An overview of ML use for Climate Model Tuning

GDR défis théoriques pour les Sc. du climat, May 2024

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Homer Durand (Universitat de València), Maya Janvier (Inria),
Aurelien Quiquet, Didier Roche (CNRS, LSCE-IPSL)

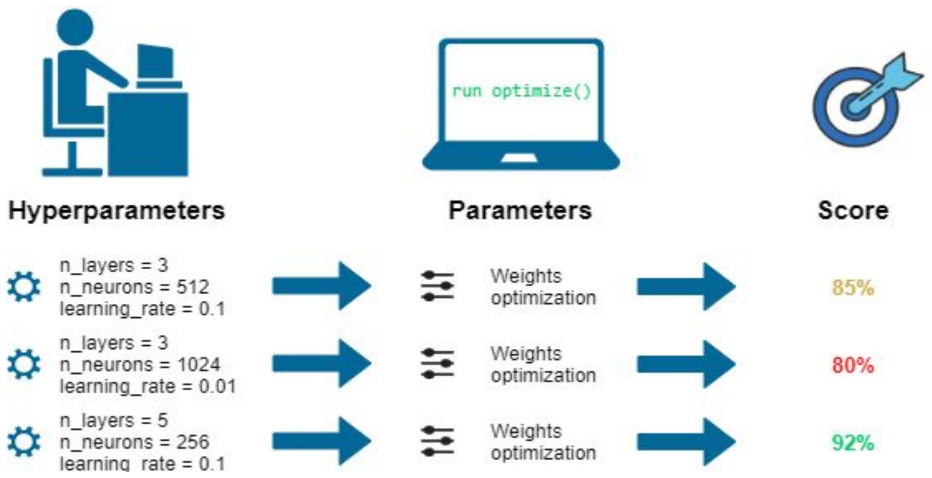
Part I

Computer design experiments aka Surrogate modeling aka Hyperparameter tuning aka....

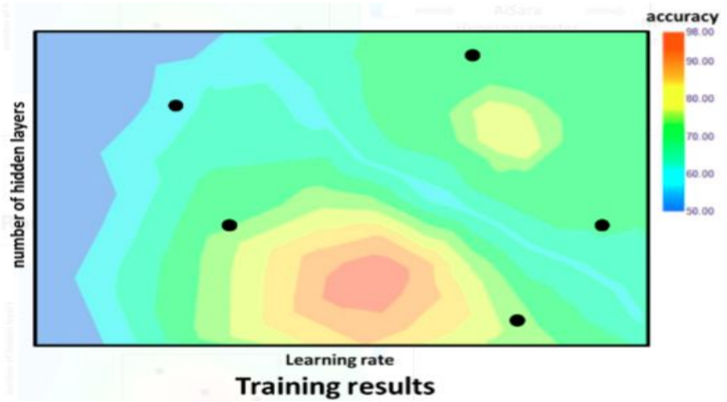
Model Tuning

The problem from a data scientist PoV

Example from a normal day of a machine learner some years ago



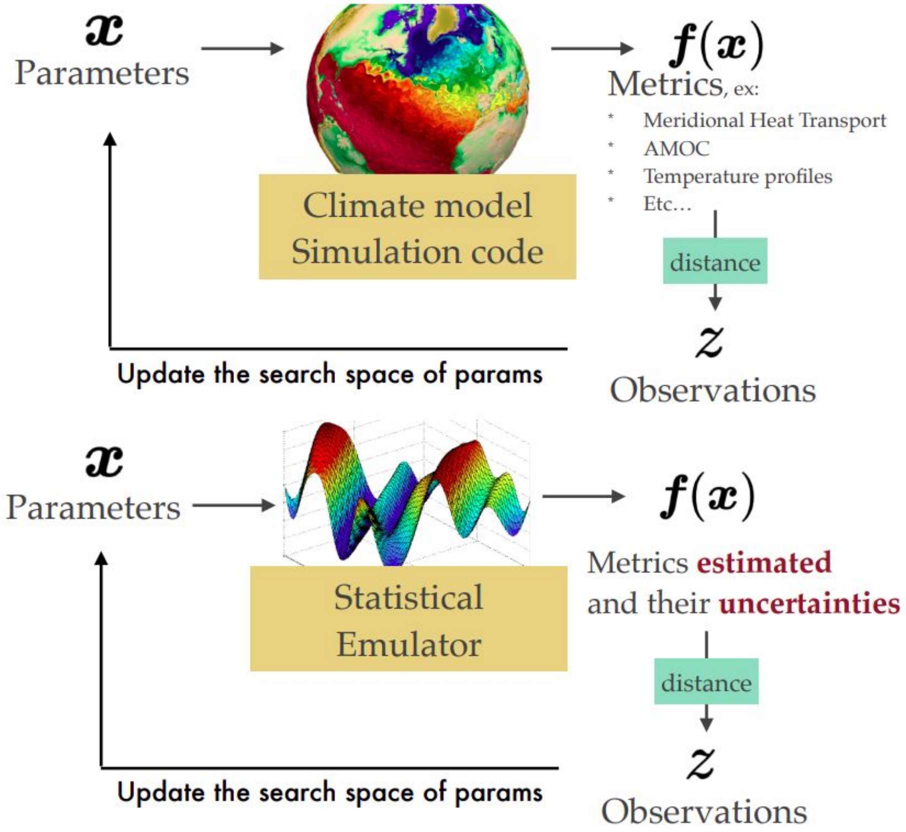
Not the case anymore (if you have the necessary computing power)



Kriging aka **Gaussian Process Regression**

Model Tuning

The problem from a climate scientist PoV



Model Tuning

The problem from a climate scientist PoV

RESEARCH ARTICLE | 31 MARCH 2017

The Art and Science of Climate Model Tuning

Frédéric Hourdin; Thorsten Mauritsen; Andrew Gettelman; Jean-Christophe Golaz; Venkatramani Balaji; Qingyun Duan; Doris Folini; Duoying Ji; Daniel Klocke; Yun Qian
Florian Rauser; Catherine Rio; Lorenzo Tomassini; Masahiro Watanabe; Daniel Williamson

Bull. Amer. Meteor. Soc. (2017) **98** (3): 589–602.

https://doi.org/10.1175/BAMS-D-15-00135.1 Article history

- It is important that modeling groups communicate their tuning strategy
- When comparing models given a metric, it is very important to know which models were tuned for that metric

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Research Article | Open Access

The Tuning Strategy of IPSL-CM6A-LR

Juliette Mignot, Frédéric Hourdin, Julie Deshayes, Olivier Boucher, Guillaume Gastineau, Ionela Musat, Martin Vancoppenolle, Jérôme Servonnat, Arnaud Caubel, Frédérique Chéruy, Sébastien Denvil, Jean-Louis Dufresne, Christian Ethé, Laurent Fairhead, Marie-Alice Foujols, Jean-Yves Grandpeix, Guillaume Levavasseur, Olivier Marti, Matthew Menary, Catherine Rio, Clément Rousset, Yona Silvy
... See fewer authors

Model Tuning

Context of my work

MOPGA project: HRMES

Using machine learning to help tuning climate models

Julie Deshayes
(CNRS, LOCEAN-IPSL)

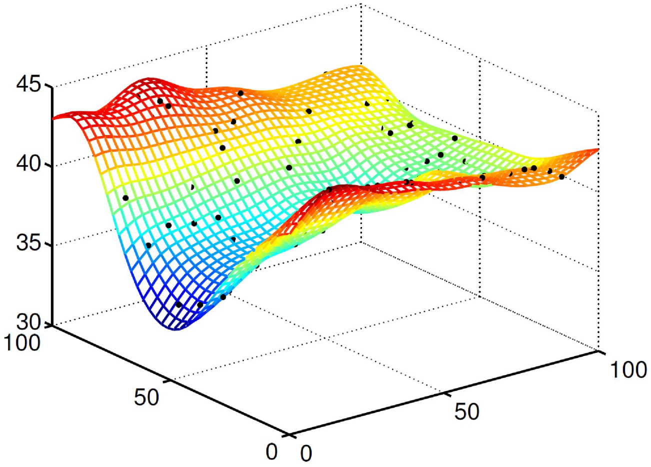
V. Balaji
(Schmidt Sciences, IPSL)

Modeling groups tune by hand models to make them match observations

Very expensive, for example it took 5 years to find an acceptable tuning of IPSL model

Our goal :

- Use ML-based emulators to replace the expensive climate model
- find one or many good tunings
- run the expensive model with these “good” tunings



Part II

History Matching

History Matching

A little bit of History

- Originated from the oil reservoir modeling
- In the recent literature for climate model tuning, History Matching seems to gain more popularity (partly thanks to the ANR HighTune), but other techniques are being investigated too such as CES (Calibrate Emulate Sample) by Cleary et al.
- HM goes beyond finding a unique reference version of a model and allows us to explore **the possible model worlds compatible with a set of observational constraints**

CHAPTER

Bayes Linear Strategies for Matching Hydrocarbon Reservoir History Get access >

P S Craig, M Goldstein, A H Seheult, J A Smith

https://doi.org/10.1093/oso/9780198523567.003.0004 Pages 69–96

Published: May 1996

Statistical Science
2014, Vol. 29, No. 1, 81–90
DOI: 10.1214/12-STS412
© Institute of Mathematical Statistics, 2014

Galaxy Formation: Bayesian History Matching for the Observable Universe

Ian Vernon, Michael Goldstein and Richard Bower

Research articles

Bayesian emulation and history matching of JUNE

I. Vernon, J. Owen, J. Aylett-Bullock, C. Cuesta-Lazaro, J. Frawley, A. Quera-Bofarull, A. Sedgewick, D. Shi, H. Truong, M. Turner, J. Walker, T. Caulfield, K. Fong and F. Krauss

Published: **15 August 2022** https://doi.org/10.1098/rsta.2022.0039

Model Tuning

Challenges

Ideally we would individually check every possible parameter setting for the input:

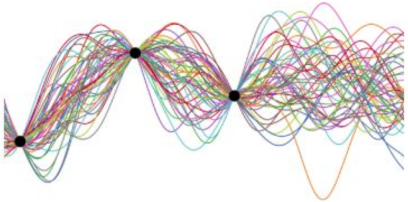
Impossible (climate models are **expensive** to run)

Need for **space-filling designs** to cover the space of parameter search

Need for replacing the expensive simulator with a rapid and cheap **emulator**

Ex: using Latin Hypercube Sampling

Surrogate modeling



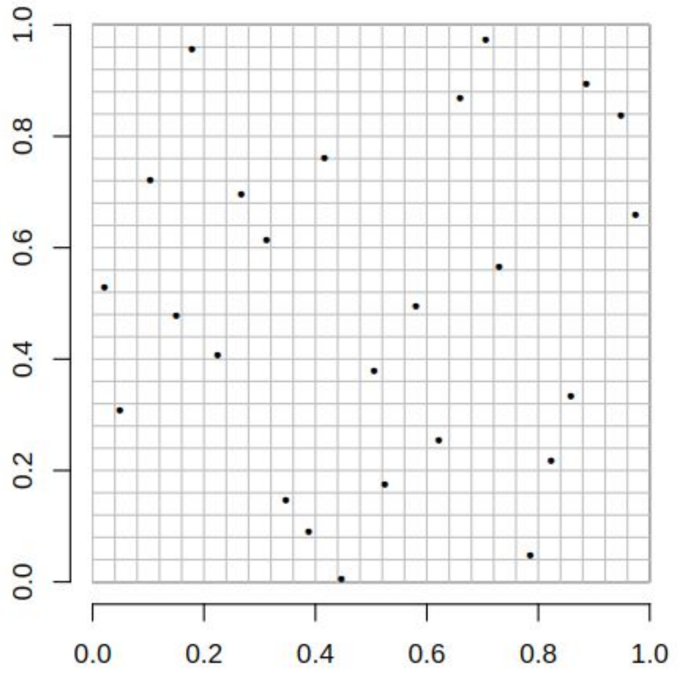
Space filling design

ex: LHS

- Old and well established technique discovered many times in the past by independent groups

- Called N-Rooks in the computer graphics community

- In practice we use the “maximin” version of LHS: values are added to the design one by one such that the maximin criteria is satisfied



25 points of a Latin hypercube sample in [0, 1]x[0, 1]

Surrogate Modeling

ex: Gaussian Processes

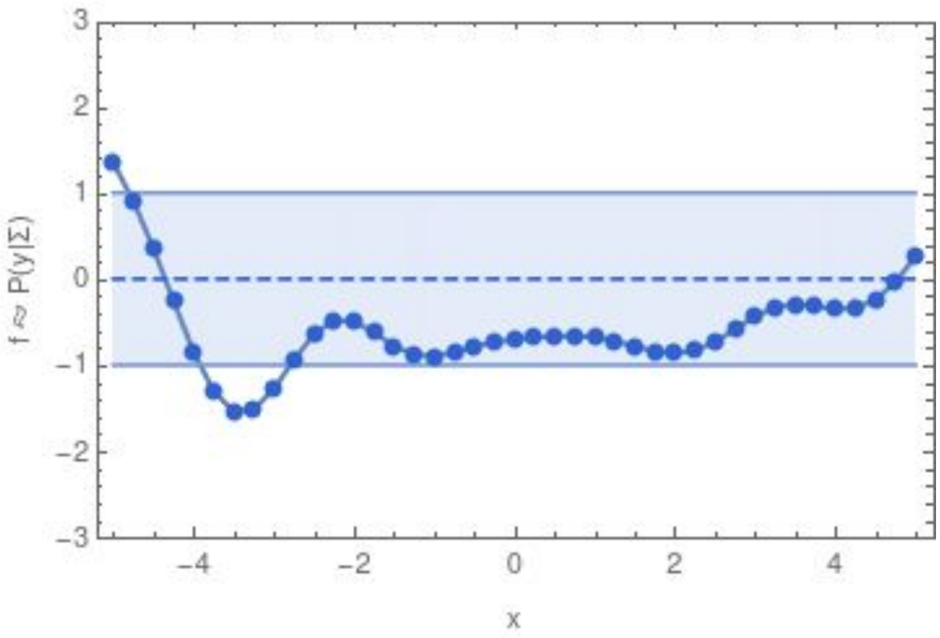


Illustration by Johannes E. M. Mosig

Surrogate Modeling

ex: Gaussian Processes

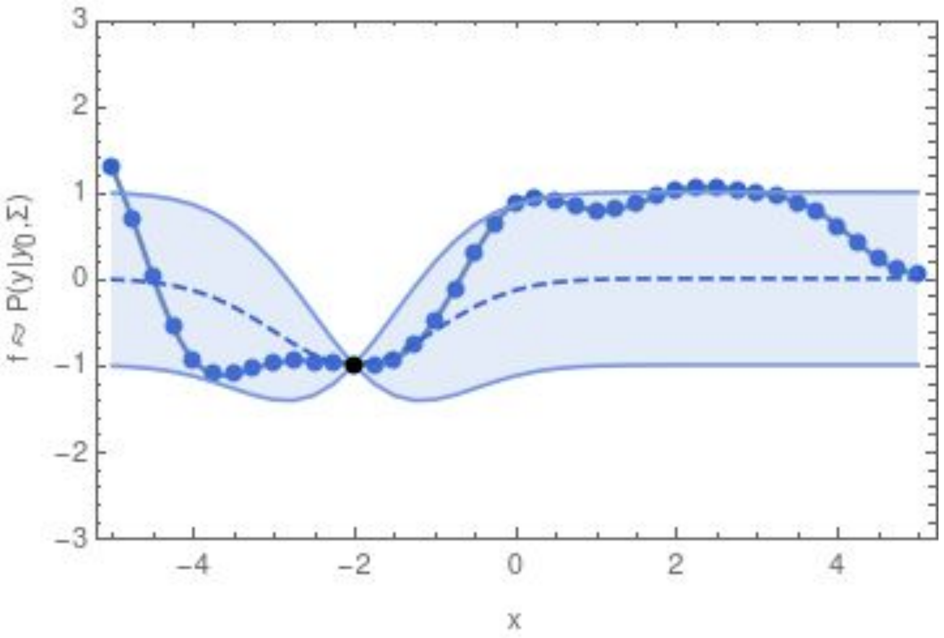


Illustration by Johannes E. M. Mosig

Surrogate Modeling

ex: Gaussian Processes

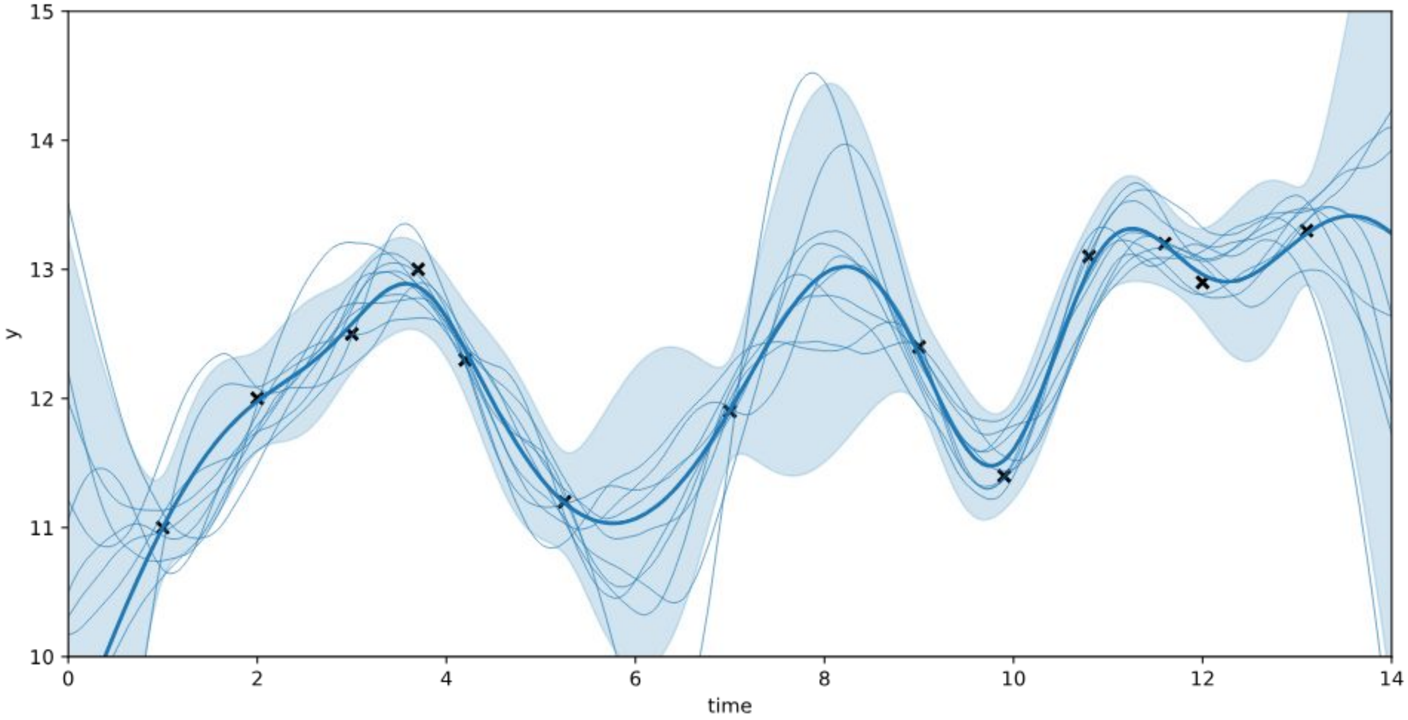


Illustration by Johannes E. M. Mosig

Gaussian Process Regression

$$y = f(\mathbf{x}) + \epsilon\,,$$

where $\mathbf{x} \in \mathbb{R}^D$, $y \in \mathbb{R}$, and $\epsilon \sim \mathcal{N}(0, \sigma_n^2)$ is i.i.d. Gaussian measurement noise. We place a GP prior on the unknown function f, such that the generative process is

$$p(f) = GP(m, k)$$
$$p(y|f, \mathbf{x}) = \mathcal{N}(y|f(\mathbf{x}), \sigma_n^2)\,,$$

where $p(f)$ is the GP prior and $p(y|f, \mathbf{x})$ is the likelihood. Moreover, m and k are the mean and covariance functions of the GP, respectively.

For training inputs $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_N]$ and corresponding (noisy) training targets $\mathbf{y} = [y_1, \ldots, y_N]$ we obtain the predictive distribution

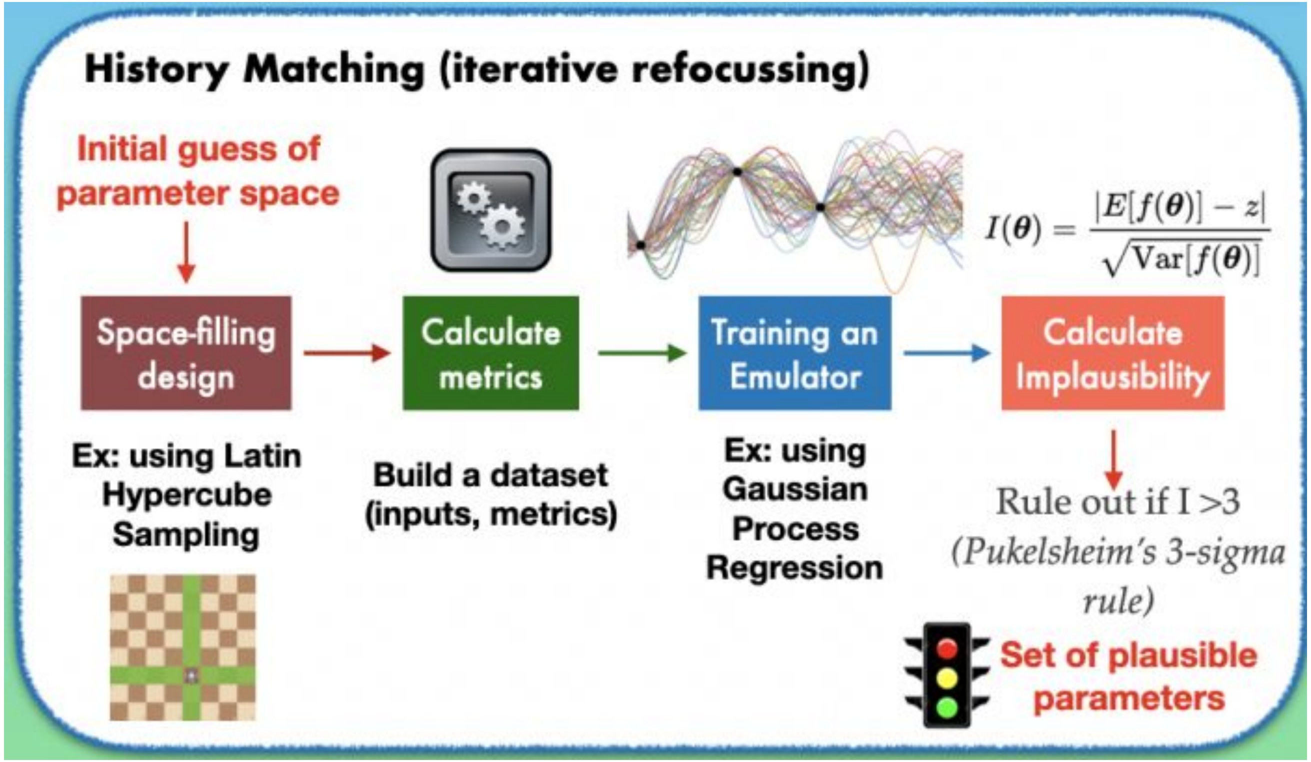
$$p(f_*|\mathbf{X}, \mathbf{y}, \mathbf{x}_*) = \mathcal{N}(f_*|\mu_*, \sigma_*^2)$$
$$\mu_* = m(\mathbf{x}_*) + k(\mathbf{x}_*, \mathbf{X})(k(\mathbf{X}, \mathbf{X}) + \sigma_n^2\mathbf{I})^{-1}(\mathbf{y} - m(\mathbf{X}))$$
$$\sigma_*^2 = k(\mathbf{x}_*, \mathbf{x}_*) - k(\mathbf{x}_*, \mathbf{X})(k(\mathbf{X}, \mathbf{X}) + \sigma_n^2\mathbf{I})^{-1}k(\mathbf{X}, \mathbf{x}_*)$$

at a test point $\mathbf{x}_*$.

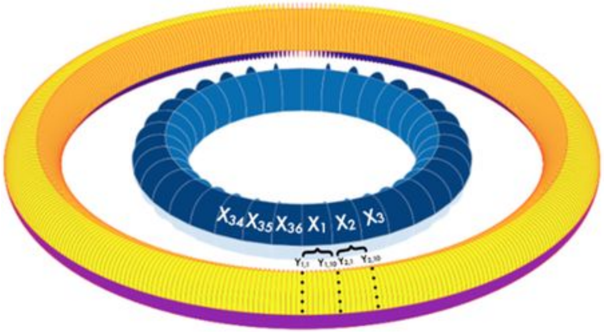
Deisenroth et al. 2020

History Matching

The Algorithm



Done in waves !



Part III

HM on simple & intermediate complexity models

Simple model: Lorenz96 model

Experimental design

* Periodic system of K (k=1,…,K) ODEs
* **Two-level version:** add periodic variable Y with its own set of ODEs.
* The X and Y ODEs are linked through coupling terms. Each X has J Y variables associated with it.

$$\frac{dX_k}{dt} = \underbrace{-X_{k-1}\left(X_{k-2} - X_{k+1}\right)}_{\text{Advection}} \underbrace{-X_k}_{\text{Diffusion}} \underbrace{+F}_{Forcing} \underbrace{-\frac{hc}{b}\sum_{j=1}^{J} Y_{j,k}}_{Coupling}$$

$$\frac{dY_{j,k}}{dt} = \underbrace{-cbY_{j+1,k}\left(Y_{j+2,k} - Y_{j-1,k}\right)}_{\text{Advection}} \underbrace{-cY_{j,k}}_{\text{Diffusion}} \underbrace{+\frac{hc}{b}X_k}_{\text{Coupling}}$$

Analogy with coupled ocean-atmosphere models:

Atmosphere	**Fast dynamics**	Y
Ocean	**Slow dynamics**	X

Experiment: HM for the tuning of parameters (F, h, c, b)

Simple model: Lorenz96 model

Experimental design

- **Metrics**: long-term time means to mimic climatological quantities

- **Ground Truth**: perfect setting K=36 X variables each coupled with J=10 Y variable. F=10, h=1, c=10, b=10, chaotic behavior.

- **HM code:** Python code run on **Jean-Zay** cluster + Parallel computation + ML models can be trained on **GPU**

$$f(X,Y) = \begin{pmatrix} X \\ \bar{Y} \\ X^2 \\ X\bar{Y} \\ \bar{Y}^2 \end{pmatrix}$$

Justified by energy conservation constraints, check Schneider et al. 2017 for details (ESM 2.0 paper)

Application to the Lorenz96 model

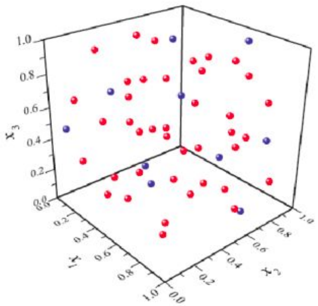
Experimental design

Initial guess of parameter space

Params	Prior	True
F	[-20,20]	10
h	[-2,2]	1
c	[0,20]	10
b	[-20,20]	10

40 samples from a LHS

Space filling design



Run the L96 model

Build a training database for the emulator:
x_train.size=(40,4)
y_train.size=(40,180)

Here, one GP Per output

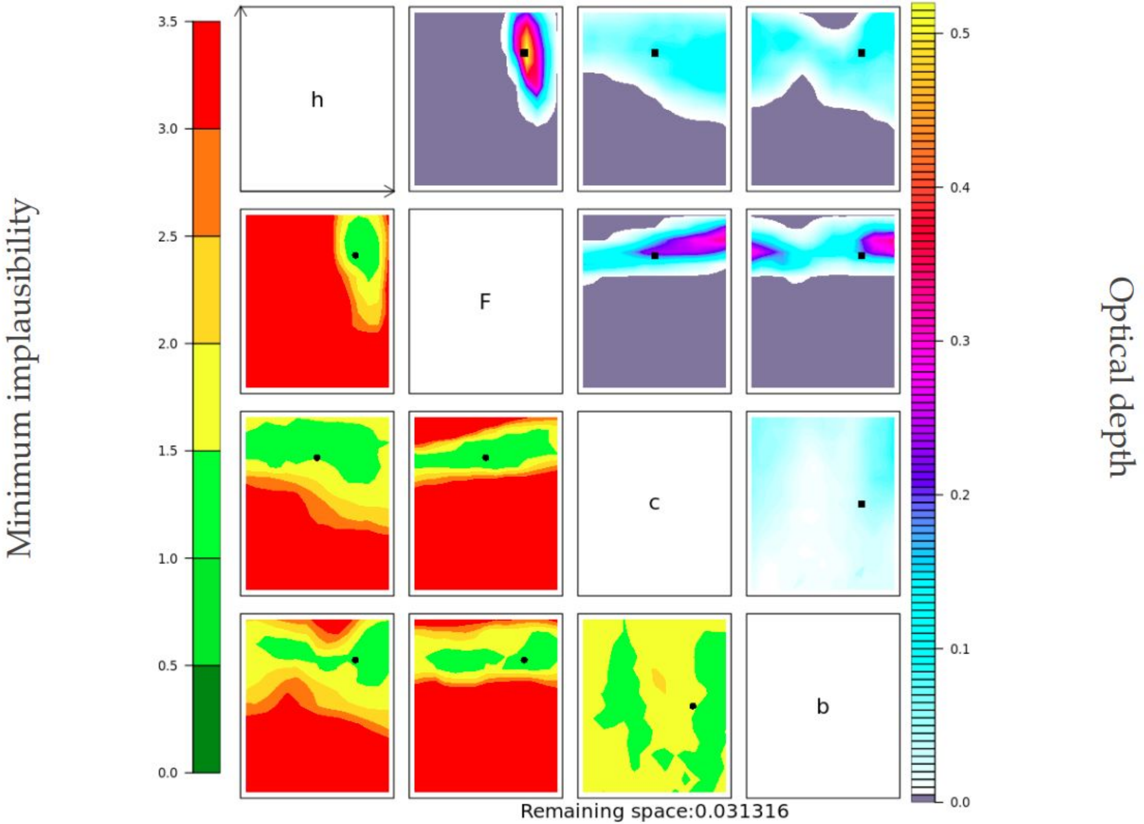
Train the emulator then use it for inference on a large number of samples

Calculate Implausibility

$$I(\boldsymbol{\theta}) = \frac{|E[f(\boldsymbol{\theta})] - z|}{\sqrt{\mathrm{Var}[f(\boldsymbol{\theta})]}}$$

Application to the Lorenz96 model

Not Ruled Out Yet space (NROY space)



Application to the Lorenz96 model

Lessons learned

- On an idealized experiment, HM combined with dimensionality reduction techniques (ex: PCA) applied to the two-scale L96 succeeded in narrowing the NROY on the ground truth values

- Incorporating as much **physical expertise** as possible (for example in the priors) helps reaching satisfying results in fewer waves than with a blind approach

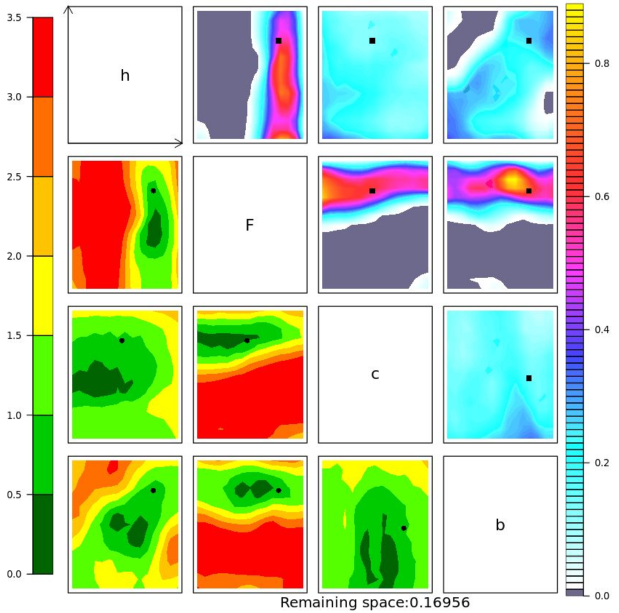
- Raising questions about the “default” choices used by practitioners. Example: After the first wave**, how to perform a space filling sampling of a discontinuous space?** and **how to select representative points from the final NROY ?**

$$\frac{dX_k}{dt} = \underbrace{-X_{k-1}\left(X_{k-2} - X_{k+1}\right)}_{\text{Advection}} \underbrace{-X_k}_{\text{Diffusion}} \underbrace{+F}_{Forcing} \underbrace{-\frac{hc}{b}\sum_{j=1}^{J} Y_{j,k}}_{Coupling}$$

SLOW

$$\frac{dY_{j,k}}{dt} = \underbrace{-cbY_{j+1,k}\left(Y_{j+2,k} - Y_{j-1,k}\right)}_{\text{Advection}} \underbrace{-cY_{j,k}}_{\text{Diffusion}} \underbrace{+\frac{hc}{b}X_k}_{\text{Coupling}}$$

FAST



Paper and Code

Lguensat et al. 2023

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Research Article | Open Access

Semi-Automatic Tuning of Coupled Climate Models With Multiple Intrinsic Timescales: Lessons Learned From the Lorenz96 Model

Redouane Lguensat, Julie Deshayes, Homer Durand, Venkatramani Balaji

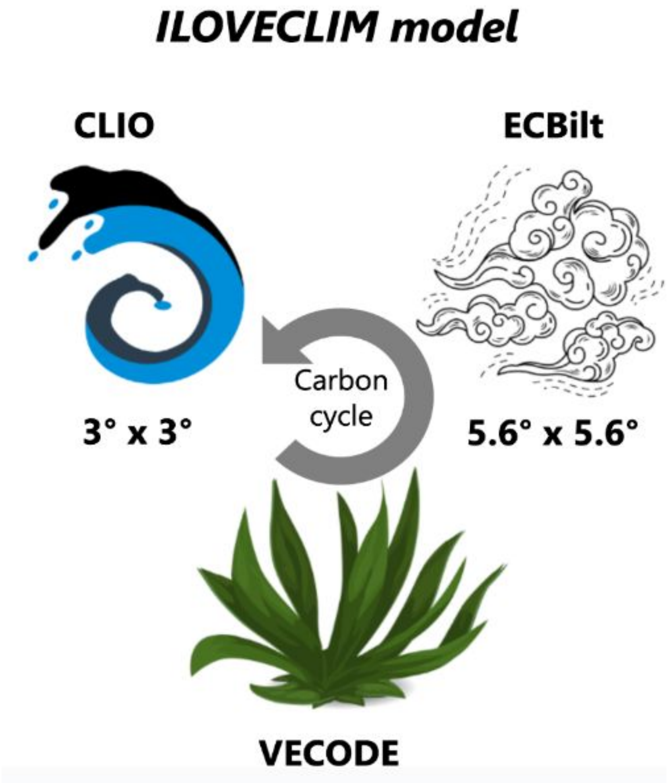
First published: 04 May 2023 | https://doi.org/10.1029/2022MS003367

https://github.com/HRMES-MOPGA/L96HistoryMatching

Intermediate complexity model: iLoveClim

Experimental design

- iLOVECLIM is a climate model of intermediate complexity, derived from the LOVECLIM model from Goose et al. (2010).
- 9 tunable parameters, affecting the **atmosphere**, the **ocean** and **land surfaces**
- Oceanic metrics are crucial to tune not only the oceanic parameters but can help improve tuning of land and atmospheric parameters as well.
- The temporality of the metrics is important, as computing 5-year-means is the best when considering atmospheric metrics alone, while computing 20-year-means seems optimal when considering atmospheric and oceanic metrics



Paper and Code

Janvier et al. 2023

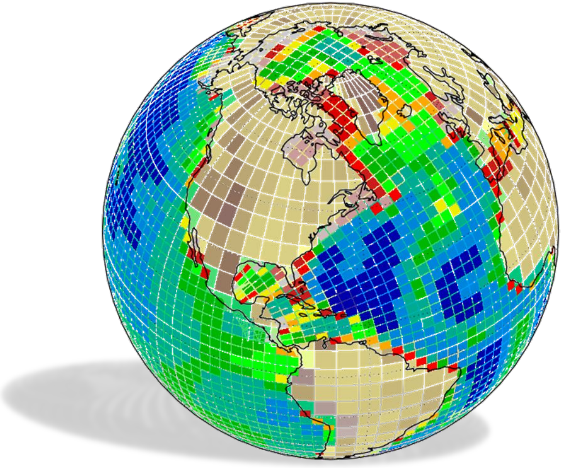
Poster
in
Workshop: NeurIPS 2023 Workshop on Tackling Climate Change with Machine Learning: Blending New and Existing Knowledge Systems

Surrogate modeling based History Matching for an Earth system model of intermediate complexity

Maya Janvier · Redouane Lguensat · Julie Deshayes · Aurélien Quiquet · Didier Roche · V. Balaji

https://github.com/mayajanvier/iLOVECLIM_HistoryMatching

Extended paper in prep..



Part IV

HM on real climate models

History Matching at IPSL & CNRM

Atmospheric Model

- HM was used to tune atmospheric models, ex: **LMDZ** (Hourdin et al. 2020, Couvreux et al. 2020)
- Using single-column models (SCMs) they afford to run several simulations with different set of parameters
- Short timescales, generating training datasets is fast
- Revisiting the “hand tuning” of IPSL-CM6A-LR configuration
- HM indicates **ARPEGE-Climat 6.3** turbulence parameterization deficiencies due to poor calibration

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Research Article | Open Access

Process-Based Climate Model Development Harnessing Machine Learning: I. A Calibration Tool for Parameterization Improvement

Fleur Couvreux, Frédéric Hourdin, Daniel Williamson, Romain Roehrig, Victoria Volodina, Najda Villefranque, Catherine Rio, Olivier Audouin, James Salter, Eric Bazile, Florent Brient, Florence Favot, Rachel Honnert, Marie-Pierre Lefebvre, Jean-Baptiste Madeleine, Quentin Rodier, Wenzhe Xu

... See fewer authors

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Research Article | Open Access

Process-Based Climate Model Development Harnessing Machine Learning: II. Model Calibration From Single Column to Global

Frédéric Hourdin, Daniel Williamson, Catherine Rio, Fleur Couvreux, Romain Roehrig, Najda Villefranque, Ionela Musat, Laurent Fairhead, F. Binta Diallo, Victoria Volodina

25 | Citations: 14

SCIENCE ADVANCES | RESEARCH ARTICLE

ATMOSPHERIC SCIENCE

Toward machine-assisted tuning avoiding the underestimation of uncertainty in climate change projections

Frédéric Hourdin[1]*, Brady Ferster[2], Julie Deshayes[2], Juliette Mignot[2], Ionela Musat[1], Daniel Williamson[3]

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Research Article | Open Access

Modeling the GABLS4 Strongly-Stable Boundary Layer With a GCM Turbulence Parameterization: Parametric Sensitivity or Intrinsic Limits?

O. Audouin, R. Roehrig, F. Couvreux, D. Williamson

History Matching at IPSL

Oceanic Model

- HM was used to tune ocean models, ex: **NEMO ORCA 2°** (Williamsson et al. 2017)

- Using an available ensemble of 400 NEMO simulations ran for 150 years

- Very long timescales in oceanic models which makes tuning complicated

Geosci. Model Dev., 10, 1789–1816, 2017
www.geosci-model-dev.net/10/1789/2017/
doi:10.5194/gmd-10-1789-2017

Geoscientific Model Development
Open Access

Tuning without over-tuning: parametric uncertainty quantification for the NEMO ocean model

Daniel B. Williamson[1], Adam T. Blaker[2], and Bablu Sinha[2]

[1]College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, UK
[2]National Oceanography Centre, Southampton, SO14 3ZH, UK

Correspondence to: Daniel B. Williamson (d.williamson@exeter.ac.uk)

Received: 20 July 2016 – Discussion started: 30 August 2016
Revised: 24 November 2016 – Accepted: 30 January 2017 – Published: 27 April 2017

Accelerating spin-up ? Emulating NEMO ?

History Matching at IPSL

Land Surface Model

- There is a trade-off to be found computationally speaking: waves in HM vs population in GA

- HM is a gradient-free technique which is seen as an advantage, as the adjoint of ORCHIDEE is expensive to maintain

Exploring the Potential of History Matching for Land Surface Model Calibration

Nina Raoult[1], Simon Beylat[2,3], James M. Salter[1], Frédéric Hourdin[4], Vladislav Bastrikov[5], Catherine Ottlé[2], and Philippe Peylin[2]

[1]Department of Mathematics and Statistics, Faculty of Environment, Science and Economy, University of Exeter, Laver Building, North Park Road, Exeter, EX4 4QE, UK
[2]Laboratoire des Sciences du Climat et de l'Environnement, LSCE/IPSL, CEA-CNRS-UVSQ, Université Paris-Saclay, Gif-sur-Yvette, 91191, France
[3]School of Geography, Earth and Atmospheric Sciences, University of Melbourne, Victoria, Australia
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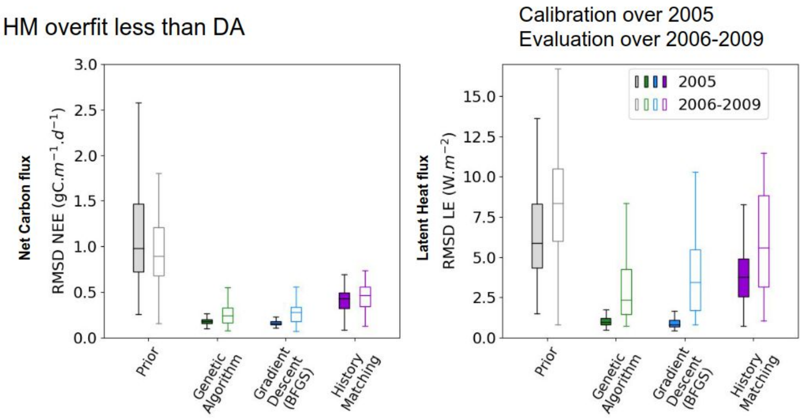
Correspondence: Nina Raoult (n.m.raoult2@exeter.ac.uk)



ORCHIDEE
LAND SURFACE MODEL

History Matching at IPSL & CNRM

Coupled models

I used DALLE3 to generate this image

Future work

PEPR TRACCS

PROGRAMME DE RECHERCHE
CLIMAT

PC-6	Calibration & uncertainties	• Julie Deshayes (IPSL-LOCEAN) • Aurore Voldoire (CNRM) • Romain Roehrig CNRM)

Towards HM-tuned IPSL/CNRM models for CMIP7 !

Tune in this Friday !

Secrétariat général pour l'investissement

I used Stable Diffusion to generate the image

I wish I had an emulator...

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