



Introduction

- India aims for 500 GW of renewable energy capacity by 2030. Wind energy accounts for a major share, with Andhra Pradesh being one of the country's top-wind-resource states.
- Coastal regions in India possess an exceptional wind energy potential, exceeding 8,000 MW, with wind speeds ranging from 6.8 to 7.1 m/s.
- However, these areas face critical data gaps in wind monitoring networks due to sparse instrumentation, station failures, and disruptions that frequently impact India's eastern coast (WMO,2018).
- Accurate, high-resolution wind field data is essential for renewable energy planning, and gap-filling methods help improve its spatial coverage and usability.

Study Area and Dataset

- Daily-mean 10-m zonal (u10) and meridional (v10) wind components are extracted from the ERA5 reanalysis data (Hersbach et al., 2020) produced by ECMWF. The analysis period spans 2013-01-01 to 2023-12-31 (T= 4,017 daily timesteps).
- The study domain covers the coastal zone of Andhra Pradesh on the southeastern coast of peninsular India, bounded by 12.5°–19.5°N and 76.5°–85.0°E (Figure 1). The domain comprises 1,015 ERA5 grid cells on a regular 29 × 35 lattice at 0.25° horizontal resolution. It is one of India's highest-potential coastal wind energy states, with offshore capacity targets exceeding 1 GW under the National Offshore Wind Energy Policy.

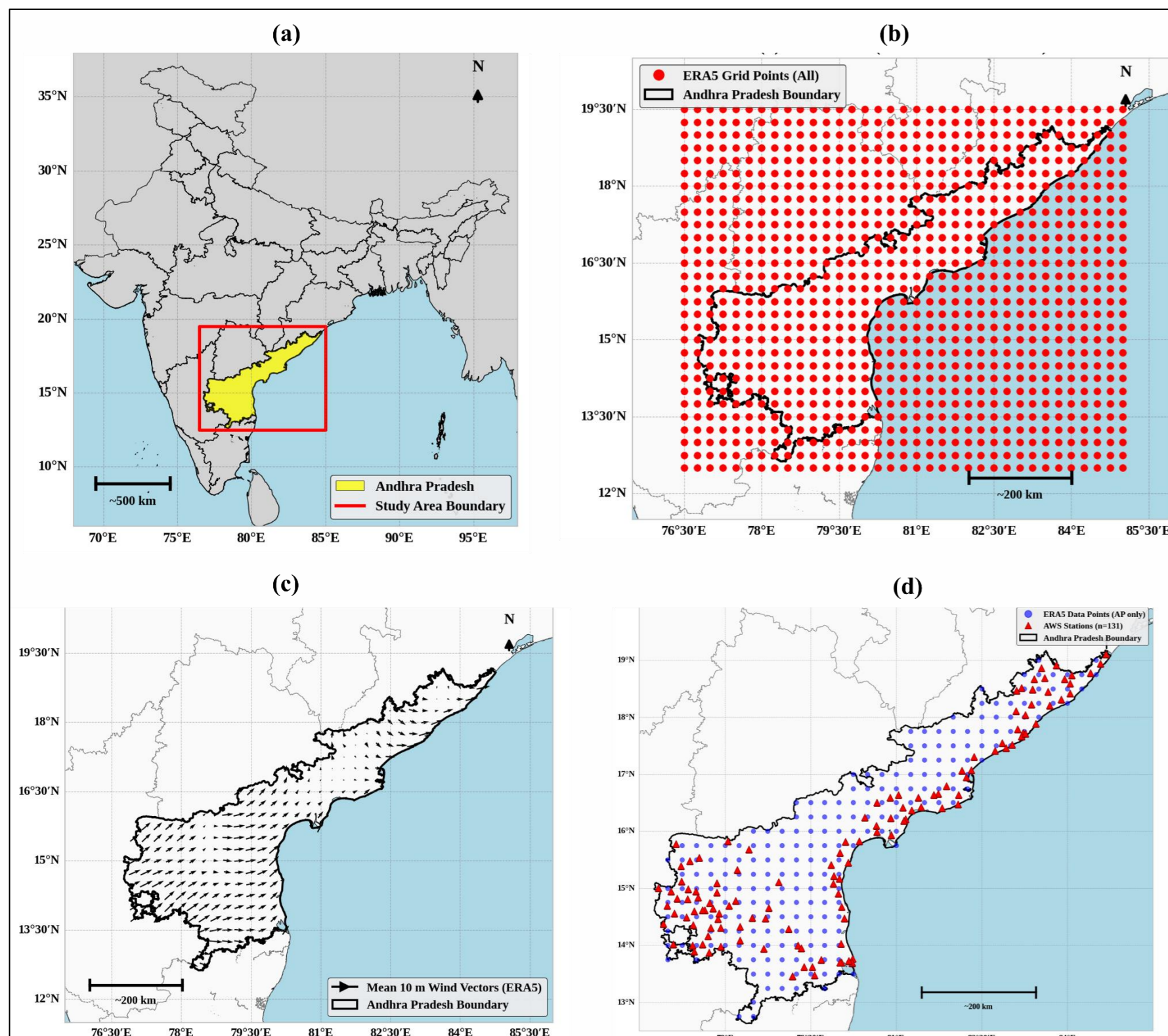


Figure 1. (a) Map of India, Andhra Pradesh in red colour; (b) ERA5 0.25° grid points (red dots); (c) Mean wind vectors shows prevailing flow pattern and (d) Cropped 29 × 35 grids and AWS locations in this study region.

Objectives

- To develop approaches for reconstructing wind field data under different gap scenarios.
- To compare the performance of Deep Learning (DL) and Multiple Point Statistics (MPS) methods.
- To assess the performance using error metrics.
- To understand how different gap types and training strategies affect reconstruction accuracy.

Methodological Framework

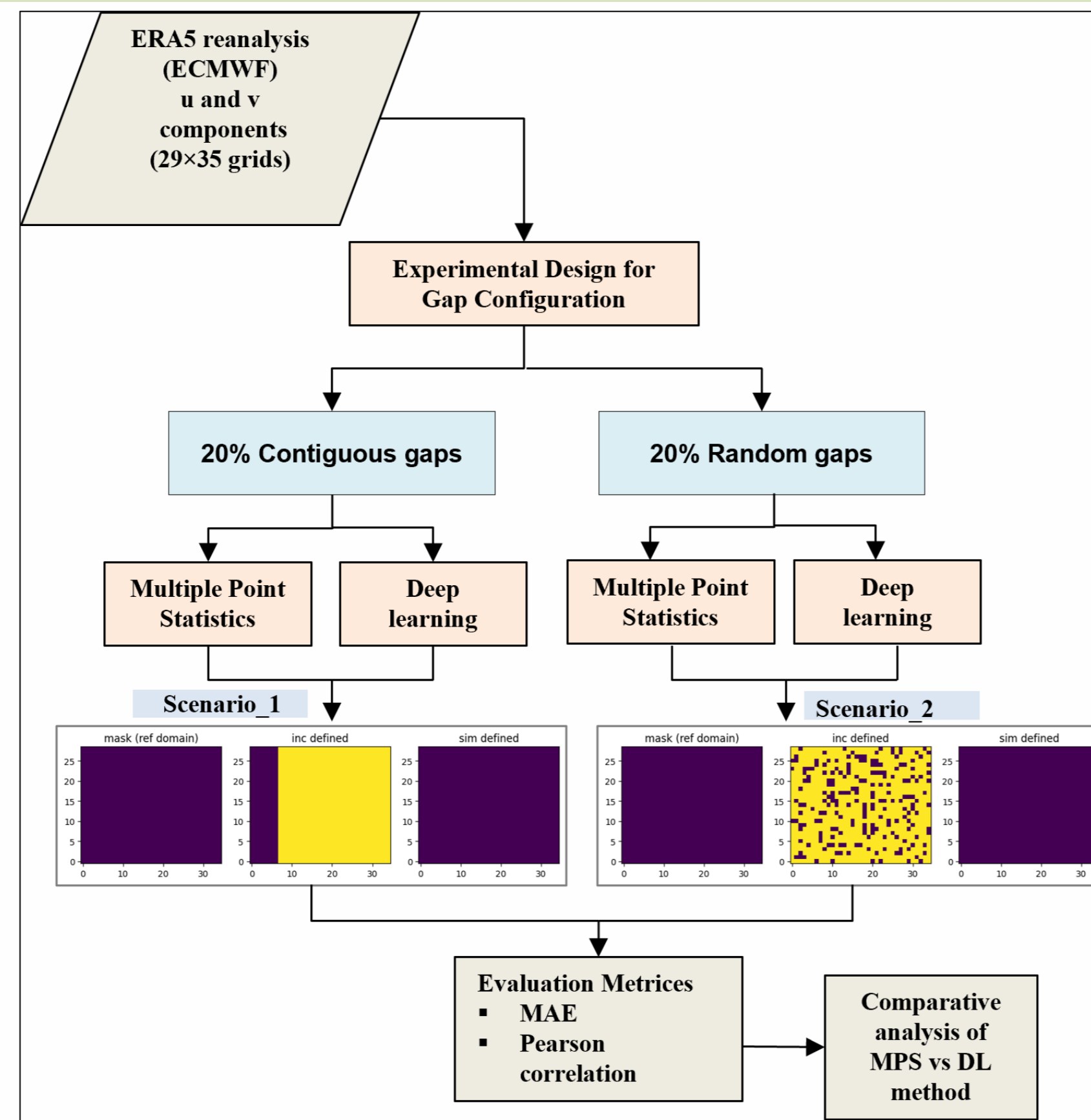


Figure 2: Methodological framework used in the study.

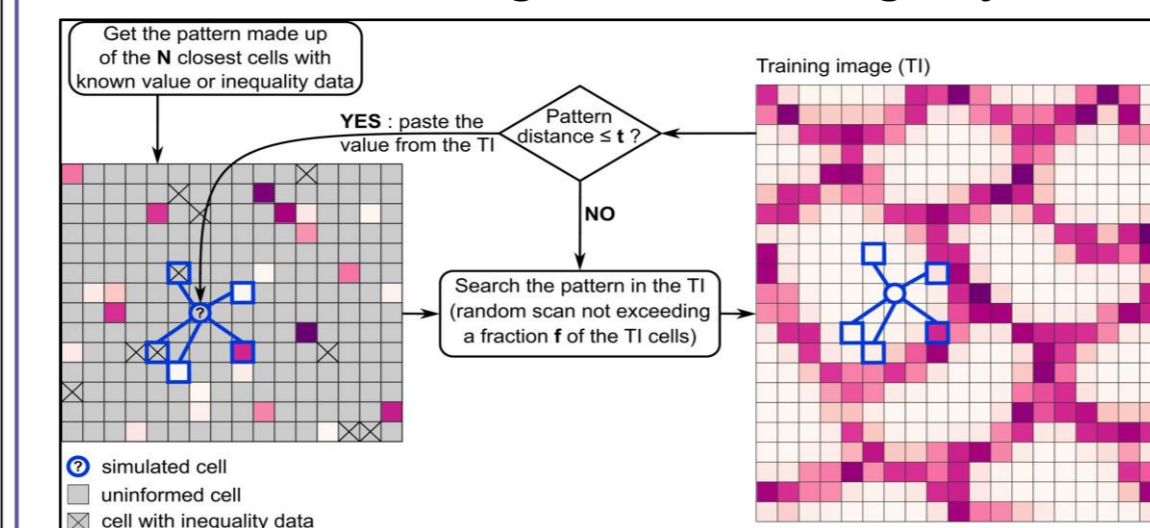


Figure 3: Illustration of the DeeSse algorithm (Straubhaar, J., & Renard, P. (2021))

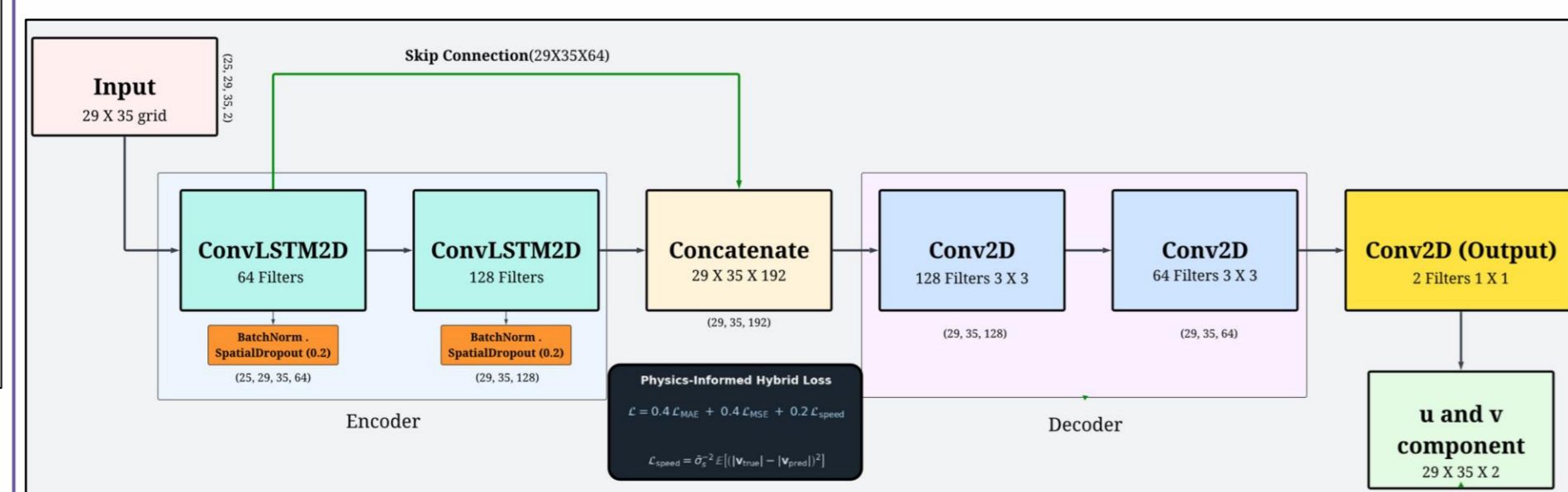


Figure 4. ConvLSTM-CNN model for 2D wind field reconstruction.

Results and Conclusions

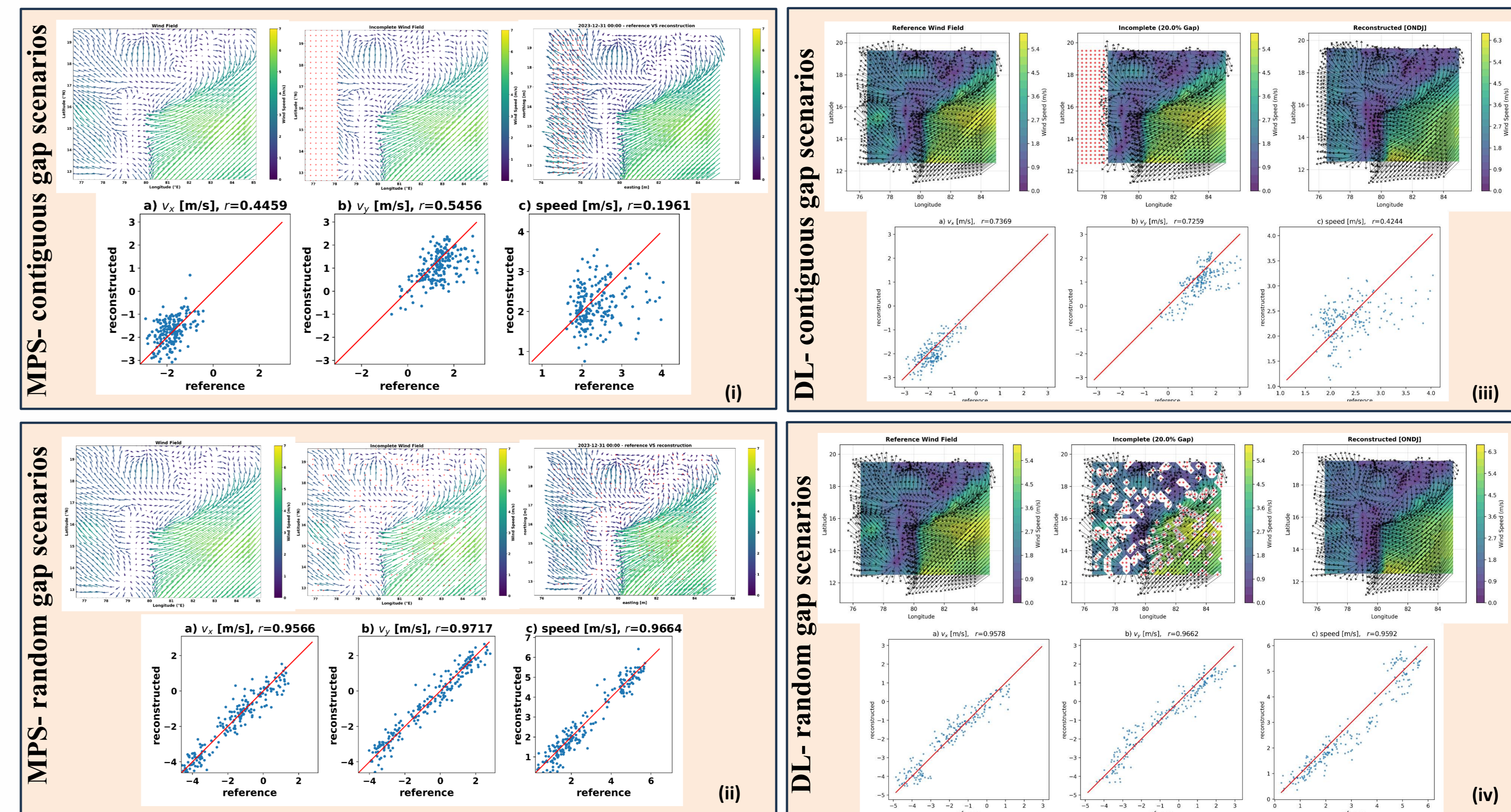


Figure 5: shows the wind field reconstruction (i-ii) for Multiple Point Statistics and (iii-iv) for Deep learning method.

Gap scenarios	MAE _u ↓	MAE _v ↓	MAE _s ↓	r _u ↑	r _v ↑
DL_Contiguous	0.317	0.472	0.378	0.737	0.726
DL_Random	0.363	0.419	0.402	0.958	0.966
MPS_Contiguous	0.46	0.51	0.49	0.48	0.61
MPS_Random	0.382	0.355	0.347	0.973	0.962

Table 1: shows the wind field reconstruction error metrics.

Future Work:

- Extending it to identify potential high wind energy sites.
- Using reconstructed wind fields to improve wind resource assessment and better decision-making for wind energy development.

Ongoing Work:

- Applying the developed reconstruction methods to ground-based Automatic Weather Station (AWS) data.
- Evaluating the performance of Deep Learning and MPS methods using real observational datasets.

Inferences

- Straubhaar, J., & Renard, P. (2021). Conditioning multiple-point statistics simulation to inequality data. Earth and Space Science, 8(5), e2020EA001515.
- Hersbach, H., et al., 2020. The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society 146, 1999–2049.
- World Meteorological Organization. (2018). Guide to Instruments and Methods of Observation (WMO-No. 8). Geneva, Switzerland: WMO.

Acknowledgements

