GENERATIVE DIFFUSION MODELS FOR DOWNSCALING & BIAS CORRECTION OF PRECIPITATION

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I. Motivation

Global warming leads to more intense rainfall events and associated **natural hazards**, e.g. in terms of floods and landslides.
Understanding and accurately **simulating precipitation** is important for adaptation planning and **mitigating damages** associated with climate change.
Earth System Models (ESMs) can simulate precipitation patterns but because they are computationally extremely demanding, we can not resolve small-scale dynamics such as many of the processes relevant to precipitation generation.
Therefore, **ESM fields are biased** compared to observations and their **coarse spatial resolution** prevents accurate projections of extremes.

II. ISSUES WITH STATE-OF-THE-ART

Statistical bias correction (**BC**) techniques are restricted to single grid cell corrections and produce unrealistic patterns.

Dynamical downscaling (**DS**) techniques are computationally demanding and require high resolution ESM simulations.

Machine learning (**ML**) based approaches are hard to train and offer no control over the generative process. Supervised training is not possible because **observations (OBS)** and ESM fields are unpaired.

III. TASK

DS & BC can be formulated as: $\omega = f^{-1} \circ g$

Training a **Diffusion Model (DM)** [2] to approximate $f^{-1} \approx DM$ allows us to transform fields from $p(ESM)$ to $p(OBS\,|\,ESM)$

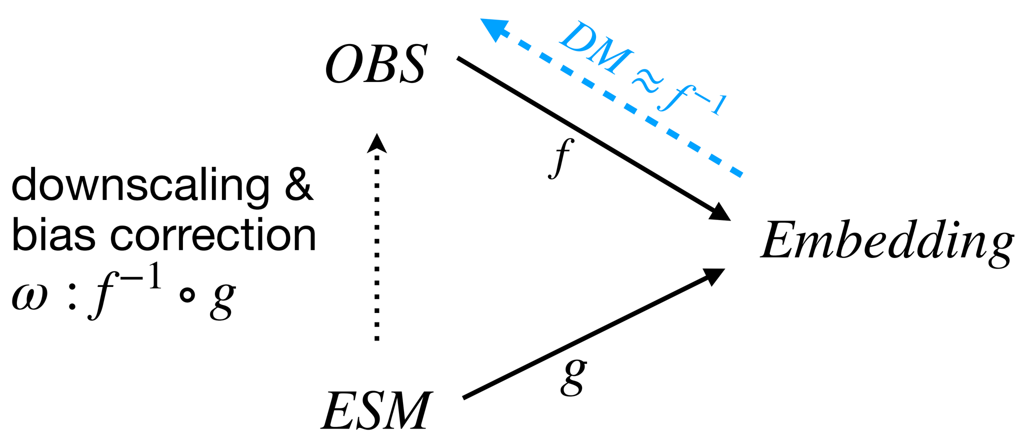

Figure 1: Our downscaling & bias correction framework.

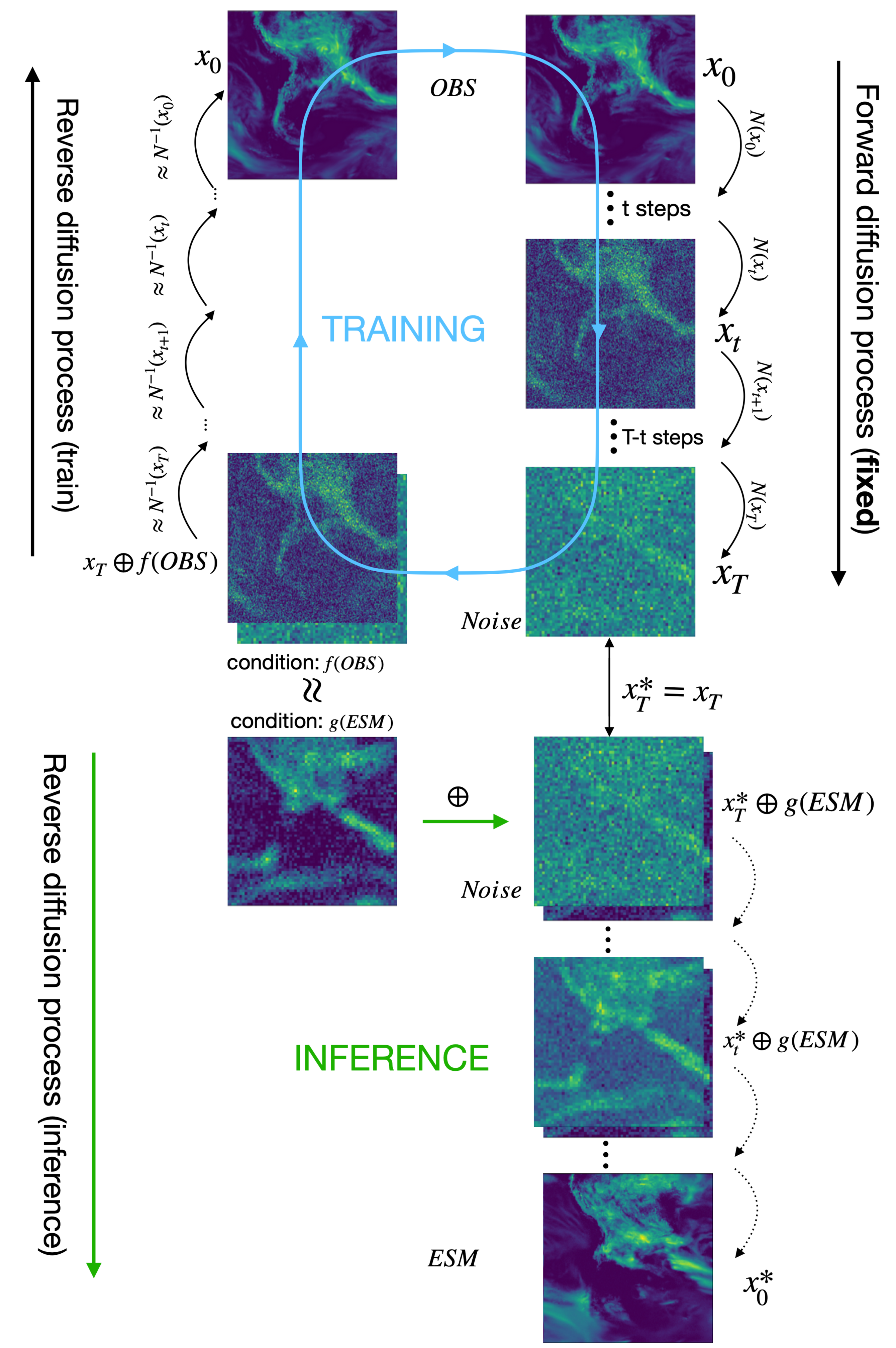

Figure 2: Schematic overview of a conditional diffusion model.

IV. METHODS

Introduce transformations f & g [3] to map OBS & ESM to a shared embedding space

$f : \mathbf{V}^{\text{obs}} \rightarrow \mathbf{V}^{\text{emb}}$

$g : \mathbf{V}^{\text{esm}} \rightarrow \mathbf{V}^{\text{emb}}$

s.t. $f(ERA5)$ is identically distributed to $g(ESM)$

Apply the trained model (**DM**) to ESM fields: $p_{DM}(OBS\,|\,g(ESM))$

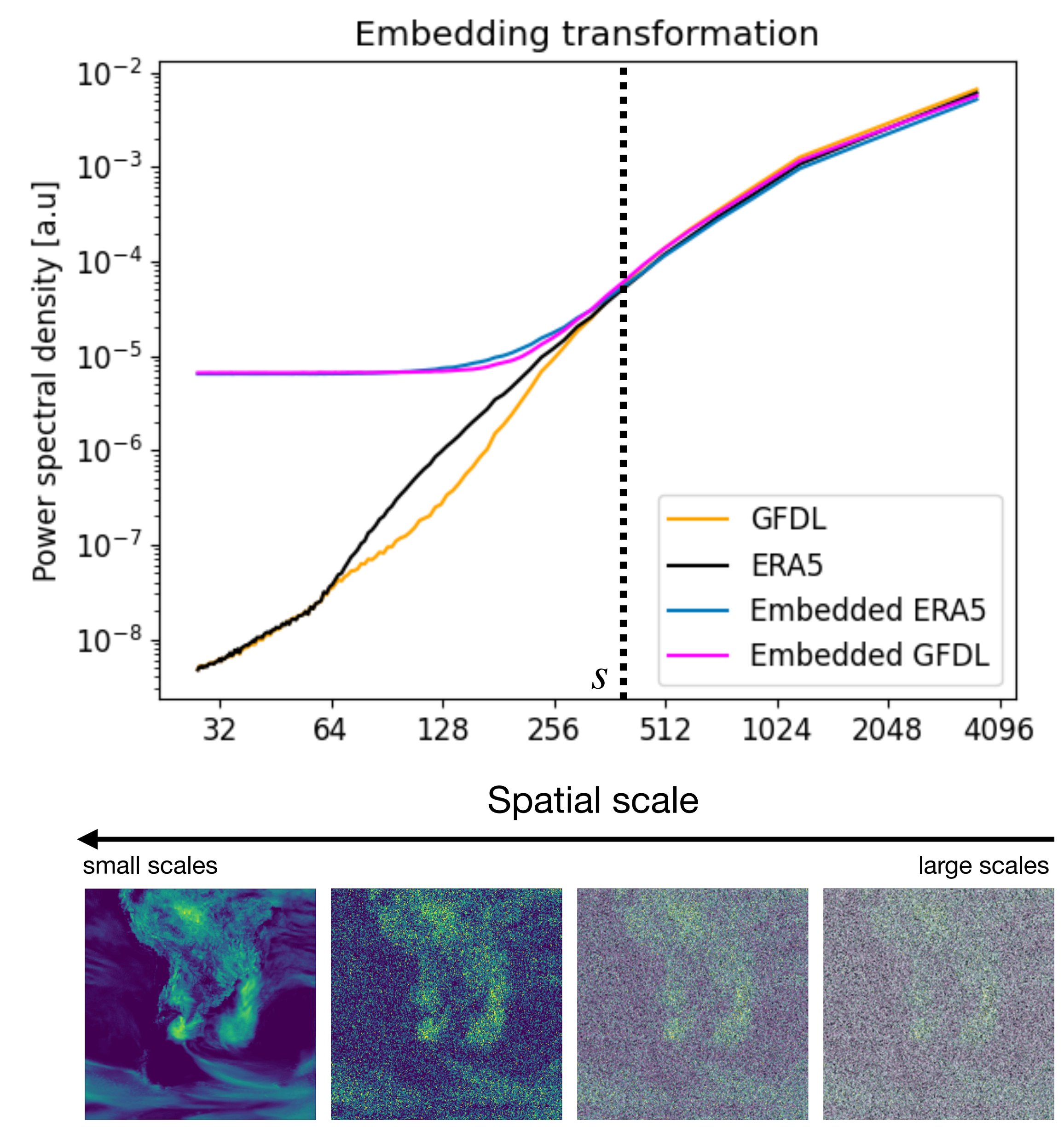

Figure 3: Adding noise to an image destroys a certain amount of information (see PSD). Small amounts of noise destroy small-scale patterns. Increasing the amount of noise will increase the scale up to which patterns are destroyed. The embedding transformations f, g match the PSD's of ERA5 and GFDL. Their PSD's roughly match until a scale s beyond which they diverge. The noise in f, g is chosen to match ERA5 and GFDL in PSD below s.

V. CONTRIBUTION

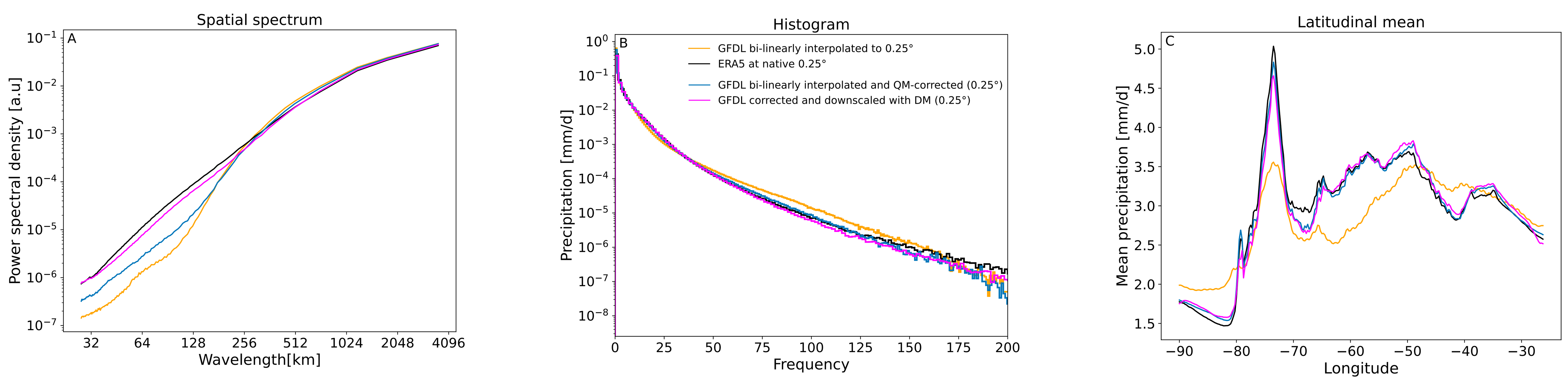

Figure 4: Comparison of ERA5, GFDL, a benchmark and our DM- correction. PSD plot reflects differences in small scale details while latitude profile and histogram indicate statistical bias.

DS [4A]**:** DM increases the ESM field resolution from 1° to 0.25°

BC [4B,4C]: small-scale bias of ESM is corrected: $p_{DM}(OBS\,|\,g(ESM)) \approx p(OBS)$

Control: choice up to which scale the ESM should be conserved

Advantages:

- framework [1] is not restricted to a specific DM architecture
- works with **any** ESM
- bias-correction and downscaling done simultaneously
- control over which information to conserve

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