Stochastic-Deterministic Fusion: A Generative Downscaling Framework for High-Resolution Atmospheric Forecasting and Hydrologic Applications

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3 Data Sources:

Dataset	Spatial/Temporal Resolution	Role in Project
ERA5	10 km / 1-hour	- Coarse-resolution input for training
AORC	~1 km / 1-hour	- High-resolution target for training
WUS-D3	~10 km / 1-hour	- Independent testing dataset - Basis for future projections (post bias-correction)

Variables:

Precipitation (Current work) - Temperature - Humidity - Wind Speed - Shortwave Radiation - Longwave Radiation

*****This work considers the interdependencies between meteorological variables to enhance forecast accuracy. Meteorological variables are inherently interconnected, influencing each other in complex ways. By capturing these interdependencies, we ensure more realistic and physically consistent forecasts, preventing inconsistencies that may arise from treating each variable in isolation.**

2 Study Area:

Location: Arizona State, USA – a semi-arid region.

Climate: Hot summers, mild winters, with distinct wet (monsoon) and dry seasons.

Precipitation: ~350 mm annually.

Topography: Features deserts, plateaus, mountains, and major river basins.

Hydrology: Home to the Colorado and Gila Rivers, with many ephemeral streams.

Weather Patterns: Influenced by monsoons, frontal storms, and prolonged droughts.

Relevance: Critical for improving water resource management and climate assessments.

1 Objective:

- **Meteorological Downscaling with Deep Learning:** Develop a novel hybrid framework that enhances weather and climate predictions by leveraging U-Net for large-scale atmospheric patterns and diffusion models for fine-scale variability.
- **Enhanced Forecasting:** Improve extreme weather prediction by downscaling short-term weather forecasts (GEFS) and long-term climate projections (GCMs), capturing key meteorological features at high resolution.
- **Real-World Integration**: Apply high-resolution downscaled outputs to hydrologic models, improving flood forecasting, drought assessment, and water resource management.

5 Phase 1: Deterministic Regression

First, we learn a deterministic regression $F_\theta(M_t, S_t)$ to estimate the conditional mean, namely

$$F_\theta(M_t, S_t) = E[M_{t+1} | M_t, S_t]$$

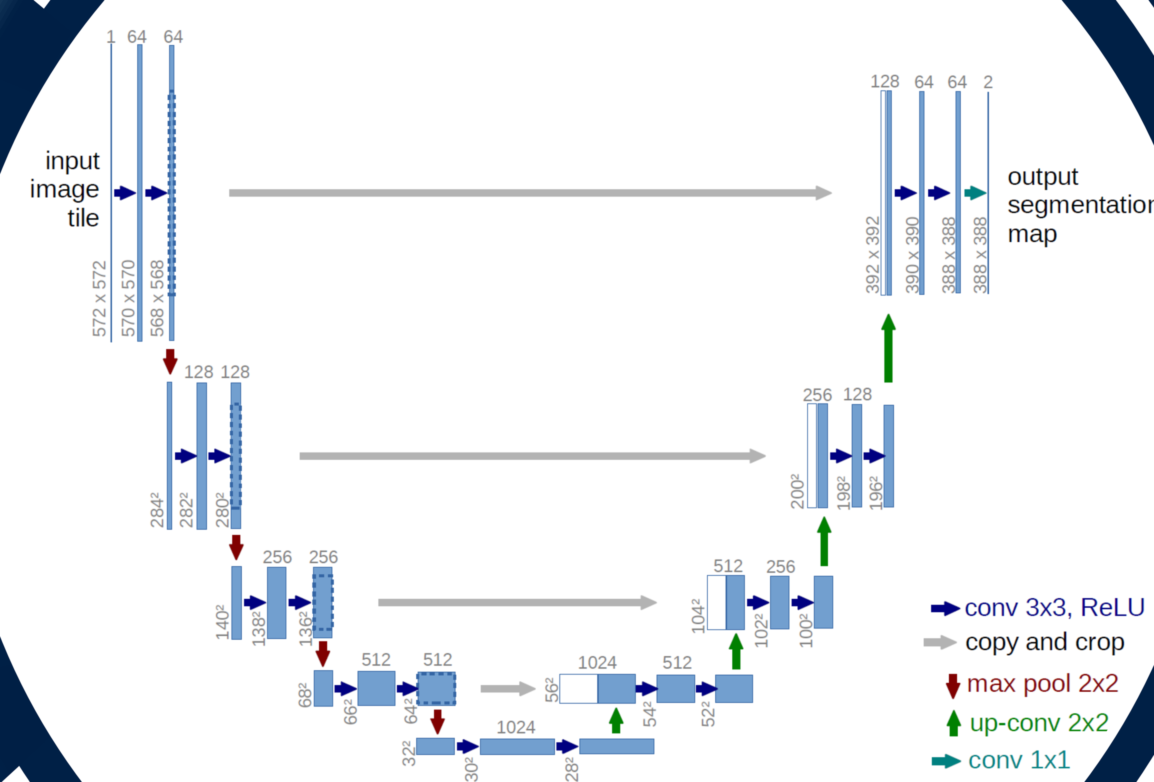
To do so, we can Train a UNet based on the paired data samples $\{(M_{t_i+1}, M_{t_i}, S_{t_i})\}_{i=0}^{N}$and, the MMSE criterion as follows

$$\theta^* = \arg_\theta \min \frac{1}{N}\sum_{i=1}^{N} ||M_{t_i+1} - F_\theta(M_{t_i}, S_{t_i})||_2^2$$

With the learned regression model at hand, we can form the residuals

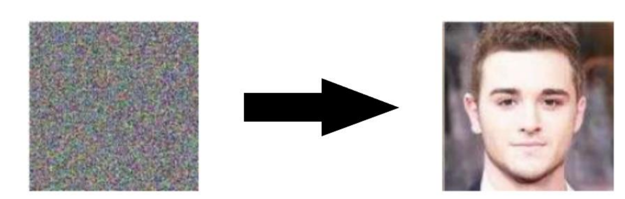
$$r_{t+1} = M_{t+1} - \mu_{t+1} \quad \text{where} \quad \mu_{t+1} := F_{\theta^*}(M_t, S_t)$$

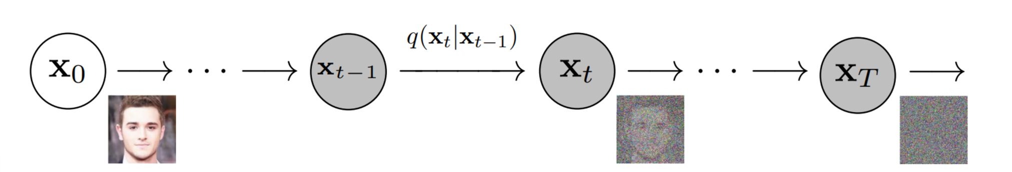
Phase 1
UNet model



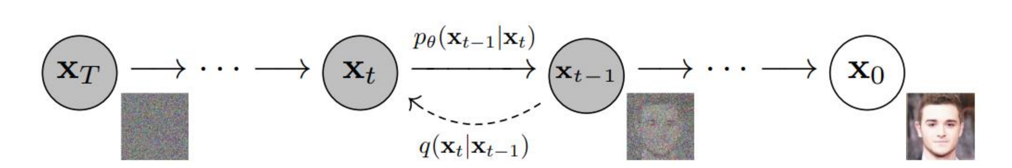
Loss Function: Mean Squared Error (MSE)
Optimizer: Adam (Learning Rate = 1e-4)
Batch Size: 16
Epochs: 60

Phase 2
Diffusion Model





$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) := \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \prod_{t=1}^{T} \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I})$$



$$p_\theta(\mathbf{x}_{0:T}) := p(\mathbf{x}_T)\prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) := p(\mathbf{x}_T)\prod_{t=1}^{T} \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

Training:

$$\mathbb{E}[-\log p_\theta(\mathbf{x}_0)] \le \mathbb{E}_q\left[-\log \frac{p_\theta(\mathbf{x}_{0:T})}{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}\right] =: L_{vlb}$$

7 Phase 2: Stochastic Diffusion

- **Residual Calculation:**

$$r_{t+1} = M_{t+1} - \mu_{t+1}$$

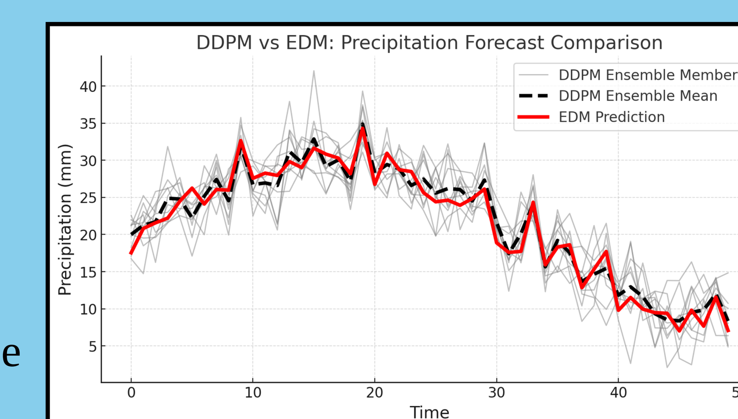
- **Diffusion Modeling:**

Learn the conditional distribution of residuals ($p(r_{t+1}|\mu_{t+1}, M_t, S_t)$) using a **denoising diffusion model**.

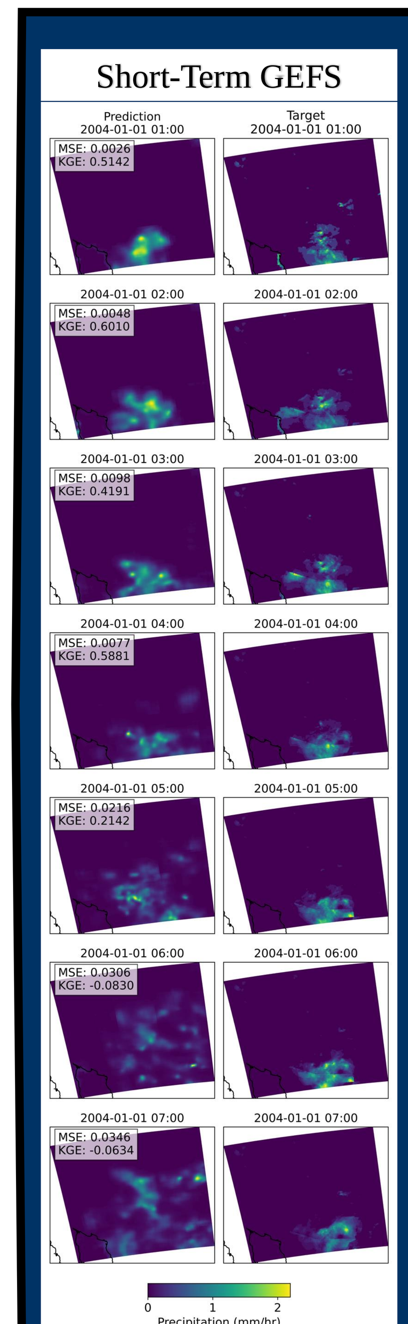
- **Methods:**

DDPM (Denoising Diffusion Probabilistic Models): Generates multiple plausible precipitation forecasts to capture uncertainty and variability.

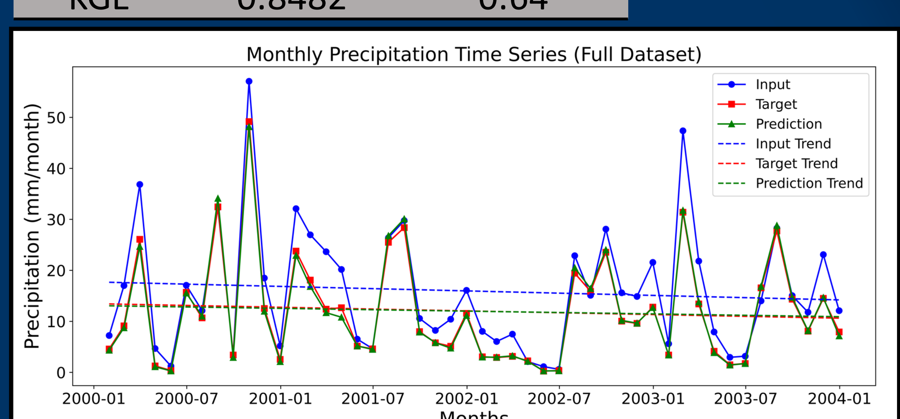
EDM (Elucidated Diffusion Models): Produces a single deterministic best-guess forecast, providing a clear but uncertainty-free prediction.

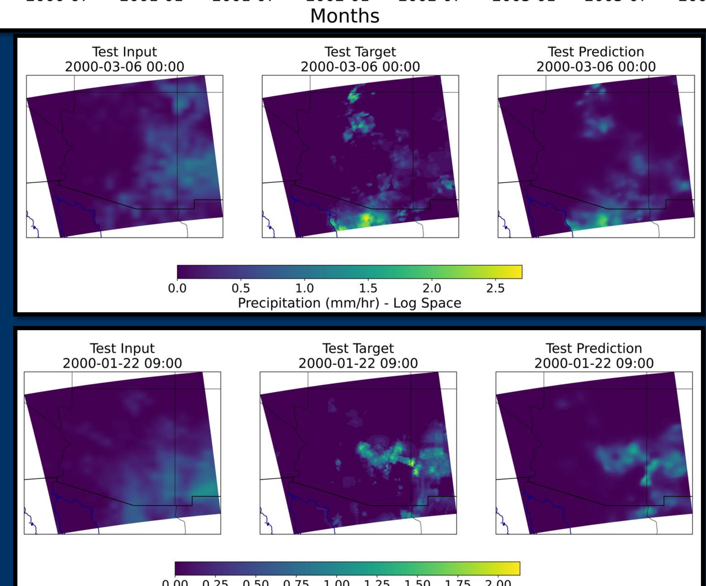


6 Results

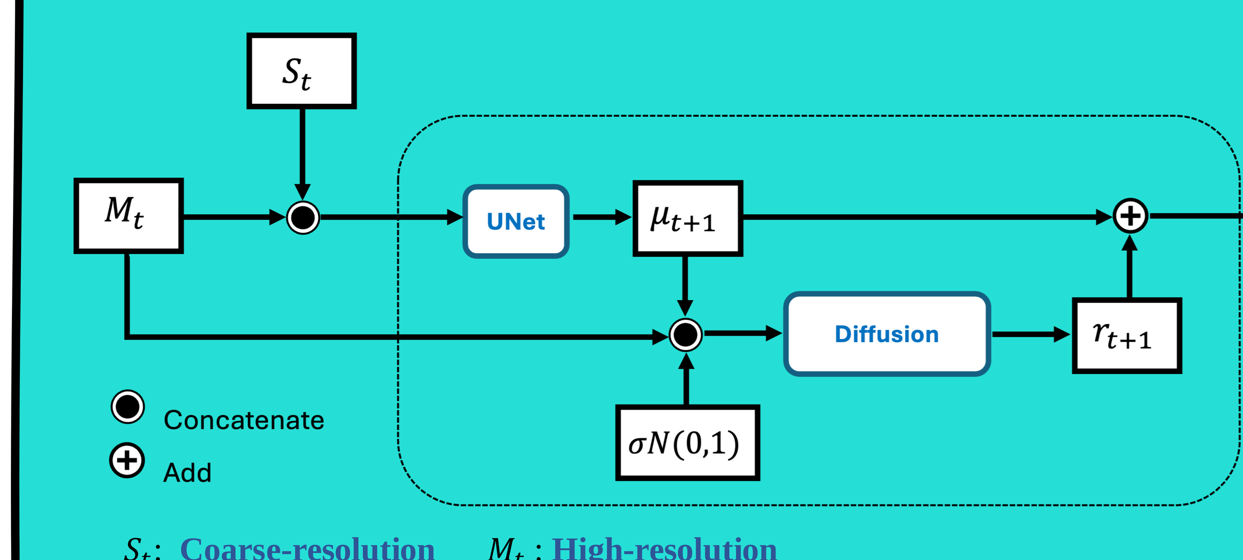


Metrics	Training Performance	Testing Performance
MSE	0.0025	0.0056
R^2	0.7702	0.50
KGE	0.8482	0.64





4 Framework



Training	Input: ERA5 Target: AORC
Testing	Input: ERA5 & WUS-D3 Target: AORC

Short-Term GEFS Forecasts

Long-Term GCM Projections

8 Key Innovations & Advantages

- **Hybrid U-Net + Diffusion Architecture:** Combines deterministic large-scale pattern recognition with stochastic fine-scale variability for accurate and uncertainty-aware downscaling.
- **Multi-Variable Interdependency Modeling:** Simultaneously downscales precipitation, temperature, humidity, and wind while preserving their physical relationships for coherent forecasts.
- **Beyond GANs – Stable & High-Resolution Outputs:** Avoids mode collapse and training instability, producing sharper, more diverse, and physically consistent high-resolution fields.
- **Near-CAM Accuracy at a Fraction of the Cost:** Delivers kilometer-scale detail comparable to convection-allowing models (CAMs) while drastically reducing computational expense.
- **Versatile Across Weather & Climate Time Scales:** Enhances short-term GEFS forecasts and long-term GCM projections, supporting both real-time forecasting and climate adaptation.

This study was partially supported by the Arizona Tri-University Recharge and Water Reliability Project.