A Pattern-aware Feedback Framework for Climate Responses

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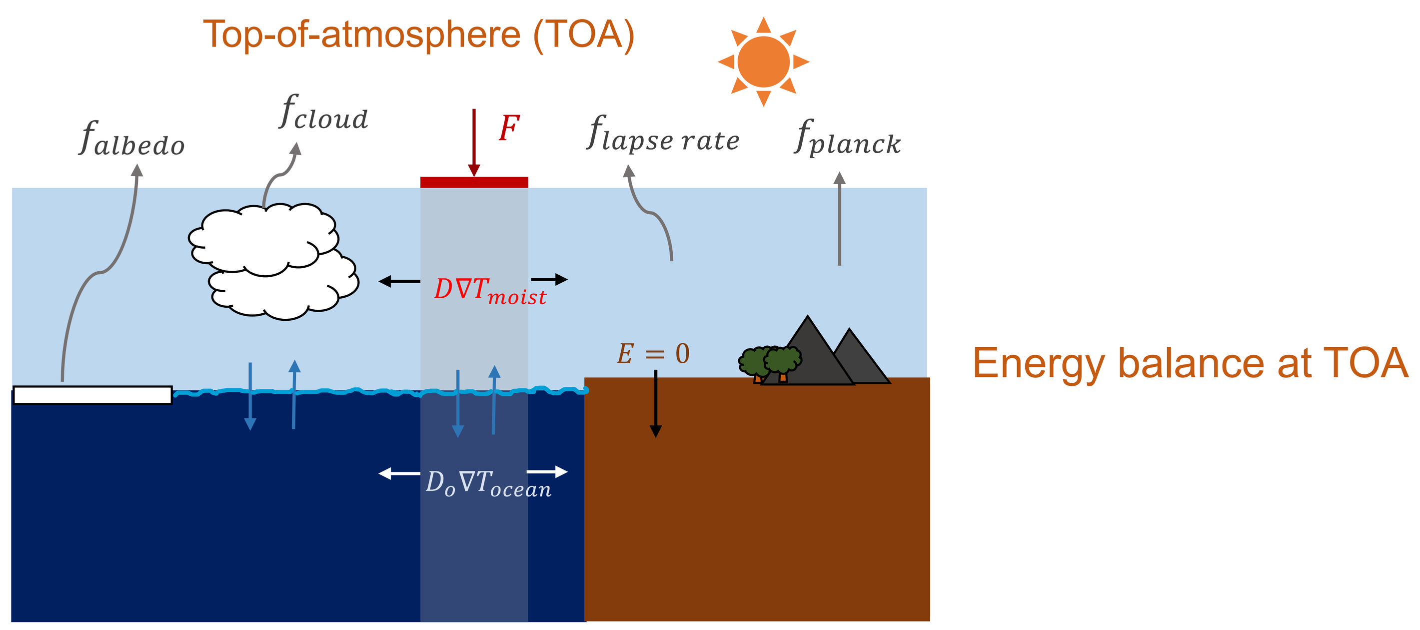
Introduction

We develop a pattern-aware feedback framework for representing the **forced climate response** using a suite of **Green's function**-based solar radiation perturbation experiments.



By considering the **energy balance** at **the top-of-atmosphere (TOA),** a comprehensive linear response function (LRF) for important climate variables and feedback quantities such as **moist static energy, sea surface temperature, albedo, cloud optical depth, lapse rate** etc., is learned from the Green's function data.

Motivation

Conventional feedback analysis is valid only for 0-dimensional systems. This analysis disregards the interaction between different feedback mechanisms.

Open question:

Can we develop a new framework that accounts for:

1. Interactive nature of various feedback mechanisms?
2. Nonlocal effects and teleconnections?

The pattern-aware feedback approach devised here is such that it considers **all feedbacks concurrently** and considers their **spatial dependence**. This framework has **predictive** and **explanatory** power.

Methodology

Comprehensive linear response function:

$$F = D\Delta T_{mse} + D_o\Delta T_o + \sum_{\alpha} K_\alpha\, \Delta\alpha$$

F: External forcing

$$F = [D\ D_0\ K_{\alpha 1}\ K_{\alpha 2}\ K_{\alpha 3}] \begin{bmatrix} \Delta T_{mse} \\ \Delta T_o \\ \Delta\alpha_1 \\ \Delta\alpha_2 \\ \Delta\alpha_3 \end{bmatrix}$$

Feedbacks α:

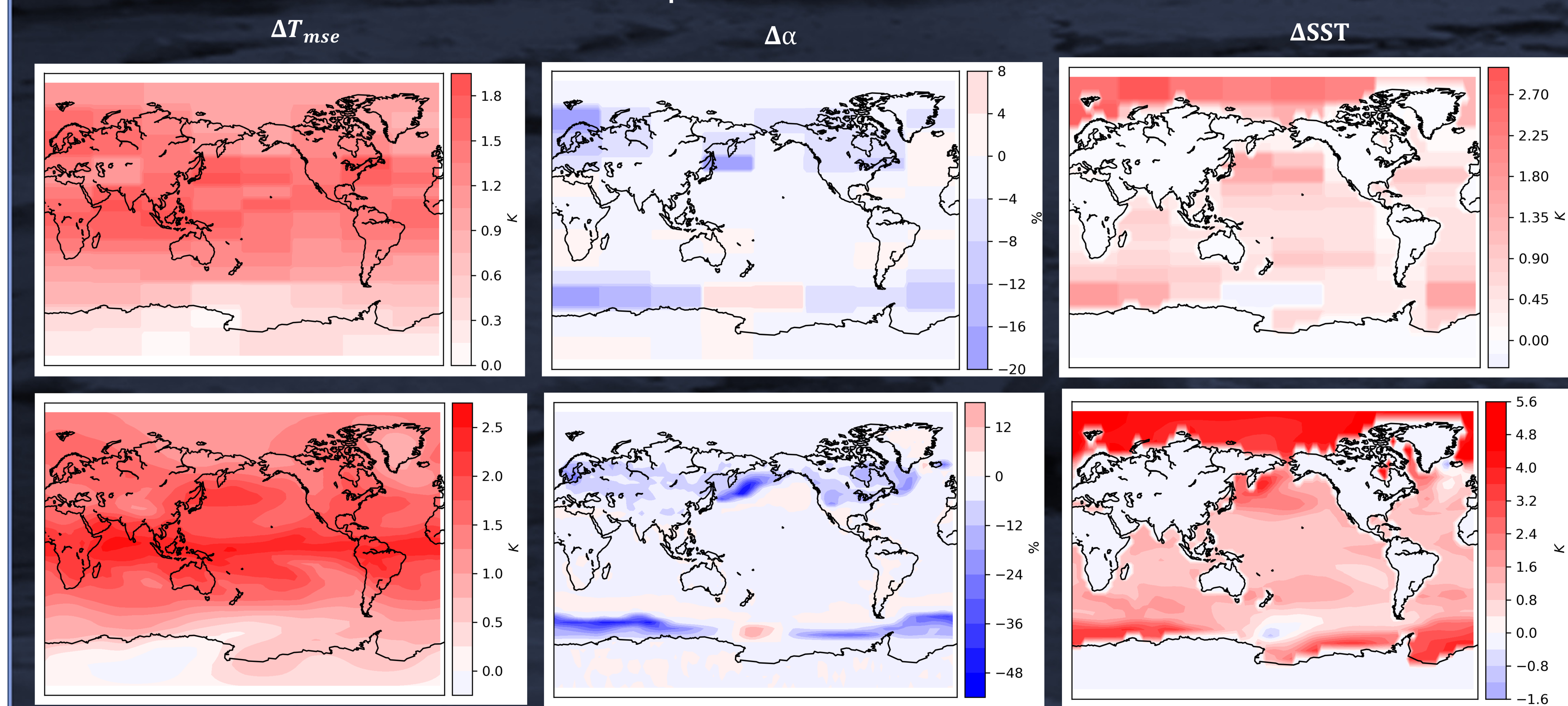
1. Albedo
2. Cloud
3. Lapse rate

Planck and water vapor feedback are absorbed into the 1st term.

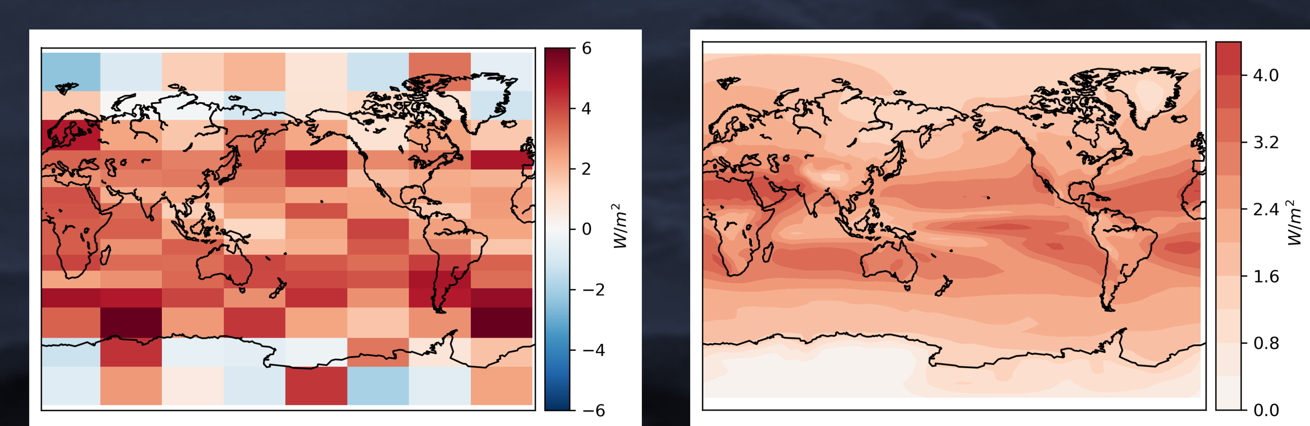
Solve for $[D\ D_0\ K_{\alpha 1}\ K_{\alpha 2}\ K_{\alpha 3}]$ by **ridge regression** using data from Green's function experiments

Predictions for $2xCO_2$ Forcing

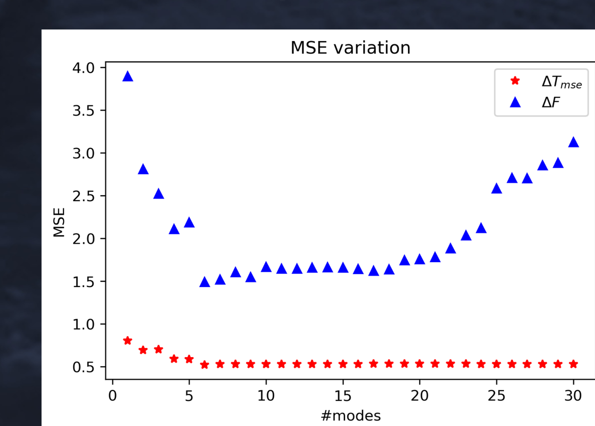
Response reconstruction



Forcing reconstruction



Mean-squared error



Key results:

- A **reduced order model** for forced (linear) climate response that captures nonlocal effects and dynamics.
- The **most excitable mode** of the ROM captures the **polar amplified response** of the climate system due to doubling of CO_2.
- The framework allows for **prediction** of forcing/responses.

Reduced order model

The LRF can decomposed into **forcing-response mode pairs** describing the dominant dynamics of climate responses. These mode pairs capture **nonlocal effects and teleconnections** in the climate and thus, make the ROM apt for capturing regional features of climate change response.

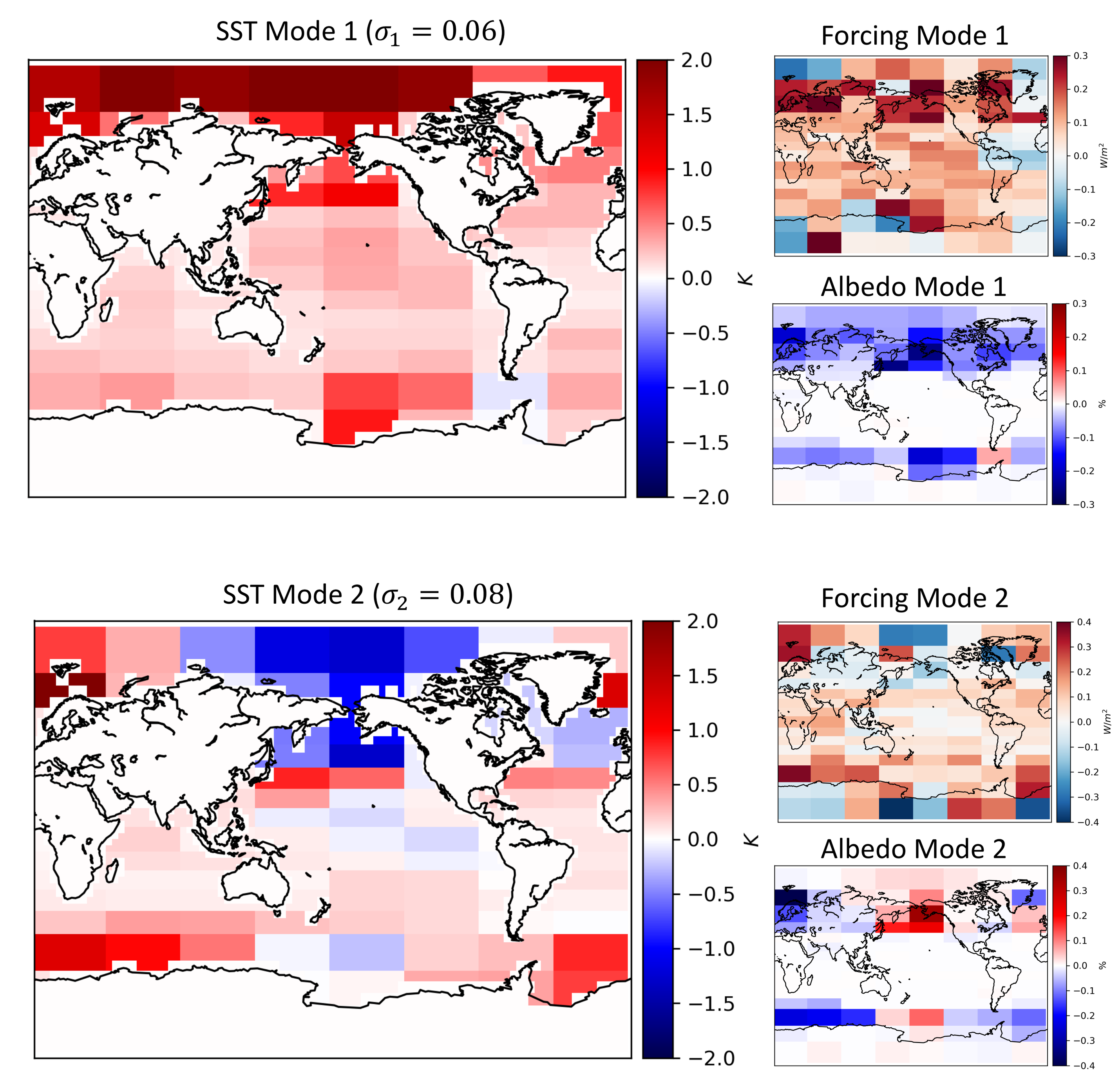
SVD of comprehensive LRF

$$\boldsymbol{K} = [D\ D_0\ K_{\alpha 1}\ K_{\alpha 2}\ K_{\alpha 3}]$$

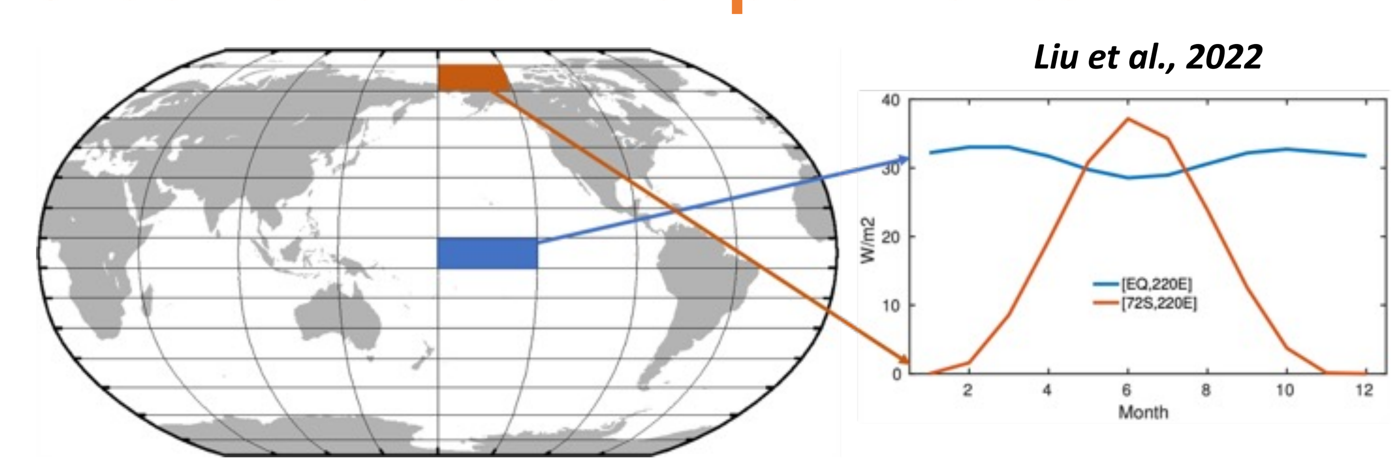
$$\boldsymbol{K} = U\,\Sigma\,V^*$$

U: Forcing mode matrix
Σ: Singular value matrix
V: Response mode matrix
Lowest singular value -> Most excitable mode

A key observation is that the **most excitable mode** of the LRF captures the **polar amplified response** of the climate system due to doubling of CO_2.



Green's function experiments



- Shortwave radiation perturbation (< 30 Wm^{-2}) at TOA on 120 patches of size 45°x12°
- Positive and negative forcing experiments for every patch (used for linearization)
- Each run is 100 years long; the last 50-year mean is used for analysis

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