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# Adaptive design experiment and non-stationary kriging: applications to uncertainty analysis in nuclear mechanical studies

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## 1. Introduction

### Context

This work aims at integrating uncertainties in mechanical analysis with complex computer codes from nuclear safety studies. More precisely, it is intended to analyse if the variations of the uncertain code inputs can drastically change the behaviour of the system or even turn the system into a non-secure state. To do so, numerical design of experiments methods based on spatial statistics can be used for launching new simulations in the most relevant areas (high variation areas, over sets, ...). These methods are based on a modeling of the response with an interpolating Gaussian process. The covariance of the process is often assumed stationary, whereas this strong hypothesis leads sometime to poor predictions.

### Objectives

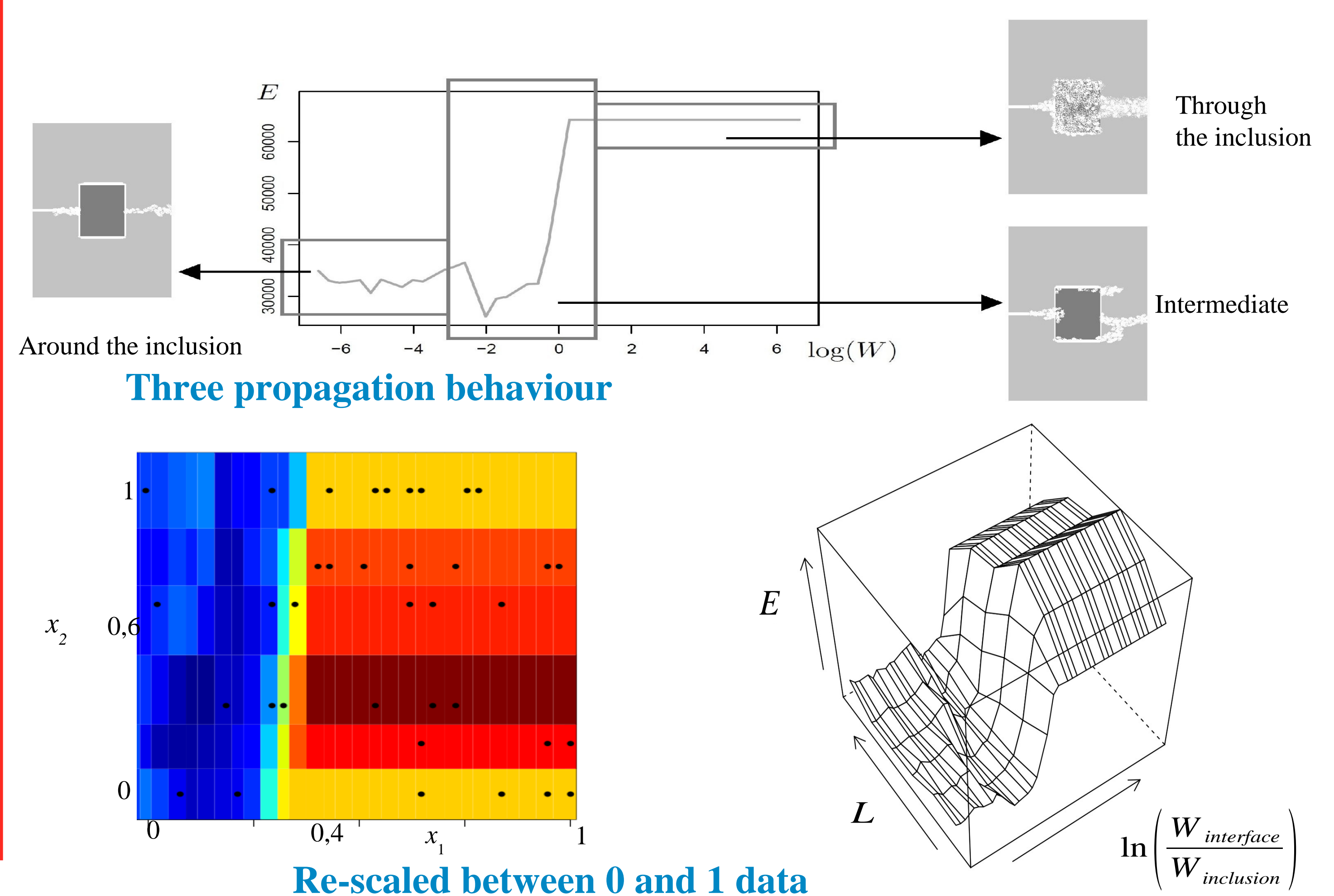
build new non-stationary Gaussian process models to describe the heterogeneous behaviour of the response.

integrate the new models in a adaptive design of experiment.

validate the methods on mechanical applications related to the cracking of heterogeneous materials.

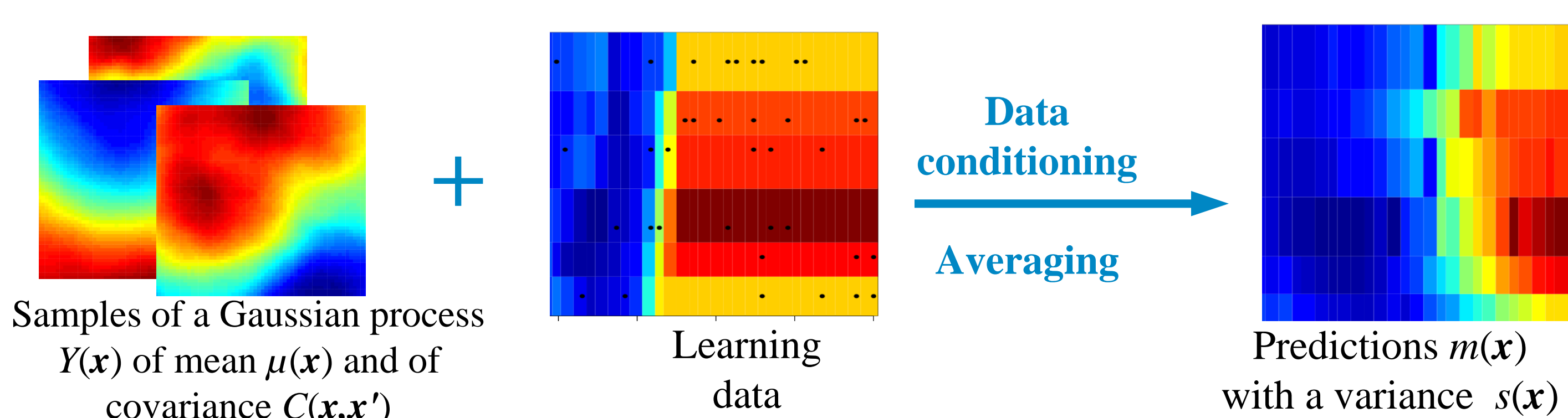
### A first example of mechanical application

It is related to the study of the heterogeneous material cracking (typically concrete) and to the simulation of the cracking energy by the code XPER. Two uncertain input parameters are considered : the length of the inclusions,  $L$  and the ratio of interface energies,  $W$ . An adaptive design of experiments is here relevant since we observe a high variation of the response  $E$  corresponding to the transition between two cracking propagation modes.

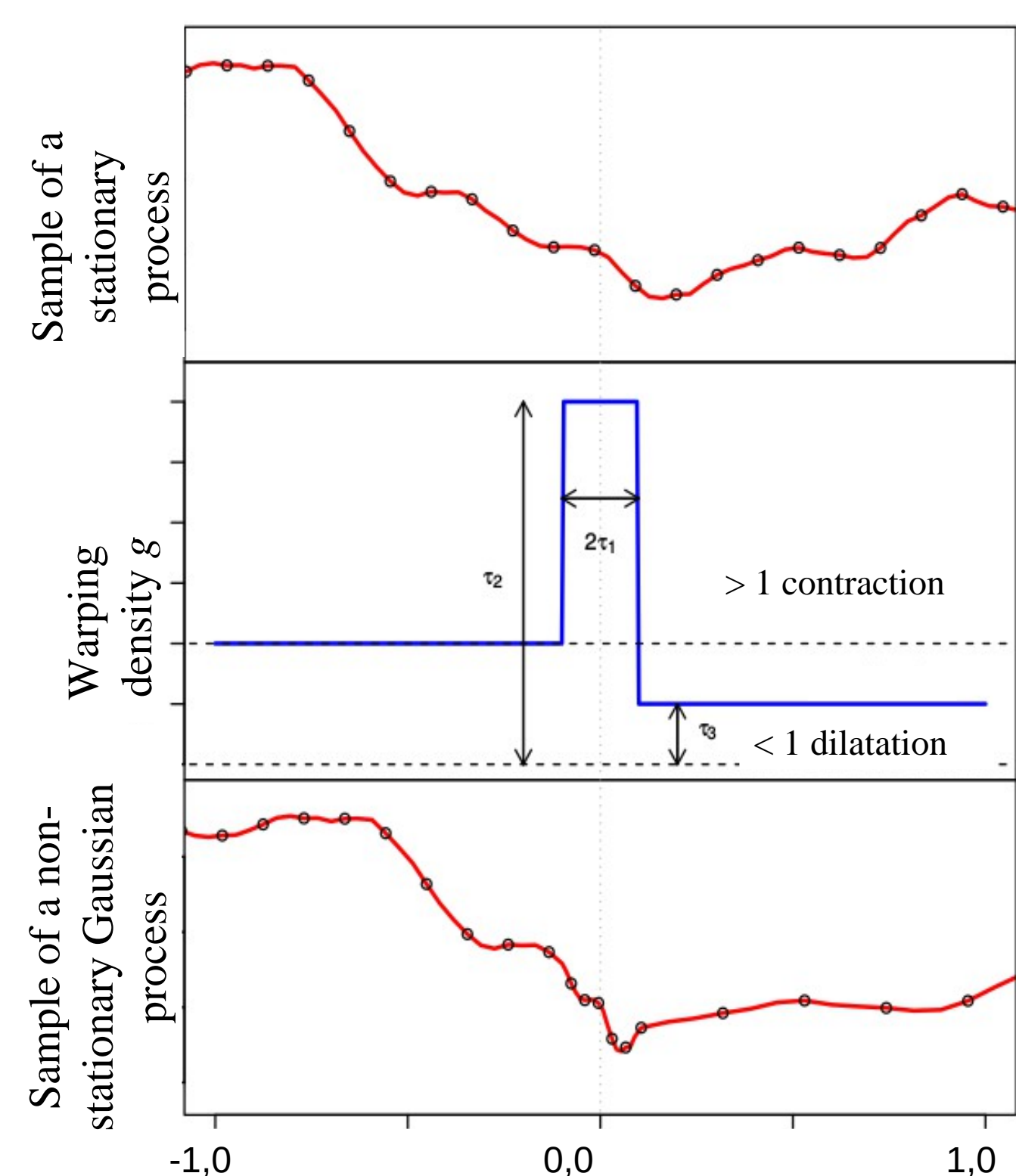


## 2. Methods

### Gaussian process modeling

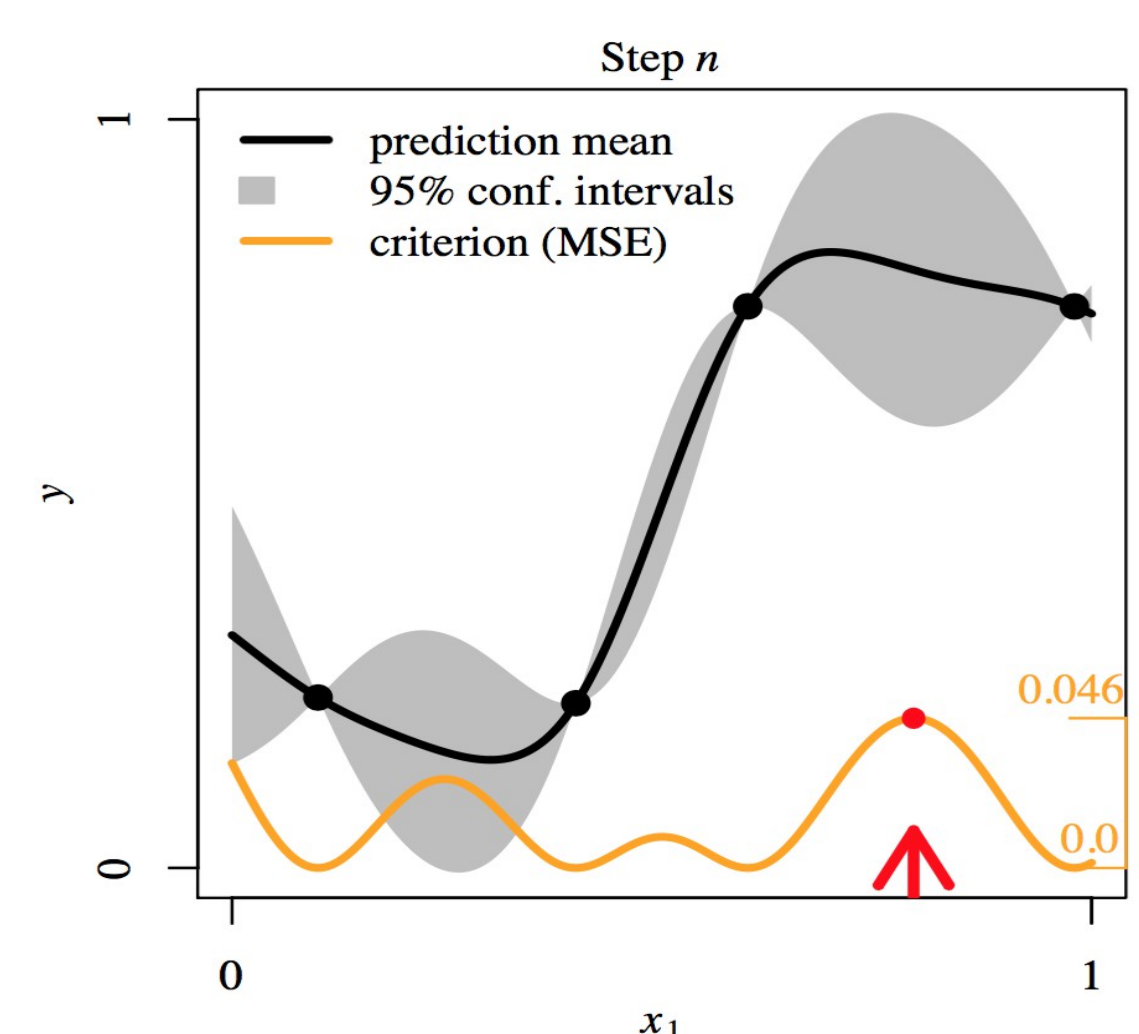


### Warping



We can interpret the idea of warping a Gaussian process to make it non-stationary as a **transformation of the input space**. The non-stationary covariance is the composition of a stationary covariance with a transformation function  $T$  locally determined by a density function  $g$ .

### Inf II criteria



We use two variance-based criteria:

$$J_n^{\text{MSE}}(\mathbf{x}) = C_n(\mathbf{x}, \mathbf{x}),$$

$$J_n^{\text{IMSE}}(\mathbf{x}) = - \int_{\mathbf{u} \in D} C_{n,\mathbf{x}}(\mathbf{u}, \mathbf{u}) d\mathbf{u},$$

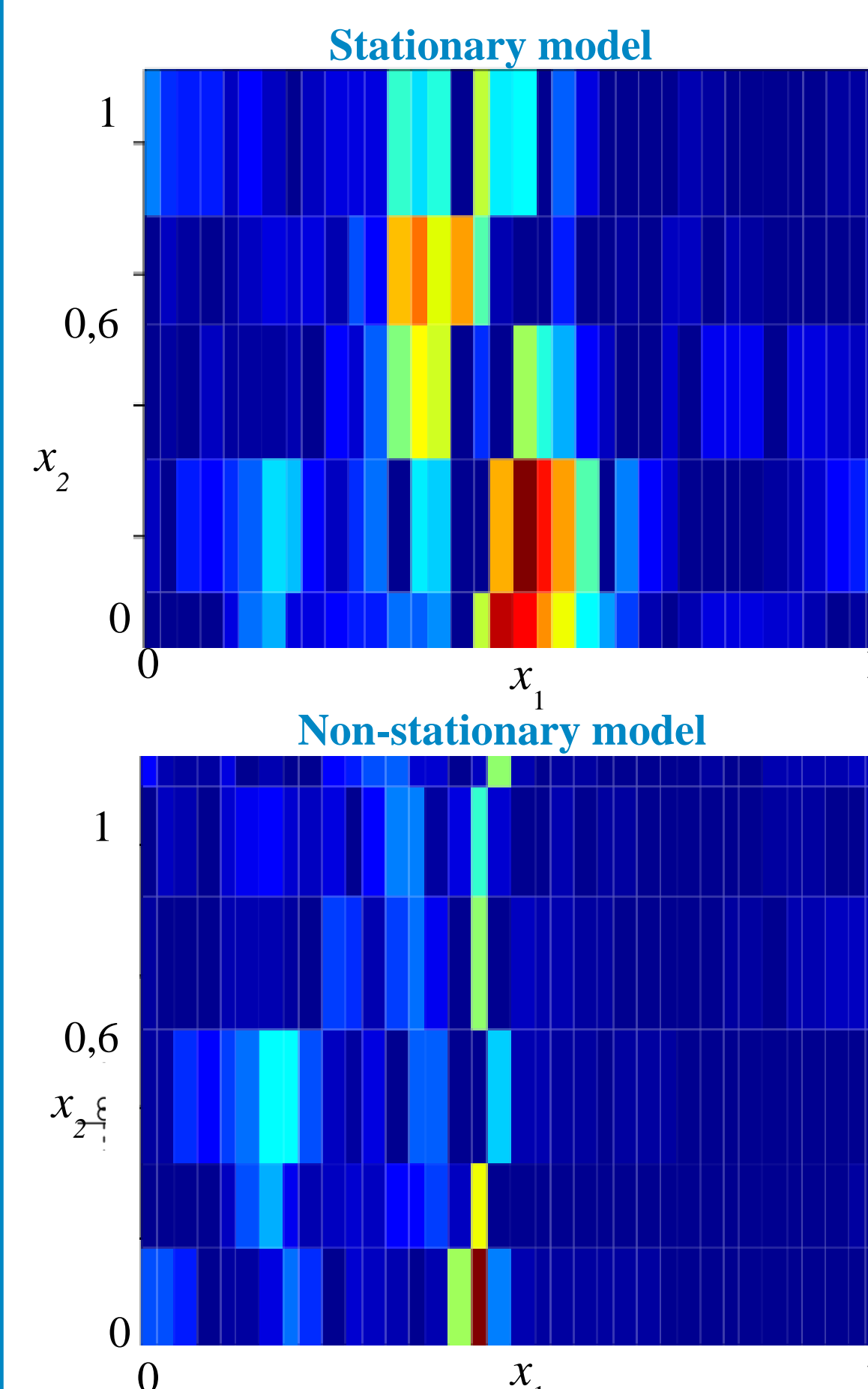
We define two gradient-based criteria focusing more on variation region:

$$J_n^{\text{G-MSE}}(\mathbf{x}) = \text{var}(\|\nabla Y_{\mathbf{x}}\|^2 | \mathcal{A}_n),$$

$$J_n^{\text{G-IMSE}}(\mathbf{x}) = - \int_{\mathbf{u} \in D} J_{\mathcal{A}_n, \mathbf{x}}^{\text{G-MSE}}(\mathbf{u}) d\mathbf{u}$$

## 3. Results

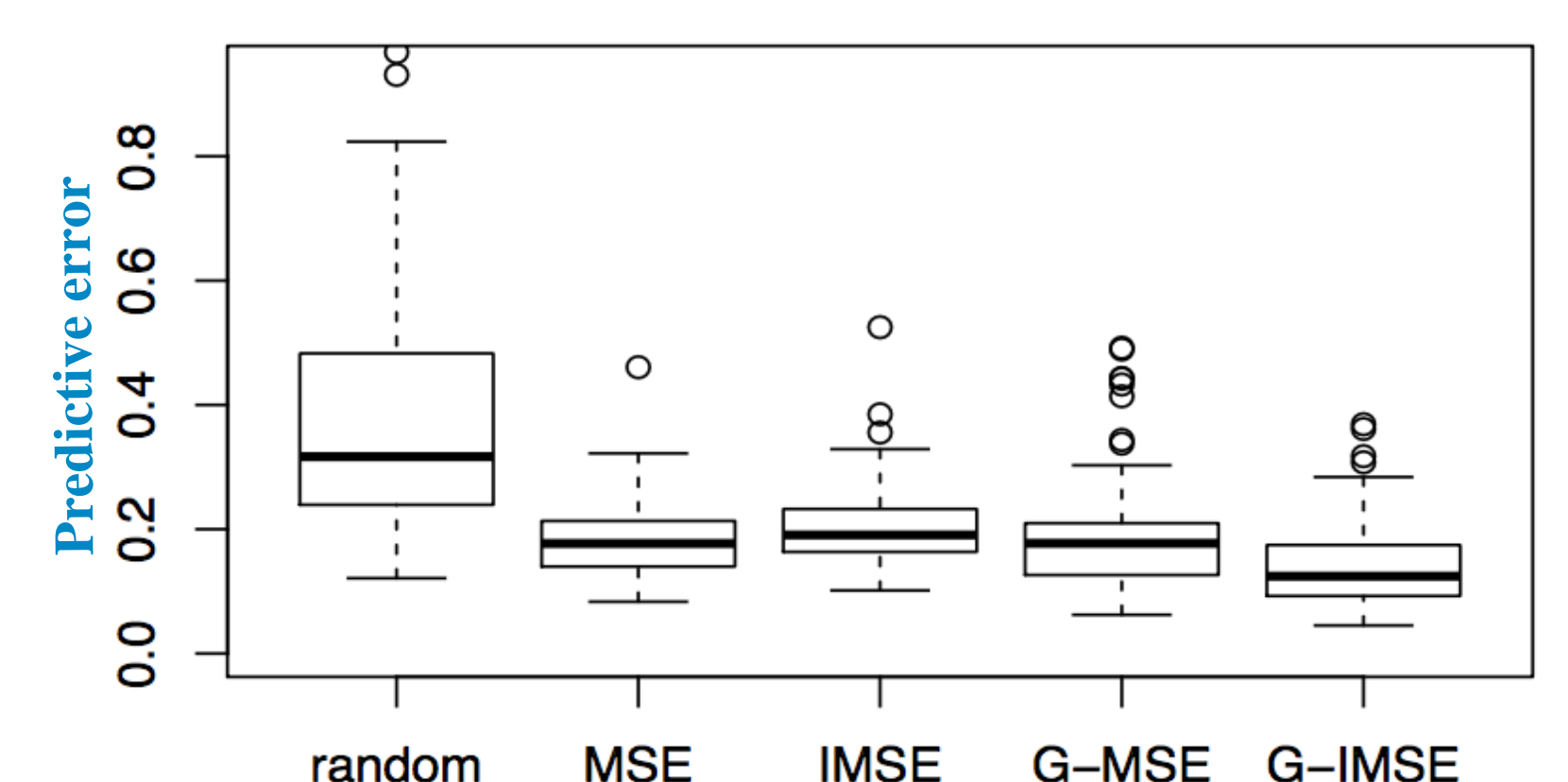
### Predictive error



We have tested seven Gaussian process models. We show that the models with warped Gaussian processes adapted to the data structure is more effective.

### Criteria comparison

To compare inf II criteria, we evaluate the prediction errors in the high variation region after adding 10 points. We repeat the experiment 10 times with different initial designs.



On the considered test case, we observed good performance of G-IMSE for the prediction in high-variation zone.

## 4. Perspectives

We will compare new derivative-based criteria with further norm and second order derivatives. Then we will aim at improving the non-stationary Gaussian process modeling by matching them with wavelets methods from the image processing field. Finally, new mechanical applications involving more uncertain code inputs and different types of non stationarity will be considered