

# Thin and deep Gaussian processes

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## TLDR:

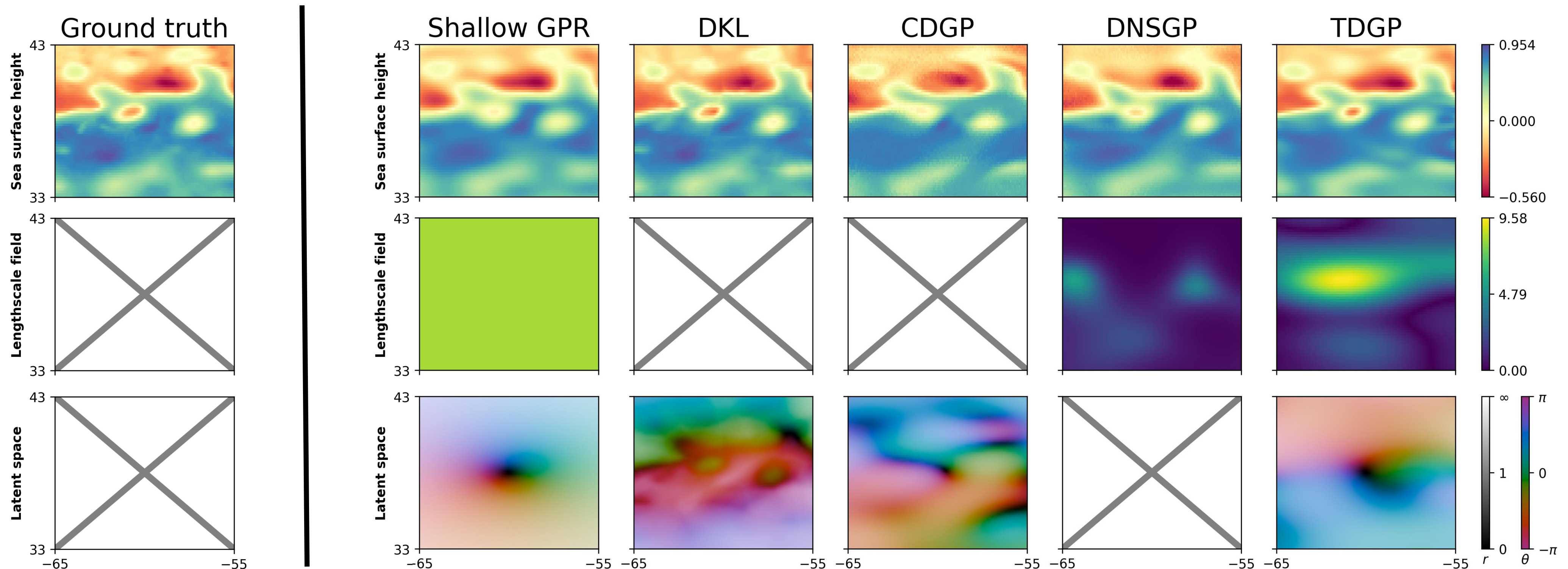
1. Current hierarchical Gaussian Process methods learn one of the following:

- latent mappings - reduce dimensionality (CDGP);
- lengthscale fields - easily interpretable (DNSGP).

2. We:

- Propose a method that learns both!
  - While also avoid pathologies of both CDGP and DNSGP.
- Prove that our method extends the traditional CDGP framework.

## Benchmark: Sea surface height – North Atlantic



## Stationary kernels

A kernel  $k$  is stationary if:

$$\begin{aligned} k(a, b) &= k(a - b, 0) \\ &= \pi_k((a - b)\Delta^{-1}(a - b)^T) \\ &= \pi_k((Wa - Wb)(Wa - Wb)^T) \end{aligned}$$

## From stationary to non-stationary

There are two well known ways to get non-stationary kernels:

1.  $k_{NS}(a, b) = k(\tau(x), \tau(y))$ , if  $\tau(x)$  follows a GP distribution, we obtain compositional deep GP (CDGP) model

2.  $k_{PA}(a, b) \propto \sqrt{\frac{|\Delta(a)|\sqrt{|\Delta(b)|}}{|\Delta(a)+\Delta(b)|}} \pi_k\left((a - b) \left[\frac{\Delta(a)+\Delta(b)}{2}\right]^{-1} (a - b)^T\right)$ ,

if  $\Delta(a)$  follows a warped GP distribution, we obtain a deeply non-stationary GP (DNSGP) model.

We choose a hybrid approach:

$$\begin{aligned} k_{TD}(a, b) &= k(W(a) \cdot a, W(b) \cdot b) \\ &= \pi_k((W(a)a - W(b)b)(W(a)a - W(b)b)^T) \end{aligned}$$

## Previous issues

- CDGP models have pathologies when hidden layers have zero mean function:
  - therefore, they don't have inductive bias for dimensionality reduction;
- DNSGP models have well known interpretability problems:
  - The presence of the expressions with the lengthscale outside the quadratic term harms their interpretability;
  - The quadratic term in the kernel violates the triangle inequality.

## Graphical models

