Climate Tech Lab
Downscaling with Generative AI

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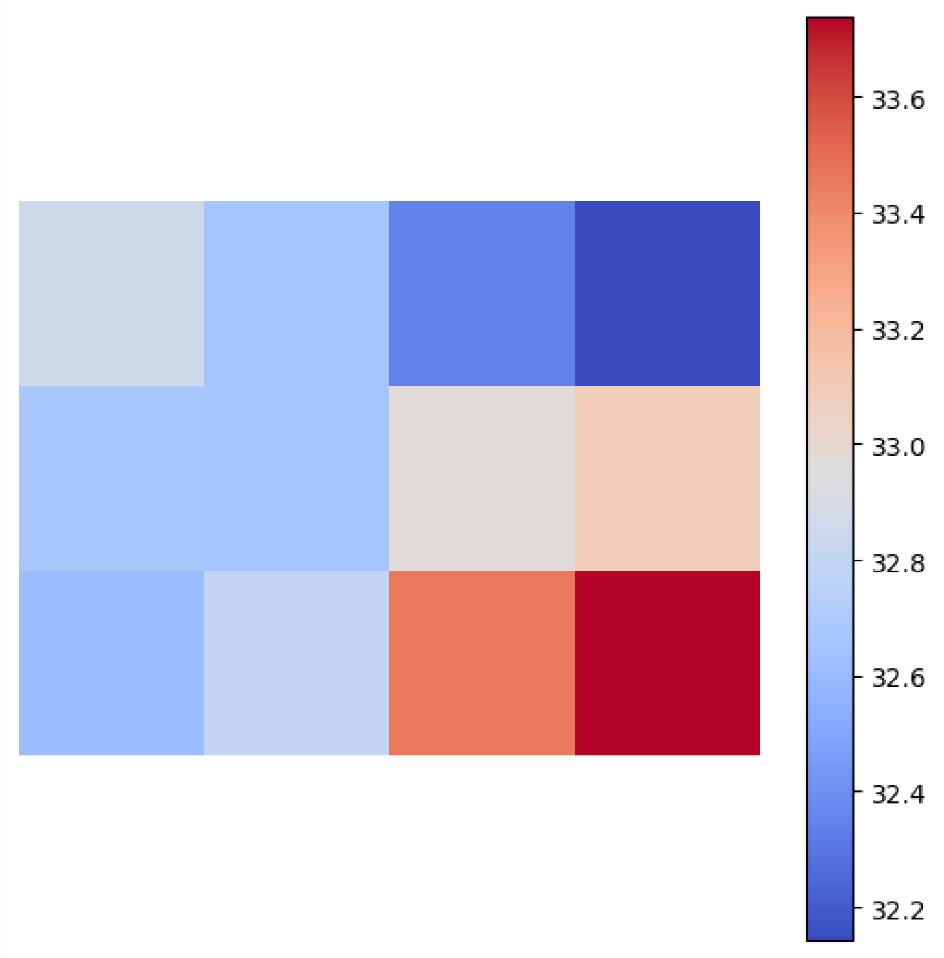
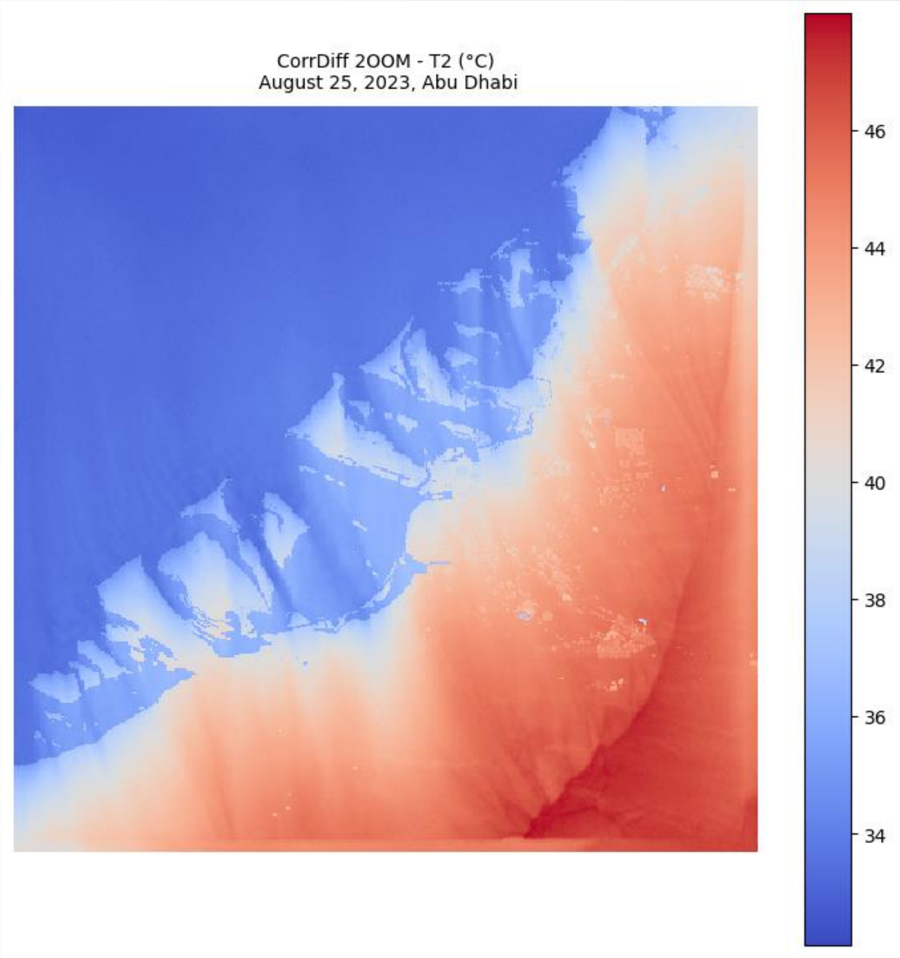
The Need for Downscaling: From Global Models to Local Insights

Where is this place (ERA5 ~25 km of resolution)?



The Need for Downscaling: From Global Models to Local Insights

Abu Dhabi at 200m of resolution!



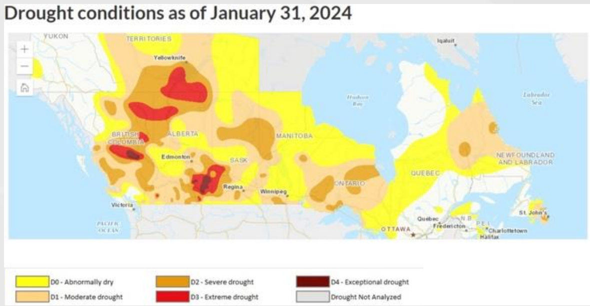
The importance of high-resolution forecasting

Urban Heat

High-resolution forecasts help identify urban heat islands and protect vulnerable populations.

Agriculture

Small-scale weather patterns affect management decisions (irrigation, pest control) and crop yields. Farmers need localized forecasts for effective decision-making.

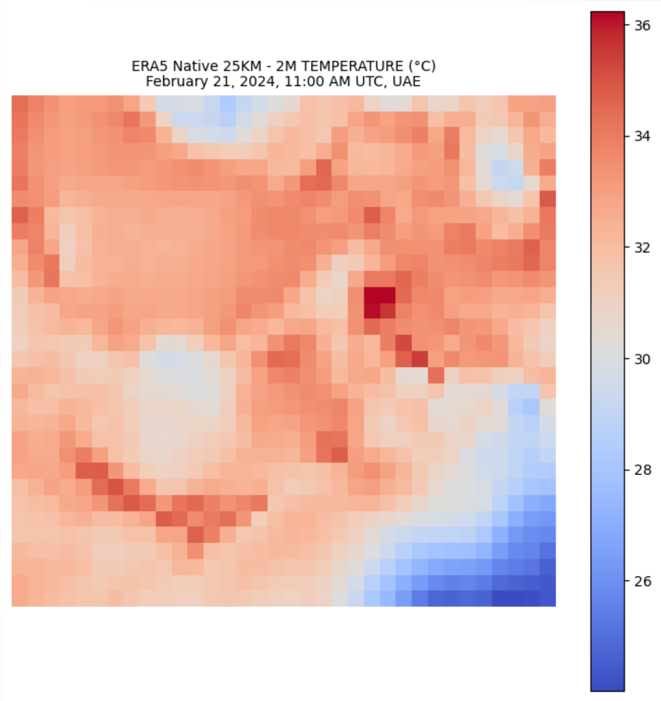


Disaster Preparedness

Floods, dust storms, and cyclones can have devastating impacts. High-resolution forecasting supports early warning systems and emergency planning.

The Need for Downscaling: From Global Models to Local Insights

Global coarse resolutions datasets:
Examples: ERA5

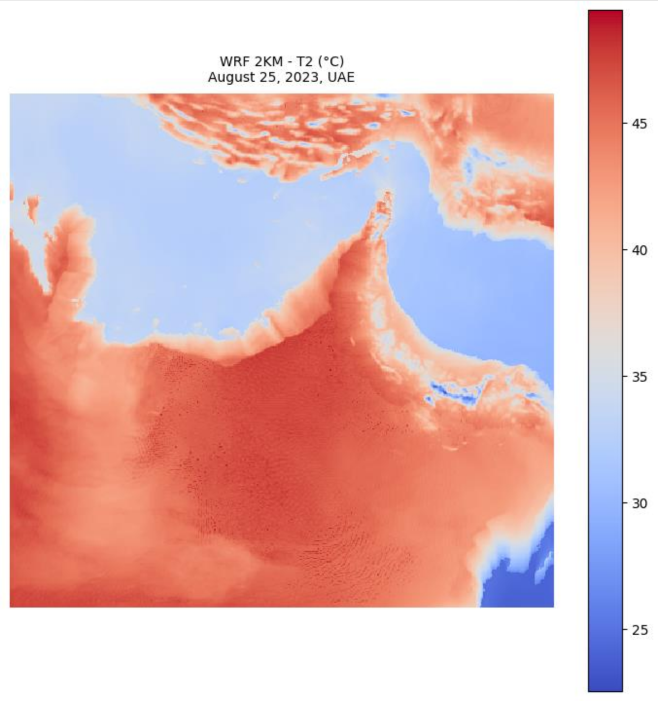


Strengths:
Physics-based
Long-term forecast

Ensemble capabilties
Multi-variable output

Limitations:
Coarse spatial resolution (10-50km)
Limited for decision-making at city or infrastructure scale.
Computational expensive
Slow

NWP Models:
Examples: WRF



Downscaling Approaches

1. Dynamical downscaling
2. Statistical downscaling
3. AI based donwscaling (non-Generative)
4. Generative AI downscaling

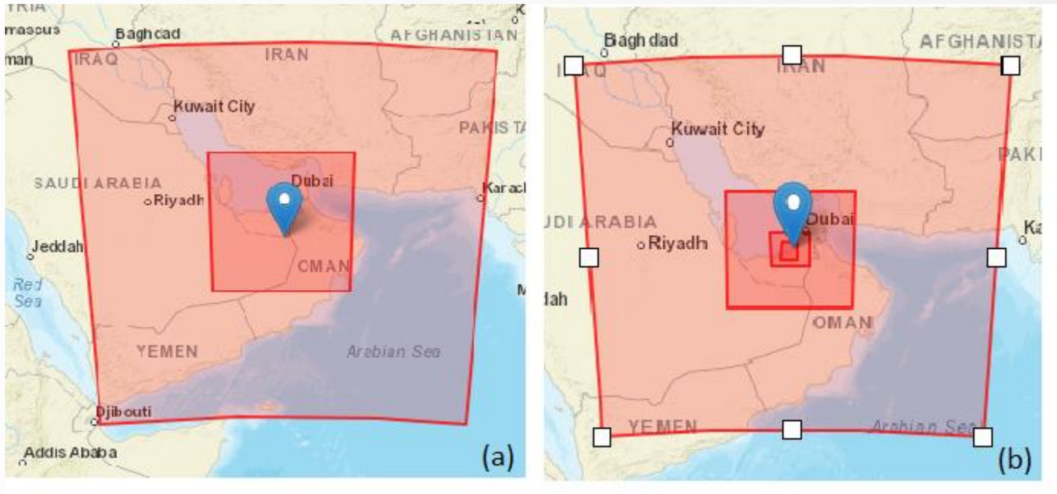
Downscaling Approaches: Dynamical Downscaling

What it is & How it works:

A high resolution regional model (e.g. WRF) is nested inside a coarse global NWP model

The coarse model provides boundary conditions (temperature, wind, ...)

The regional model resolves small-scale phenomena



Pros and Cons:

Pros:

- Physically consistent
- Interpretable
- Flexible
- Widely used & validated

Cons:

- Computationally expensive
- Limited coverage
- Dependent on boundary conditions
- Time-consuming

Downscaling Approaches: Statistical Downscaling (non-AI)

What it is & How it works:

Uses **statistical relationships** to map coarse NWP outputs to fine-scale variables.

Can include:

- Linear regression
- Bias correction

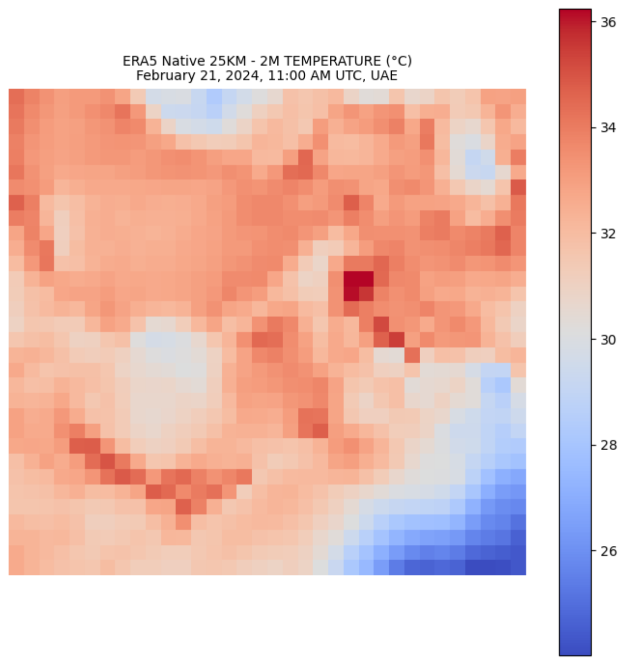
Pros and Cons:

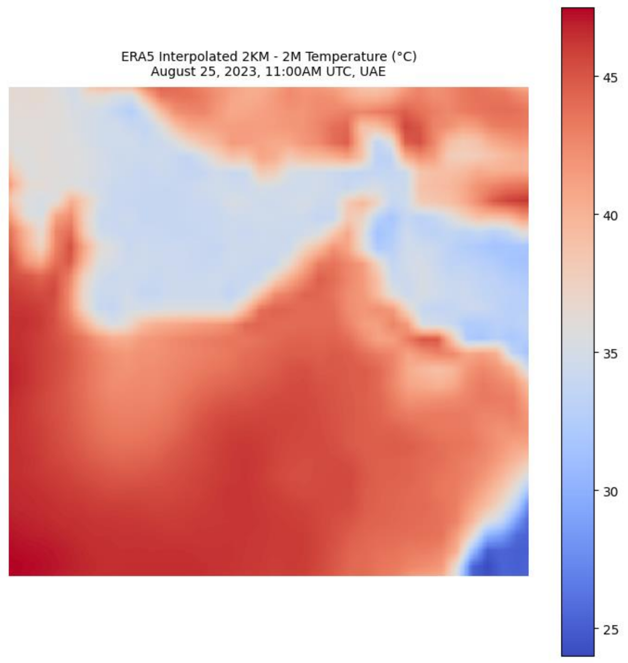
Pros

- Fast and computationally inexpensive
- Simple to implement

Cons:

- Limited generalization
- Fails to capture extremes
- Spatial patterns may be unrealistic





Downscaling Approaches: Machine Learning

What it is & How it works:

Uses **machine learning algorithms** to learn relationships between coarse NWP outputs and high-resolution observations.

Typical approaches:

- Convolutional Neural Networks (CNNs)
- Random Forests
- Gradient Boosting

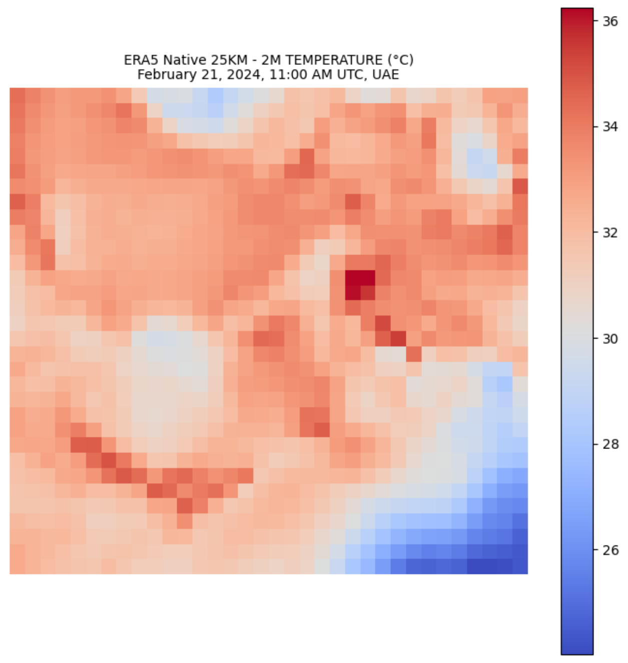
Pros and Cons:

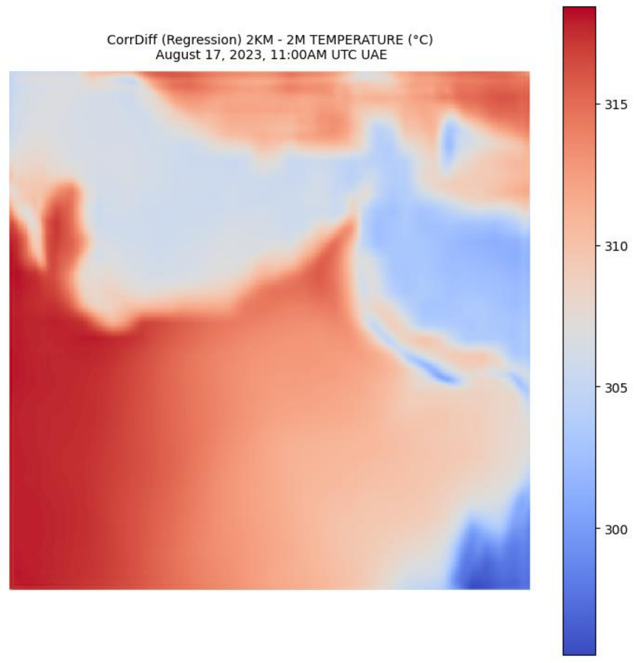
Pros:

- Flexible
- Fast at inference
- Captures non-linear patterns

Cons:

- Data hungry
- May not respect physics
- Training is resource-intensive
- Generalization risk





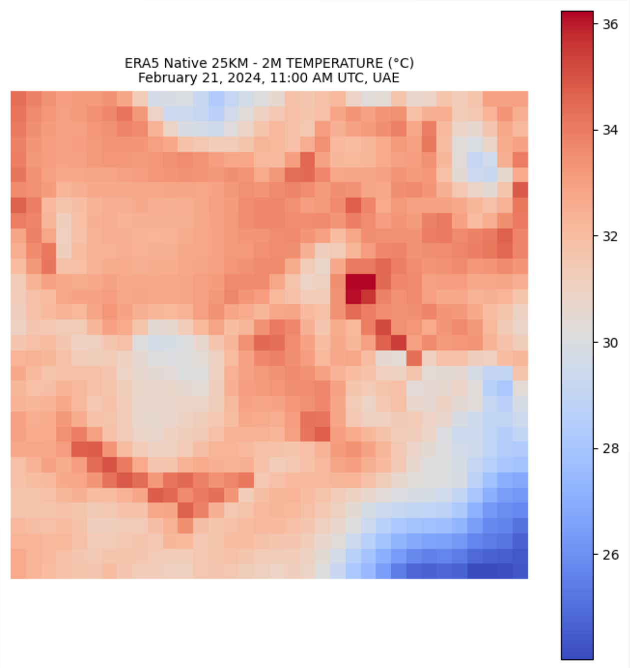
Downscaling Approaches: Generative AI based

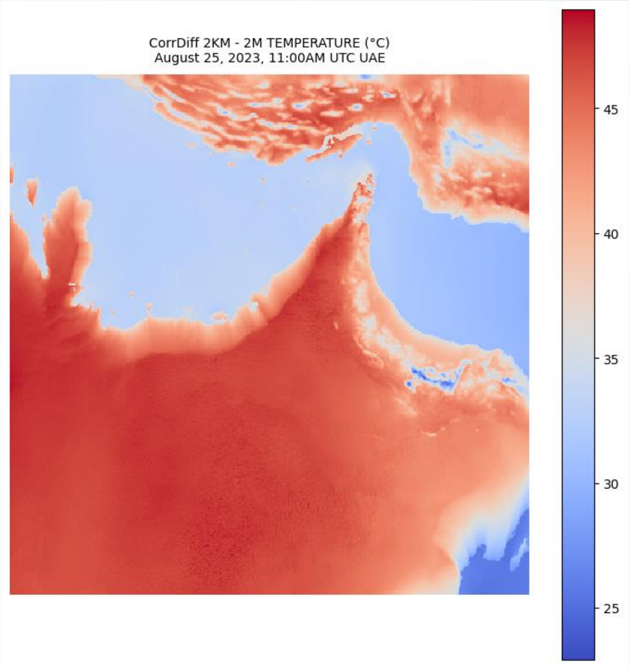
What it is & How it works:

Uses **generative AI models** to progressively refine coarse NWP forecasts into high-resolution fields.

Methods include:

- Generative Adversarial Networks (GANs)
- Variational Autoencoders (VAEs)
- Diffusion models





Pros and Cons:

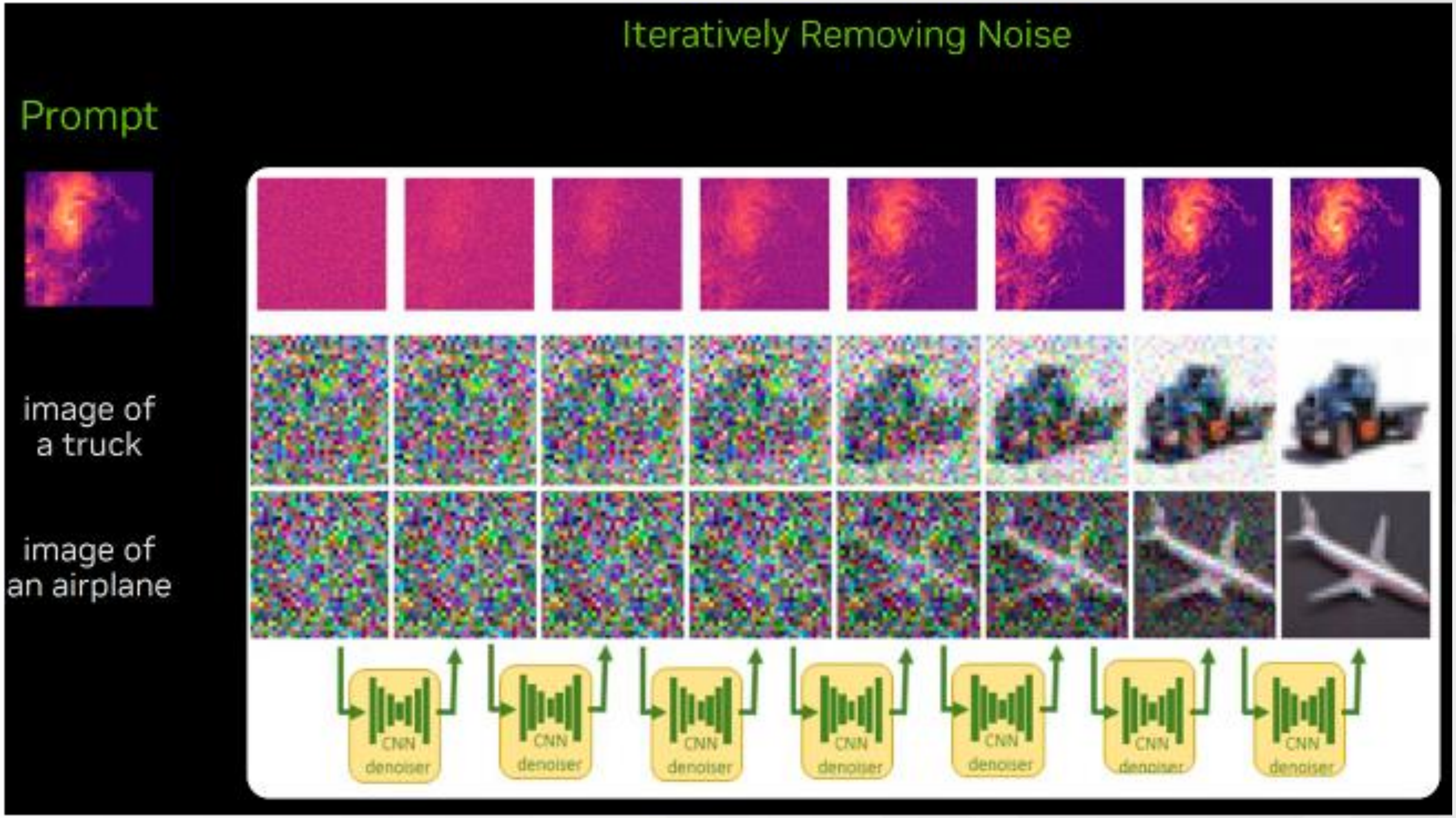
Pros:

- Captures complex spatial and temporal patterns beyond traditional ML
- Provides uncertainty estimates
- Flexible
- Fast once trained

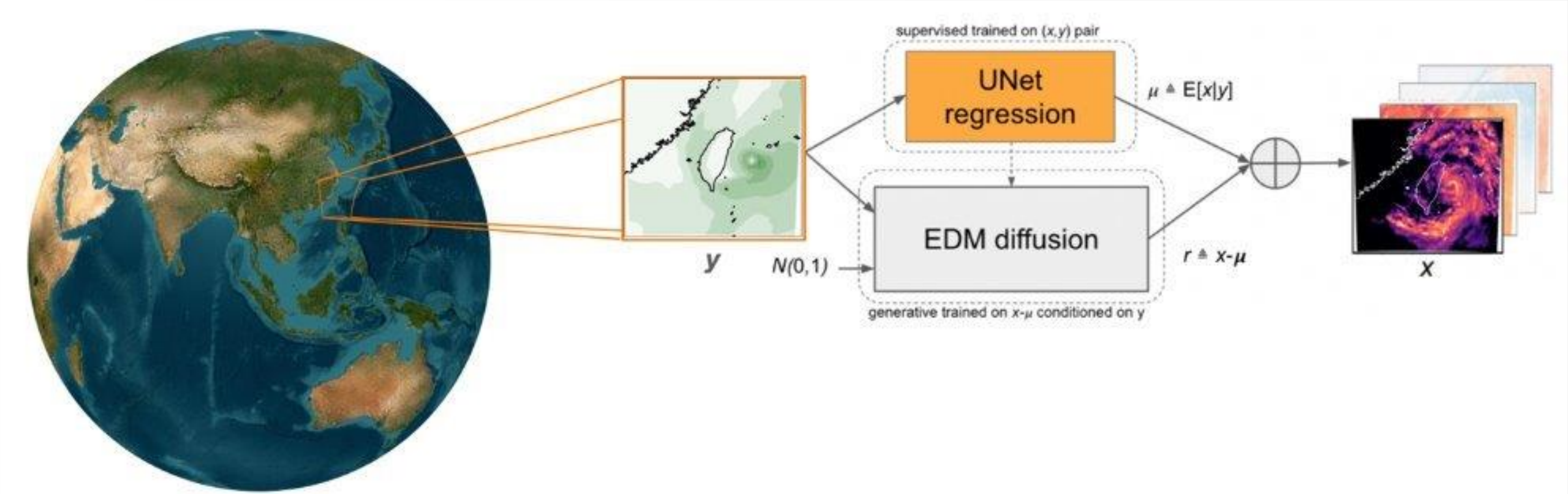
Cons:

- Prone to model collapse (GANs)
- Training intensive
- Inference may require multiple GPUs
- Risk of artifacts

Diffusion Models for Downscaling



Correction Diffusion Model (Corrdiff)

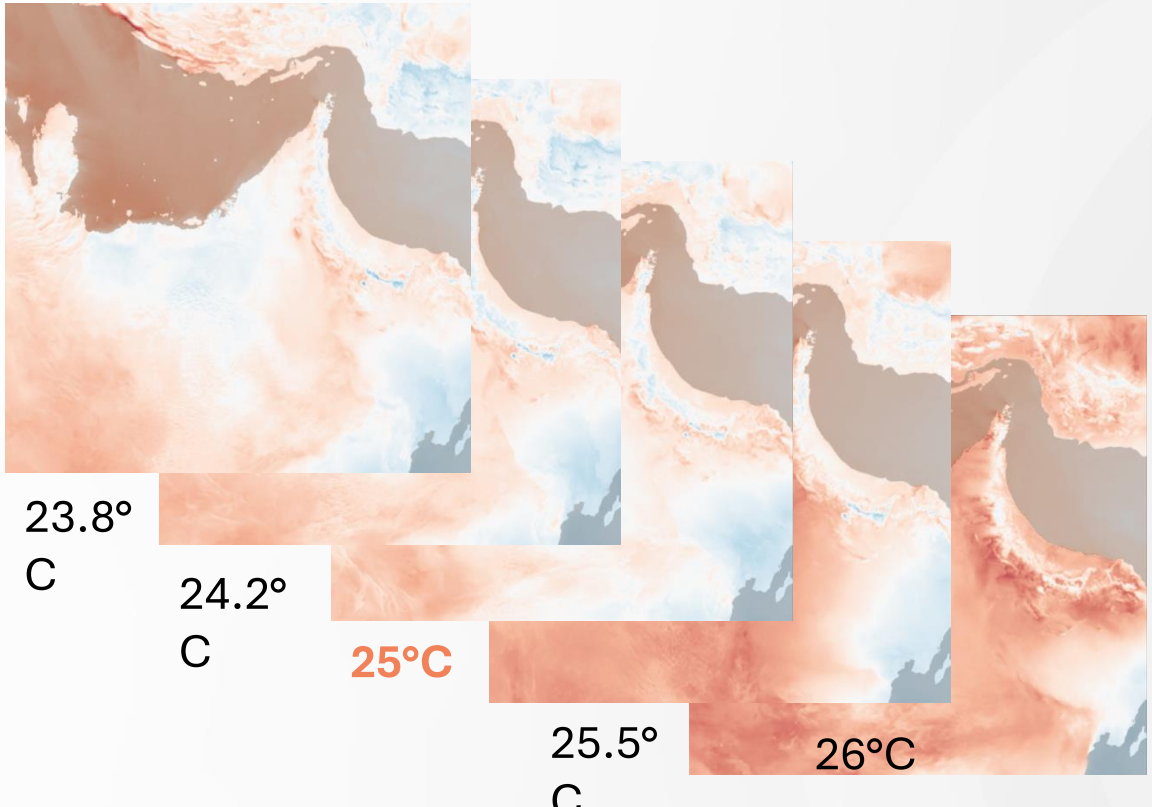


How quantifying the uncertainties of Climate can provide better visibility into possible futures and solutions

We **quantify uncertainties**

- Baseline models predicts expected values
- A diffusion model learns the probability distribution of the residuals

Mean output: 25°C
Residual prediction: ±1.5°C

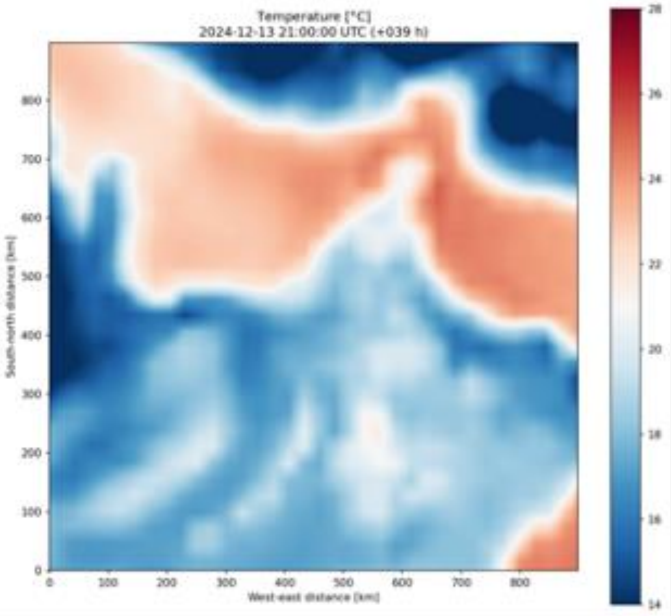


Key Advantages:

- Learning the small-scale physics
- Improved prediction of extreme weather events
- Better decision making and risk assessment
- Reduction in biases = more reliable forecasting
- Model trust and interpretability
- Optimize resource allocation and preparedness

UAE Corrdiff: What do we need?

STANDARD 25KM RESOLUTION NWP WEATHER MODEL

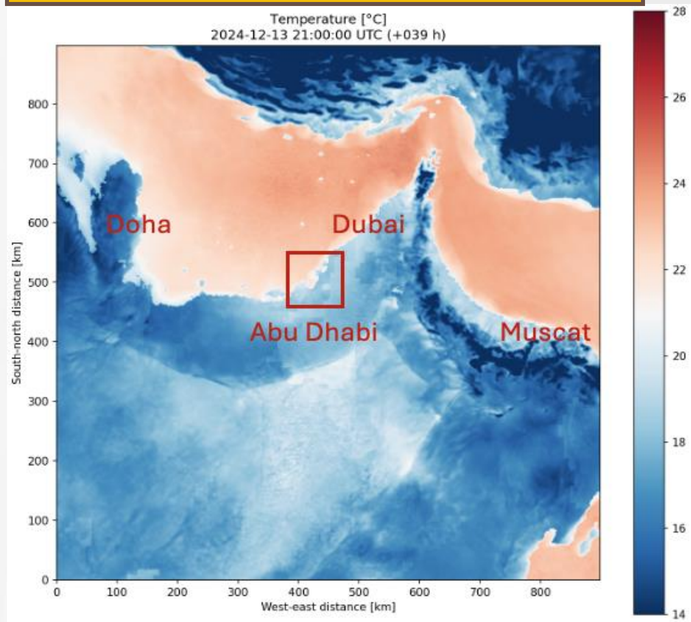


Typical weather forecast (25 km)

OUTPUT INPUTS

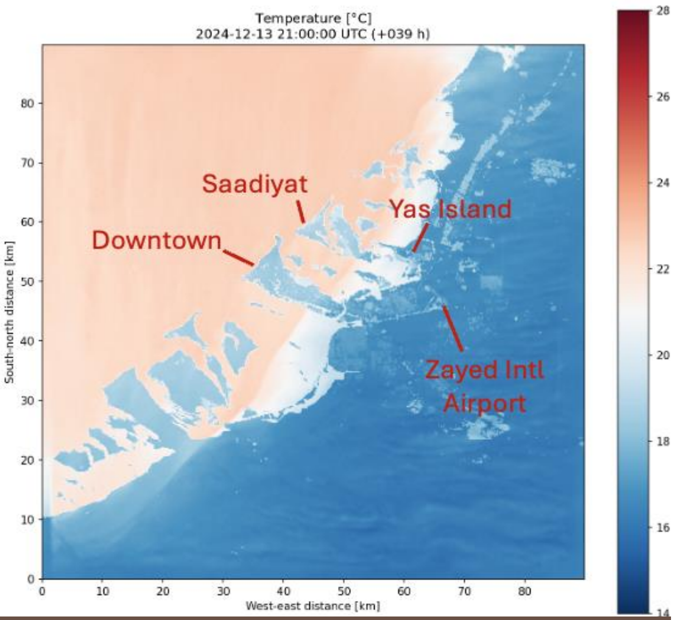
ERA5 – GLOBAL MODEL
5 years weather data (25km x 25km resolution)

WRF-REGIONAL NWP
5 years weather data (2km x 2km resolution)



ERA5 – GLOBAL MODEL
2 years weather data (25km x 25km resolution)
Corrdiff 2km output

WRF-REGIONAL NWP
2 years weather data (200m x 200m resolution)



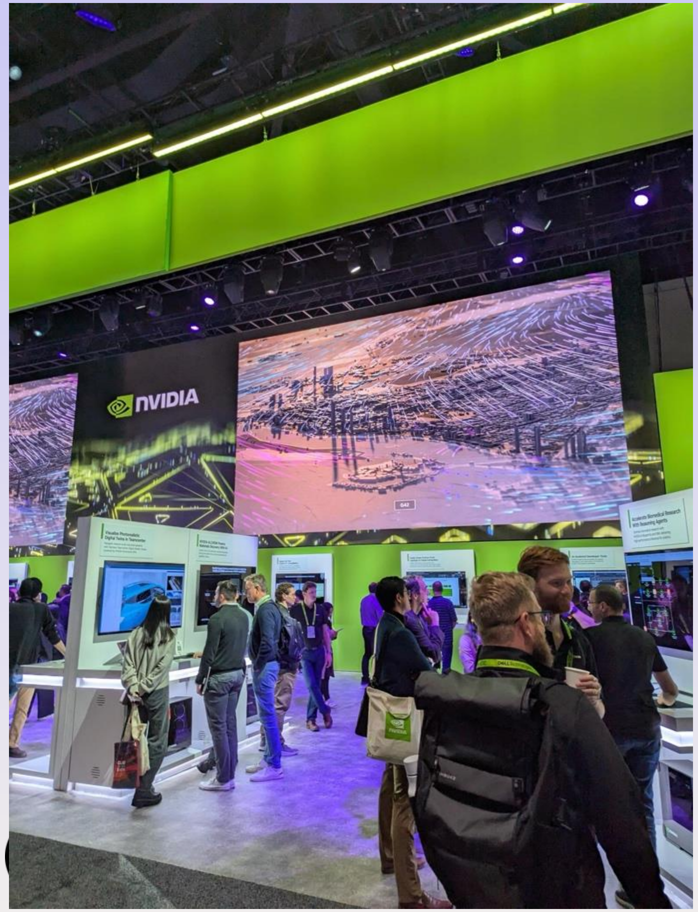
G42 UAE CORRDIFF
Regional weather downscaling (2km x 2km and 200M x 200M resolution)

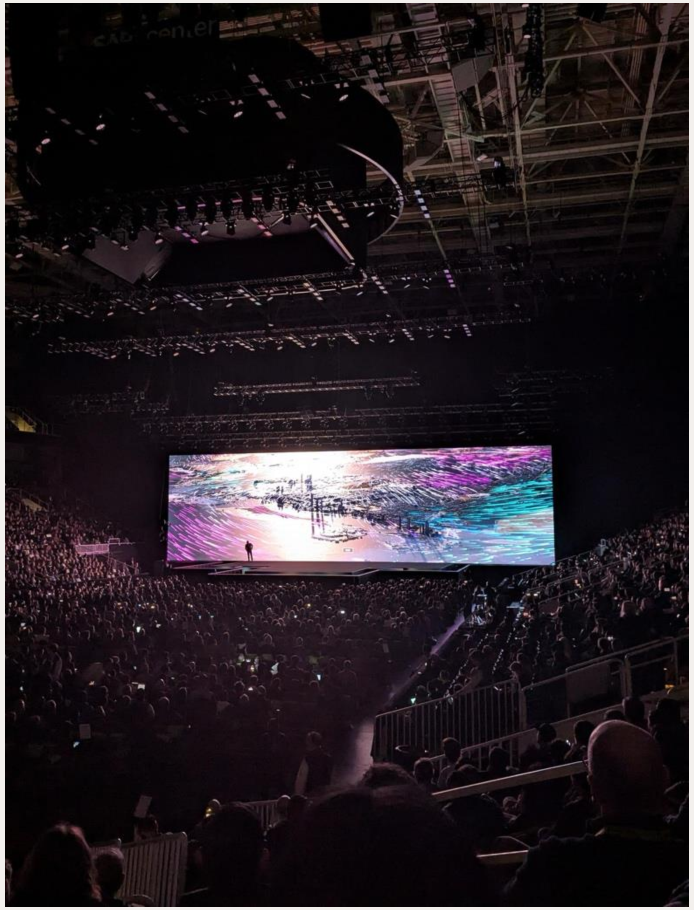
AI weather forecast (2 km)

AI weather forecast (200 m)

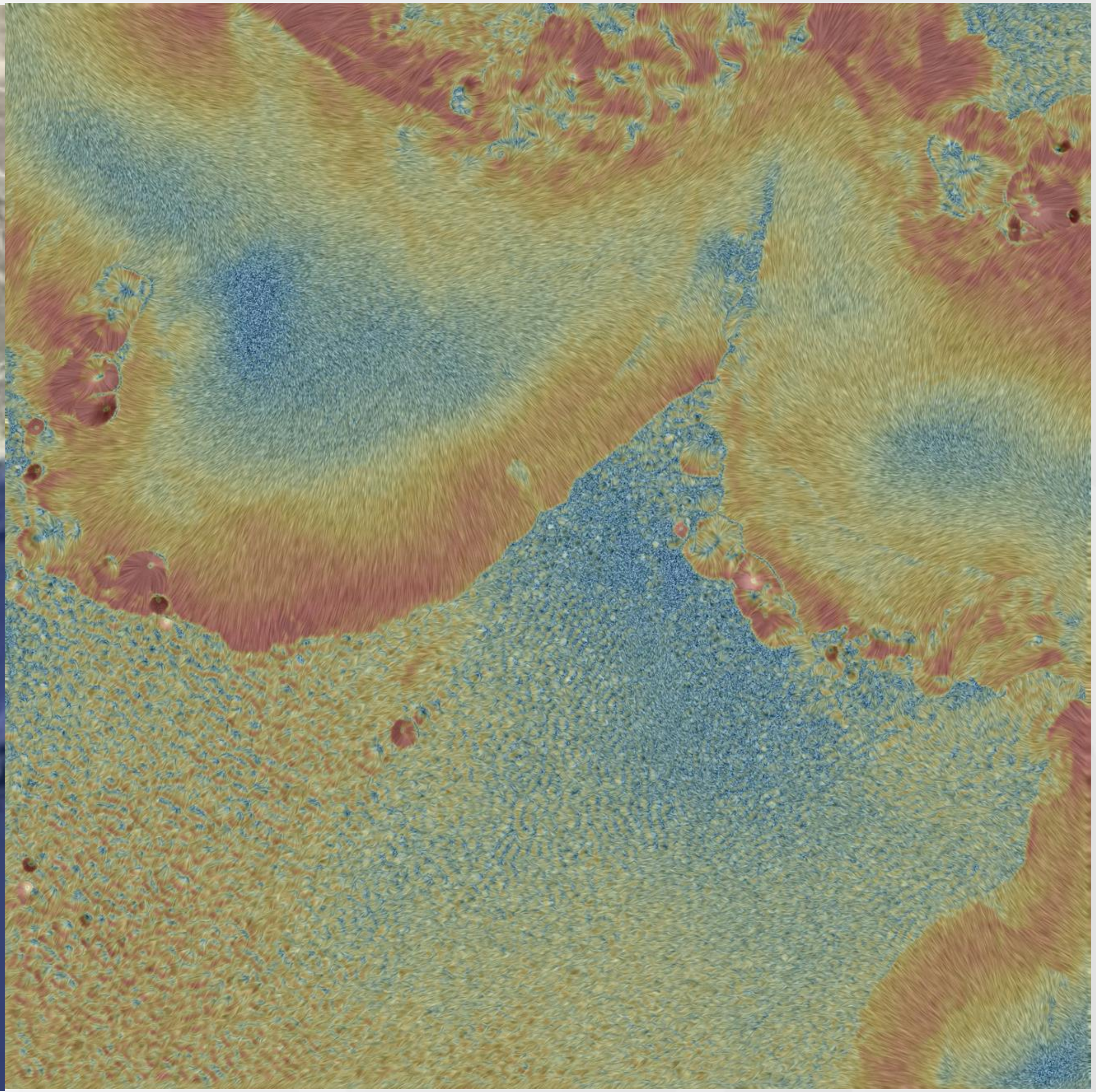
Our work was presented at NVIDIA GTC 2025!

- NVIDIA's Flagship AI conference
- In front of **~25,000** in-person attendees
- Part of NVIDIA's CEO **keynote**
- Dedicated **booth** with interactive **demos** running for 3 consecutive days





Our model is very good at learning small-scale physics: See example of Wind



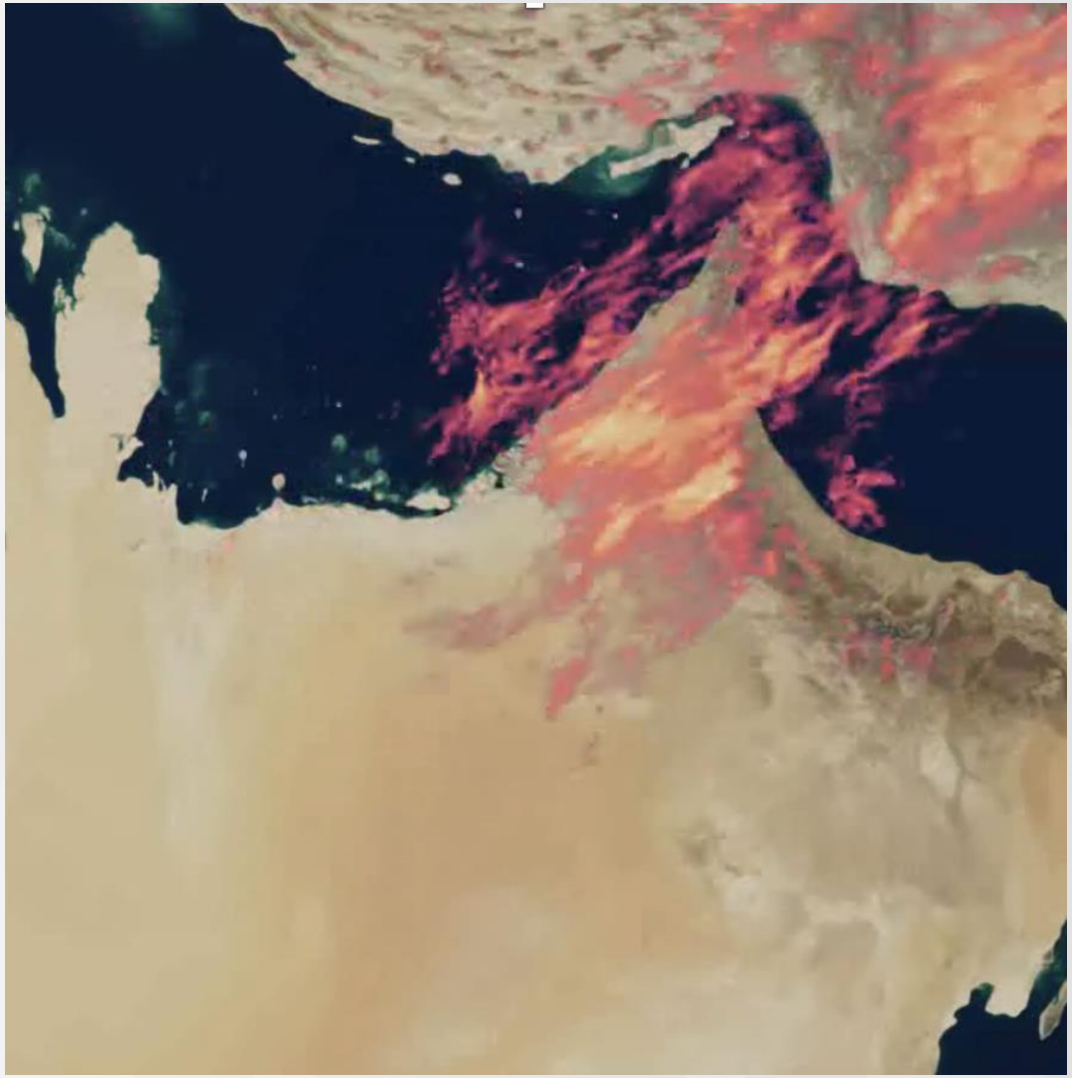
Extreme weather prediction: Rainfall

- Extreme events are **rare and underrepresented**
  - Uncertainty quantification allows models to generate **multiple possible outcomes**

- Many extreme events are driven by **fine-scale physical processes** (e.g., turbulence, convection).
  - **Small variations** in initial conditions can **significantly impact** event severity

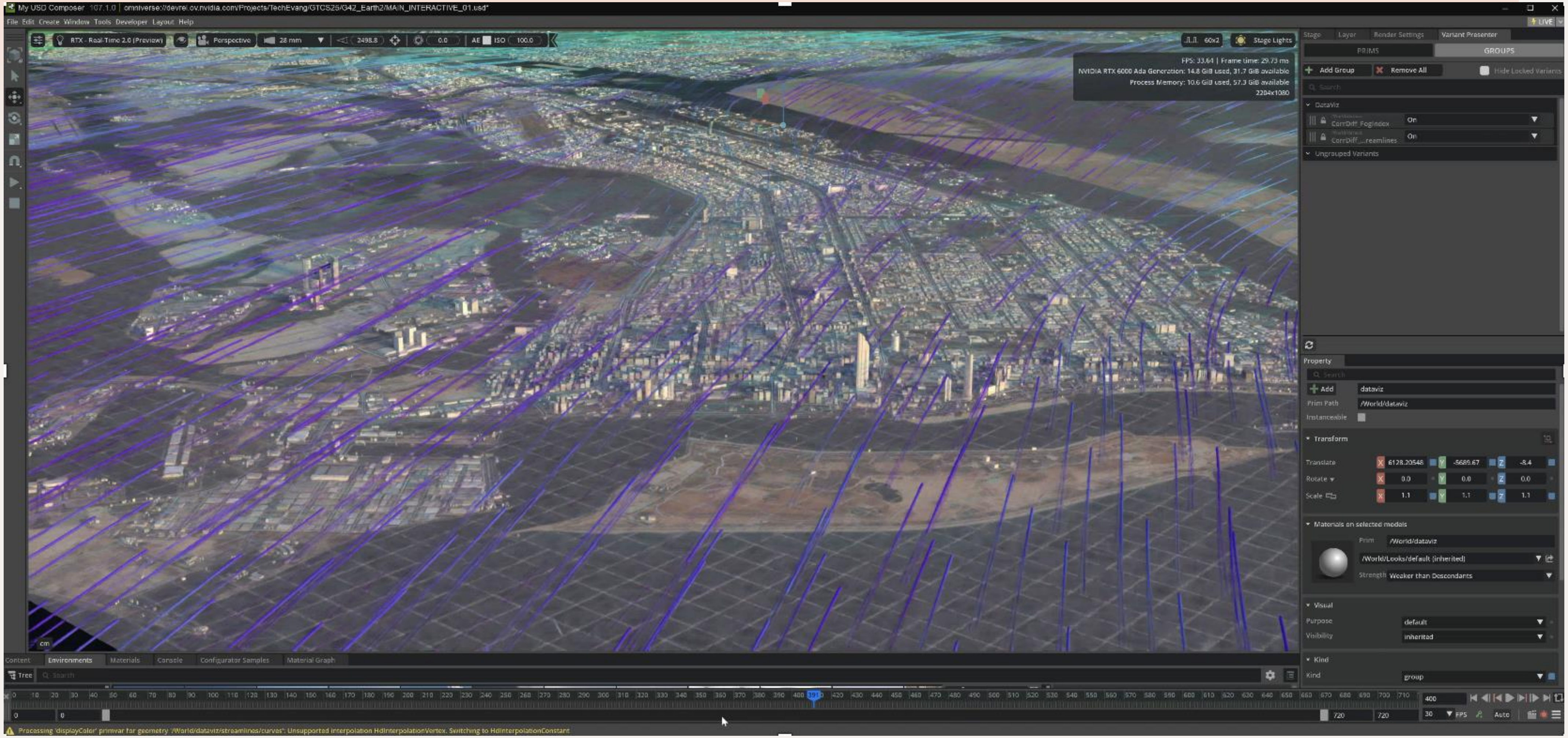
- Traditional models struggle where observational **data is limited** (e.g., remote areas, oceanic regions).
  - Uncertainty-aware methods can **infer missing details** and provide more robust predictions.

Rainfall 16/04/2024
Reported total amount of 259.5mm
Predicted 260 mm



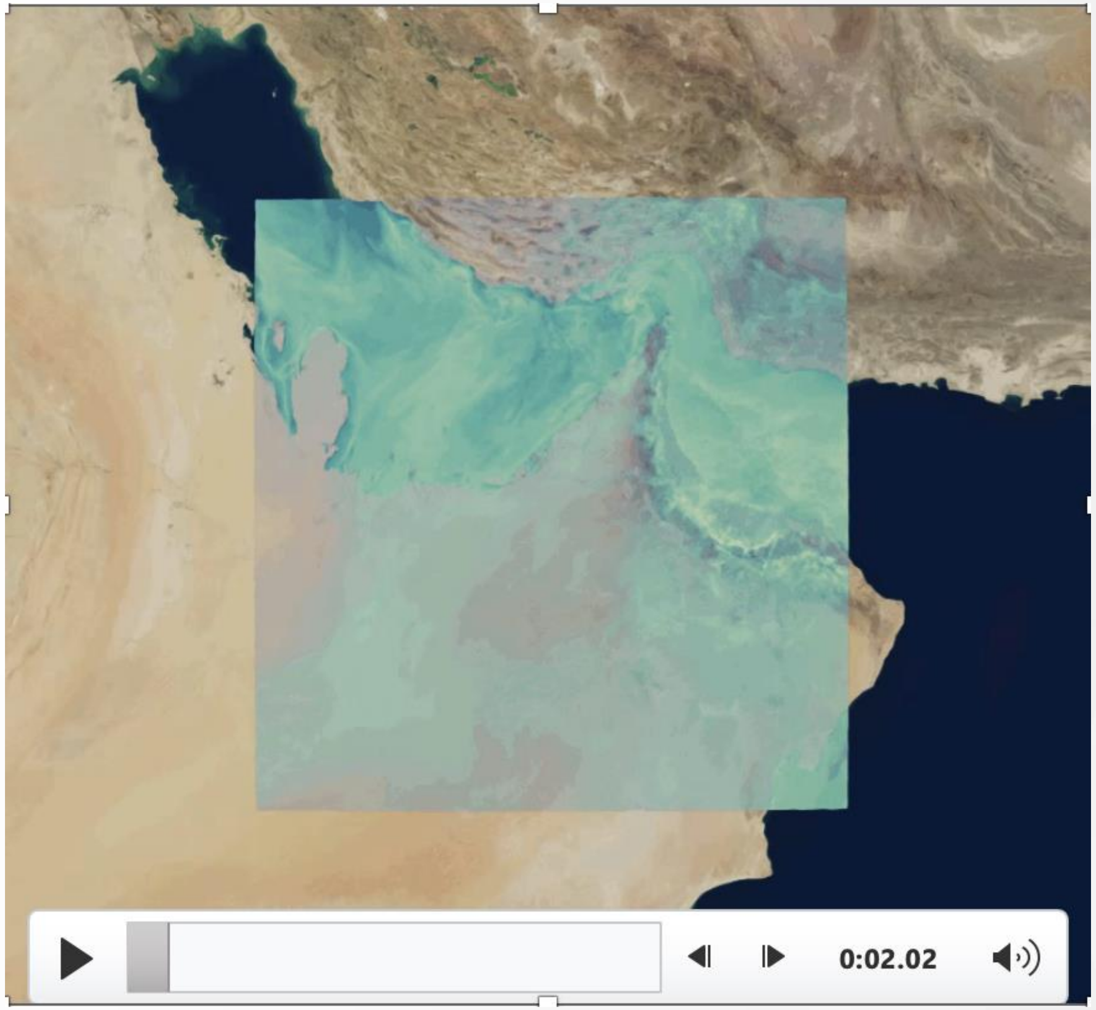
Our weather model can be customized to specific conditions and additional datasets

Our model can be tuned for local “pain points” such as **dense sea-fog, dust storms, coastal flooding and 50 °C heat bursts**—hazards that regularly disrupt UAE operations.

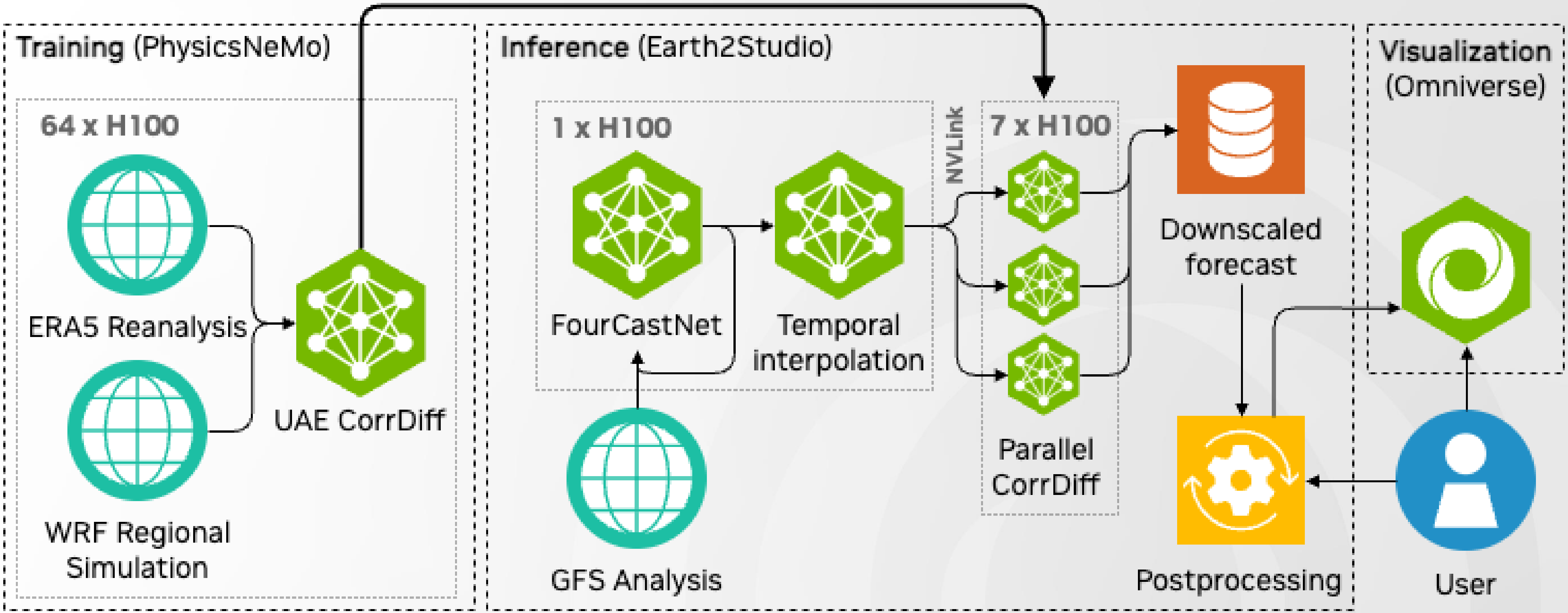


How can a 14-day fog forecast save lives?

While only a small percentage of crashes, foggy or dusty weather was linked to **2% of severe or fatal** vehicle crashes in the UAE



Building a High Resolution Weather Forecasting Pipeline



Applications in Practice

Inference Pipeline

Applications in Practice

Data Retrieval

```
from earth2studio.data import GFS
data = GFS()
```

Applications in Practice

Forecasting

```python
from earth2studio.models.px import SFNO
fc_model = SFNO.load_model(SFNO.load_default_package())
```

Applications in Practice

Interpolation

```
from earth2studio.enterprise.models.px import ForecastInterpolation
interp_model = ForecastInterpolation.load_model(
    Package(interp_package_path, cache=False),
    fc_model=fc_model
)
```

Applications in Practice

Downscaling

```
from earth2studio.enterprise.models.dx.corrdiff import CorrDiff
corrdiff_model = CorrDiff.load_model(
    Package(corrdiff_package_path, cache=False
)
```

Applications in Practice

Running the Workflow

```python
from earth2studio.run import diagnostic
from earth2studio.io.netcdf4 import NetCDF4Backend
io = NetCDF4Backend(output_file)
time = ["2025-03-17T00:00:00"]
timesteps = 168
diagnostic(
    time, timesteps, interp_model, corrdiff_model, data, io,
    output_prognostic=False
)
```

How downscaling models for Weather change the Paradigm

DIMENSION	NWP / AI DOWNSCALERS	G42 × NVIDIA CORRDIFF STACK
Spatial scale	1–3 km at best for UAE; coarse urban detail. Typically 25KM grids	**200 m** Abu Dhabi grid nested inside 2 km UAE mesh
Inference latency	Forecasting time of 1–3h on large CPU clusters	**< 2 min on 8× H100 GPUs** (40× faster) making multiple forecast ensembles cost and time-effective
Compute cost	960 CPU-core-hours/day	~0.2 GPU-node-hours/day; 1 400× energy-efficient
Industrial integration	Stand-alone met service feeds	Able to run inside Core42 cloud; API hooks to feed existing platforms and agentic workflows for automation

Jupyter Notebooks

Wrap-Up & Discussion

Why Downscaling Matters – Global models (10–50 km) miss critical local detail; diffusion-based downscaling delivers high-resolution (2–5 km) forecasts essential for urban heat, flooding, agriculture, and energy planning.

Diffusion & Correction Diffusion – By combining a regression step with diffusion refinement, we can progressively enhance coarse forecasts into realistic fine-scale features, while also quantifying uncertainty—something traditional methods struggle with.

Advantages over Classical Approaches – Compared to dynamical or empirical/statistical methods, diffusion models balance physical realism with computational efficiency, offering both scalability and adaptability to local contexts.

Impact in Practice – High-resolution diffusion downscaling is already being tested and used in real-world cases, showing strong potential to transform disaster preparedness, agricultural stress monitoring, and climate resilience planning.

INCEPTION

A G42 company