

LATENT DIFFUSION MODELS AND MULTI-CHANNEL DATA INTEGRATION

A new road to high-resolution statistical downscaling

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OVERVIEW

To understand and mitigate climate change, we require **high-resolution climate projections**, especially when investigating **impacts on a local scale**. This work is focused on developing models for **statistical downscaling** of climate model outputs for **Danish hydrology** by integrating advanced **deep learning** and computer science techniques. We present a **Diffusion Model** [1,2] tailored for generating high-resolution (2.5 km x 2.5 km) climate variables relevant for hydrological models: precipitation, evaporation, and temperature.

Our approach is inspired by advancements made in Computer Vision, specifically in the areas of **latent image generation** and **conditional diffusion models** [3,4]. It further incorporates **multi-channel climate data** and geographical features to improve model accuracy and stability. The model attempts to map between two reanalysis products, **ECMWF Reanalysis v5 (ERA5)** [5] and the **DANish atmospheric ReAnalysis (DANRA)** [6], as a proof of concept, and future work will focus on creating a **synchronized training dataset** between DANRA and realisations from the Regional Climate Model ensemble **EURO-CORDEX** [7], to develop a model for actual climate projection downscaling.

This work is part of a broader effort to **narrow the gap** between **global climate projections** and **local-scale analysis**. It covers the initial phase, where future advancements will focus on integrating this model with **RCM** and possibly **GCM** outputs instead of reanalysis data, to explore ensemble downscaling methods. Our end-goal is to **establish a robust pipeline for translating global climate projections into more actionable local climate statistics**.

WHAT'S NEW?

DATA

TRAINING

- Loss function**
 - Signed Distance Function for weighted loss
 - Hybrid loss [6] to capture multi-modality
$$L_{hybrid} = L_{simple} + \lambda L_{vib}$$
- Data split**
 - Training: 9 years (1991-1999)
 - Validation: 1 year (2000)
 - Test: 100 randomly selected dates in 2001-2005

PRELIMINARY RESULTS

Quantitative

Distributions of generated and evaluation images (masked to land only)

Not capturing the mean: May be an issue with standardization in code.

Qualitative

Predictions are masked with a land-sea mask to omit pixels over sea during evaluation.

DIFFUSION MODEL

Generative diffusion models [1] [2] work by **computing a forward diffusion** process by iteratively adding gaussian noise with cosine sampling, then **learning the reverse diffusion** process with a U-Net, and finally **sampling through iterative denoising** of random noise.

TRAINING

- Select random t and encode**
 $t = 14 \rightarrow \text{encode} \rightarrow [0.12, 0.31, 0.34, \dots, 0.02]$
- Add assigned noise to image**
 Original image + Pure Gaussian noise = Noisy image
 $\epsilon \sim \mathcal{N}(0, 1)$
 $\alpha_t = 1 - \beta_t$
 $\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$
 $\sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon = x_t$
- Train the U-Net by predicting noise**
 Noisy image x_t is processed by a U-Net with time step embedding to predict noise ϵ_θ . Loss is calculated against true noise ϵ .

SAMPLING

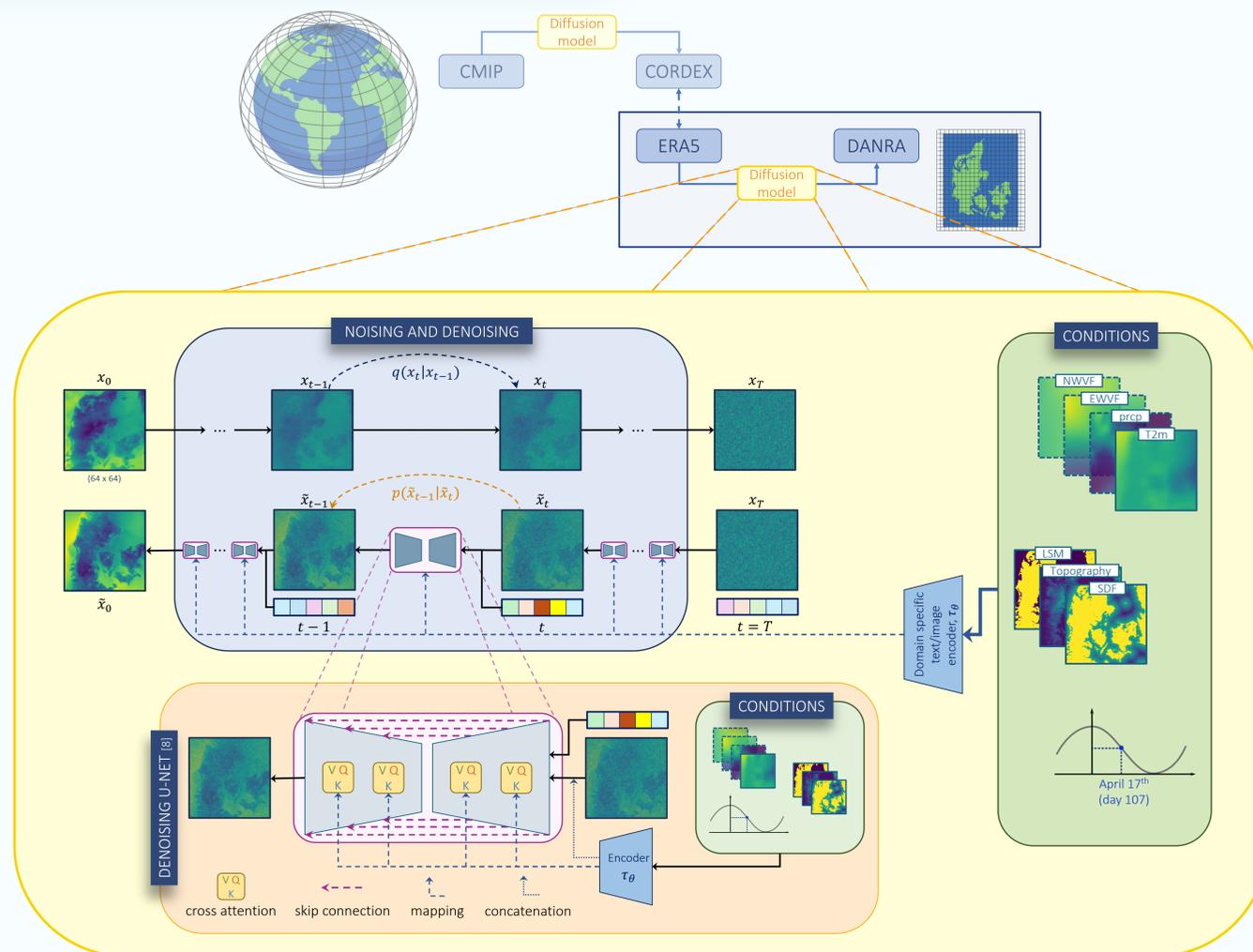
Sample by iteratively removing predicted noise through all time steps

Denoised image = Noisy image - Predicted noise

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(x_t, t) \right) + \sqrt{\beta_t} \epsilon$$

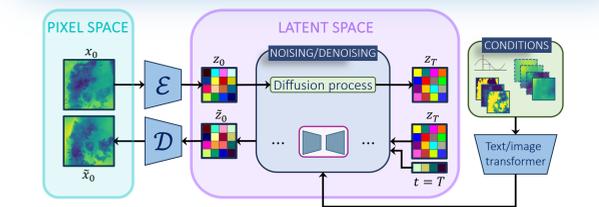
TRAINING

SAMPLING



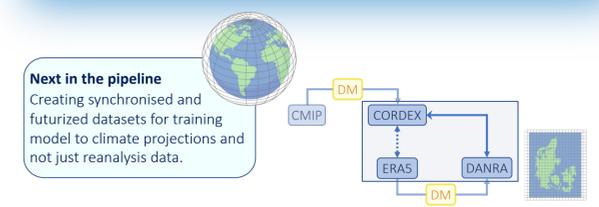
WHAT'S NEXT?

ON THIS MODEL
 An ongoing effort is currently underway to speed up the training process through the implementation of a **Latent Diffusion Model** [4]. Alongside this, the conditioning will be modified to incorporate a **larger geographical and temporal domain** for capturing **large-scale atmospheric dynamics**.



Extended domains
 To capture larger atmospheric dynamics, especially in the North Atlantic. Adding a temporal component (synoptic scale) for more accurate projections.

ON NEXT STEPS
 The immediate next work will focus on generating a synthetic synchronised dataset between select EURO-CORDEX realisations and DANRA, to create a training dataset useful for making climate projection downscaling – for single models and full ensembles.



Next in the pipeline
 Creating synchronised and futurized datasets for training model to climate projections and not just reanalysis data.