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Transforming Weather Data from Pixel to Latent Space

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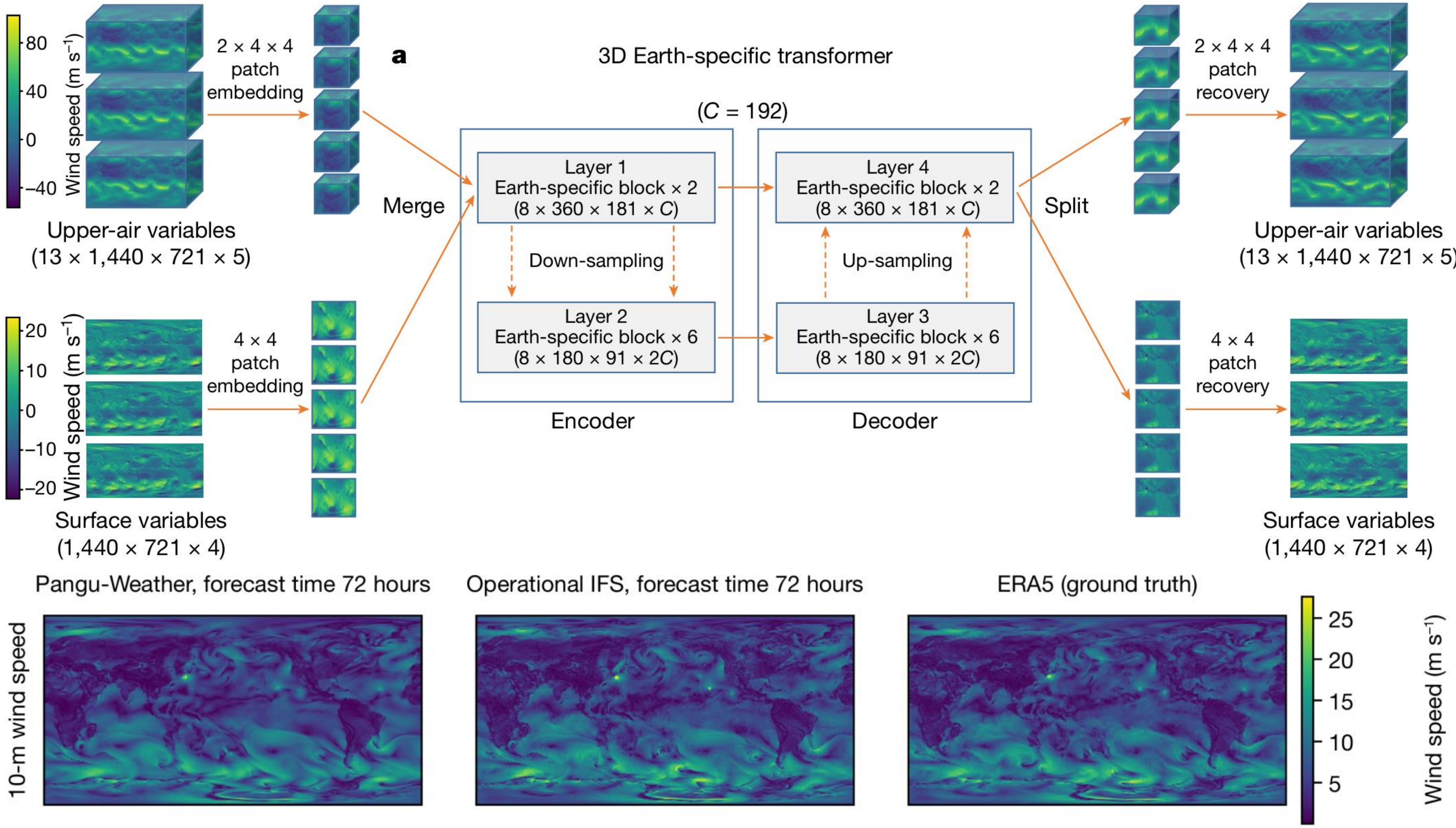
Weather modeling in Pixel Space

ERA5 data subset occupies 93.6 TB

Forecasts a single pressure-variable subset

(PVS = selected pressure levels × weather variables)

Over-smoothed forecasting results

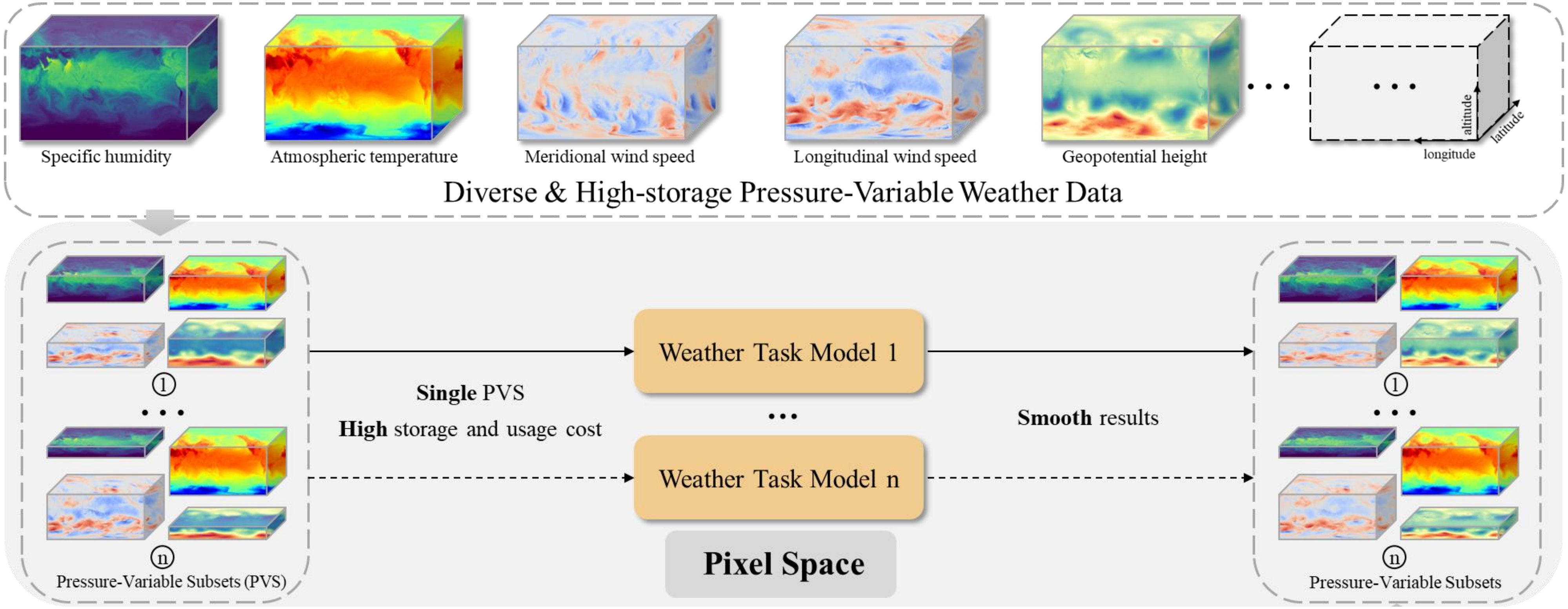


Pixel-space models face three bottlenecks

Over-smoothed
Task uncertainty leads to overly smooth weather-task outputs

Fragmented
Models are typically limited to a single pressure–variable subset

Resource-intensive
Pixel-space data incur high storage and computational costs



Latent space addresses these bottlenecks

Sharp

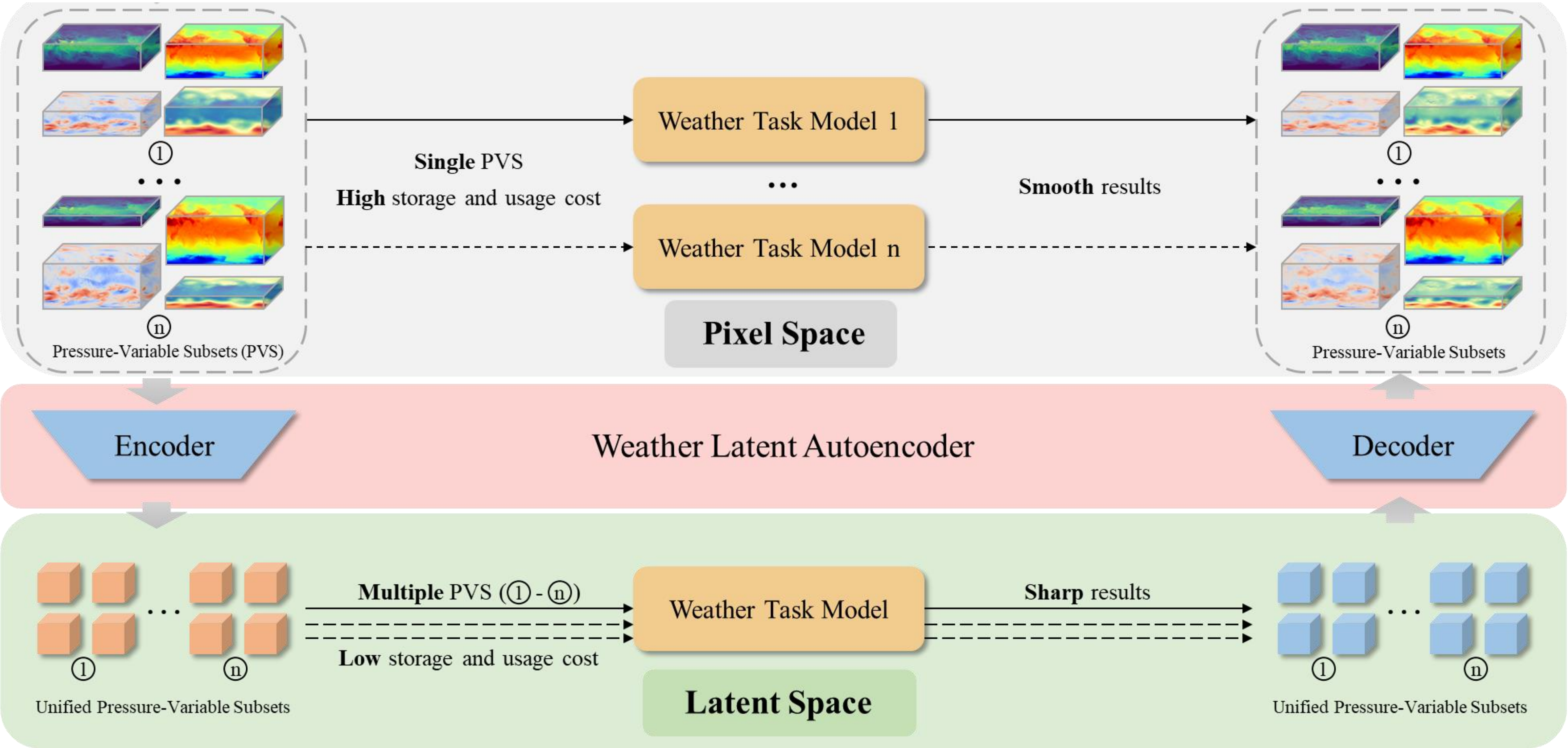
Decoupling reconstruction from downstream tasks enables sharper results

Unified

Diverse pressure–variable subsets are mapped into a unified latent representation

Resource-efficient

Compact representations reduce data storage and computational costs



Weather latent autoencoder structure

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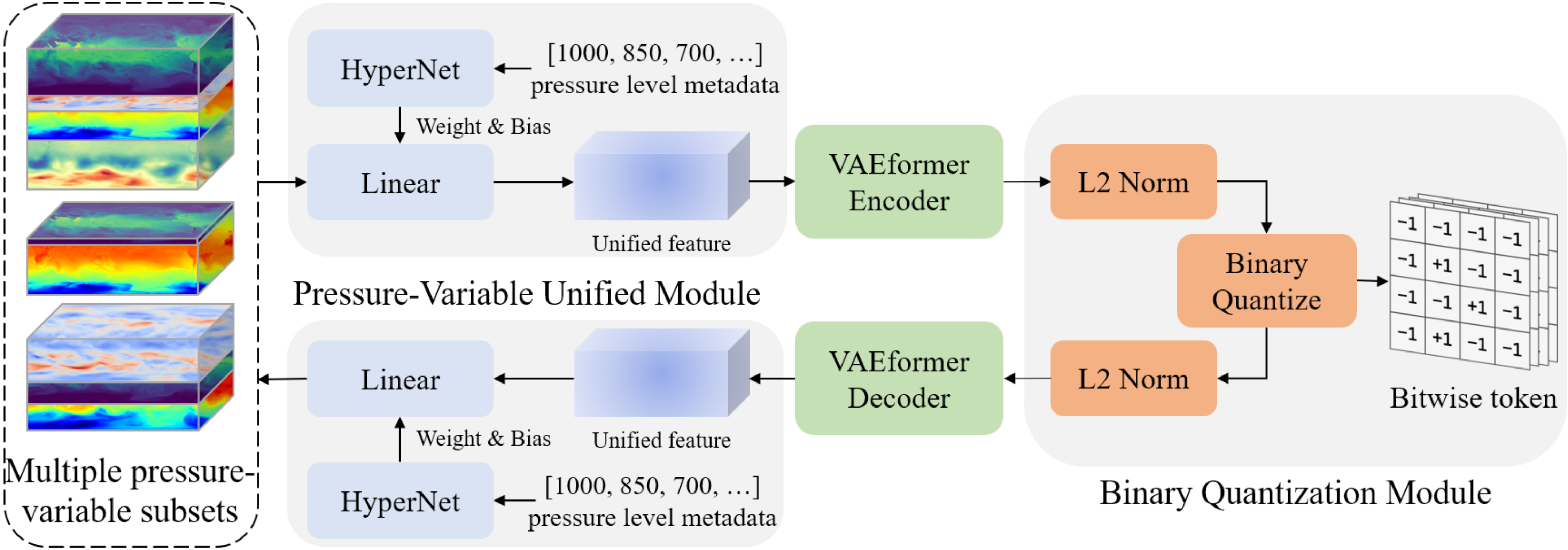
PVUM
Map diverse pressure-variable subsets to unified features

VAEFormer
Encode unified features and decode compact representation

BQM
Mapping between continuous features & discrete binary tokens



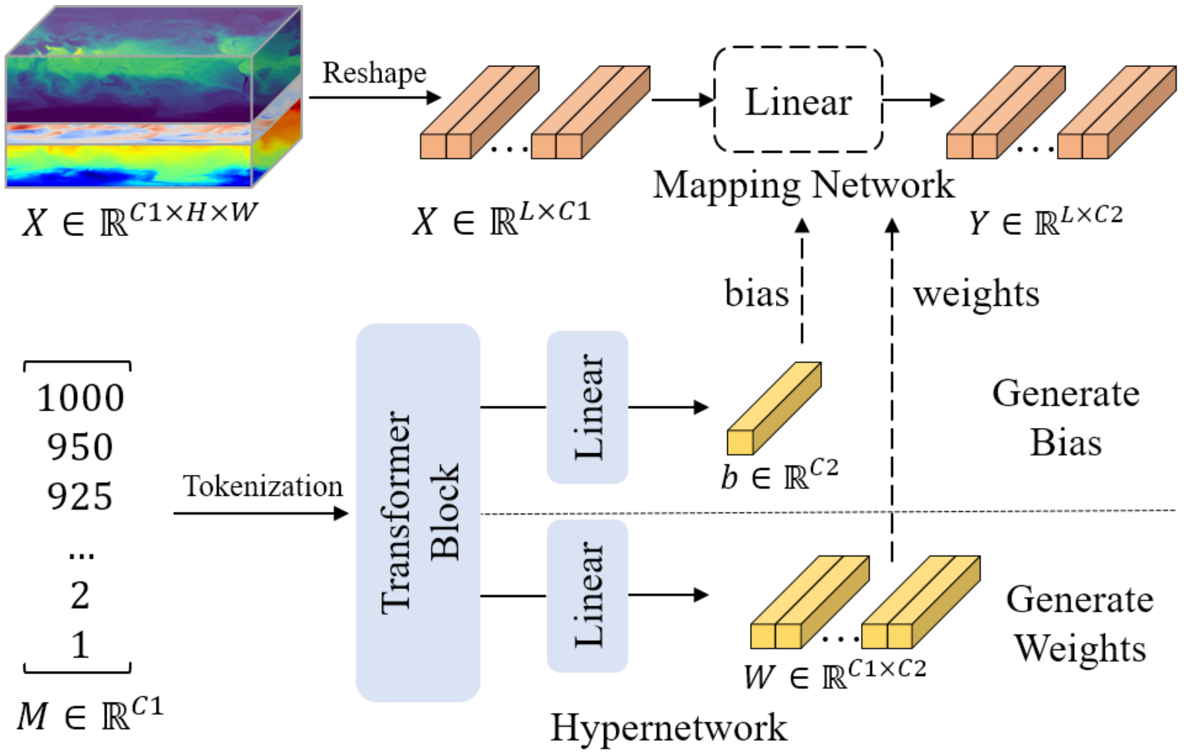
PVUM unifies diverse pressure-variable subsets

Metadata-conditioned Hypernetwork

- Dimensional Metadata Embedding
- Cross-Variable Relation Modeling
- Adaptive Parameter Generation

Adaptive Mapping Network

- Projection with generated weight and bias
- Mapping diverse PVS to unified representations



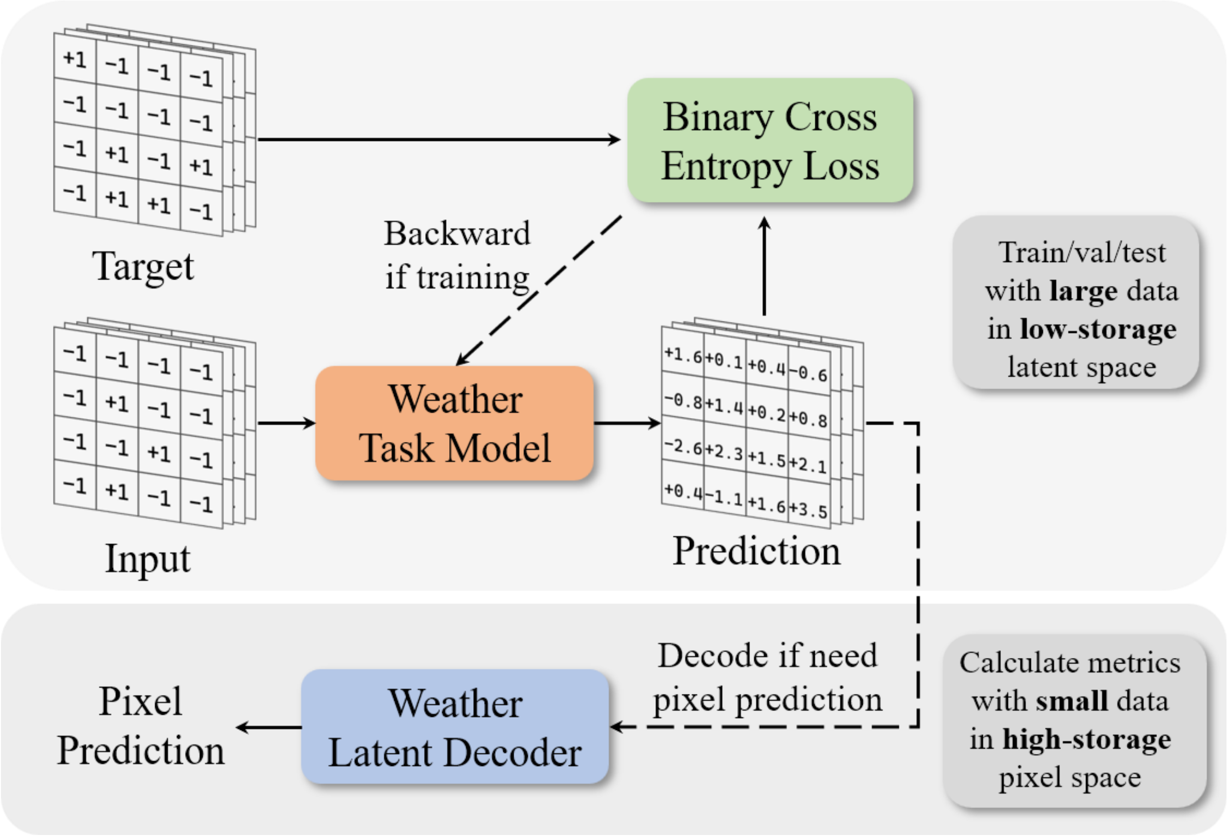
Latent space framework reduces data costs

Compact Latent Space

- Preserves essential features in latent representations
- Handles data-intensive stages in latent space
- Enables efficient model training and validation

Full-resolution Pixel Space

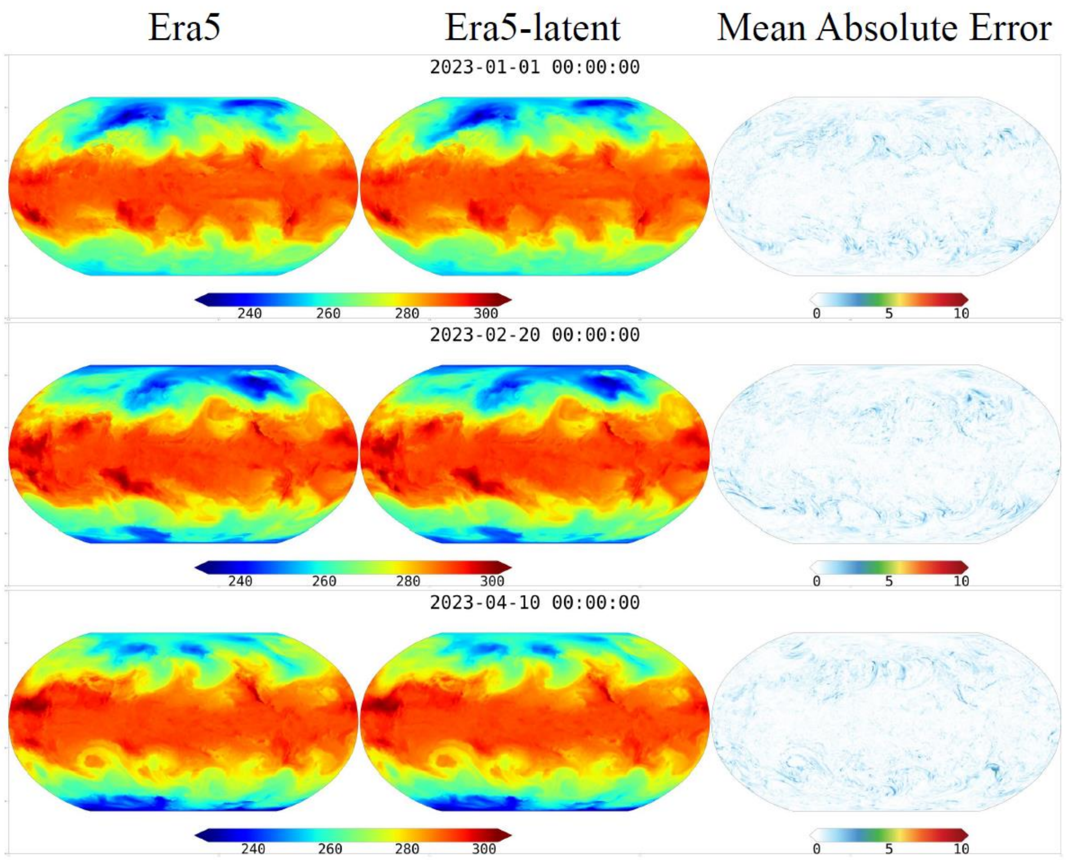
- Reserved only for lightweight pixel-level tasks
- Used for metric computation and result visualization
- Reduces data storage and computational costs



ERA5-Latent dataset overview

Compression

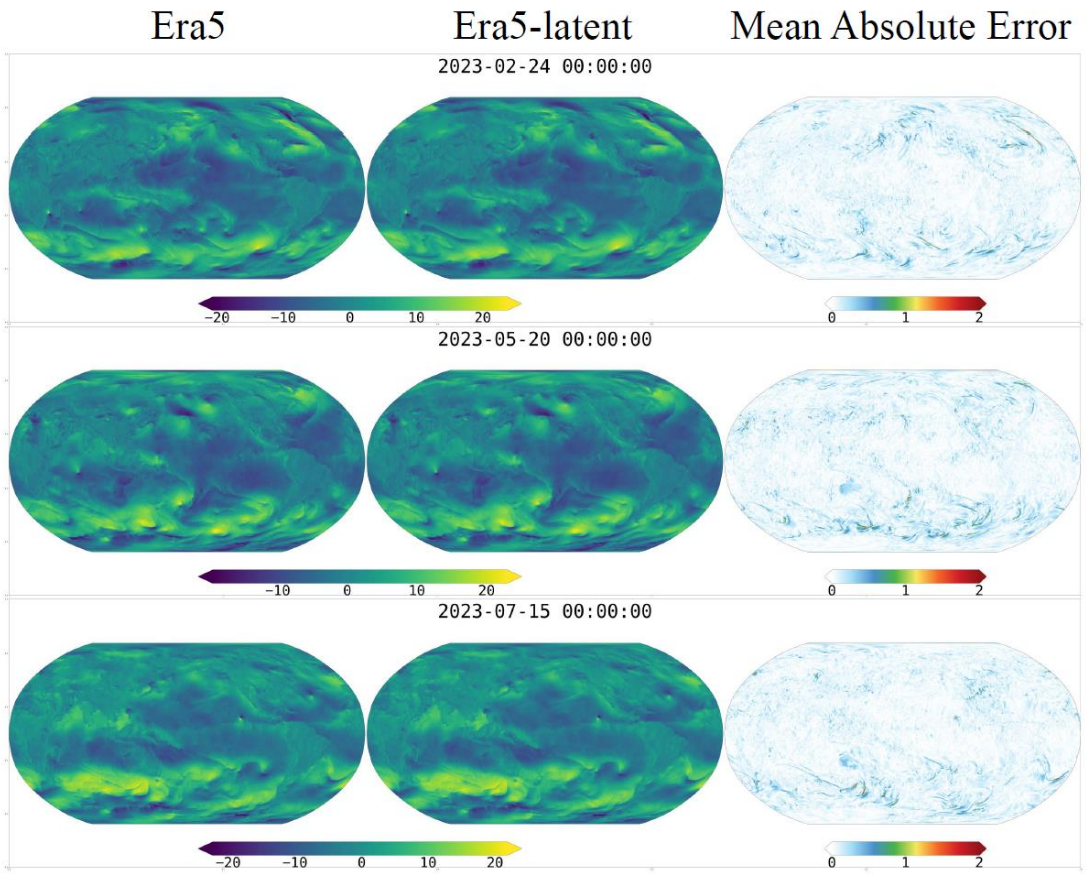
244.34 TB → 0.43 TB, with a 566.3× compression ratio



Atmospheric temperature at 850hpa (T850)

Reconstruction

Preserves spatial patterns and small-scale weather structures



U-component of wind at 10 meters (10u)

WLA improves compression and reconstruction

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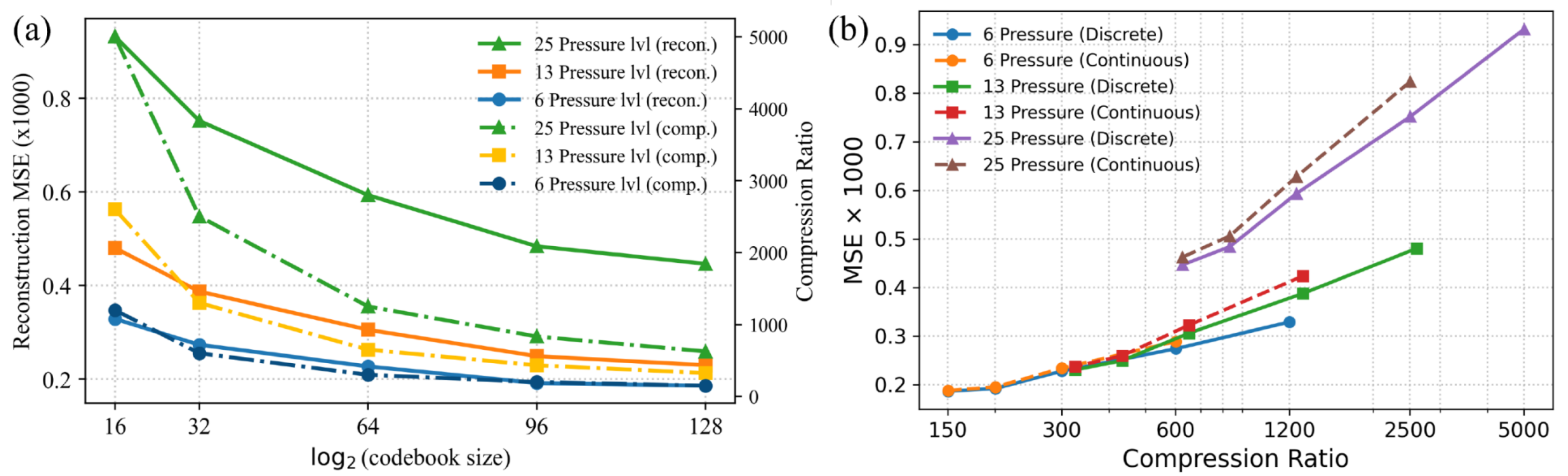
Compression Results

Better compression–reconstruction trade-off while unifying diverse pressure-variable subsets

Ablation Study

Larger codebooks improve reconstruction, and discrete latent space enables efficient compression

Method	Weighted RMSE ↓							Comp. Ratio ↑	BPSP ↓
	Upper-air Variables				Surface Variables		Precipitation		
	w500	w700	q700	q1000	TCC	SP	tp6h		
Var. Std (ref.)	0.218	0.240	0.0025	0.0059	0.36	9584.49	1.57	–	–
ELIC (He et al., 2022)	0.197	0.233	0.00076	0.00087	0.18	537.82	1.19	648.3	0.112
IEN (Xie et al., 2021)	0.213	0.247	0.00084	0.00092	0.23	688.27	1.03	202.5	0.158
VQVAE (Mirowski et al., 2024)	0.382	0.401	0.00108	0.00113	0.19	673.32	1.29	1100.0	0.029
VQGAN (Mirowski et al., 2024)	0.367	0.371	0.00101	0.00107	0.18	652.38	1.20	1100.0	0.029
VAEformer (Han et al., 2024a)	0.117	0.134	0.00031	0.00035	0.12	376.90	0.80	323.1	0.099
WLA_{small}	0.126	0.168	0.00038	0.00041	0.087	328.4	0.64	**1251.7**	**0.025**
WLA	**0.076**	**0.083**	**0.00027**	**0.00028**	**0.055**	**257.88**	**0.47**	625.9	0.051



Latent-space forecasting preserves extremes

Extreme-value preservation

Latent models achieve stronger SEDI across high-quantile thresholds

(SEDI: extreme-event detection score, higher is better)

Competitive 7-day forecasts

RMSE remains comparable to leading pixel-space and operational baselines

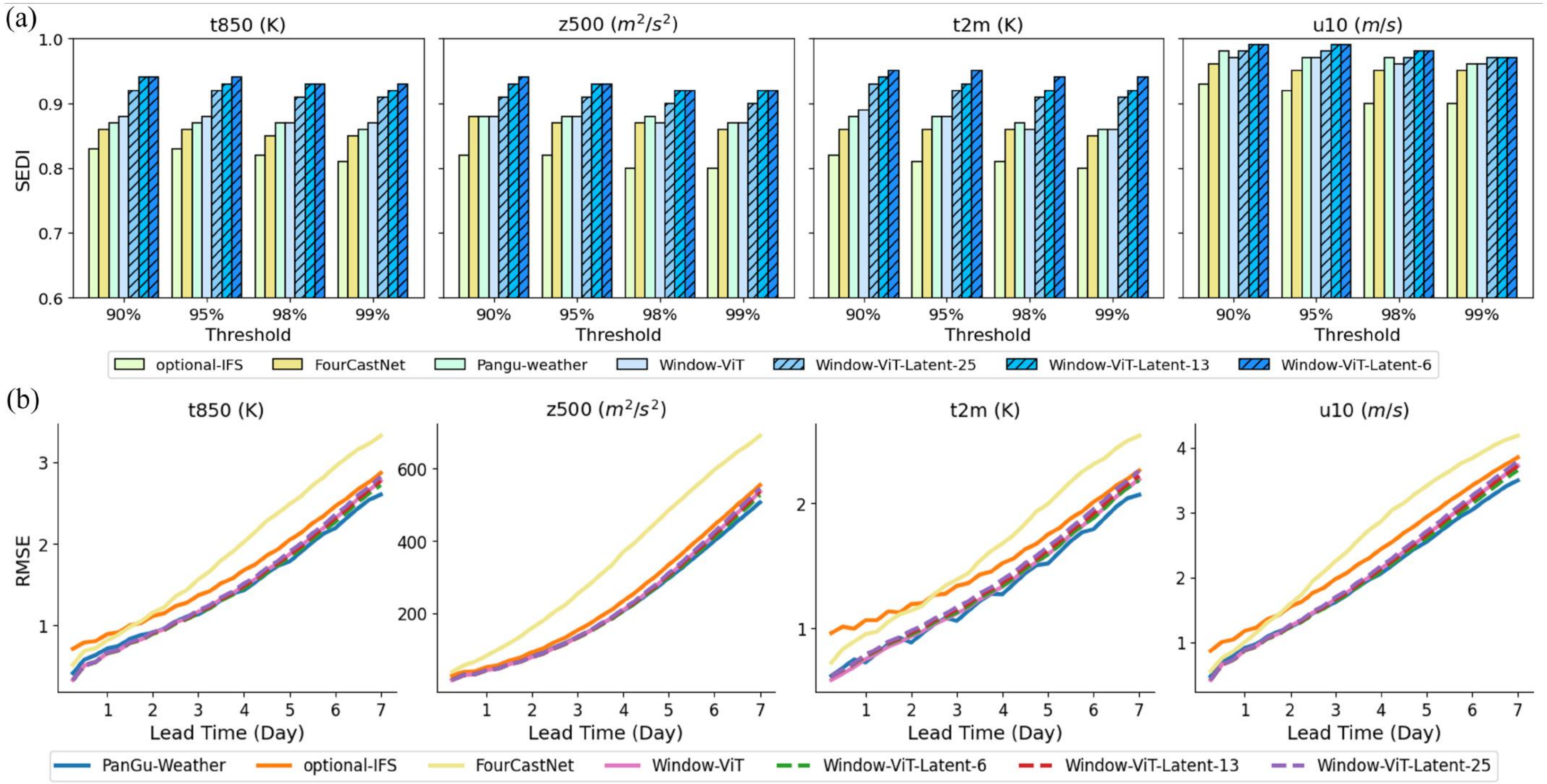


Figure 6. Comparison on the weather forecasting task. (a) Extreme weather forecasting performance on the SEDI metric. (b) RMSE for weather forecasting over a 7-day period. The number following "Window-ViT-latent" indicates the number of input pressure levels.

Key Takeaways

Weather Latent Autoencoder

Maps diverse, redundant data into unified, compact latent representations

Era5-Latent Dataset

Compresses 244.34 TB of ERA5 into 0.43 TB while preserving weather structure

Weather Modeling in Latent Space

Reduces data storage and computational costs and enables sharper model results

One Sentence

Transforming weather data into latent space to enable unified and efficient weather modeling while reducing data costs and preserving extreme values

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