

# HiResCastNet: A 3D Deep Learning Surrogate Model for High-Resolution Subseasonal Forecast over the Arabian Peninsula

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## 01 INTRODUCTION & DATASET

- Dynamical downscaling models are computationally demanding and require substantial computing resources and time.
- This challenge becomes more pronounced for subseasonal forecasting, particularly when downscaling multiple ensemble members.
- We introduce HiResCastNet, a 3D deep learning surrogate model for subseasonal weather forecasting.
- The proposed framework downscales ECMWF subseasonal forecasts from  $0.25^\circ$  and 12-hourly resolution to 4 km and 3-hourly resolution.
- HiResCastNet is capable of efficiently downsampling all ECMWF ensemble members to their corresponding high-resolution counterparts.

- The dataset used to develop the framework is the subseasonal reforecast data which is obtained by dynamically downscaling the ECMWF S2S forecasts using WRF physical model.
- Training was performed on a randomly chosen ensemble member over a 20-year period.
- During inference the framework was applied to all ECMWF ensemble members.

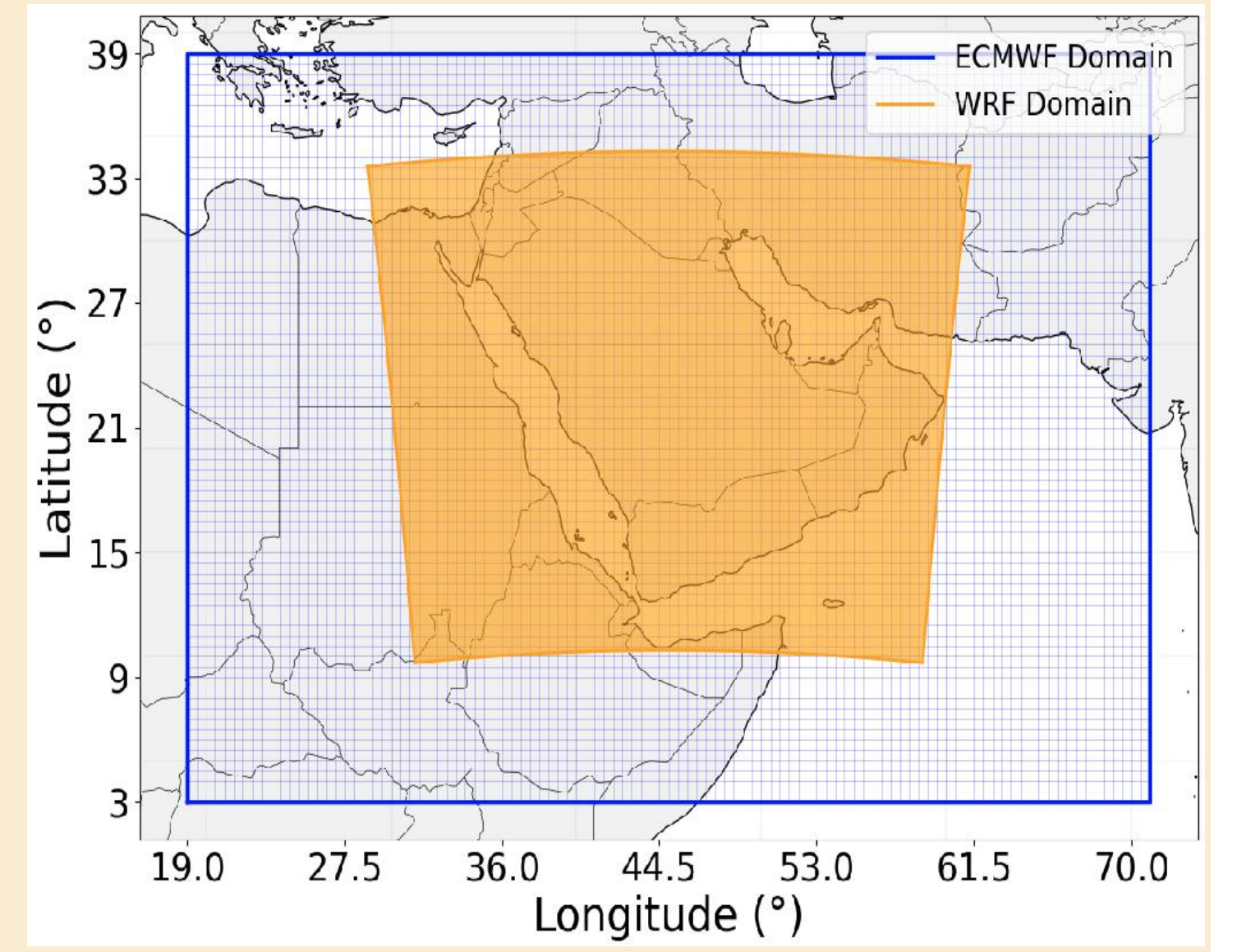


Fig 1: WRF physical domain

## 02 METHODOLOGY

- **Deterministic Backbone:** is the core engine of the forecasting framework.
- The inputs are the ECMWF coarse resolution forecasts and the outputs are their high resolution in space and time counterpart.
- Given that the task is challenging, the outputs of the backbone might be smoothed out.

- **Probabilistic Refinement:** we want to refine the output of the backbone using generative AI.
- The diffusion model learns the missing fine-scale features.
- The forward process progressively noise the inputs.
- The backward process learn the denoising function.
- The diffusion model takes the output of the backbone (only surface variables) as conditioning and generates a refined prediction.

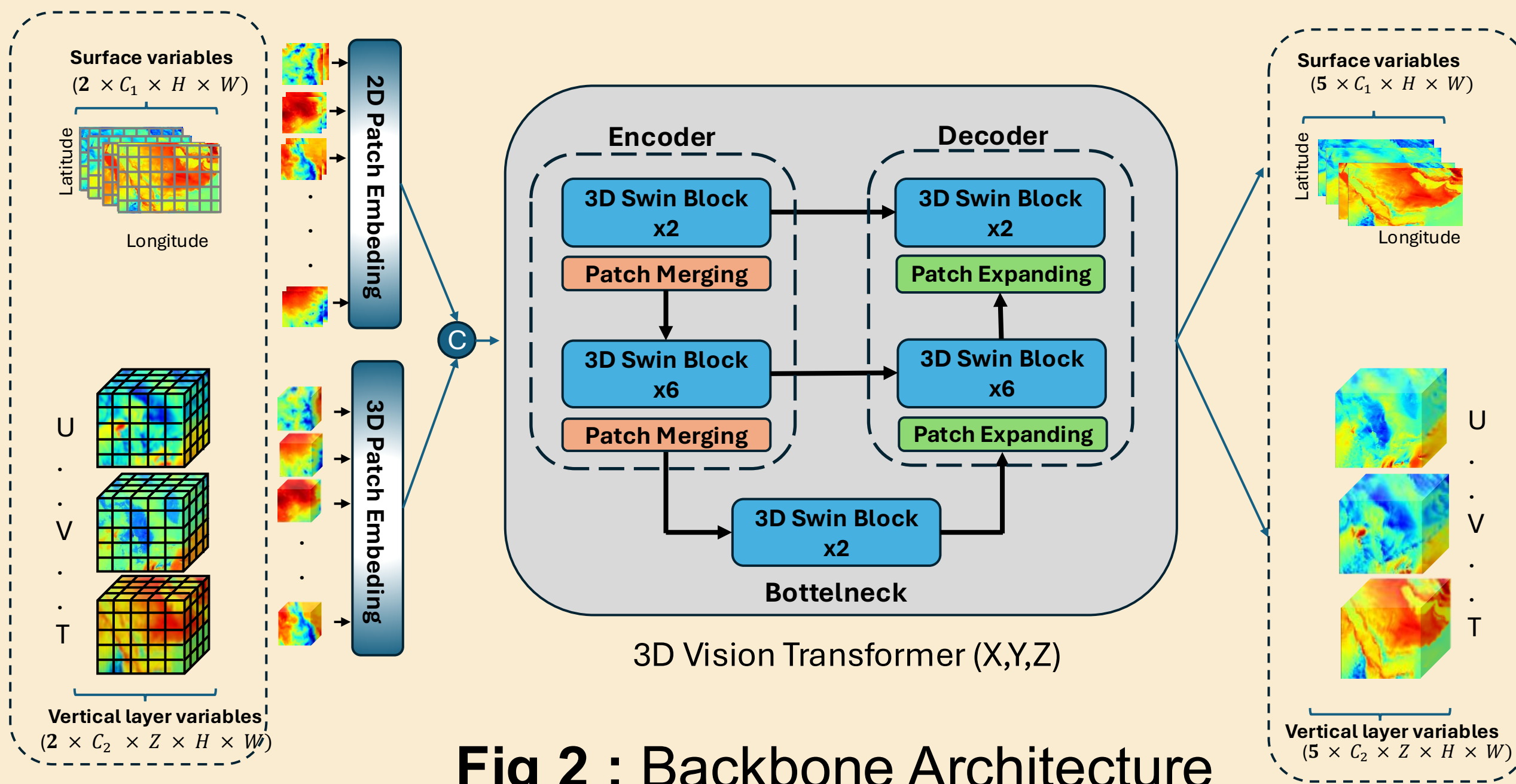


Fig 2 : Backbone Architecture

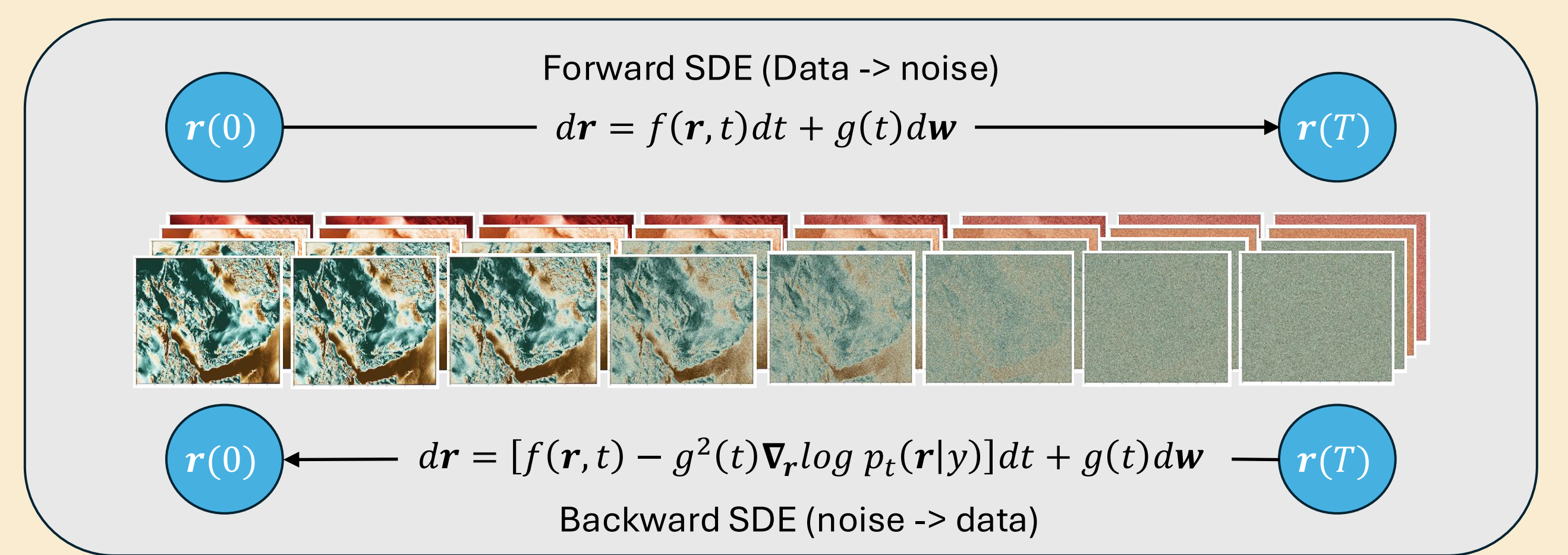


Fig 3: Diffusion pipeline

## 03 RESULTS

- **Ensemble mean evaluation:** The diffusion improves the ensemble mean by reducing errors over time and recover the fine scale features.

- **Ensemble spread evaluation:** The diffusion improves the predicted ensemble spread and improves the spread ratio, indicating a better uncertainty representation

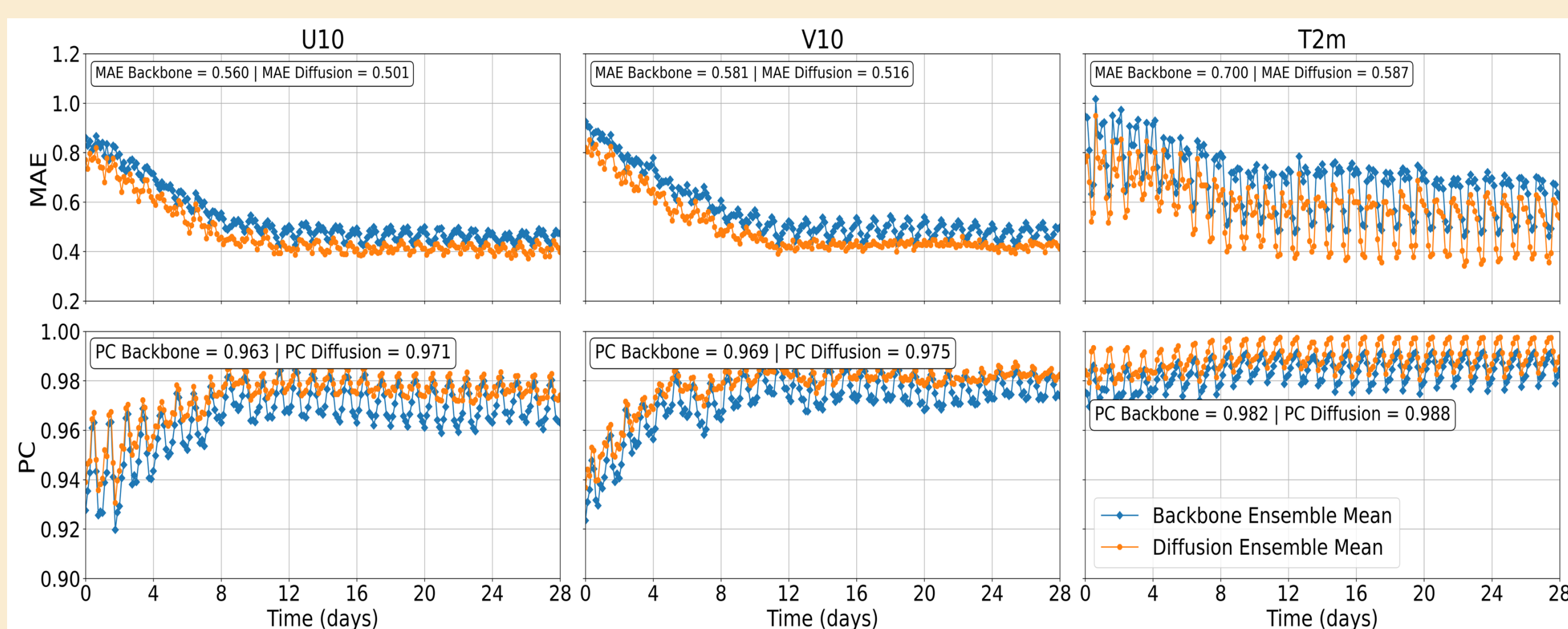


Fig 4: Error evolution over time of the ensemble mean

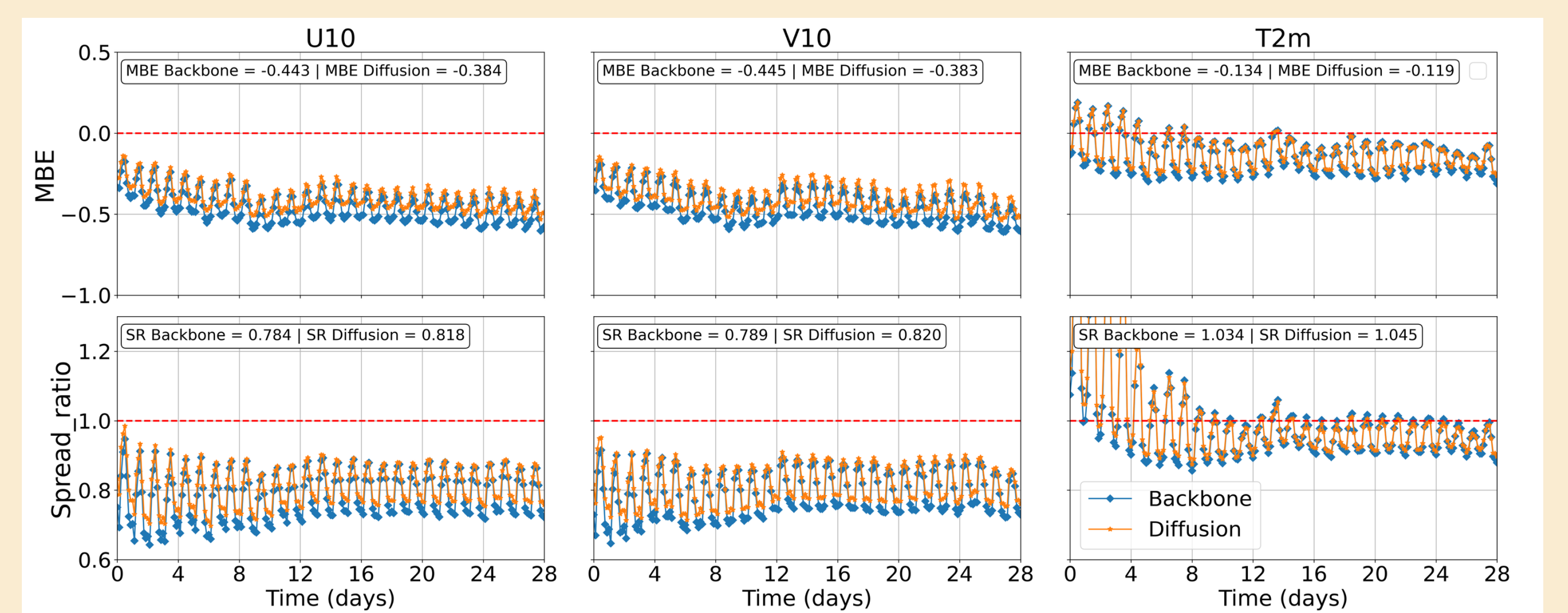


Fig 5: MBE of ensemble spread and spread ration evolution over time

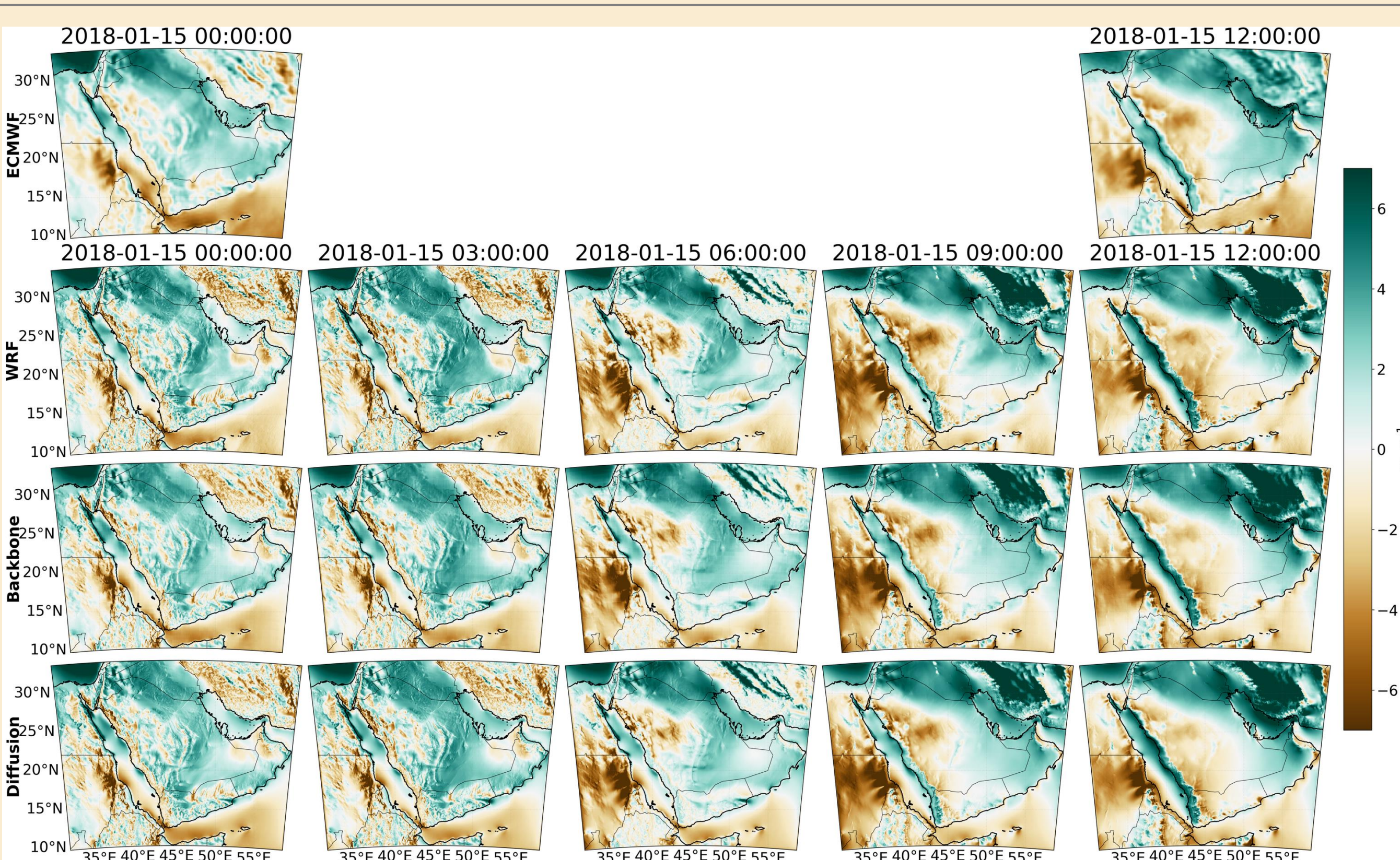


Fig 6 : U10 forecast example initialized on 7th January 2018

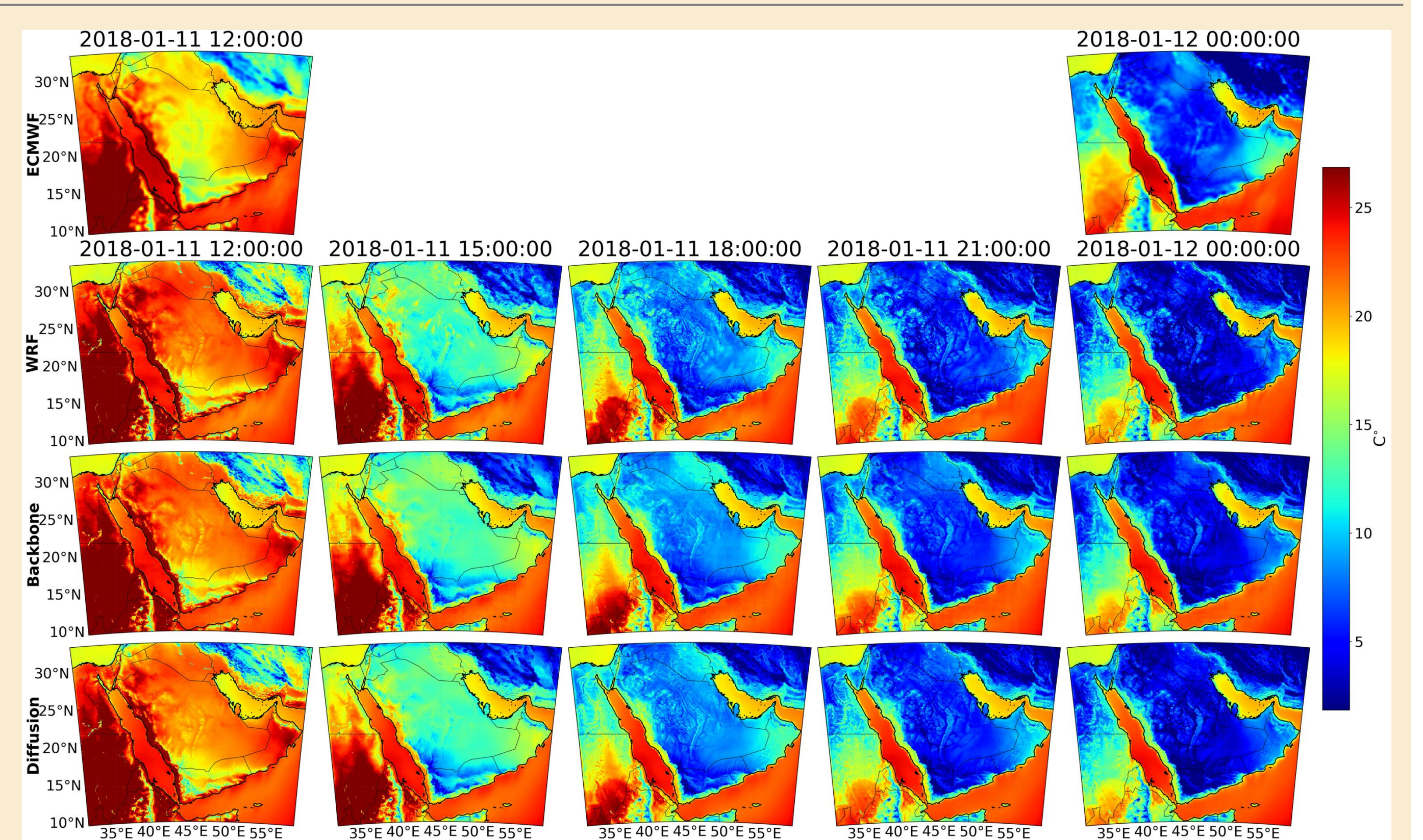


Fig 7 : T2m forecast example initialized on 7th January 2018

## 04 CONCLUSIONS

- The backbone efficiently downscales 11 ECMWF ensemble members in around 12 minutes.
- Given the difficulty of the task the backbone outputs might be smoothed.
- The diffusion models improves the overall performance of the backbone and refines the backbone predictions.
- The developed framework can be used in an operational mode.