Temporal Downscaling Using Deep Learning for Sub-hourly Time Series

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INTRODUCTION

Background and Objectives

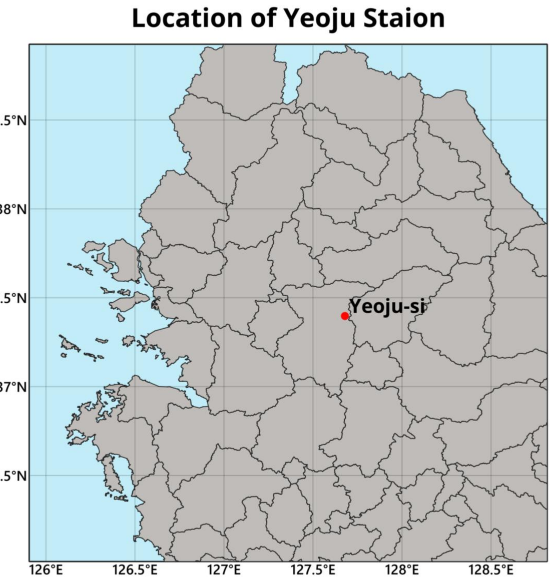
Recent climate change is associated with increasingly frequent and intense short-duration rainfall extremes, which in turn heighten the risk of urban water-related hazards such as pluvial flooding. In small urban catchments, flooding can develop within minutes due to rapid runoff response, underscoring the importance of rainfall information at sub-hourly resolution for hydrologic analysis and hazard assessment.

In this study, an AI-based temporal downscaling framework is presented to produce 10-minute rainfall time series from hourly observations using a conditional diffusion generative model.

METHODELOGY

Study Area & Data

Location of Yeoju Staion



◊ **Study Area**: Han River Flood Control Office (HRFCO), Yeoju(10074100) station, South Korea (37.397°N, 127.679°E)

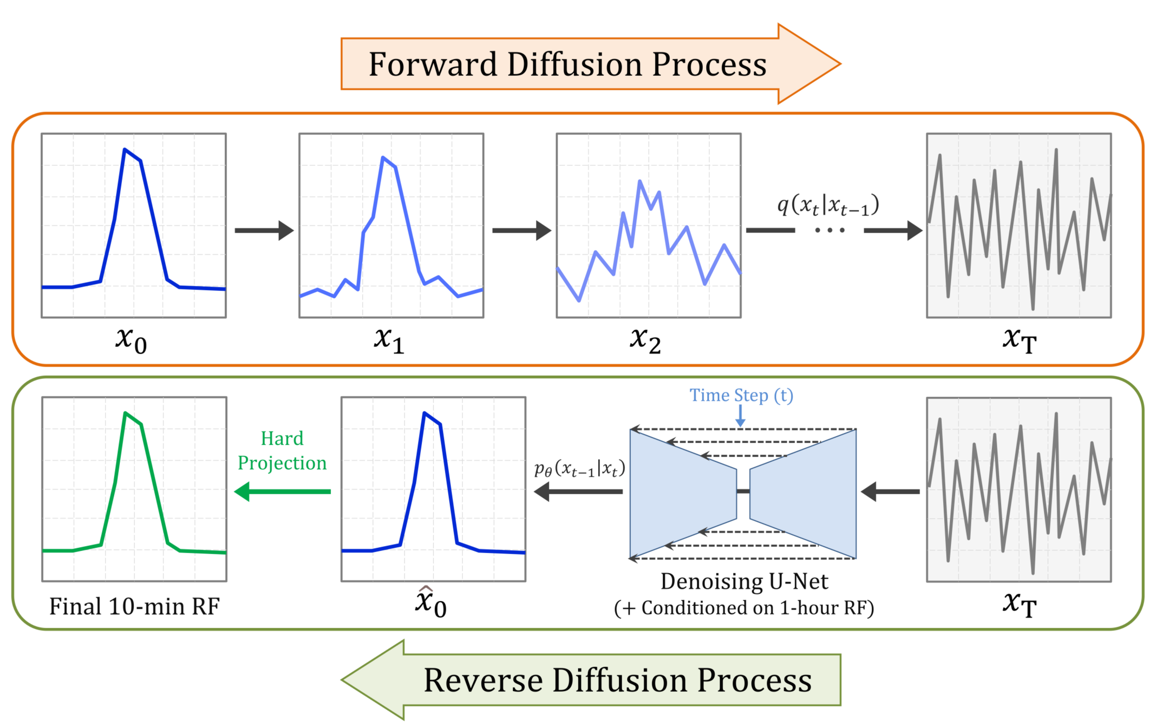
◊ **Data**: Hourly & 10-minutes rainfall observations (2020-2025)

◊ **Data Division:** Train: 2020-2022 / Validation: 2023 / Test: 2024-2025

Model Architecture and Validation

◊ **Model**: Conditional Denoising Diffusion Probabilistic Model (DDPM)

○ The proposed model reconstructs high-resolution (10-min) rainfall time-series from coarse (1-hour) observations by learning to reverse a Markovian noise-injection process.



◊ **Diffusion Process & Model Structure**

○ Forward Diffusion Process: Gradually corrupts the original 10-min rainfall peak (x_0) into pure Gaussian noise (x_T) over $T = 1000$ steps. A Cosine noise schedule is employed to better preserve the fine-scale signals of extreme rainfall peaks.

○ Reverse Denoising Process: A 1D U-Net (Base channels: 32, with skip-connections) iteratively removes noise from x_T to predict the denoised sequence ($\hat{x}_0$).

- Conditioning: The noisy sequence is concatenated with the repeated 1-hour observation at the input layer.
- Time Embedding: The diffusion timestep (t) is dynamically injected into hidden layers via FiLM (Feature-wise Linear Modulation) to stabilize learning.

○ Physics-Informed Post-processing: A Hard projection step guarantees mass conservation, ensuring the sum of the generated 10-min predictions strictly matches the 1-hour target (Final 10-min RF).

◊ **Loss Function**

○ Hybrid Loss: $L_{total} = L_{noise} + \lambda_{EMA} \cdot L_{stats}$

- L_{noise}: Standard diffusion noise matching objective (MSE).
- L_{stats}: MSE of non-linearly transformed temporal statistics (Coefficient of Variation (CV), Lag-1 Autocorrelation (AR1), Skewness) for stable optimization.
- λ_{EMA}(Auto-scaling): Dynamically balances the scale difference between loss terms using Exponential Moving Average(EMA).

◊ **Training Settings & Data**

○ Data Sampling: Exclusively trained on rainy events (daily accumulated precipitation > 0 mm).

○ Settings: Epochs = 100, Batch Size = 8

○ Optimizer: AdamW (lr = 2×10^{-4}) with Mixed Precision.

◊ **Performance Metrics**

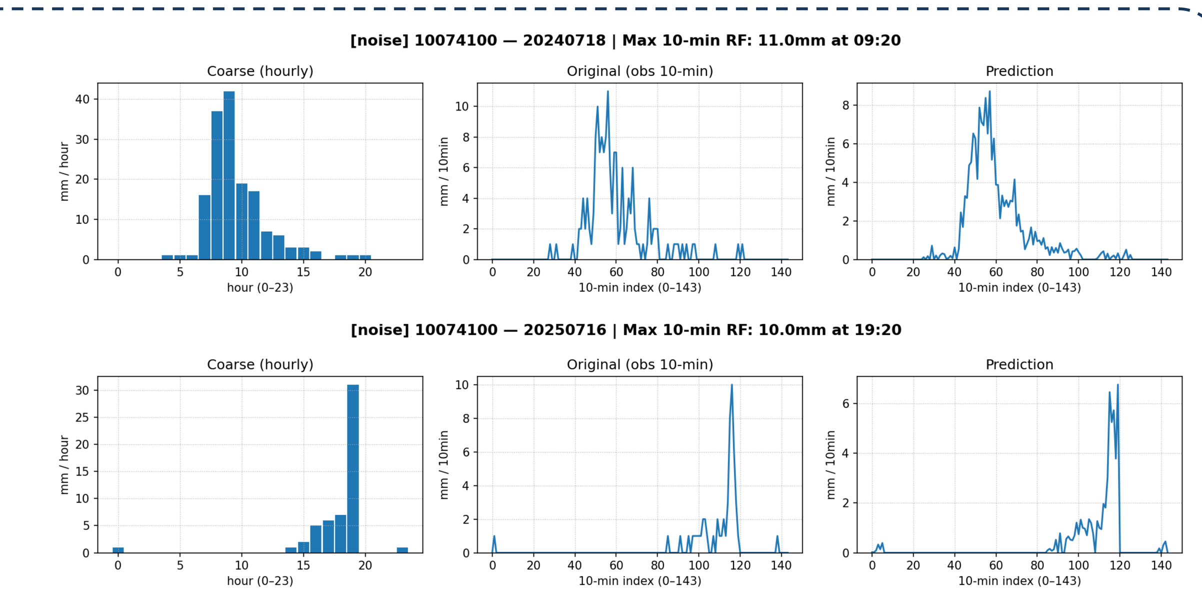
○ Key Statistical Metrics: Mean, Variance, Coefficient of Variation (CV), Lag-1 Autocorrelation (AR1), and Skewness.

○ Comprehensive Index: Aggregates relative errors across multiple durations (10, 30, and 60-min).

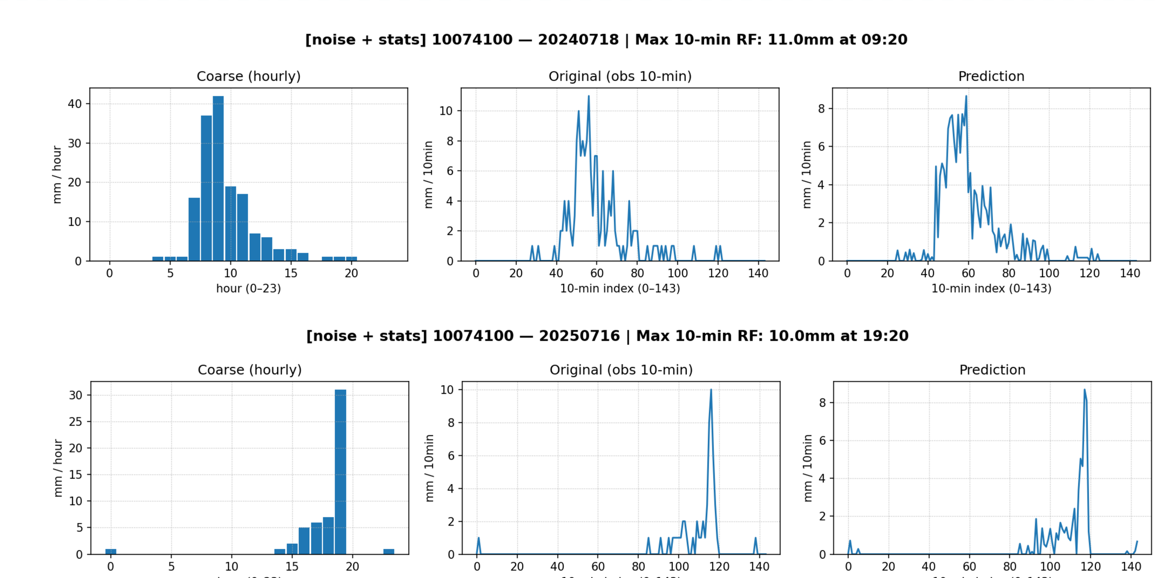
RESULTS

Comparative Evaluation of Downscaling Results

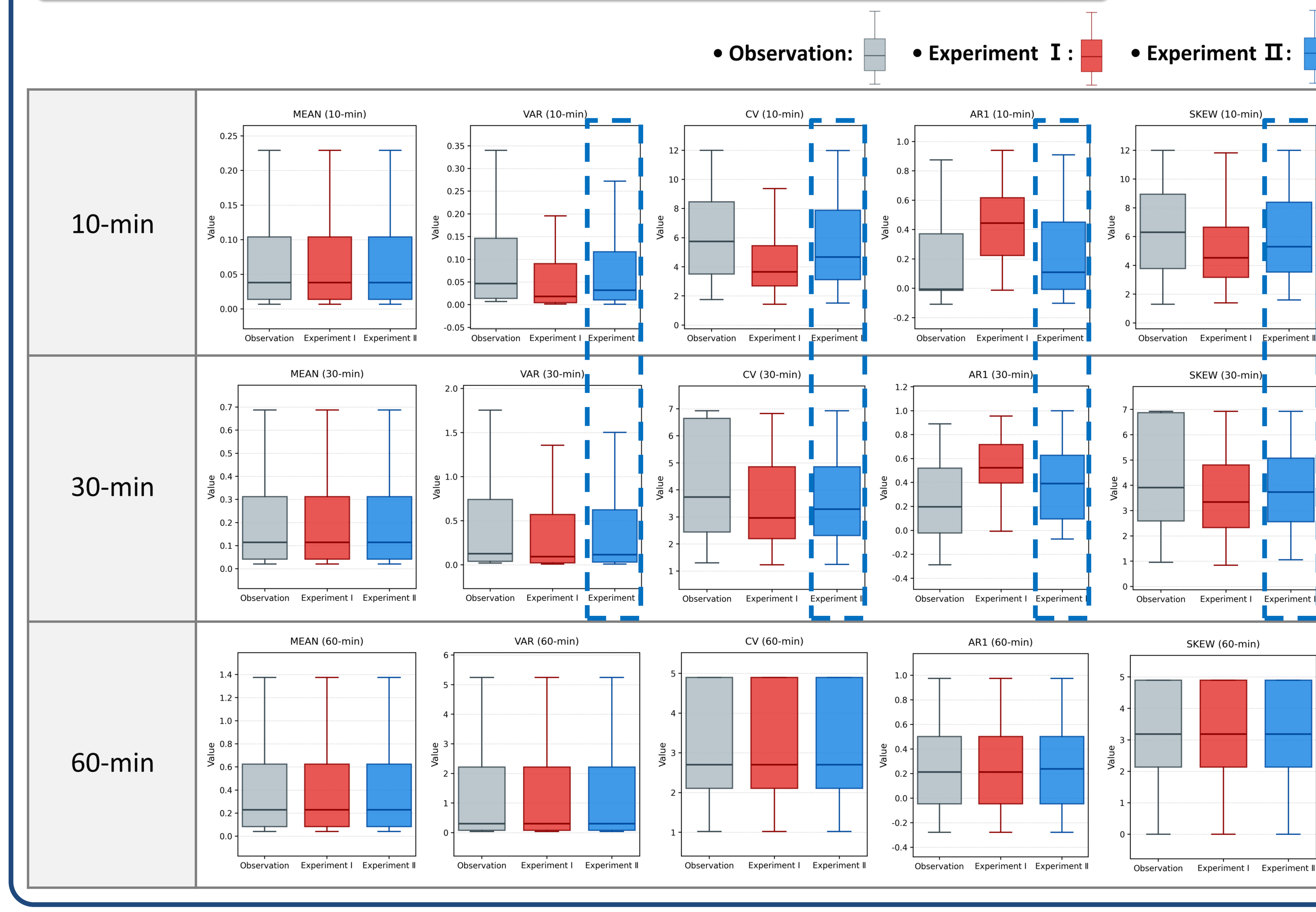
◊ **Experiment Ⅰ**: $L_{total} = L_{noise}$



◊ **Experiment Ⅱ**: $L_{total} = L_{noise} + \lambda_{EMA} \cdot L_{stats}$



Statistical Distribution of Sub-hourly Rainfall



CONCLUSION

◊ This study presents a diffusion framework to downscale coarse hourly precipitation into high-resolution (10-minute) sequences.

◊ By integrating non-linearly transformed statistical penalties(L_{stats}), the framework effectively resolves the chronic variance shrinkage and peak underestimation common in standard generative AI.

◊ The proposed approach accurately captures extreme temporal variability, demonstrating exceptional agreement with the observed Variance and Skewness at the critical 10-minute scale.

◊ These results confirm that customized generative AI is a highly reliable tool for producing structurally and statistically realistic meteorological inputs.

◊ Consequently, this approach provides a solid foundation for reducing hydrological uncertainties and supporting robust urban flood disaster management.

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