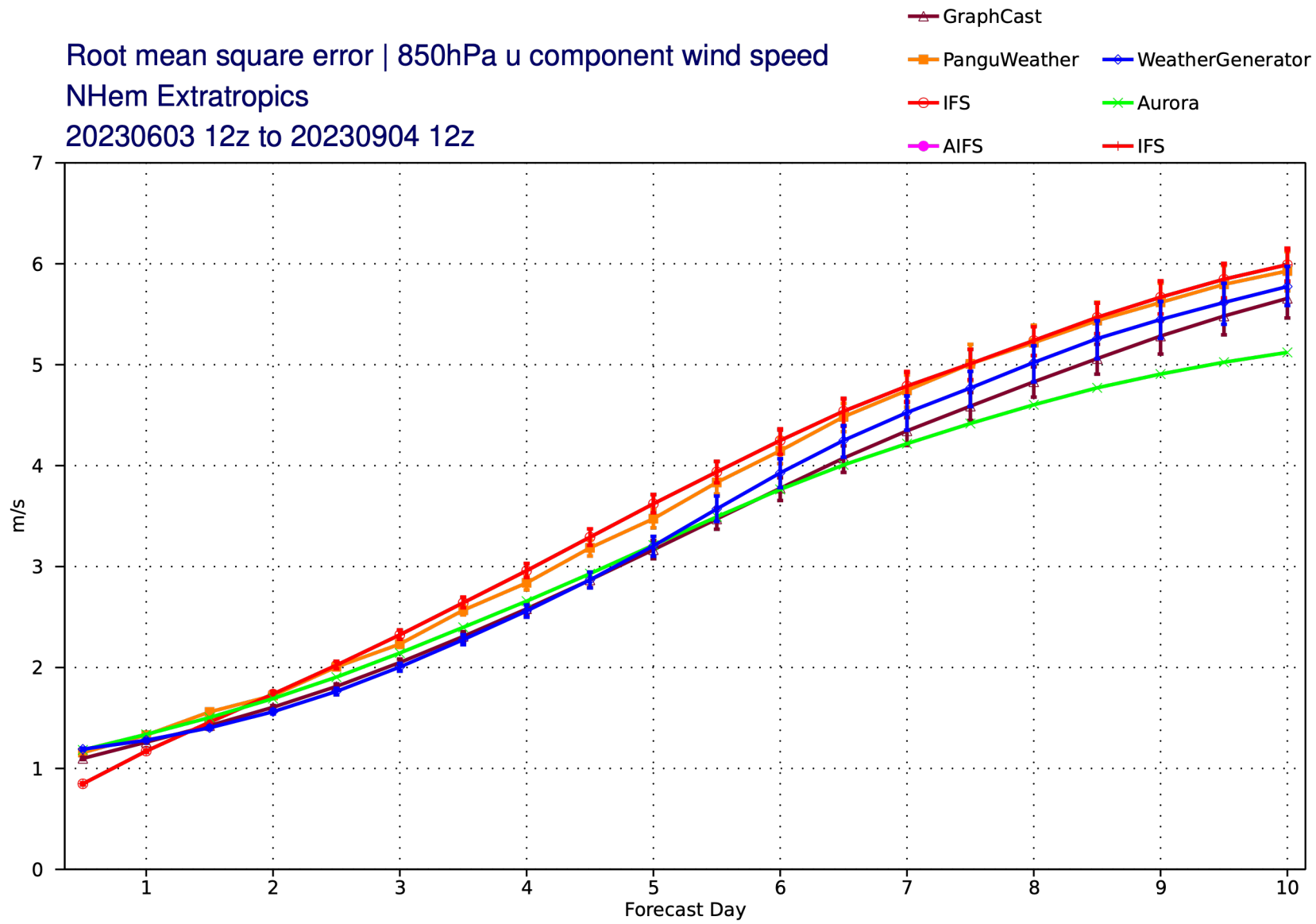
Results


Root mean square error | 10m wind speed
NHem Extratropics
20230603 00z to 20230904 12z
OperAn input
WeatherGenerator
IFS
AIFS
m/s
Forecast Day
0.5
1
1.5
2
2.5
3
1
2
3
4
5
6
7
8
9
10

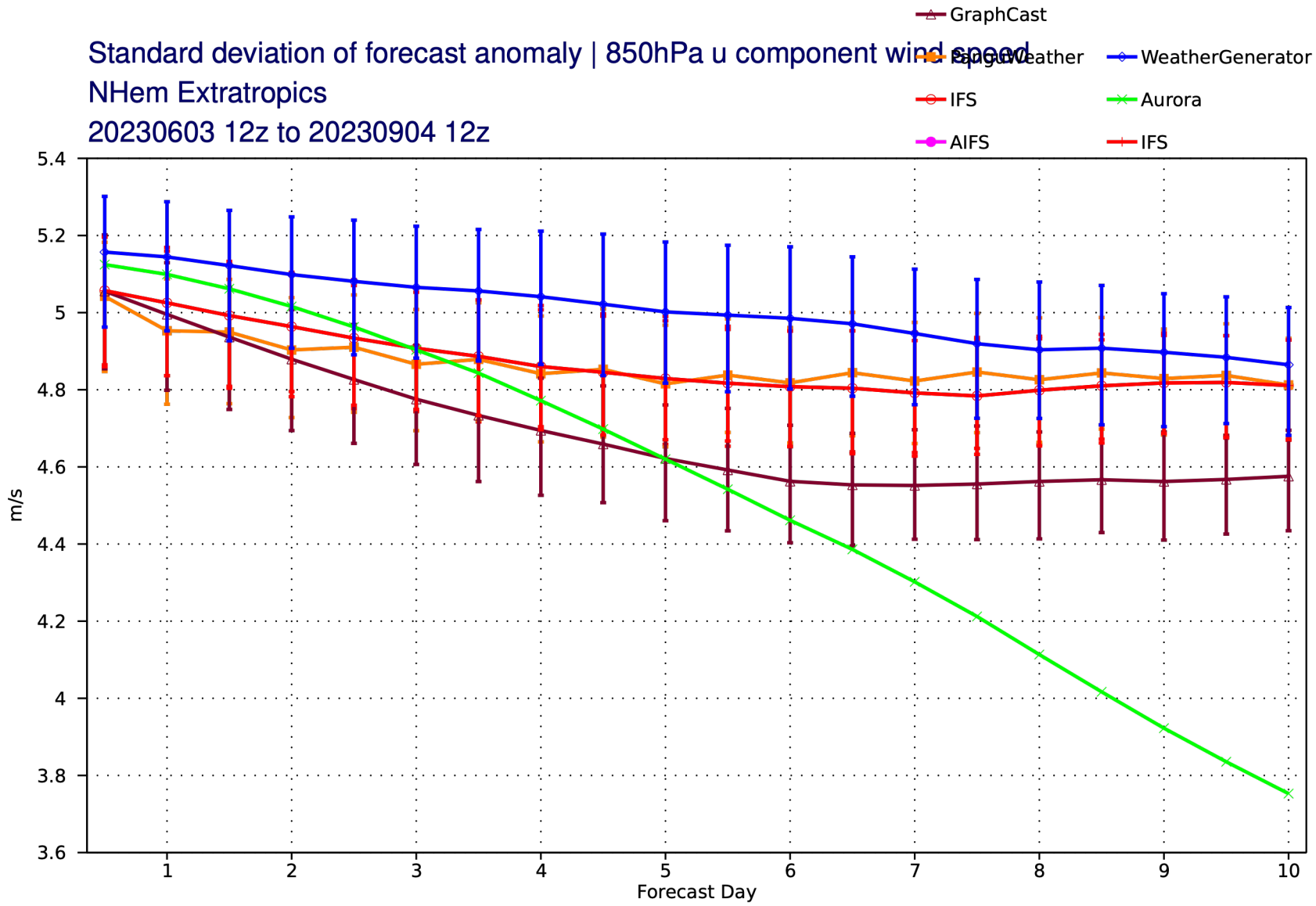
Results


Root mean square error | 850hPa temperature
NHem Extratropics
20230603 12z to 20230904 12z
GraphCast
PanguWeather
WeatherGenerator
IFS
Aurora
AIFS
IFS
K
Forecast Day
0
0.5
1
1.5
2
2.5
3
3.5
4
1
2
3
4
5
6
7
8
9
10

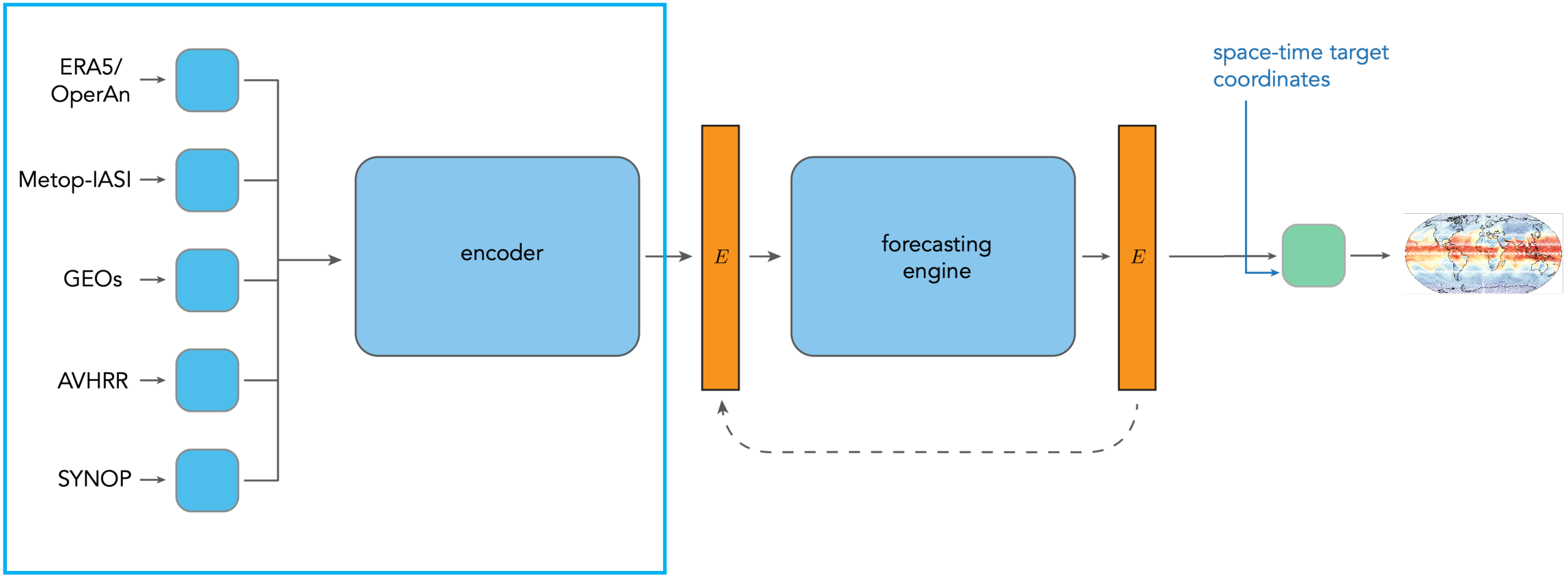
Results


Root mean square error | 850hPa u component wind speed
NHem Extratropics
20230603 12z to 20230904 12z
GraphCast
PanguWeather
WeatherGenerator
IFS
Aurora
AIFS
IFS
m/s
Forecast Day
0
1
2
3
4
5
6
7
1
2
3
4
5
6
7
8
9
10

Results


Standard deviation of forecast anomaly | 850hPa u component wind speed
NHem Extratropics
20230603 12z to 20230904 12z
GraphCast
FuXi
WeatherGenerator
IFS
Aurora
AIFS
IFS
m/s
5.4
5.2
5
4.8
4.6
4.4
4.2
4
3.8
3.6
1
2
3
4
5
6
7
8
9
10
Forecast Day

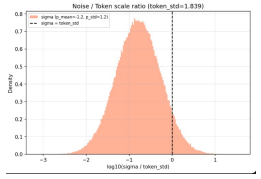
Results: benefit of observations



combine multiple inputs to obtain more complete state estimate

Probabilistic Forecasting Diffusion

Forecasting: Latent diffusion model



noise injection

inputs at t

inputs at $t+1$

encoder

denoiser

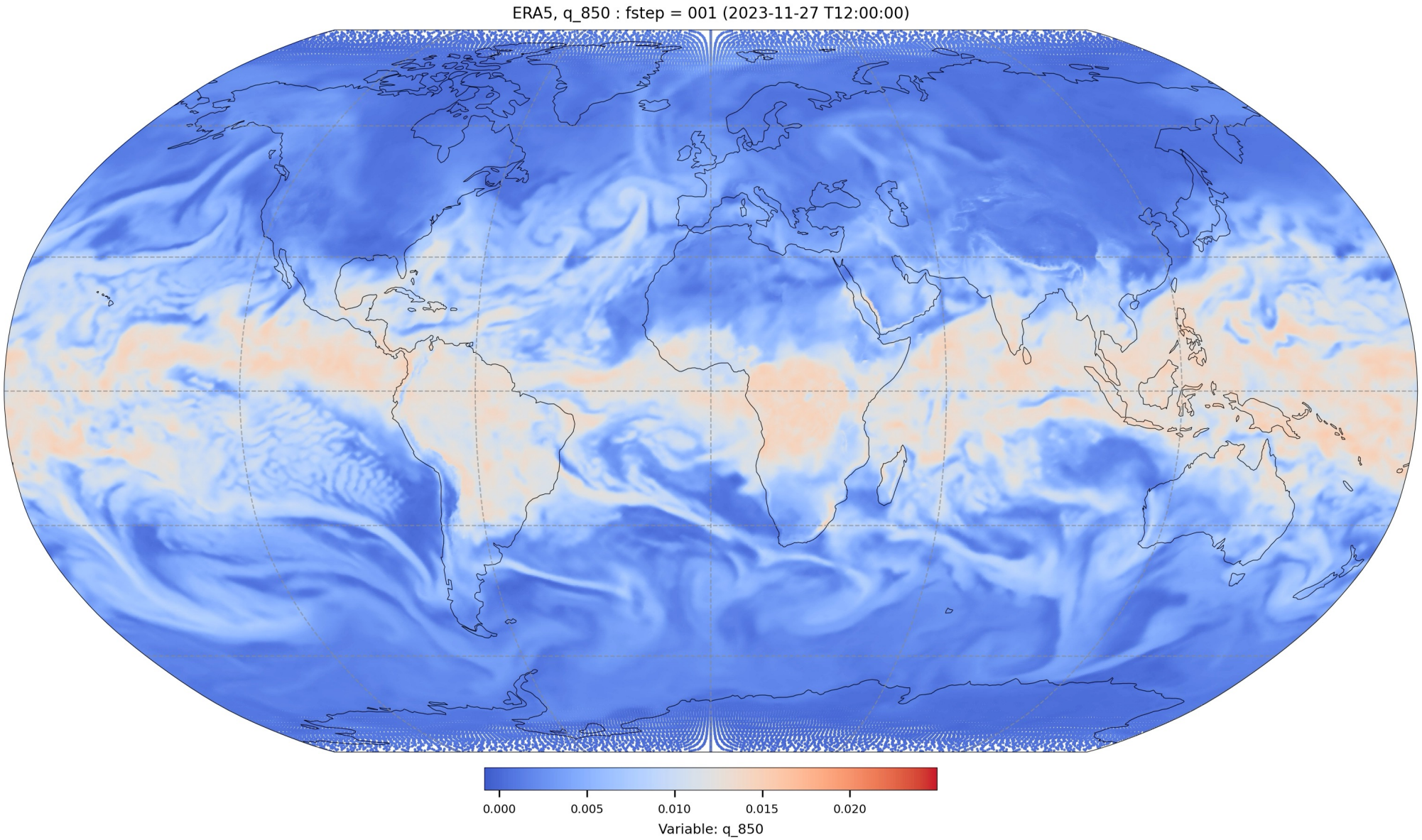
encoder

E

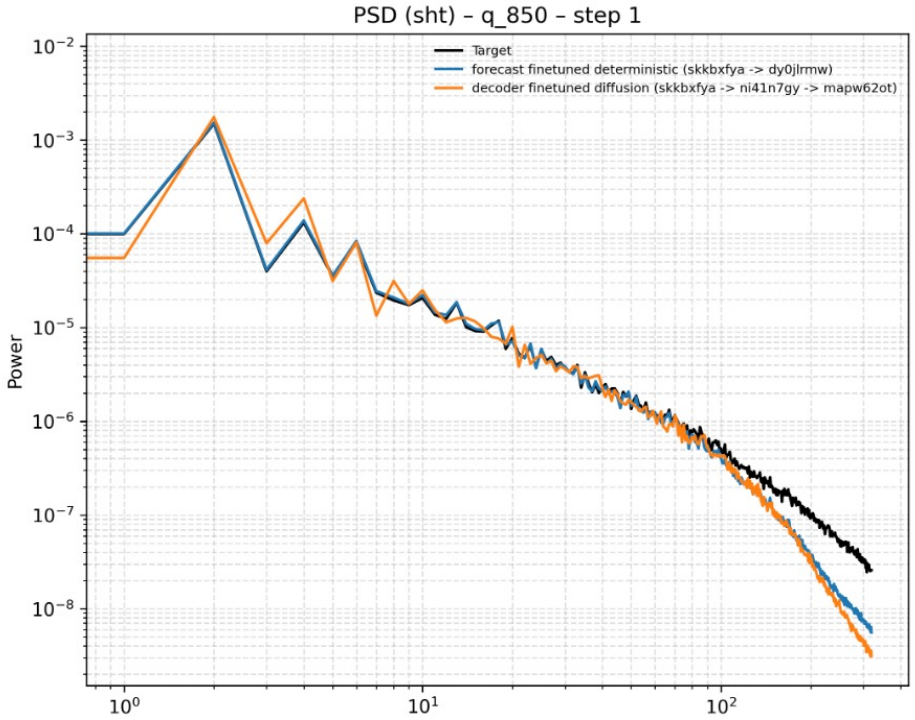
E'

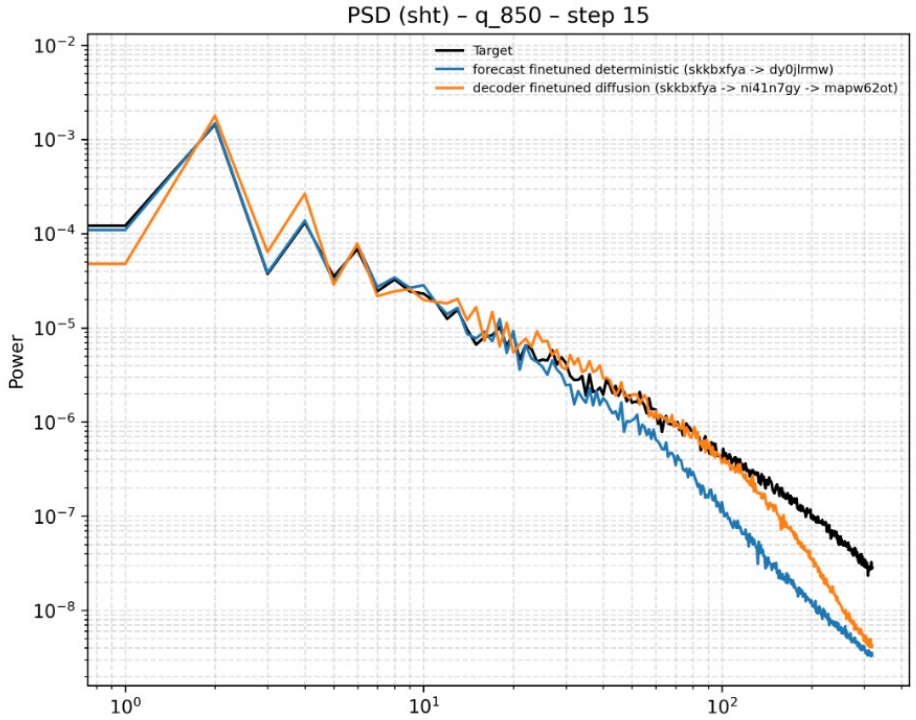
loss (noise-weighted)

Forecasting: Latent diffusion model



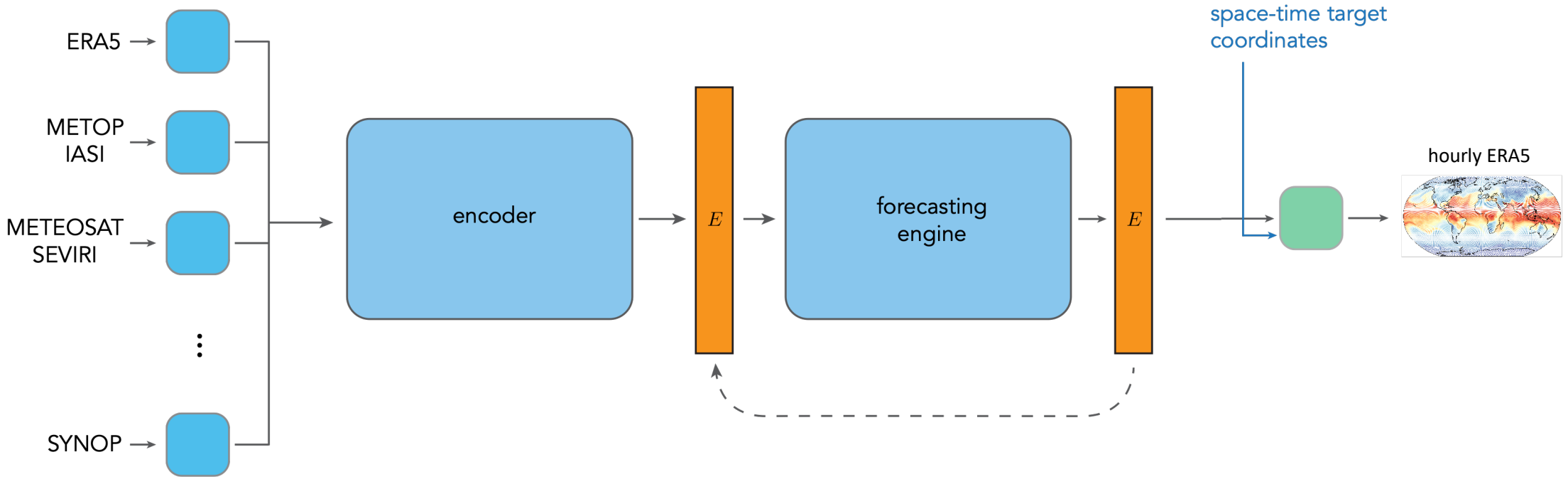
Forecasting: Latent diffusion model



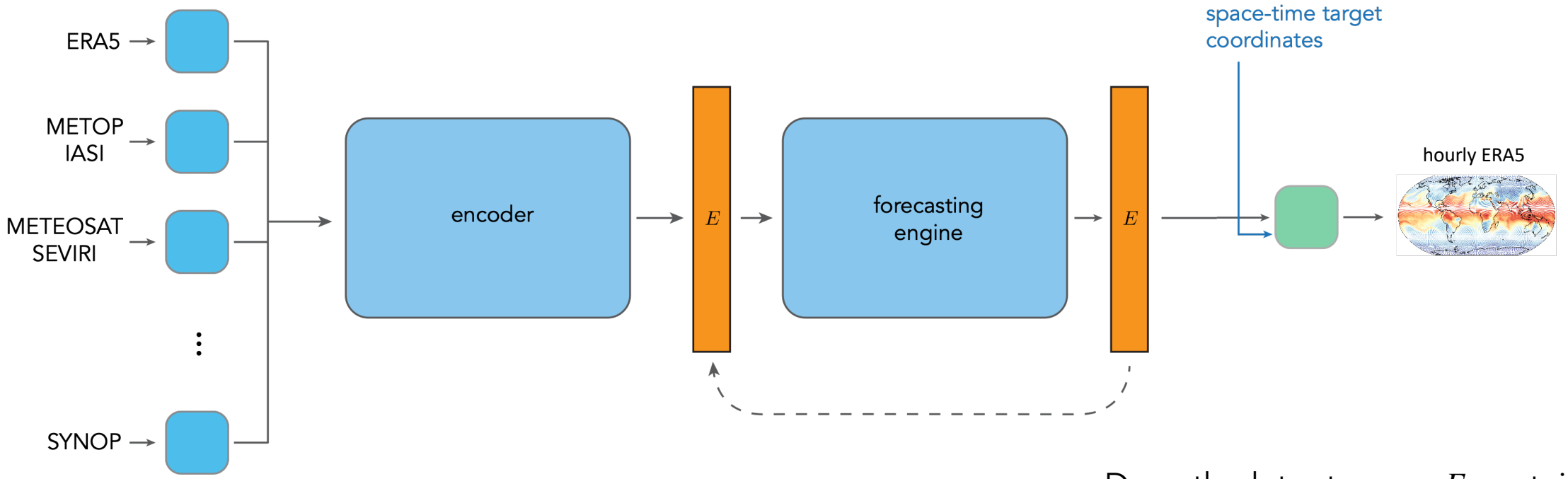


Decoder Finetuning

Decoder finetuning

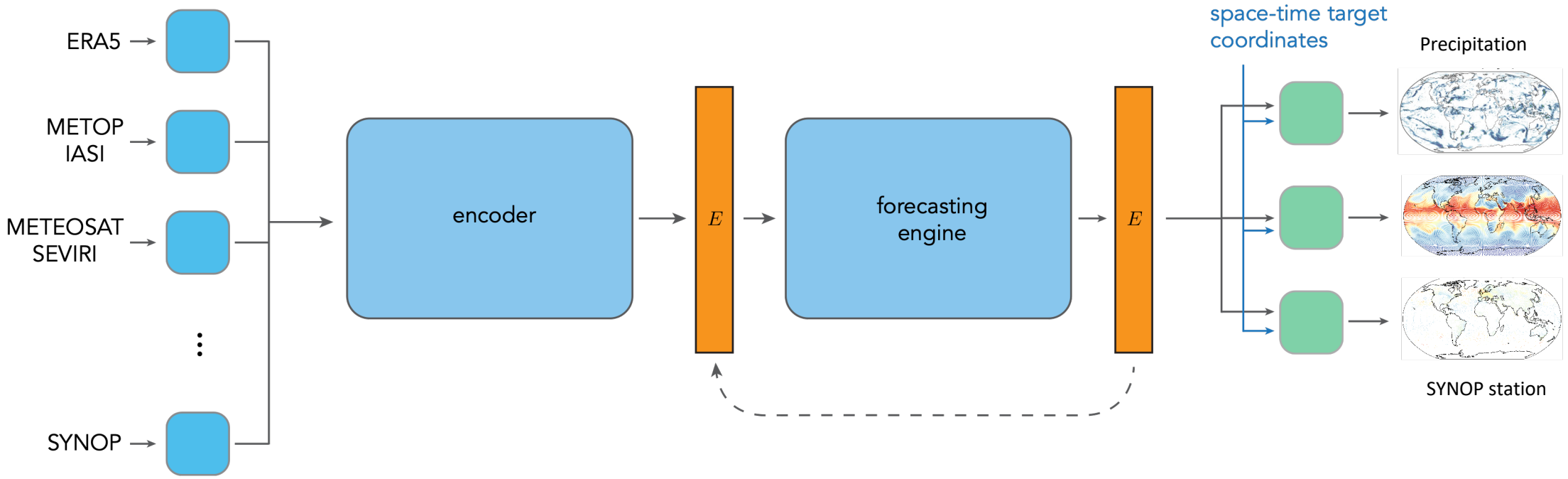


Decoder finetuning

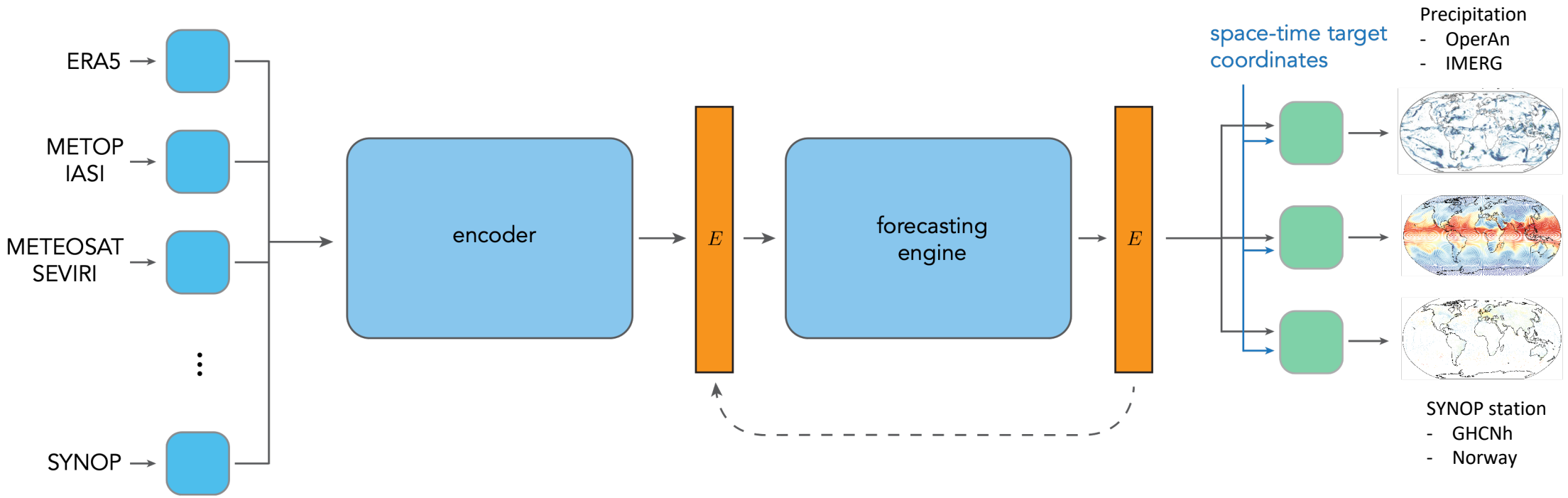


Does the latent space E contain general atmospheric state?

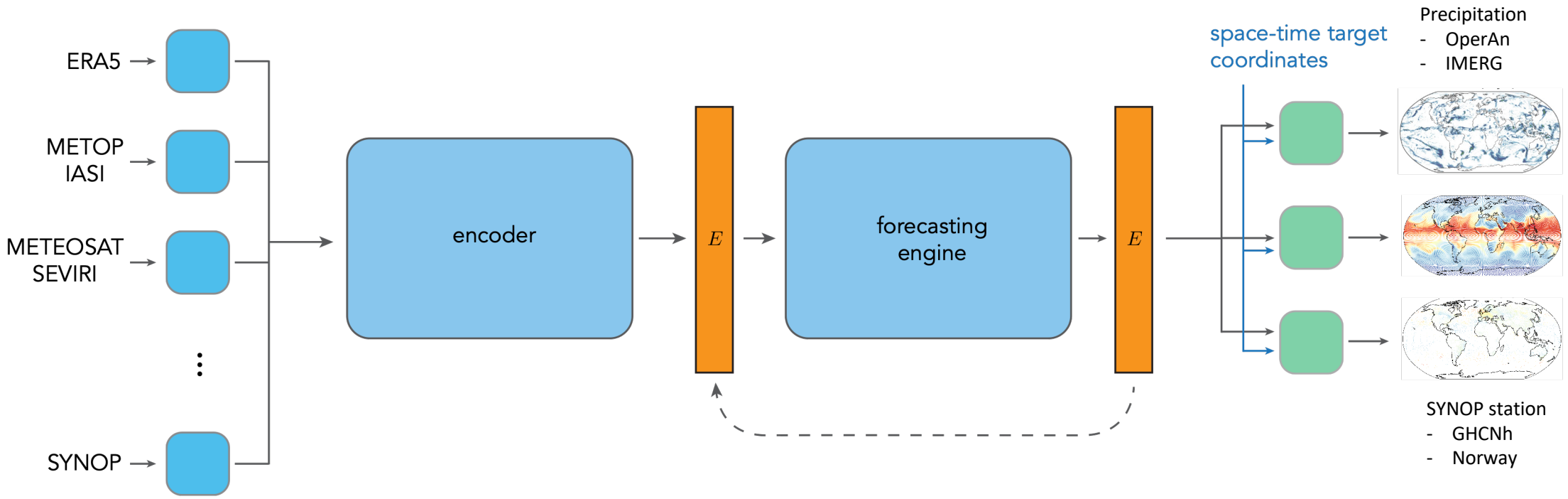
Decoder finetuning



Decoder finetuning



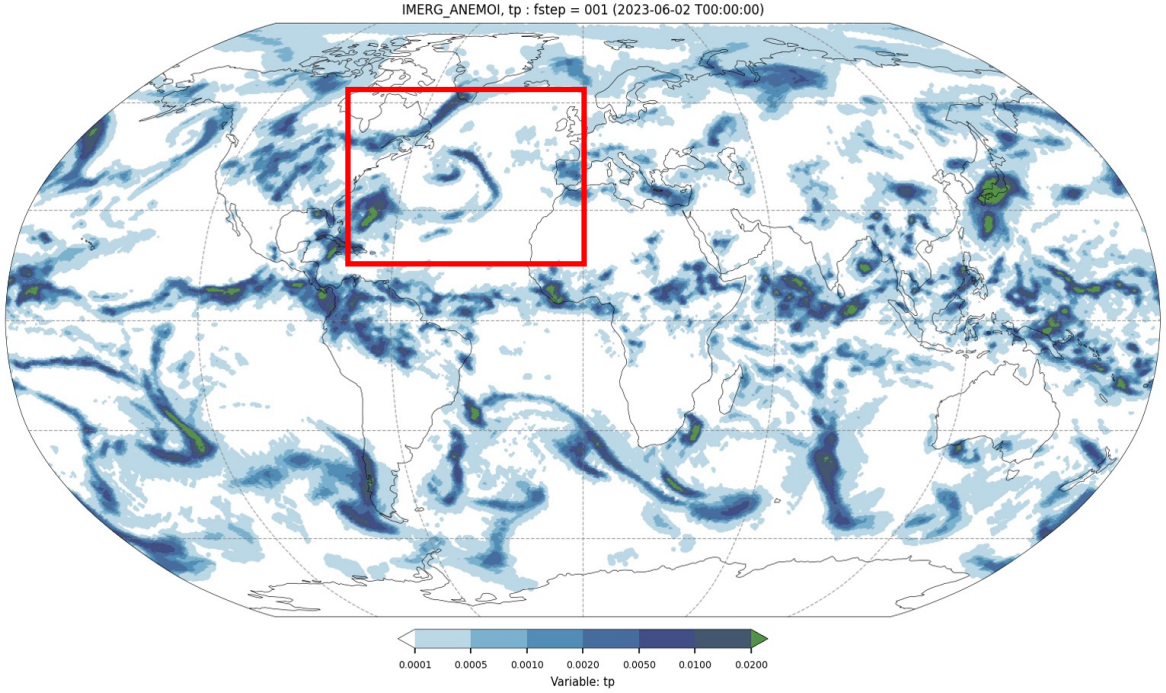
Decoder finetuning



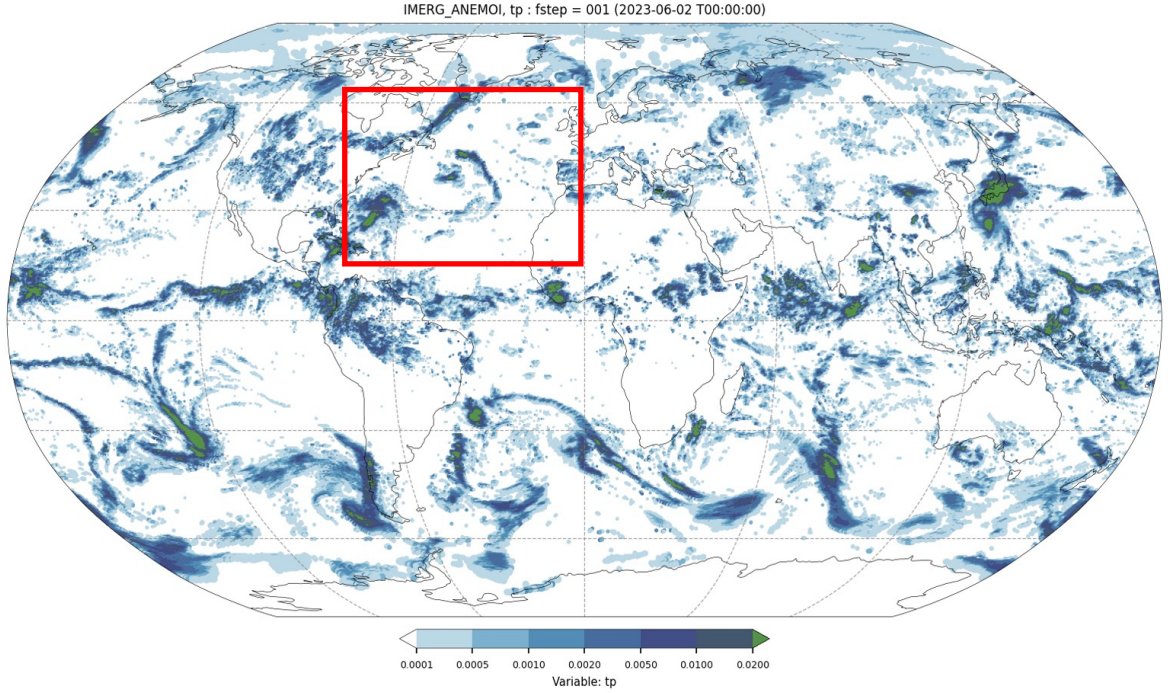
supervised fine-tuning
for small number of epochs

Decoder finetuning: precipitation

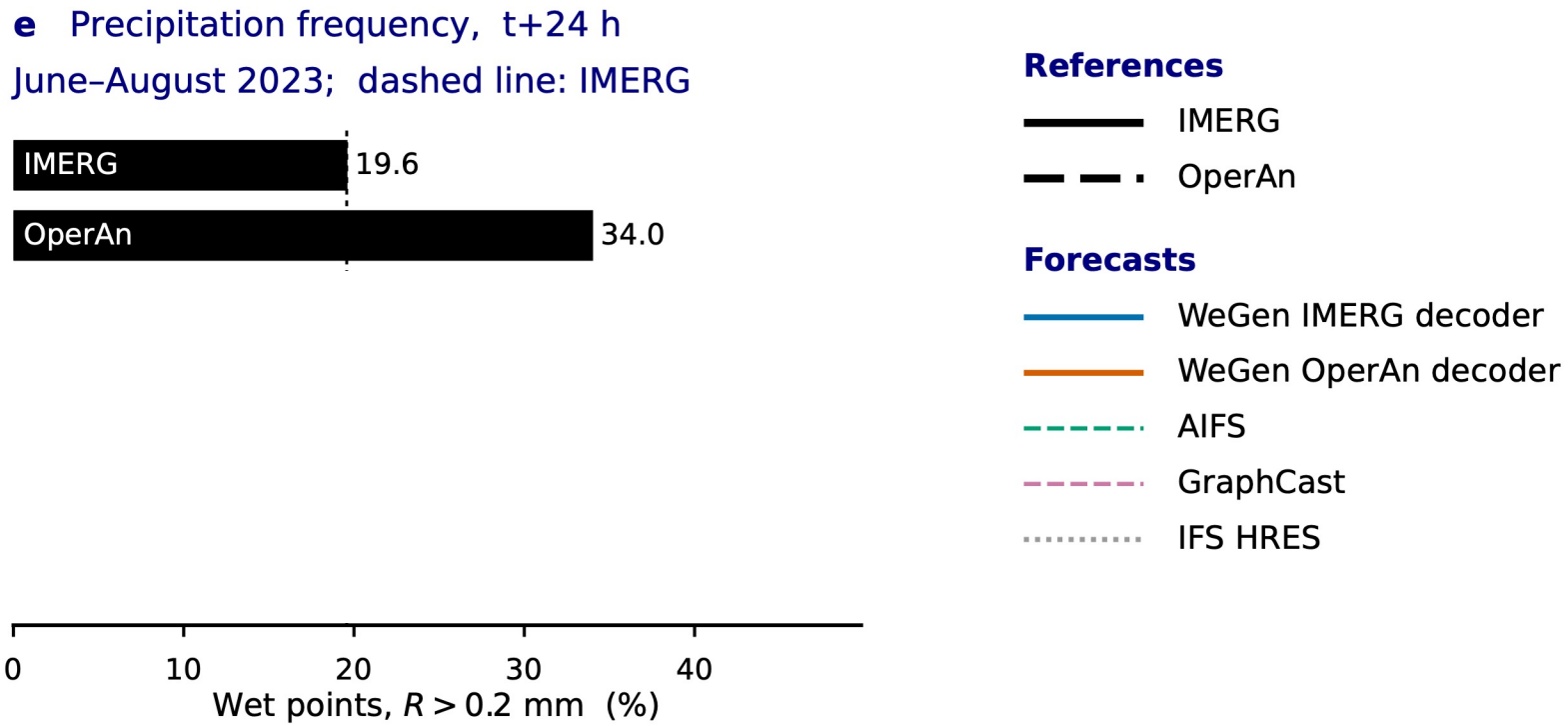
prediction



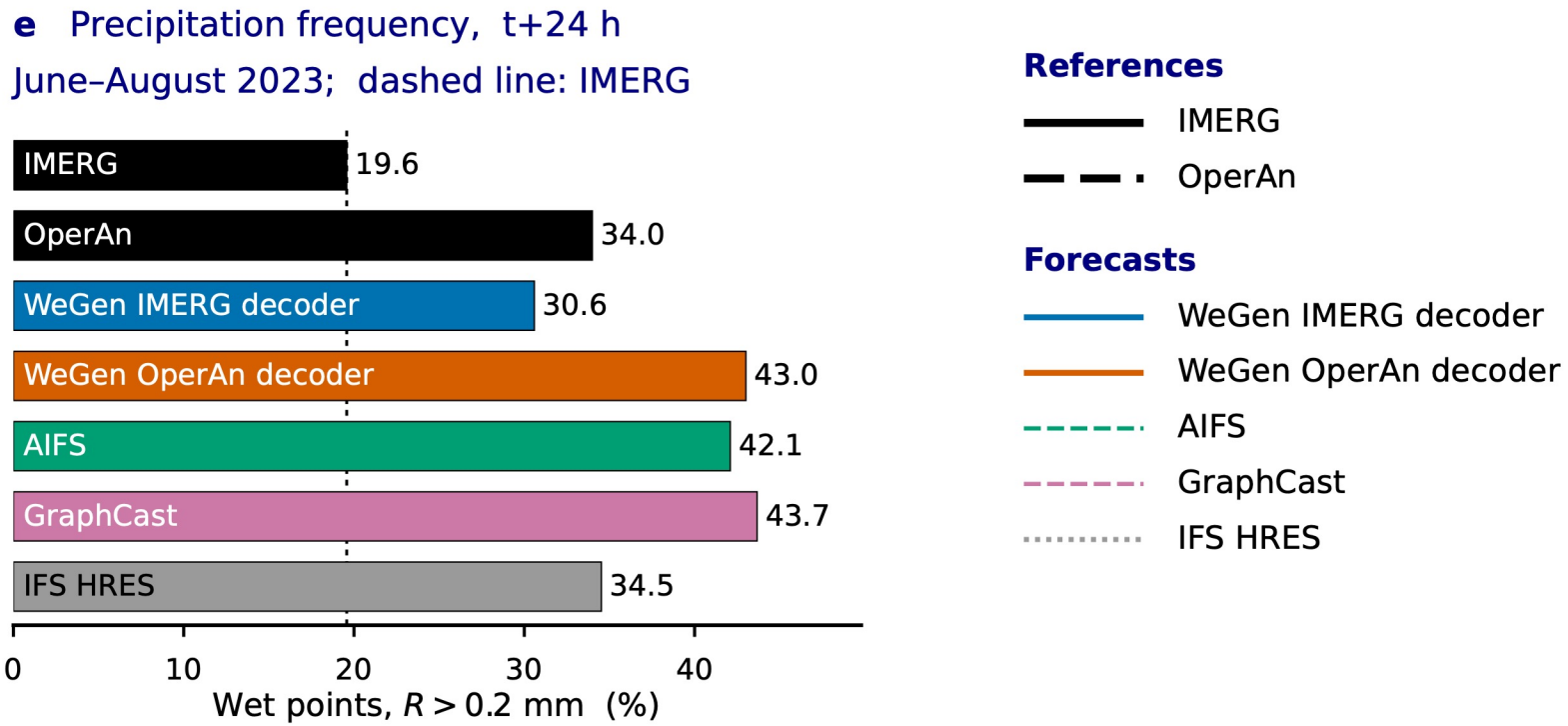
IMERG



Decoder finetuning: precipitation



Decoder finetuning: precipitation

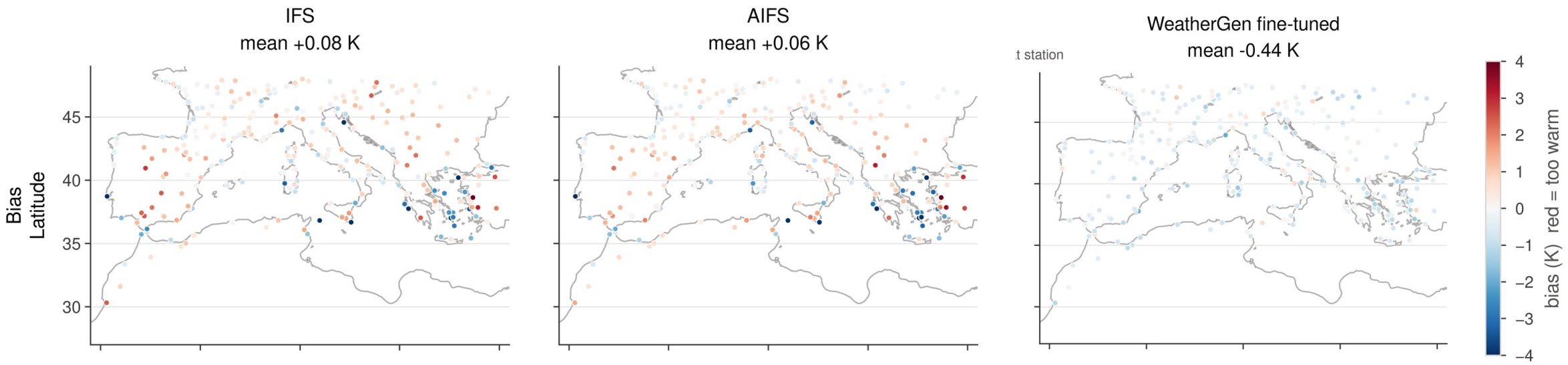


Decoder finetuning: station data

WeatherGen trained against GHCNh
T2m, 60h lead time, station verification for July/August 2023, Southern Europe

Decoder finetuning: station data

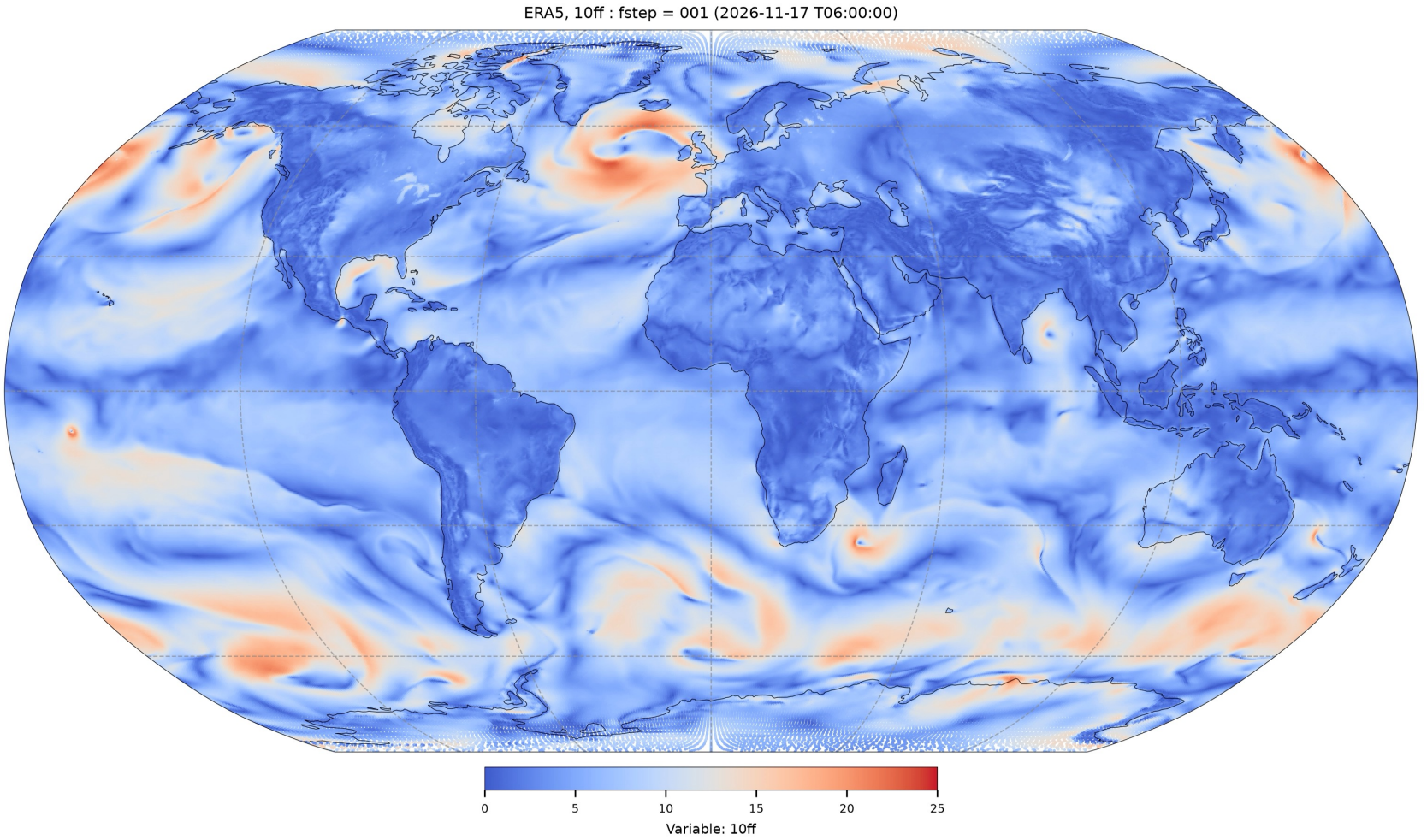
WeatherGen trained against GHCNh
T2m, 60h lead time, station verification for July/August 2023, Southern Europe



Real-time Setup

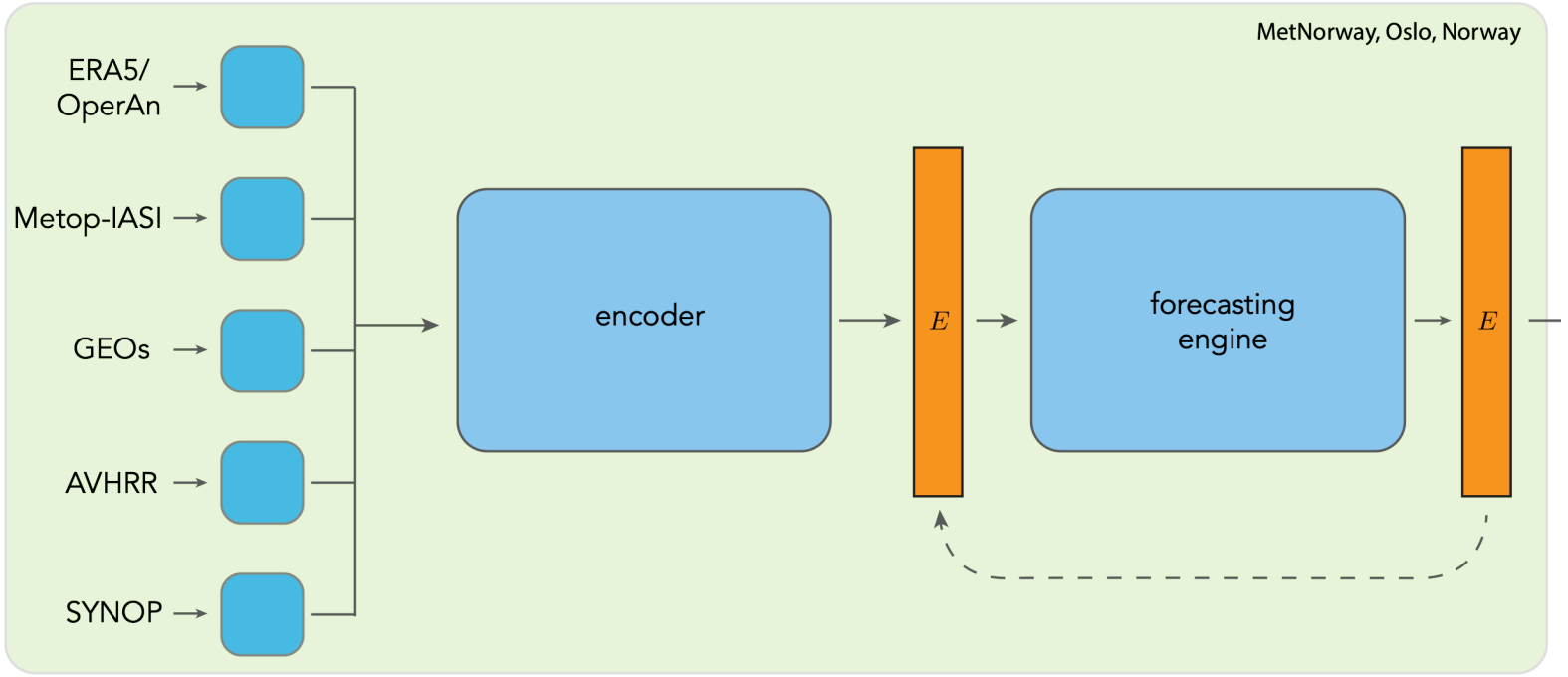
Real-time WeatherGenerator

Met Norway runs WeatherGenerator in real-time now every hour



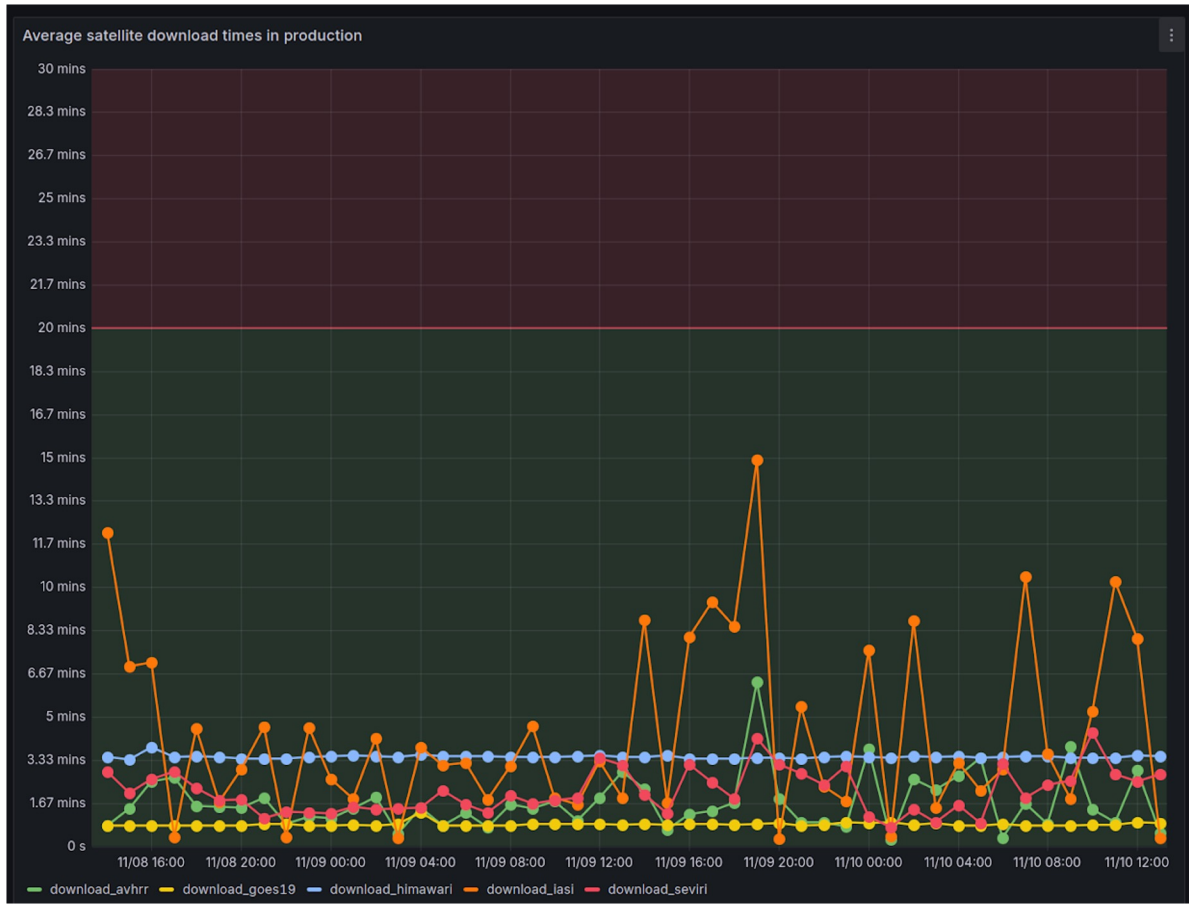
Real-time WeatherGenerator

MetNorway runs WeatherGenerator in real-time now every hour



Real-time WeatherGenerator

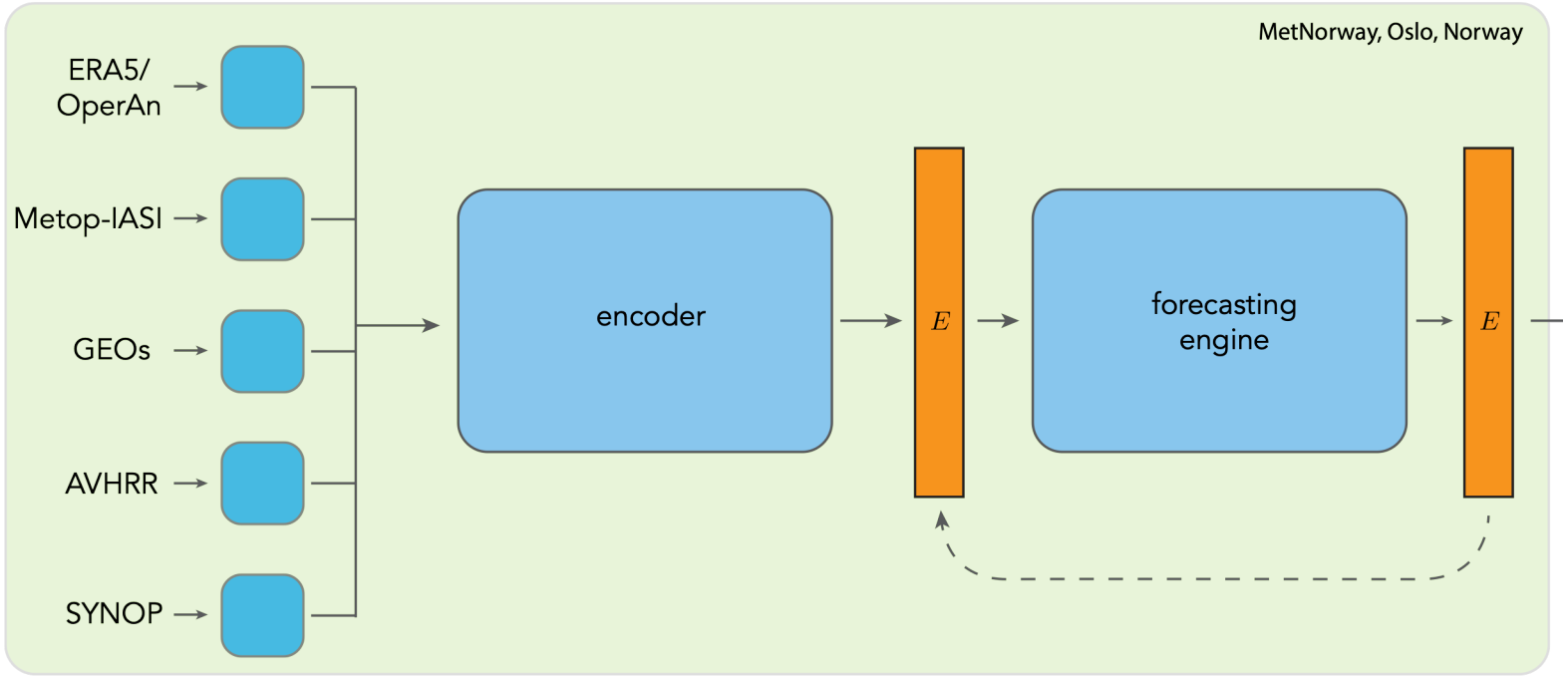
MetNorway runs WeatherGenerator in real-time now every hour



Download time for different observations

Real-time WeatherGenerator

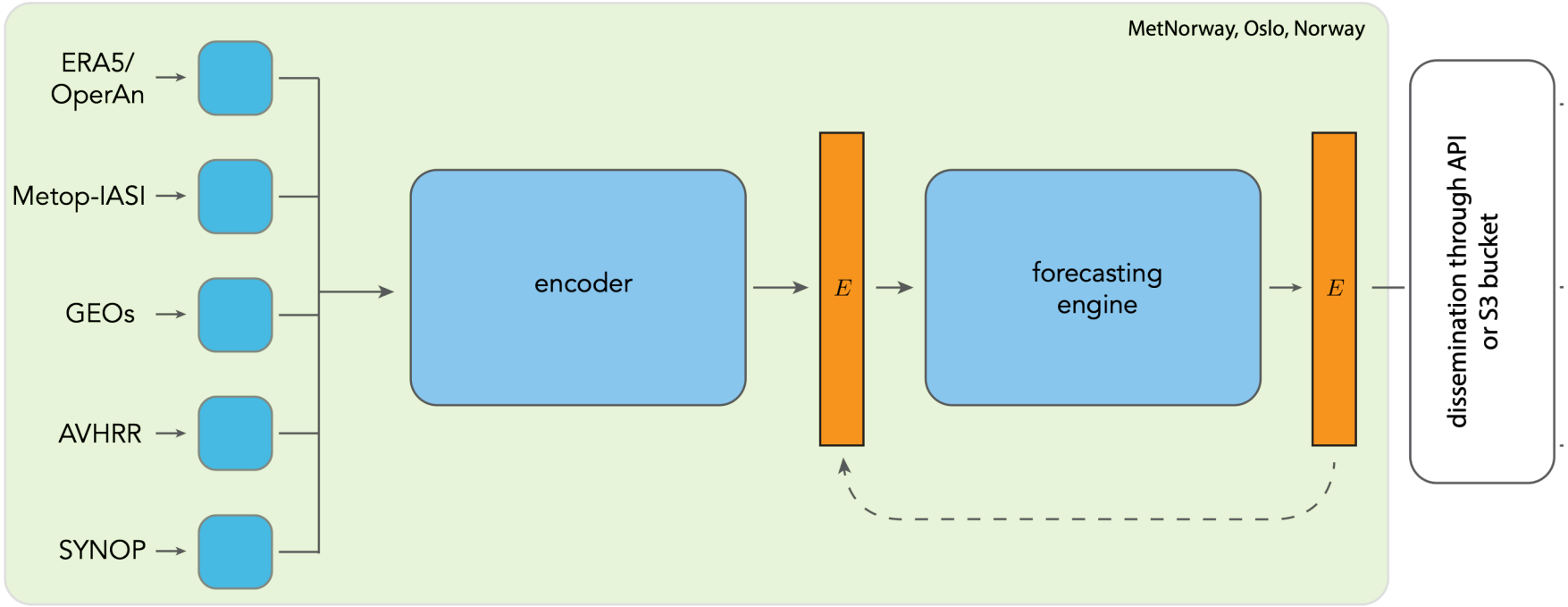
MetNorway runs WeatherGenerator in real-time now every hour



generate latent states
for 10 day forecast

Real-time WeatherGenerator

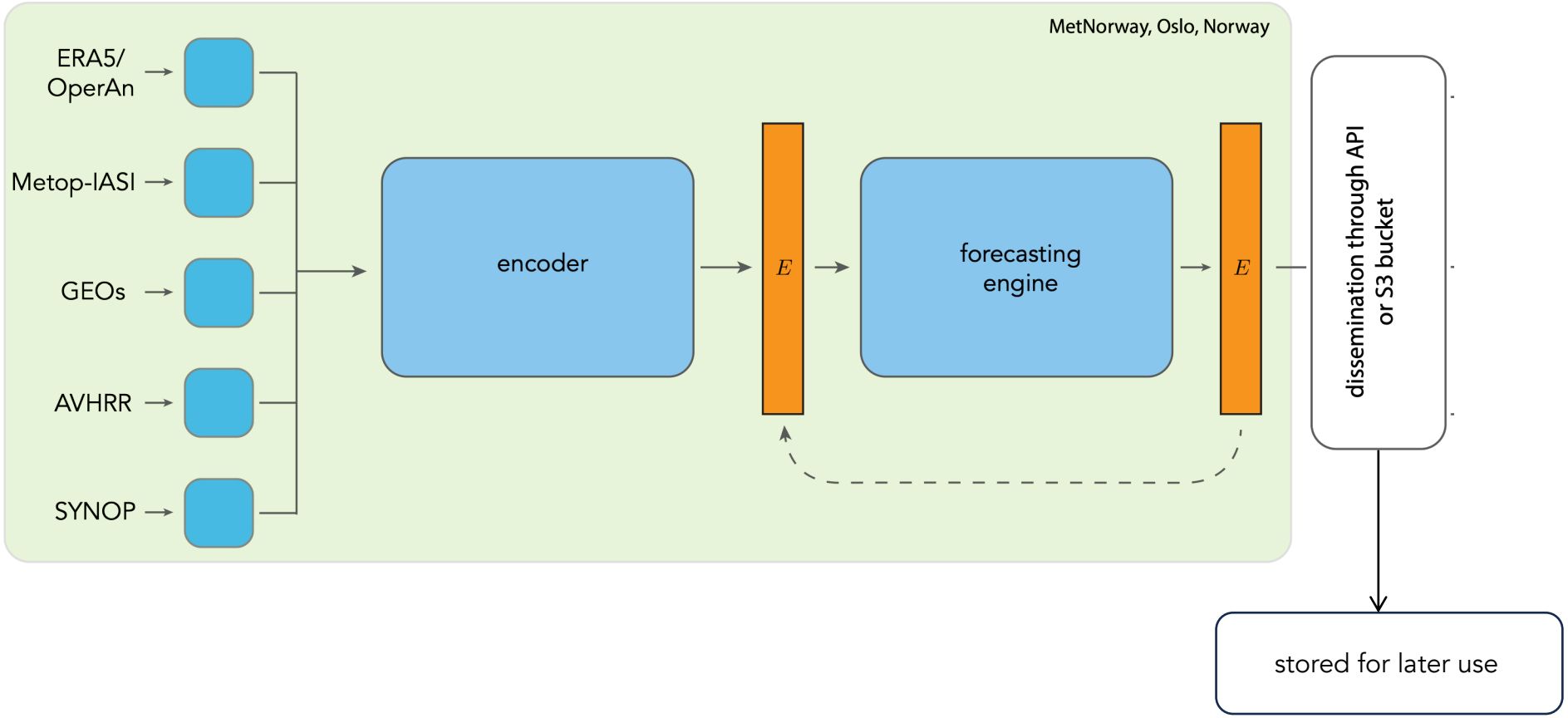
MetNorway runs WeatherGenerator in real-time now every hour



distribute compact latent state instead of physical fields

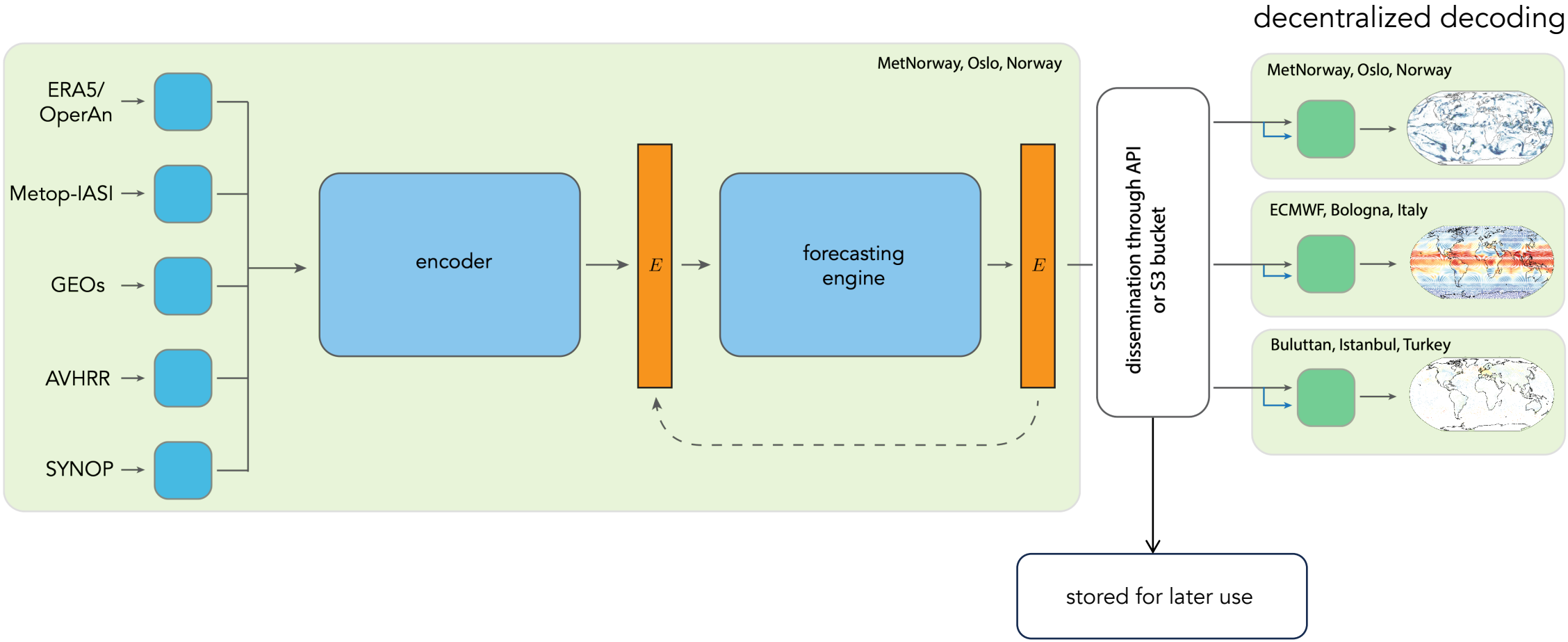
Real-time WeatherGenerator

MetNorway runs WeatherGenerator in real-time now every hour



Real-time WeatherGenerator

MetNorway runs WeatherGenerator in real-time now every hour



Real-time WeatherGenerator

Highly efficient decoder training/inference from latent space reanalysis:

latent reanalysis
hindcast/dataset

Real-time WeatherGenerator

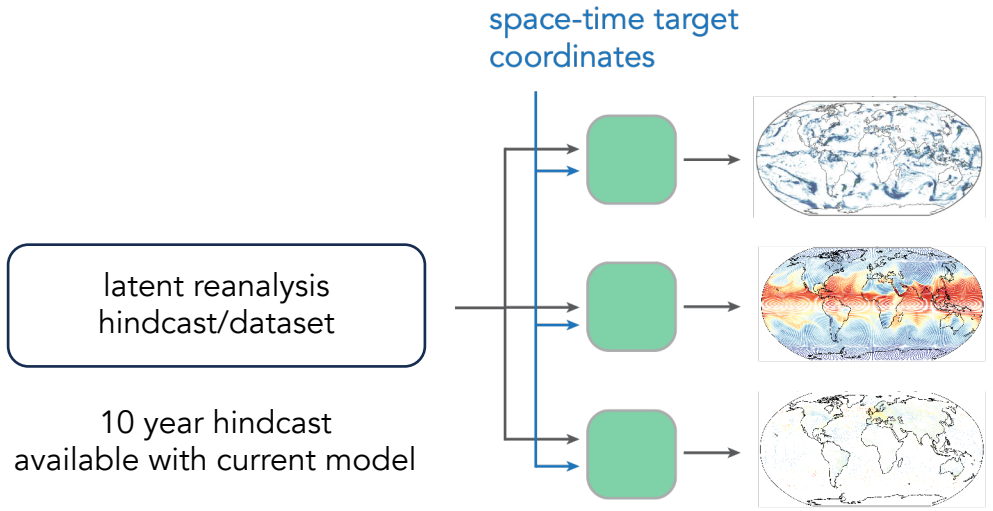
Highly efficient decoder training/inference from latent space reanalysis:

latent reanalysis
hindcast/dataset

10 year hindcast
available with current model

Real-time WeatherGenerator

Highly efficient decoder training/inference from latent space reanalysis:



Conclusion

Conclusion

Demonstration of key technologies with current WeatherGenerator

- Benefit of combining analysis with real-time observations
- Self-supervised pre-training
- (Probabilistic) latent space roll-out
- Post-hoc training of decoders

Conclusion

Next steps:

Conclusion

Next steps:

- Systematic use of observations to improve forecast skill
  - Different model configurations to explore design space between analysis-only and obs-only



Conclusion

Next steps:

- Systematic use of observations to improve forecast skill
  - Different model configurations to explore design space between analysis-only and obs-only



Conclusion

Next steps:

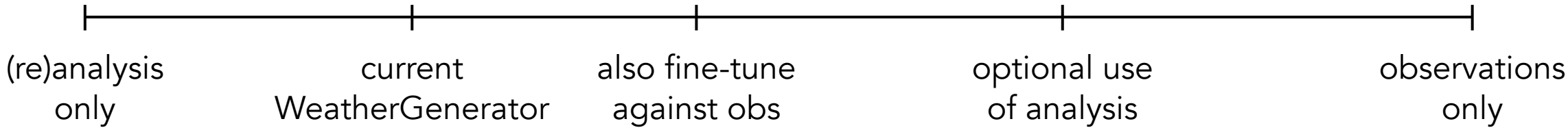
- Systematic use of observations to improve forecast skill
  - Different model configurations to explore design space between analysis-only and obs-only



Conclusion

Next steps:

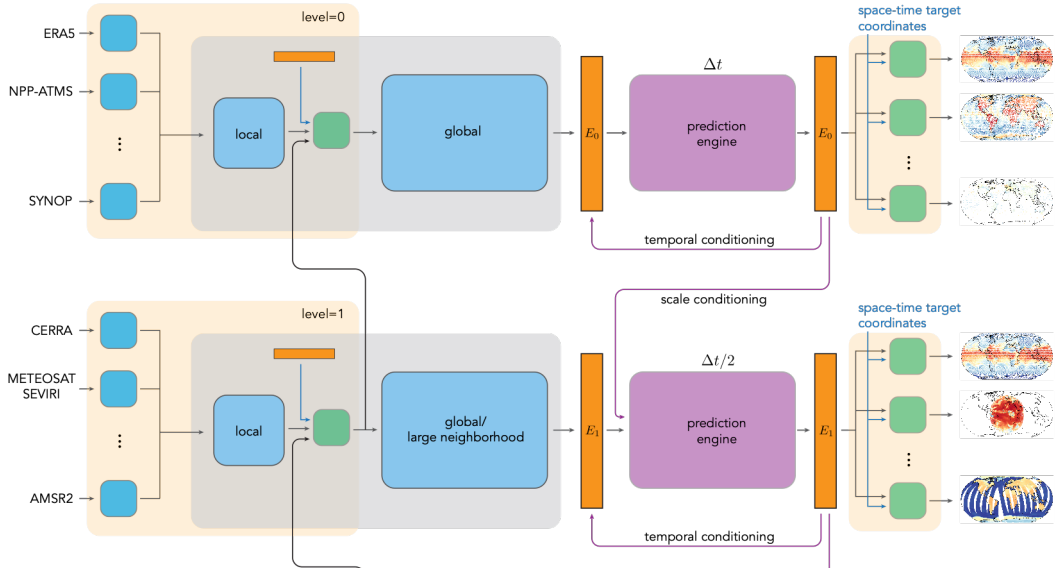
- Systematic use of observations to improve forecast skill
  - Different model configurations to explore design space between analysis-only and obs-only



Conclusion

Next steps:

- Systematic use of observations to improve forecast skill
  - Different model configurations to explore design space between analysis-only and obs-only
- High-resolution / multi-resolution
  - Use multiple latent spaces time-stepped at appropriate time-steps



Conclusion

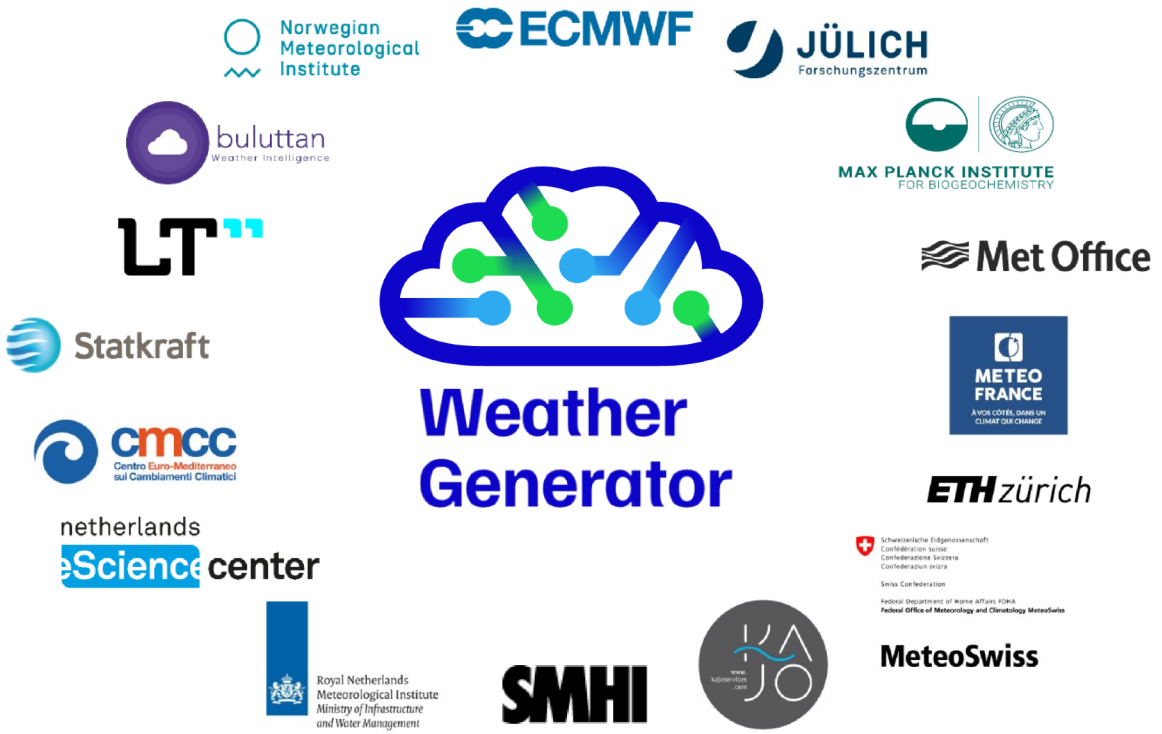
Next steps:

- Systematic use of observations to improve forecast skill
  - Different model configurations to explore design space between analysis-only and obs-only
- High-resolution / multi-resolution
  - Use multiple latent spaces time-stepped at appropriate time-steps
- Longer term predictions (sub-seasonal to decadal)
  - Train for behavior at sub-seasonal to decadal time scales instead of emergent behavior

We thank many, many people at ECMWF, its member states and other project partners for their contributions to make this work possible.

Code available at https://github.com/ecmwf/WeatherGenerator/

Preprint coming very soon!



THANK YOU

www.weathergenerator.eu

The WeatherGenerator project (grant agreement No101187947) is funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the Commission. Neither the European Union nor the granting authority can be held responsible for them.