Enhancing Production of Synthetic Radar Images from Geostationary Satellite Observations through Generative Diffusion Models

Yuguang Hu[a], Daochang Liu[b], Alain Protat[c], Valentin Louf[c], Jordan Brook[c], and Chang Xu[a]
[a]The University of Sydney, [b]The University of Western Australia, [c]Bureau of Meteorology.

Introduction

- Limited spatial coverage of weather radars restricts availability, especially across remote regions of Australia.
- Early machine learning methods (e.g., U-Net, Hilburn et al. 2021) demonstrated the feasibility of transforming satellite observations into radar imagery but remained constrained by deterministic outputs and limited spatial detail.

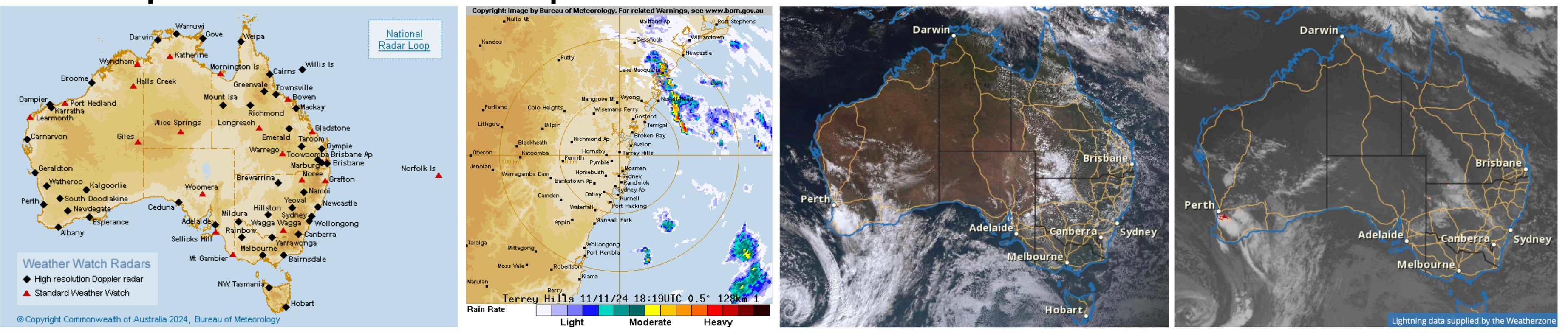

Fig. 1. Weather radars; radar image; satellite image; lightning observation.

Contribution

This study presents a generative diffusion-based approach that converts satellite infrared and lightning observations into synthetic radar reflectivity imagery.

- Enabling probabilistic radar synthesis that captures uncertainty in satellite-to-radar transformation.
- Improved key metric (e.g., average Fractions Skill Score (FSS) increased from 0.40 → 0.50).
- Enhanced fine-scale structure and visual fidelity.
- Practical impact: expands radar-like coverage, supporting improved severe weather nowcasting.

Dataset

- 1 February – 30 April 2021. Total 7,068 paired images.
- Satellite: Himawari-8, 10-min, 2 km resolution. C7 (3.9 μm) short-wave IR, C9 (7.0 μm) water vapor and C13 (10.4 μm) long-wave IR.
- Lightning: 5-min, 1 km resolution (WeatherZone ground network).
- Radar: S-band dual-polarization. Calibrated via S3CAR and gridded with the Brook et al. (2022)

Methods

- Baseline U-Net: a convolutional encoder–decoder model based on Hilburn et al. (2021).
- Diffusion Framework: diffusion model based on the Denoising Diffusion Implicit Models (DDIM, Song et al. 2022).

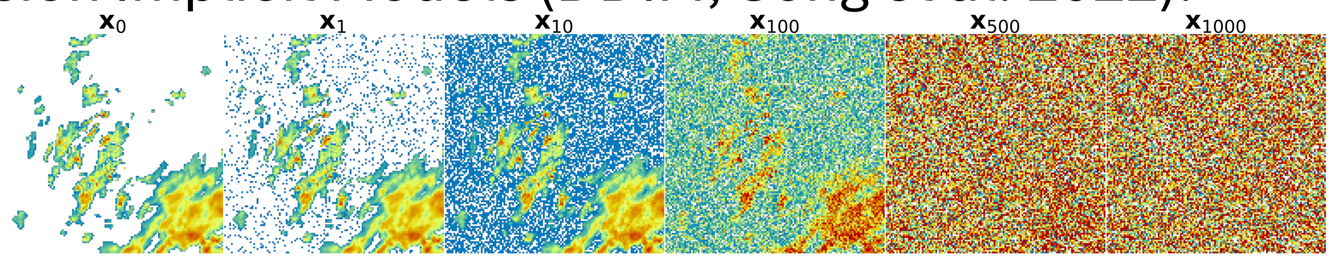

Fig 2. Diffusion process.

- A modified U-Net as the diffusion backbone: 5 input channels, Progressive feature scales [64, 128, 256, 512], Time embedding TE(t).

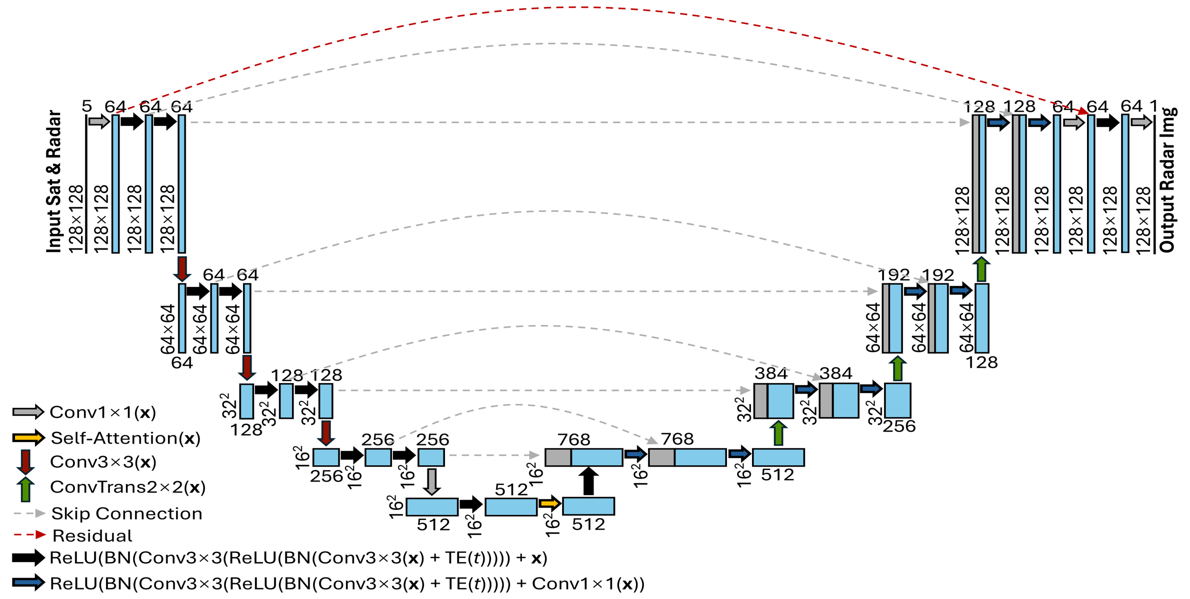

Fig. 3. Diffusion backbone U-Net.

- During training: random noise is added to radar images over T = 1000 steps using a linear schedule. At step t, the network predicts the clean radar image x_0 from noisy input x_t ,minimizing MSE loss.
- During sampling: generation starts from pure noise and iteratively denoises into a radar image x_0, guided by conditional inputs.

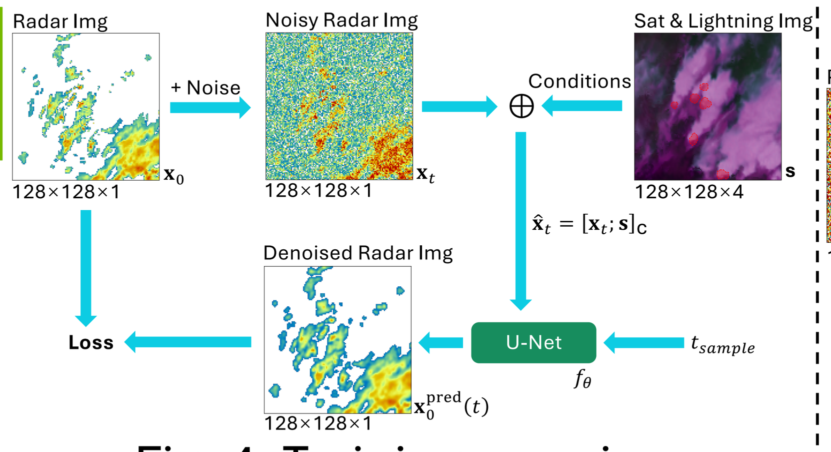

Fig. 4. Training overview.

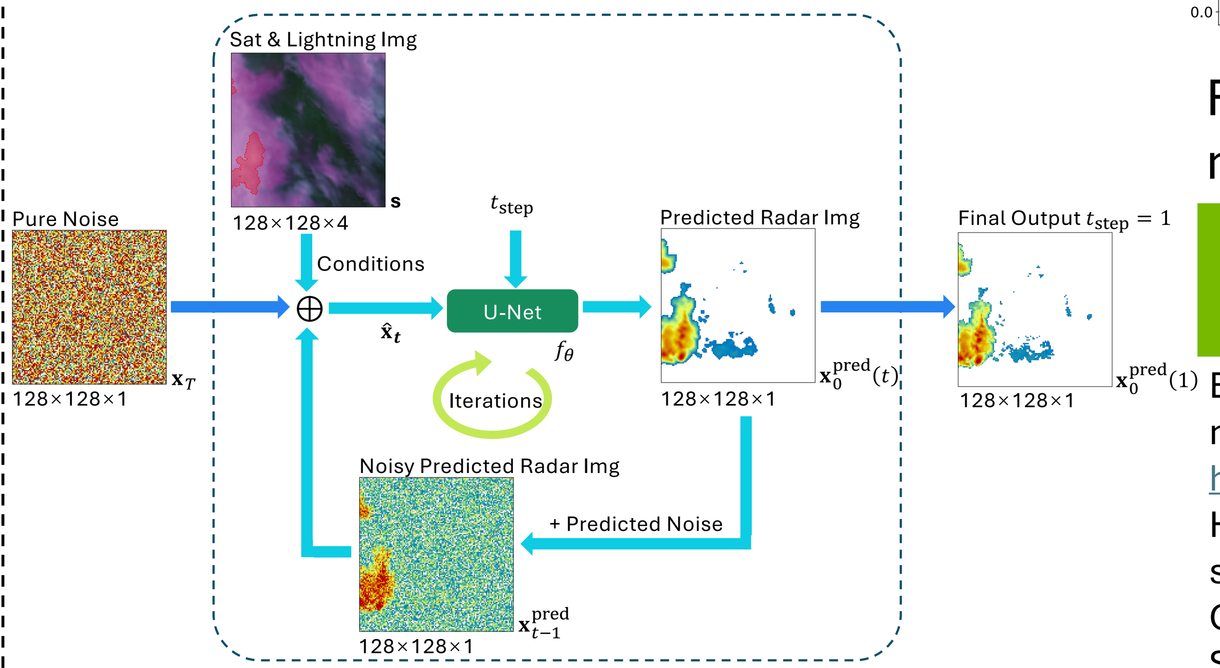

Fig 5. Sampling overview.

Results

- Diffusion model produces diverse ensembles.
- Improves FSS by +0.10, with richer texture, realistic variability.
- Reflectivity PDFs match real radar distributions, especially for <10 dBZ and >35 dBZ ranges.
- Trade-off: minor increase in MSE, false alarms and computational cost.

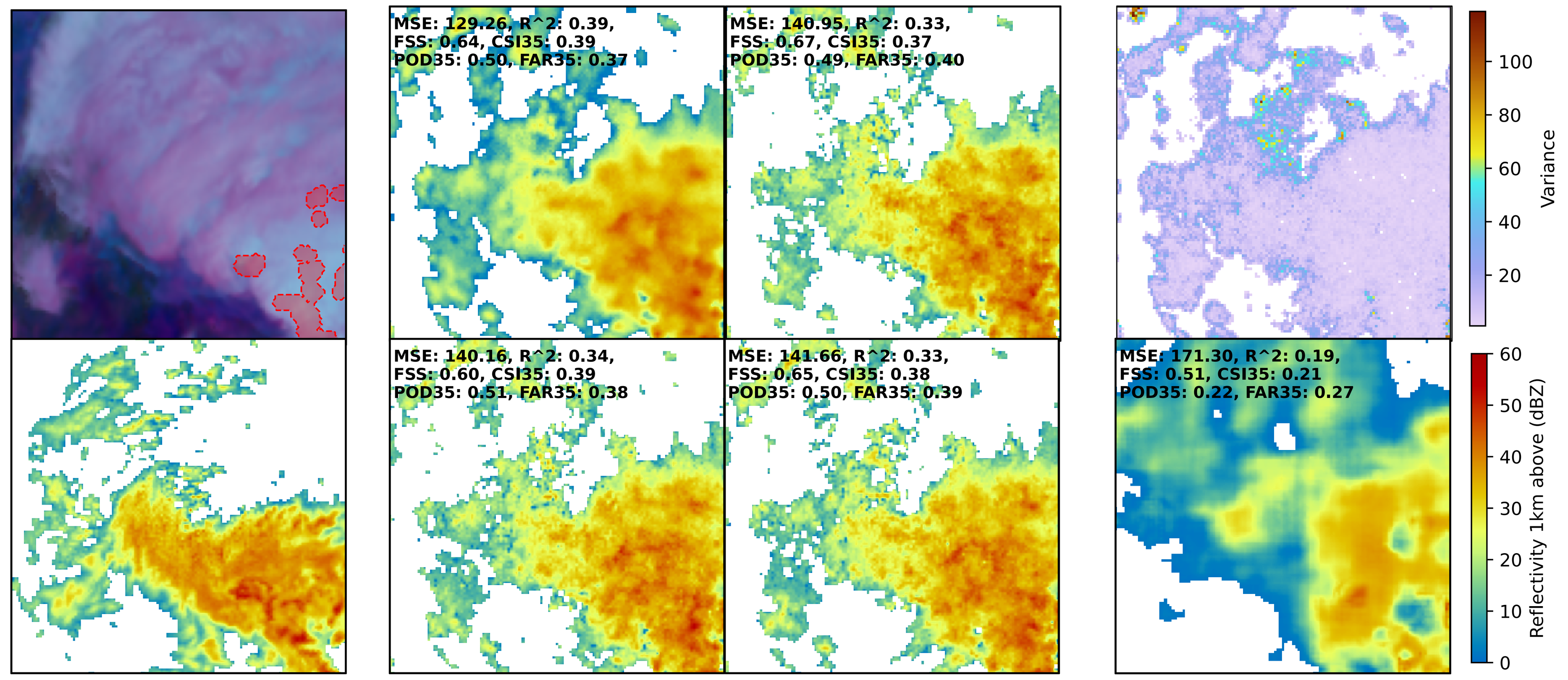

Fig 6. (1) Sat, radar image; (2) avg, best, worst, median diu output; (3) variance map, baseline U-Net output.

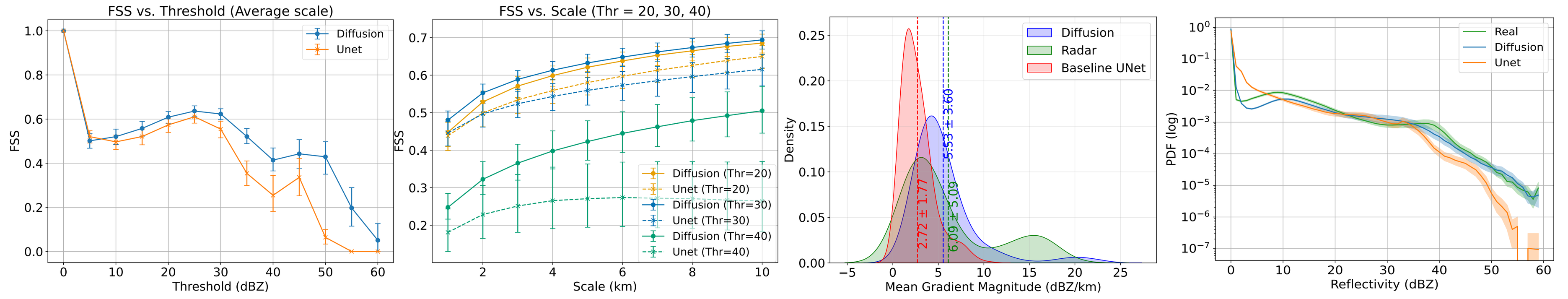

Fig 7. Metrics. (1) FSS vs. thr; (2) FSS vs. scale; (3) KDE of mean gradient magnitude; (4) reflectivity PDF.

Reference

Brook, J. P., A. Protat, J. S. Soderholm, R. A. Warren, and H. McGowan, 2022: A variational interpolation method for gridding weather radar data. Journal of Atmospheric and Oceanic Technology, 39, 1633–1654, https://doi.org/10.1175/JTECH-D-22-0015.1

Hilburn, K., I. Ebert-Uphoff, and S. D. Miller, 2021: Development and interpretation of a neural-network-based synthetic radar reflectivity estimator using goes-r satellite observations. Journal of Applied Meteorology and Climatology, 60, 3–21, https://doi.org/10.1175/JAMC-D-20-0084.1.

Song, J., C. Meng, and S. Ermon, 2022: Denoising diffusion implicit models. URL https://arxiv.org/abs/2010.02502, 2010.02502.