ClimGen: Learning the Forcing-Response Relationship in Climate System

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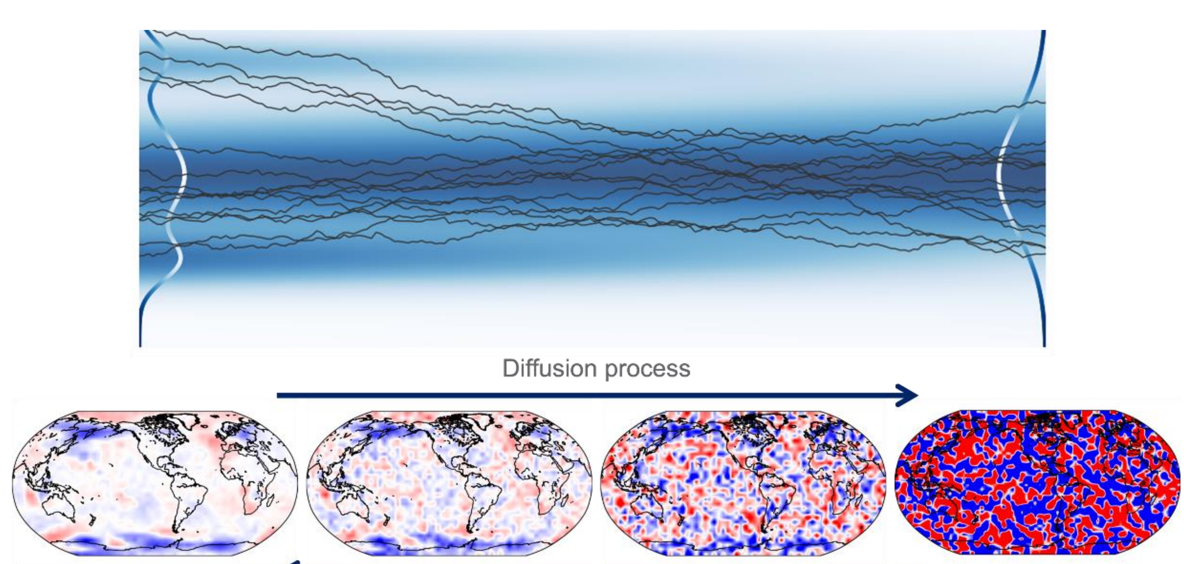
TL;DR: A conditional denoising diffusion probabilistic model was trained to learn the distribution of surface temperature responses conditioned on top of the atmosphere solar radiation forcing.

Problem and Research Gap

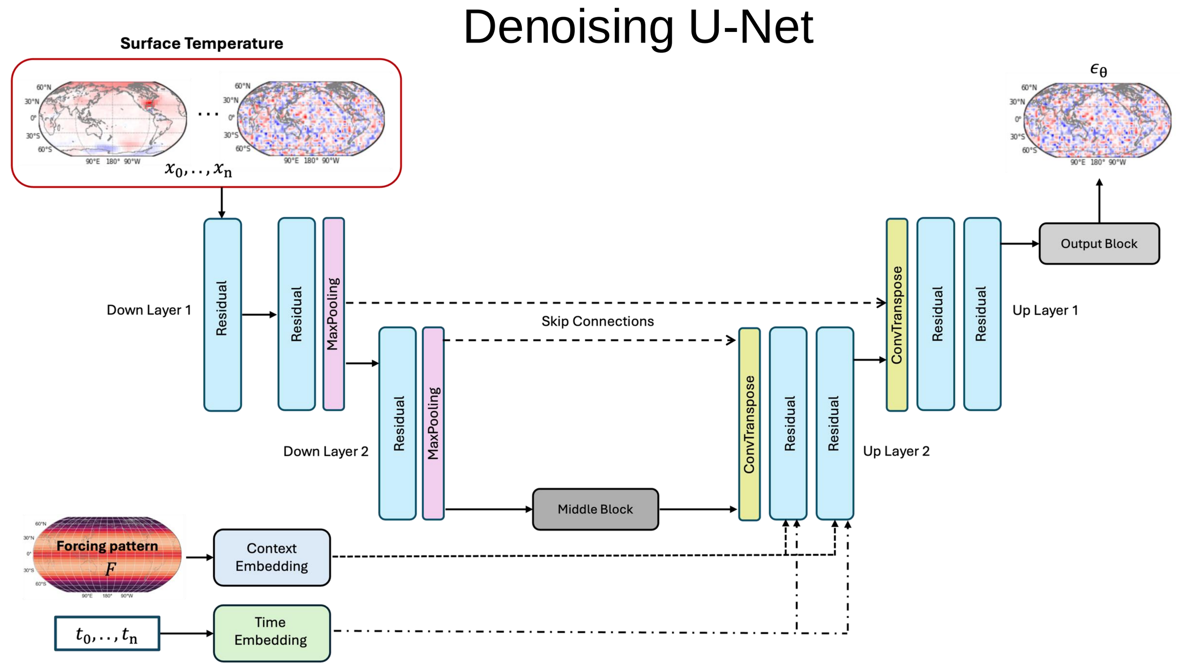
- Predicting climate change responses and uncertainties under external forcing is crucial for climate change mitigation, emissions policy design, and solar radiation management (SRM) strategies.
- Initial studies focused on equilibrium climate sensitivity (ECS) to doubled CO_2. Recent efforts have explored regional response heterogeneity.
- Challenges: Capturing full nonlinear responses is difficult due to the climate system's complexity. Large Earth system model ensembles are reliable but computationally expensive.
- Traditional Methods: Assumed linear and time-invariant responses, using pattern-scaling, 1D impulse response functions, and linear regression.
- Machine Learning Advances: Deep learning has improved medium-range forecasts but struggles with extended projections. Some stabilize forecasts up to 10 years, yet generalization to different forcings remains unproven.
- Study Focus: Compiles Green's function solar perturbation data with an intermediate complexity model, using a denoising diffusion model to generate extensive projections of global surface temperature responses inexpensively while capturing internal variability.

Conditional Denoising Diffusion Probabilistic Model



$$p_\theta(\mathbf{x}_{i-1}|\mathbf{x}_i, \mathbf{c}) = \mathcal{N}(\mathbf{x}_{i-1}; \mu_\theta(\mathbf{x}_i, i, \mathbf{c}), \Sigma_\theta(\mathbf{x}_i, i)).$$

Denoising U-Net



Basic DDPM

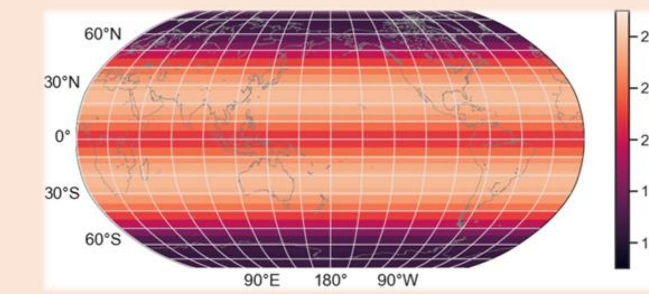
- Core Concept: A generative approach that learns to transform pure noise into structured data by reversing a stochastic noise process.
- Forward Diffusion Process:
  - Gradually adds Gaussian noise to data samples over T timesteps.
  - Transforms a complex data distribution into a simple Gaussian noise distribution using a fixed, predetermined noise schedule.
- Reverse Denoising Process:
  - Trains a neural network to predict and remove the noise added at each timestep, transforming pure noise back into samples that resemble the original data distribution.
- Training Objective:
  - Minimizes the difference between the network's predicted noise and the actual noise injected during the forward process.

Conditional DDPM

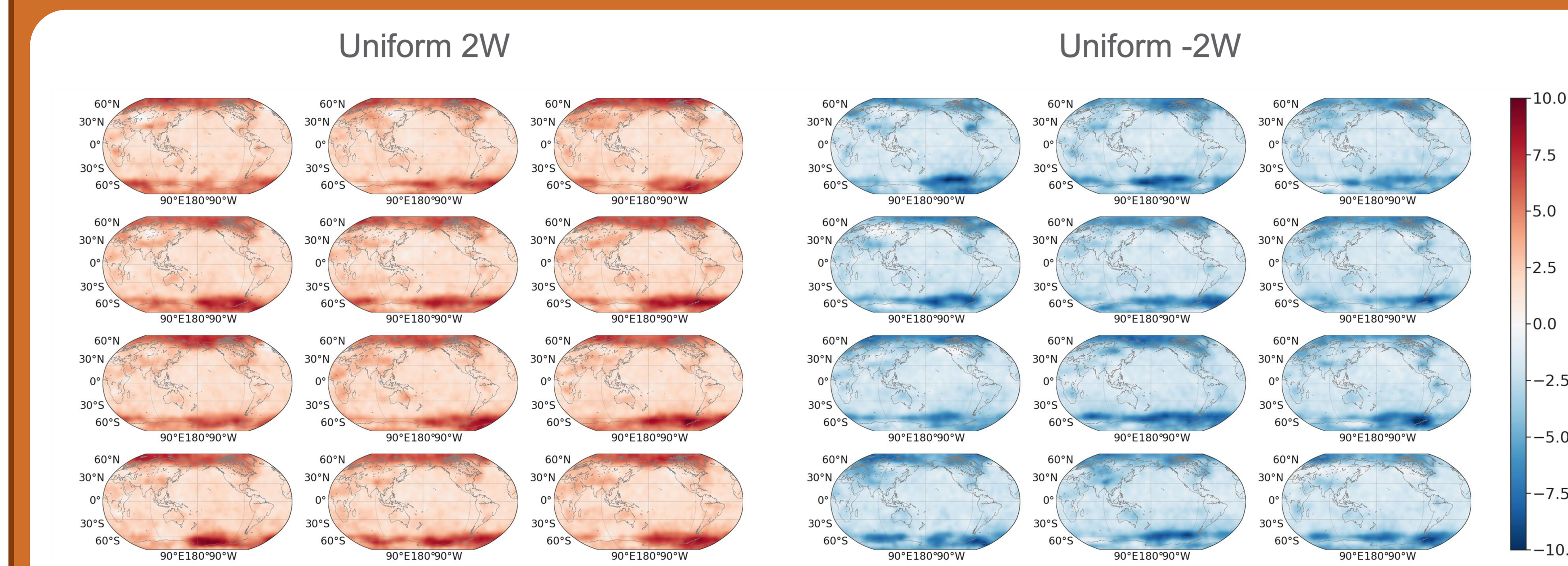
- Enhanced Generation with Guidance: Incorporates additional information (e.g., class labels, text descriptions, or image embeddings) to steer the generative process toward desired outputs.
- Concatenation conditioning mechanism: Directly appends condition vectors to the input features, allowing the model to contextualize its predictions.
- Context and Time Embedding: Integrates conditioning data alongside time-step embeddings, ensuring the guidance is applied consistently throughout the denoising steps.
- Classifier-Free Guidance: Trains the model to generate both conditional and unconditional outputs, enabling flexible control by adjusting the balance between these modes during sampling.

Dataset – Green's function experiments using PlaSim

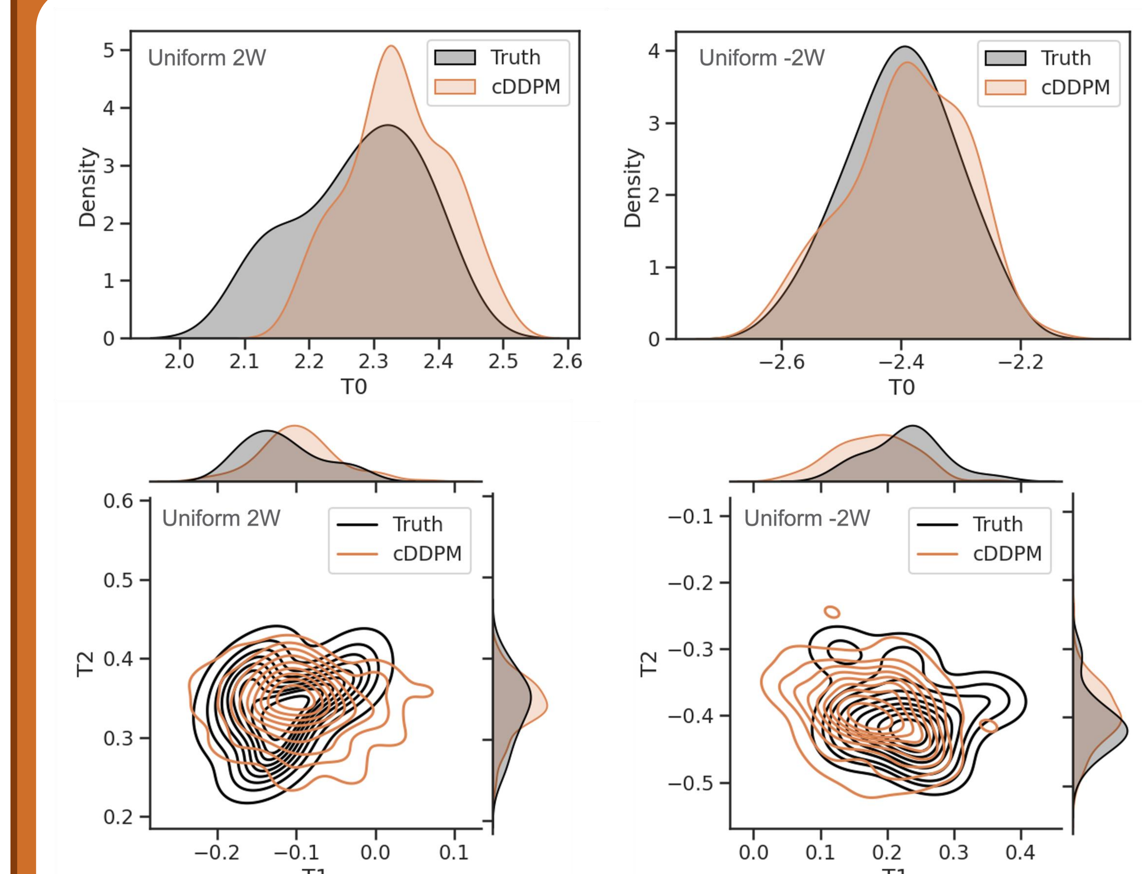
- Planet Simulator, an intermediate complexity GCM
- Atmospheric dynamics + simple physical schemes
- Slab ocean with tuned meridional diffusivity ($Kh_{NH}=1\times10^5$ m²/s, $Kh_{SH}=1\times10^4$ m²/s)
- Horizontal resolution: T21 spectral discretization.
- Vertical levels: 10 layers in sigma coordinate.
- Shortwave forcing at TOA with 16x16 patches: ±15, ±30, and ±60 W/m²



Results



Ensemble of cDDPM-generated projections of surface temperature responses to uniform ±2 Wm⁻² forcing perturbations



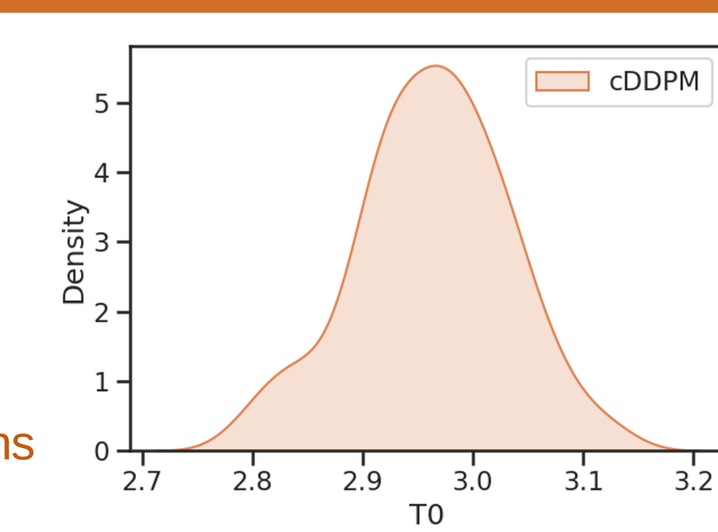
Comparison of the cDDPM-generated with the true distribution of the changes in: global mean temperature (T0), inter-hemispherical temperature difference (T1), and equator-polar temperature difference (T2).

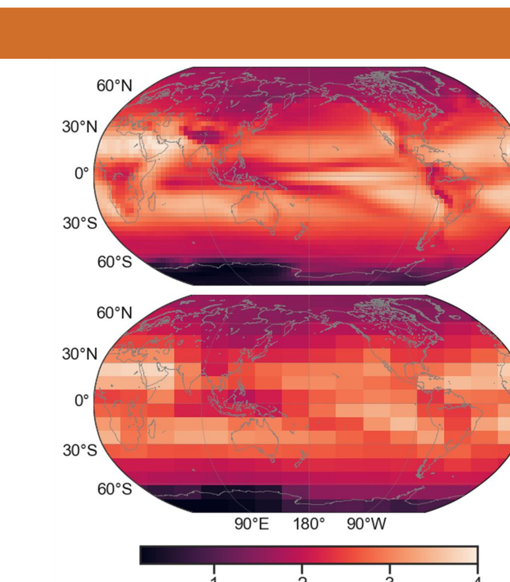
$$T_0 = \frac{1}{A}\int_{-\pi/2}^{\pi/2} T(\psi)dA$$

$$T_1 = \frac{1}{A}\int_{-\pi/2}^{\pi/2} T(\psi)\sin(\psi)dA$$

$$T_2 = \frac{1}{A}\int_{-\pi/2}^{\pi/2} T(\psi)\frac{1}{2}(3\sin^2(\psi)-1)dA$$

The distribution of an ensemble of the cDDPM-generated mean surface temperature response to the $2xCO_2$ forcing is consistent with CMIP5 (2.1 - 4.7K) and CMIP6 (1.8 - 5.6K) projections range.





CESM $2xCO_2$ forcing

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