

Laboratório Nacional de Computação Científica

Programa de Pós-Graduação em Modelagem Computacional

Generalized Lambda Distribution for Uncertainty Quantification of Large-scale Spatio-temporal Models

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Petrópolis, RJ - Brasil

Abril de 2018

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Thesis submitted to the examining committee
in partial fulfillment of the requirements for
the degree of Doctor of Sciences in Computa-
tional Modeling.

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Abril de 2018

Dedication

To my little and special family.

Acknowledgements

O autor manifesta reconhecimentos às pessoas e instituições que colaboraram para a execução de seu trabalho.

“Essentially, all models are wrong, but some are useful.”
(George Edward Pelham)

Abstract

Segundo a ??, 3.1-3.2), o resumo deve ressaltar o objetivo, o método, os resultados e as conclusões do documento. A ordem e a extensão destes itens dependem do tipo de resumo (informativo ou indicativo) e do tratamento que cada item recebe no documento original. O resumo deve ser precedido da referência do documento, com exceção do resumo inserido no próprio documento. (...) As palavras-chave devem figurar logo abaixo do resumo, antecedidas da expressão Palavras-chave:, separadas entre si por ponto e finalizadas também por ponto.

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Abstract

Large-scale spatio-temporal simulations with quantified uncertainty enable scientists/decision-makers to precisely assess the degree of confidence of their simulation-based predictions. This uncertainty could be quantified or characterized in different ways, from the use of low order statistical moments (the most commonly used), to the evaluation of a complete PDF (a most complete approach). The latter provides a more comprehensive description of the uncertainty leading to aware decisions. However, fitting PDFs to the data is computational intensive. Moreover, due to heterogeneity the uncertainty computed in regions of the dataset is hampered by the existence of different PDF types.

In this thesis, we propose a new method to quantify the uncertainty in large-scale spatio-temporal models based on the Generalized Lambda Distribution (GLD). GLD is a family of PDFs that nicely models the heterogeneity of uncertainty as discussed above. It is specified by 4 parameters that simplifies PDFs comparisons easing analytical processing, such as clustering. We show how the dataset modeled through GLDs can be used to answer queries, such as: *(i)* how to group the output of the UQ process based on the similarity of the uncertainty?, *(ii)* what is the uncertainty in some spatio-temporal locations not previously analysed?, *(iii)* what is the uncertainty of an specific spatio-temporal region?, *(iv)* how to compare two regions as a function of its uncertainty?, and *(v)* what is the less uncertain model from a set of models? The proposed method has been tested in realistic use cases from various scientific areas. Additionally, an R package has been implemented with all the functionalities discussed in the thesis.

Keywords: Uncertainty Quantification, Large-scale spatio-temporal models, Big Data, Generalized Lambda Distribution

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List of abbreviations and acronyms

UQ	Uncertainty Quantification
FP	Forward Problem
<i>QoI</i>	Quantity of Interest
GLDEX	r package to compute the GLD

List of symbols

Γ	Letra grega Gama
Λ	Lambda
ζ	Letra grega minúscula zeta
\in	Pertence

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1 Introduction

The rapid growth of high-performance computing and the advances in numerical techniques in the last two decades have provided an unprecedented opportunity to explore complex physical phenomena using large-scale spatio-temporal modeling and simulation. At the same time, scientific community is leaving behind the traditional deterministic approach, which offers point predictions with no associated uncertainty (JOHNSTONE et al., 2016); to include Uncertainty Quantification (UQ) as a common practice in their researches.

Large-scale spatio-temporal simulations with quantified uncertainty enable scientists to make precise statements about the degree of confidence they have in their simulation-based predictions. These approaches find practical applicability in models for predicting the behavior of weather, hurricane forecasts (TOBERGTE; CURTIS, 2013), subsurface hydrology (BARONI; TARANTOLA, 2014), geology (GUERRA et al., 2016), nuclear reactor design, financial portfolios (CHEN; FLOOD; SOWERS, 2008), and biological phenomena, just to name a few. They also allow to study physical phenomena that are impossible to assess experimentally, for example: simulate nuclear accidents, or the conditions that some spatial vehicle will find at landing in Mars, and so on. The success of these techniques has made them increasingly important tools for high impact predictions and decision making.

UQ includes different aspects that warranty the predictive fidelity of a numerical simulation, such as the uncertainty in the experimental data, which is used for defining the parameter values of a model; the propagation of uncertain parameters through the model; and the choice of the model itself. UQ is a complex process that covers the following main tasks: (i) uncertainty characterization (CRESPO; KENNY; GIESY, 2014), also called model calibration (FARRELL, 2015) or statistical inverse problem (ESTACIO-HIROMS; PRUDENCIO, 2012); (ii) sensitivity analysis; (iii) forward problem or uncertainty propagation; and (iv) model selection.

This paper is focused on *forward propagation*, whose objective is to quantify the uncertainties in model output(s) propagated from uncertain inputs. The targets of *forward propagation* analysis can be: (i) evaluate low-order moments (i.e. mean and variance) of the outputs, (ii) evaluate the reliability of the outputs, and/or (iii) assess the complete probability distribution (PDF) of the outputs.

When dealing with large-scale spatio-temporal models, a huge amount of data is generated as a result of the simulation process. Indeed, on each spatio-temporal location $(s_i, t_j) \in \mathcal{S} \times \mathcal{T} \subseteq \mathbb{R}^3 \times \mathbb{R}$, usually more than 10^4 simulations are performed. Then, the size

of the output dataset is in the order of $N_s \times N_t \times N_{sim}$, where: N_s is the number of spatial locations, N_t is the number of time steps, and N_{sim} is the number of simulations. An example of the volume of data generated by these simulations is given in the experimental section ?? of this paper, where the output dataset is about 2.4 TB. This turn *forward propagation* in a data intensive problem.

Another important aspect, which is often not taken into account, is that the uncertainty need to be quantified in some way that can be used after, to answer questions that arise in the *UQ* context. In that sense, assess the complete *PDF* could be the best way to quantify uncertainty, because if you can find the *PDF* that best fit the dataset with reasonably accurately, you can get all the statistical properties under one roof. At the same time, we can substitute the original data by the *PDFs*, which represents a huge reduction in the volume of data to manipulate.

Contradictorily, statistical moments (e.g. mean and standard deviation) are possibly the most used ways to quantify the uncertainty, despite the fact that they doesn't have information about the manner in which the data are distributed (LAMPASI; Di Nicola; PODESTA, 2006). This is because of the difficulty to find the *PDF* that best fit a dataset (KARIAN; DUDEWICZ, 2011), even more, when dealing with large-scale spatio-temporal models where the *PDF* needs to be derived on each spatio-temporal location, and therefore the *forward propagation* problem becomes time consuming and computationally intensive too.

However, the use of low order moments alone prevents us from making accurate analysis with respect to the uncertainty. They are not enough neither for the characterization nor for the quantification of the uncertainty, and questions such as:

- What is the uncertainty in the spatio-temporal region $\mathcal{S}_i \times \mathcal{T}_j$ associated to the *QoI* q_k and a computational model \mathcal{M}_m ?
- How to compare different spatio-temporal regions $\mathcal{S}_i \times \mathcal{T}_j$ with respect to the uncertainty?
- What is the less uncertain model from the set of models $\mathcal{M} = \mathcal{M}_1, \mathcal{M}_2, \dots, \mathcal{M}_m$, to predict the value of a *QoI* q_k , over a spatio-temporal region $\mathcal{S}_i \times \mathcal{T}_j$?

can be poorly answered. So, we emphasize that only the characterization of the uncertainty by using the *PDF* allows aware decisions.

A first effort to try to estimate the *PDFs* on large-scale spatio-temporal simulations was done by (LIU et al.,) Ji et. al. in ***Parallel Computation of PDFs on Big Spatial Data Using Spark***. They propose a new solution to efficiently compute the *PDFs* in parallel using Spark, through three methods: data grouping, machine learning

prediction and sampling. The main drawback of the proposed approach is that you should try many different distributions, to find the PDF that best fits the dataset on each specific spatio-temporal location. Another drawback is that, as we mentioned above, the uncertainty needs to be quantified in the way that facilitates its further use; and the heterogeneity of the functions used in the approach doesn't facilitate it.

To face these challenges, in this paper we propose a general framework to quantify the uncertainty in large-scale spatio-temporal models. It uses a data-driven approach and combines the generalized lambda distribution (*GLD*), clusters algorithms and information entropy, for helping researchers to answer the above questions and many others that arise in *UQ* context. Our proposal provides a generally applicable and easy-to-use tool that supports the representation and analysis of uncertainty, as was suggested in the "*Workshop on Quantification, Communication, and Interpretation of Uncertainty in Simulation and Data Science*" (TOBERGTE; CURTIS, 2013).

In order to illustrate the use of the proposed framework, a case study is discussed. The main results obtained are: (i) the *GLD* good fits for more than the 80 % of the dataset, (ii) the use of the *GLD* allows to include clustering algorithms to group the spatio-temporal locations with similar uncertainty, (iii) the centroids of the clusters can be used as a faithful representation of the rest of the spatio-temporal locations, which significantly reduces the data corresponding to the simulation outputs, (iv) with the use of these centroids we can characterize the uncertainty in any spatio-temporal region as a mixture of *GLDs*.

The rest of the paper is organized as follows: Section ?? gives the theoretical foundations of *UQ* and highlights some interesting aspects included in our proposal. Section ?? describes the principal characteristics of the *GLD* that make it suitable for this proposal. Section ?? presents the proposed approach, the workflow we implement and some considerations of the implementation. Section ?? presents a use case and discusses the results. This use case allows us to explain our approach in the context of a real problem, which facilitates its understanding. Section ?? covers the related works and finally, section 8 concludes the paper and proposes some future works.

1.1 Research Objectives

The main objective of this thesis is the proposal of a new method to quantify the uncertainty in large-scale spatio-temporal models based on the Generalized Lambda Distribution (*GLD*).

To achieve that goal the following research questions need to be answered:

RQ1. how to group the output of the UQ process based on the similarity of the uncertainty?

RQ2. what is the uncertainty in some spatio-temporal locations not previously analysed?

RQ3. what is the uncertainty of an specific spatio-temporal region?

RQ4. how to compare two regions as a function of its uncertainty?

RQ5. what is the less uncertain model from a set of models?

RQ1 and **RQ2** are answered in chapter 5, while **RQ3**, **RQ4** and **RQ5** are answered in chapter 6. In chapter 7 all the questions are answered again for all the use cases.

1.2 Highlights of the Dissertation

1.3 Organization of the Dissertation

The structure of the remainder of this thesis is outlined for reference.

Chapter 2 background of UQ.

Chapter 3 Ji paper.

Chapter 4 GLD.

Chapter 5 GLD clustering and kriging.

Chapter 6 Workflow.

Chapter 7 Use cases.

Chapter 8 Conclusions and future works.

2 Uncertainty Quantification

“UQ cannot tell you that your model is ‘right’ or ‘true’, but only that, if you accept the validity of the model (to some quantified degree), then you must logically accept the validity of certain conclusions (to some quantified degree)”
(Sullivan, 2015)

In this chapter, we summarize some definitions in UQ context that are important to understand the rest of the document. Also, different ways of representation of the uncertainty are discussed, with a brief justification of those we are going to use in the thesis. A general workflow of the UQ process is presented where we contextualize our contributions. A detailed discussion about forward propagation is presented. And finally, we summarize the chapter.

2.1 Definitions

2.1.1 Errors vs Uncertainties

2.1.2 Aleatoric vs Epistemic Uncertainty

It is sometimes assumed that uncertainty can be classified into two categories, aleatoric and epistemic, (KIUREGHIAN; DITLEVSEN, 2009) although the validity of this categorization is open to debate.

Aleatoric uncertainty arises from an inherent randomness in the properties or behavior of the system under study. For example, the weather conditions at the time of a reactor accident are inherently random with respect to our ability to predict the future. Other examples include the variability in the properties of a population of weapon components and the variability in the possible future environmental conditions that a weapon component could be exposed to. Alternative designations for aleatory uncertainty include variability, stochastic, irreducible and type A. (HELTON, 2009)

Epistemic uncertainty derives from a lack of knowledge about the appropriate value to use for a quantity that is assumed to have a fixed value in the context of a particular analysis. For example, the pressure at which a given reactor containment would fail for a specified set of pressurization conditions is fixed but not amenable to being unambiguously defined. Other examples include minimum voltage required for the operation of a system and the maximum temperature that a system can withstand before failing. Alternative

designations for epistemic uncertainty include state of knowledge, subjective, reducible and type B. (HELTON, 2009)

2.2 Uncertainty Representation

An immediate challenge in the development of an appropriate treatment of uncertainty is the selection of a mathematical structure to be used in its representation (HELTON et al., 2010). Traditionally, probability theory has provided this structure [48-55]. However, in the last several decades, additional mathematical structures for the representation of uncertainty such as evidence theory [56-63], possibility theory [64- 70], fuzzy set theory [71-75], and interval analysis [76-81] have been introduced. This introduction has been accompanied by a lively discussion of the strengths and weaknesses of the various mathematical structures for the representation of uncertainty [82-90]. For perspective, several comparative discussions of these different approaches to the representation of uncertainty are available [72; 91-98]

This section briefly summarizes some of this approaches, and discuss in more details probability theory as this is the main one used in the rest of the thesis.

2.2.1 Interval Analysis

2.2.2 Variance

2.2.3 Information Entropy

The concept of information entropy was first defined by Shannon (1948) in a study performed to identify the amount of information required to transmit English text. The underlying idea was that, given the probabilities of letters occurring in the English alphabet, it is possible to derive a measure describing the missing information to determine the full text of a partially transmitted message, where information is understood as the information required to identify the message, not the information of the message itself. Based on several theoretical considerations, Shannon derived the following equation to classify a measure of the missing information, often referred to as information entropy:

$$H = - \sum_i^N p_i \log p_i \quad (2.1)$$

The information entropy H is defined as the sum of the product of the probability p for each possible outcome i of N , total possible outcomes, with its logarithm. The minimum value is 0, because $\log 1 = 0$.

2.2.3.1 Information entropy in a spatio-temporal context

For each spatio-temporal region, the information entropy can be described as:

$$H(s, t) = - \sum_{m=1}^M p_m(s, t) \log p_m(s, t) \quad (2.2)$$

where s denotes the location of the subregion, M represents the number of possible (exclusive) members the subregion may contain, and t is the physical time.

2.2.3.2 Information entropy as a measure of uncertainty

Based on 2.2.3 and 2.2.3.1, if the possible outcomes of the model and the probability of each outcome on each (s, t) , are known, then the information entropy could be used as a qualitative measure of the uncertainty of the model output. For example, in a spatio-temporal region (s, t) where the outcome is always the same, the information entropy is 0, because the outcome is known. On the other hand, in the worse case where all the outcomes have the same probability in (s, t) , the entropy is maximum and the uncertainty too.

2.2.4 Probability Theory

2.3 Methods for Uncertainty Propagation

2.3.1 Sampling Methods

2.3.1.1 Monte Carlo

Monte Carlo simulations (MCS) provide the most robust and straightforward way to solve PDEs with random coefficients. In the case of (22.2), for instance, they consist of (i) generating multiple realizations of the input parameters a and b , (ii) solving deterministic PDEs for each realization, and (iii) evaluating ensemble statistics or PDFs of these solutions. MCS do not impose limitations on statistical properties of input parameters, entail no modifications of existing deterministic solvers, and are ideal for parallel computing (HIGDON, 2017).

2.4 Software and Tools for UQ

Currently, advances in uncertainty propagation and assessment have been paralleled by a growing number of software tools for uncertainty analysis, but none has gained recognition for a universal applicability, including case studies with spatial models and spatial model inputs. (K. Sawicka; SOIL, 2016)

These include both free software, like OpenTURNS (Andrianov et al., 2007), DACOTA (Adams et al., 2009) and DUE (Brown and Heuvelink, 2007), commercial, like COSSAN (Schuëller and Pradlwarter, 2006), or free, but written for a licenced software, e.g. SAFE (Pianosi et al., 2015) or UQLab (Marelli and Sudret, 2014) toolboxes for MATLAB. A broad review of existing software packages is available in Bastin et al. (2013). To the best of our knowledge, however, none of the existent software is specifically designed to be extended by the environmental science community. The use of powerful but complex languages like C++ (e.g. Dakota), Python (e.g. OpenTURNS) or Java (e.g. DUE) often discourages relevant portions of the non-highly-IT trained scientific community from the adoption of otherwise powerful tools. spup-R package (K. Sawicka; SOIL, 2016). De aqui saque lo de arriba tambien, aunque lo de arriba lo puedo buscar en sus respectivos papers y hablar un poco de cada uno de ellos.

2.5 Summary

2.6 Concepts

high-dimensional parameter spaces computationally demanding forward models nonlinearity and/or complexity in the forward model

2.7 Ideas a usar

HPC and computational modeling play a dominant role in shaping the methodological developments and research in uncertainty qualification. Depending on the complexity of the uncertainty qualification investigation, anywhere from 10^2 to 10^8 runs of the computational model may be required. Thus, uncertainty qualification investigations may require extreme-computing environments (e.g., exascale) to obtain results in a useful time frame, even if a single run of the computational model does not require such resources.

Advances in computing over the past few decades—both in availability and power—have led to an explosion in computational models available for simulating a wide variety of complex physical (and social) systems. These complex models—which may involve millions of lines of code, and require extreme-computing resources—have led to numerous scientific discoveries and advances. This is because these models allow simulation of physical processes in environments and conditions that are difficult or even impossible to access experimentally. However, scientists’ abilities to quantify uncertainties in these model-based predictions lag well behind their abilities to produce these computational models. This is largely because such simulation-based scientific investigations present a set of challenges that is not present in traditional investigations.

Until recently, the original approach of describing model parameters using single values has been retained, and consequently the majority of mathematical models in use today provide point predictions, with no associated uncertainty. (JOHNSTONE et al., 2016)

a 'typical' UQ problem involves one or more mathematical models for a process of interest, subject to some uncertainty about the correct form of, or parameter values for, those models.

Often, though not always, these uncertainties are treated probabilistically.

but how will you actually go about evaluating that expected value when it is an integral over a million-dimensional parameter space? Practical problems from engineering and the sciences can easily have models with millions or billions of inputs (degrees of freedom).

the language of probability theory is a powerful tool in describing uncertainty

UQ cannot tell you that your model is 'right' or 'true', but only that, if you accept the validity of the model (to some quantified degree), then you must logically accept the validity of certain conclusions (to some quantified degree). (SULLIVAN, 2015)

"UQ studies all sources of error and uncertainty, including the following: systematic and stochastic measurement error; ignorance; limitations of theoretical models; limitations of numerical representations of those models; limitations of the accuracy and reliability of computations, approximations, and algorithms; and human error. A more precise definition is UQ is the end-to-end study of the reliability of scientific inferences."

UQ is not a mature field like linear algebra or single-variable complex analysis, with stately textbooks containing well-polished presentations of classical theorems bearing August names like Cauchy, Gauss and Hamilton. Both because of its youth as a field and its very close engagement with applications, UQ is much more about problems, methods and 'good enough for the job'. There are some very elegant approaches within UQ, but as yet no single, general, over-arching theory of UQ.

In

Probability theorists usually denote the sample space of a probability space by Ω ; PDE theorists often use the same letter to denote a domain in \mathbb{R}^n on which a partial differential equation is to be solved. In UQ, where the worlds of probability and PDE theory often collide, the possibility of confusion is clear. Therefore, this book will tend to use Θ for a probability space and \mathbf{X} for a more general measurable space, which may happen to be the spatial domain for some PDE.

3 Parallel Computation of PDFs on Big Spatial Data Using Spark

3.1 Introduction

3.2 Architecture for Computing PDFs in Spark

3.3 Experimental Evaluation

4 The Generalized Lambda Distribution

“There are good reasons for using the GLD distribution methods... GLD fits have been used successfully in many fields ... Try the GLD first and stop there if the results are acceptable.”
(Karian and Dudewicz, 2011)

4.1 The Generalized Lambda Distribution

4.1.1 The Ramberg and Schmeiser Parametrization

The Generalized Lambda Distribution (GLD) was defined by Ramberg and Schmeiser in 1974 by the quantil function:

$$F^{-1}(p|\lambda) = F^{-1}(p|\lambda_1, \lambda_2, \lambda_3, \lambda_4) = \lambda_1 + \frac{p^{\lambda_3} - (1-p)^{\lambda_4}}{\lambda_2} \quad (4.1)$$

where p are the probabilities, $p \in [0, 1]$, λ_1 and λ_2 are the location and scale parameters, and λ_3 and λ_4 determine the skewness and kurtosis of the $GLD(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$.

Some restrictions in the values of $\lambda_1, \lambda_2, \lambda_3$ and λ_4 define if the GLD is valid. Those restrictions define 6 regions as is shown in table

The probability density function of the GLD at the point $x = F^{-1}(p)$ is given by:

$$f(x) = f(F^{-1}(p)) = \frac{\lambda_2}{\lambda_3 p^{\lambda_3-1} + \lambda_4 (1-p)^{\lambda_4-1}} \quad (4.2)$$

Note that the valid parameters of λ guaranty that:

$$f(x) \geq 0 \quad (4.3)$$

Table 1 – The range of the GLD parameters and the minimum and maximum values corresponding to the labeling of the regions given in Figure

Region	λ_1	λ_2	λ_3	λ_4	Minimum	Maximum
1 and 5	all	< 0	< -1	> 1	$-\infty$	$\lambda_1 + \frac{1}{\lambda_2}$
2 and 6	all	< 0	> 1	< -1	$\lambda_1 - \frac{1}{\lambda_2}$	∞
3	all	> 0	> 0	> 0	$\lambda_1 - \frac{1}{\lambda_2}$	$\lambda_1 + \frac{1}{\lambda_2}$
	all	> 0	$= 0$	> 0	λ_1	$\lambda_1 + \frac{1}{\lambda_2}$
	all	> 0	> 0	$= 0$	$\lambda_1 - \frac{1}{\lambda_2}$	λ_1
4	all	< 0	< 0	< 0	$-\infty$	∞
	all	< 0	$= 0$	< 0	λ_1	∞
	all	< 0	< 0	$= 0$	$-\infty$	λ_1

$$\int f(x)dx = 1 \quad (4.4)$$

4.1.2 The FMKL Parametrization

4.2 Fitting Mixture Distributions Using a Mixture of Generalized Lambda Distributions

Esto esta en ([TOBERGTE; CURTIS, 2013](#))

4.3 From Emperimental Data to GLD Paremeters

([LAMPASI; Di Nicola; PODESTA, 2006](#))

4.4 GLD Shapes

4.5 The GLDEX R package

4.6 GLD mixture

5 Clustering Uncertain Data Based on GLD Similarity

5.1 Related Works

(JIANG et al., 2011)

5.2 Clustering Based on GLD

Seudo codigo aqui con la explicacion de que es lo que pensamos hacer.

Algorithm 1 Fitting the GLD to a spatio-temporal dataset

```

1: function GLDFIT( $S(s_i, t_j, \langle q_1, q_2, \dots, q_n \rangle)$ )
2:    $\langle \lambda_1, \lambda_2, \lambda_3, \lambda_4 \rangle \leftarrow \text{FIT.GLD.LM}(\langle q_1, q_2, \dots, q_n \rangle)$ 
3:    $isValid_{(s_i, t_j)} \leftarrow \text{VALIDITYCHECK}(\langle \lambda_3, \lambda_4 \rangle)$ 
4:   if  $isValid_{(s_i, t_j)}$  then
5:      $[pvalue, D]_{(s_i, t_j)} \leftarrow \text{KS}(\langle \lambda_1, \lambda_2, \lambda_3, \lambda_4 \rangle_{(s_i, t_j)})$ 
6:   if  $pvalue_{(s_i, t_j)} > 0.05$  then
7:      $\text{STORELAMBDAS}(\langle \lambda_1, \lambda_2, \lambda_3, \lambda_4 \rangle, s_i, t_j)$ 

```

5.3 Empirical Study

In this section we are going to test our hypothesis in two synthetic datasets.

5.4 Synthetic Data I

To generate the first synthetic data set we use 11 probability density functions, where 5 are Gaussian, 5 Exponential, and one Uniform. The variance of the 5 Gaussian distributions is $0.05 * i$, with $i = 1, 2, 3, 4, 5$, and we generate 90 samples of each distribution. This is, the first 90 objects where generated from a Gaussian distribution with variance 0.05, and so on. Similarly, the rate of the 5 Exponential distributions is $0.05 * i$, and again we generate 90 samples of each one. Finally, 100 samples of a Uniform distribution between $[0, 1]$ were generated. In resume, we have 1000 objects, where the first 450 were sampled from Gaussian distributions, the next 450 from an Exponential and the last 100 from a Uniform distribution. As we generate a synthetic dataset in this way, we have the ground truth of the clustering in the dataset. This ground truth is used to evaluate the clustering quality of our algorithms.

5.4.1 Clustering using λ_2 , λ_3 and λ_4

Clusters que formaron la imagen normal exponencial uniform2 cl clusters size 86
86 100 93 90 195 102 84 5 90 69

Clusters que formaron la imagen normal exponencial uniform3 cl clusters size 82
93 5 198 102 83 91 82 90 84 90

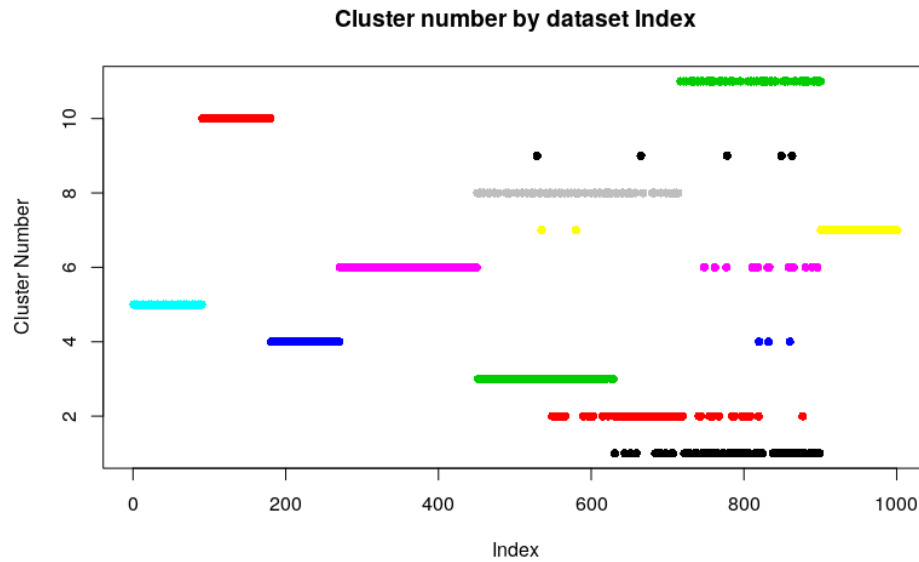


Figure 1 – Goodness of the fit based on the p -value

5.4.2 Clustering using λ_3 and λ_4

cl1 clusters size 197 118 110 35 41 65 2 131 74 105 122

5.4.3 Effectiveness of the Clustering

5.5 Synthetic Data II

5.5.1 Clustering using λ_2 , λ_3 and λ_4

cl2 clusters size 100 106 91 20 67 89 90 6 26 52 92 95 73 90 90 363

5.5.2 Clustering using λ_3 and λ_4

5.5.3 Effectiveness of the Clustering

5.6 Conclusions

6 Our Approach

In the more general case the computational model $\mathbf{q} = \mathcal{M}(\boldsymbol{\theta})$ represents the spatio-temporal evolution of a complex systems, and the *QoI* \mathbf{q} could be represented as:

$$\mathbf{Q} = (\mathbf{q}(s_1, t_1), \mathbf{q}(s_2, t_2), \dots, \mathbf{q}(s_n, t_n)) \quad (6.1)$$

where:

- $(s_1, t_1), (s_2, t_2), \dots, (s_n, t_n) \in \mathcal{S} \times \mathcal{T} \subseteq \mathbb{R}^3 \times \mathbb{R}$ represent a set of distinct spatio-temporal locations, and
- $\mathbf{q}(s_i, t_j)$ represents a value of the *QoI* at the spatio-temporal location (s_i, t_j)

We could have many *QoI*, but for simplicity here we are going to consider just one.

In the presence of a stochastic problem, on each spatio-temporal location (s_i, t_j) we have many realizations of $q(s_i, t_j)$. A structure of a database to store this information can be modeled as:

$$S(s_i, t_j, \text{simId}, q(s_i, t_j)) \quad (6.2)$$

where *simId* represents the *id* of one simulation (realization).

The first step of our approach consists of trying to find the *GLD* that best fits our simulations on each spatio-temporal location. The algorithms are described in the next section.

6.1 Fitting a GLD to a spatio-temporal dataset

Given a random sample $q_1, q_2, q_3, \dots, q_n$, the basic problem in fitting a statistical distribution to these data is that of approximating the distribution from which the sample was obtained. In our approach we divide this step in three task:

- Fit the *GLD* to the data.
- Evaluate the validity of the resulting *GLD* on each spatio-temporal location.
- Perform a ks-test to evaluate the quality of the fit on each spatio-temporal location.

The fitting process has been implemented following the algorithm 2. Before starting the fitting process, we need to group all the simulations that correspond to the same spatio-temporal location (s_i, t_j) . As a result we get a new dataset $S^*(s_i, t_j, \langle q_1, q_2, \dots, q_n \rangle)$, where $q_i, 1 \leq i \leq n$, represents a vector of all the values of q at point (s_i, t_j) .

6.1.1 Fitting process

Now, for each spatio-temporal location $(s_i, t_j) \in \mathcal{S} \times \mathcal{T}$ we use a function of the GLDEX R package described in section ??, to fit the *GLD* to a vector $\langle q_1, q_2, \dots, q_n \rangle$, line 2 of algorithm 2. As a result of this task we get the lambda values of the *GLD* that best fit the dataset at each spatio-temporal location, equation 6.3.

$$S'(s_i, t_j, GLD(\lambda_1, \lambda_2, \lambda_3, \lambda_4)) \quad (6.3)$$

6.1.2 GLD validity check

As we mention in section ?? the *GLD* is not always valid, it depends of the λ_3 and λ_4 values. The evaluation of the validity of the *GLD* is straightforward, if λ_3 and λ_4 are in the gray regions of Figure ?? the *GLD* is not valid, on the other case is valid.

The validity check is performed in line 3 of the algorithm 2, and as a result we get:

$$S_{\text{validity}}(s_i, t_j, \text{valid}(s_i, t_j)), \quad (6.4)$$

where:

$$\text{valid}(s_i, t_j) = \begin{cases} 1 & \text{if GLD is valid in } (s_i, t_j) \\ 0 & \text{otherwise} \end{cases} \quad (6.5)$$

6.1.3 Quality of the fit

Now at the remaining points, where the *GLD* is valid, we need to evaluate how good is the fit. That is, we evaluate whether the *GLD* (PDF) correctly describes the dataset. We use here the Kolmogorov-Smirnov test (KS-test). The KS-test determines if two datasets differ significantly. In this case, these datasets are: the original dataset and a second one generated using the fitted *GLD*. As a result, this test returns two values: a Kolmogorov-Smirnoff Distance (D); and a p-value, line 5 of algorithm 2. The distance D is the maximum distance between both cumulative density functions (CDF), as shown in Figure 2. A small distance means that both, the dataset and the fitted PDF, are similar.

The second value, the p-value, is a more robust test, as it helps us to determine the significance of our results. Suppose we have two hypotheses, the null hypothesis is that our PDF is a good fit to our dataset, and the alternative hypothesis is that it is not. Then, a small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject the null hypothesis. A large p-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis. p-values very close to the cutoff (0.05) are considered to be marginal (could go either way).

At the end of this task we have two new multidimensional arrays with the values of \mathcal{D} and p-value on each spatio-temporal locations.

$$S_{\mathcal{D}}(s_i, t_j, \mathcal{D}(s_i, t_j)) \quad (6.6)$$

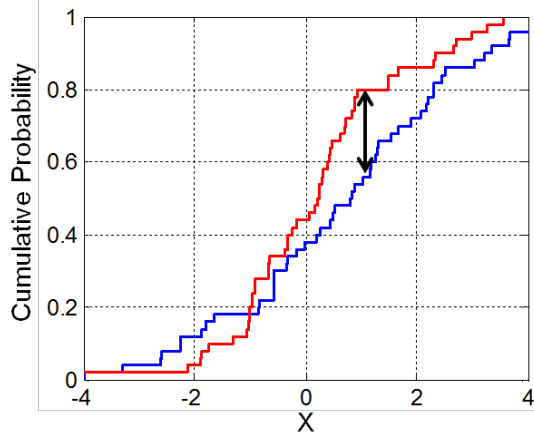


Figure 2 – Illustration of the two-sample Kolmogorov–Smirnov statistic. Red and blue lines each correspond to an empirical distribution function, and the black arrow is the two-sample KS statistic.

$$S_{pvalue}(s_i, t_j, pvalue(s_i, t_j)) \quad (6.7)$$

Finally, in line 7 of the algorithm 2 we store the lambda values of those *GLDs* that are valid and return p-values greater than 0.05.

Algorithm 2 Fitting the GLD to a spatio-temporal dataset

```

1: function GLDFIT( $S(s_i, t_j, < q_1, q_2, \dots, q_n >)$ )
2:    $< \lambda_1, \lambda_2, \lambda_3, \lambda_4 > \leftarrow \text{FIT.GLD.LM}(< q_1, q_2, \dots, q_n >)$ 
3:    $isValid_{(s_i, t_j)} \leftarrow \text{VALIDITYCHECK}(< \lambda_3, \lambda_4 >)$ 
4:   if  $isValid_{(s_i, t_j)}$  then
5:      $[pvalue, D]_{(s_i, t_j)} \leftarrow \text{KS}(< \lambda_1, \lambda_2, \lambda_3, \lambda_4 >_{(s_i, t_j)})$ 
6:   if  $pvalue_{(s_i, t_j)} > 0.05$  then
7:      $\text{STORELAMBDAS}(< \lambda_1, \lambda_2, \lambda_3, \lambda_4 >, s_i, t_j)$ 

```

6.2 Clustering the GLD based on its lambda values

In section ?? we discussed the different shapes of the GLD and define the regions of the (λ_3, λ_4) space where the shapes are similar. In Figure ??, we show how similar values of λ_3 and λ_4 lead to similar shapes. This fact suggests that one can clusterize the *GLD* based on its lambda values. The result of this clusterization are groups of *GLDs* with similar shapes (behaviors).

In addition to λ_3 and λ_4 , which represent the right and left tails of the distribution, we have also to consider λ_2 , as the latter represents the dispersion of the distribution.

Then, in this step of our workflow, we clusterize the *GLDs* using λ_2 , λ_3 and λ_4 values. The final result of this step is:

$$S_{\mathcal{C}}(s_i, t_j, GLD_k, clusterID) \quad (6.8)$$

where: *clusterID* represents the ID of the cluster to which the *GLD* at the spatio-temporal location (s_i, t_j) belongs.

With the *GLD* clusterized, we can use this result to characterize the uncertainty in a particular spatio-temporal region, or to measure numerically the corresponding uncertainty. In subsections 6.3 and 6.4, we describe how those approaches are implemented (see Figure 3).

6.3 Use of GLD mixture to characterize the uncertainty in an spatio-temporal region

One of the main advantages of assessing the complete probability distribution of the outputs, in place of low order moments (mean and standard deviation), is that we can use the *PDFs* to answer queries. For example, suppose we want to know the mean and standard deviation in a particular spatio-temporal region $(\mathcal{S}_i \times \mathcal{T}_j)$, or we want to observe graphically the distribution of the raw data generated in the simulation process in a spatio-temporal region.

Let us consider the second query. Up to this point, we have discussed the fit of *GLDs* that characterize the uncertainty at each spatio-temporal locations (s_i, t_j) , and the cluster to which the *GLD* at that particular spatio-temporal location would belong to. If we consider the clusterization of *GLD* to be of good quality, we can pick the *GLD* at the centroid of each cluster as a representative of all its members. In this context, in a particular spatio-temporal region, each cluster may be qualified with a weight given by:

$$w_k = \frac{1}{N} \sum_{i=1}^S \sum_{j=1}^T w(s_i, t_j) \quad (6.9)$$

where:

$$w(s_i, t_j) = \begin{cases} 1 & \text{if } clusterID(s_i, t_j) = k \\ 0 & \text{otherwise} \end{cases} \quad (6.10)$$

and N is the number of points in the region $(\mathcal{S}_i \times \mathcal{T}_j)$.

The weight w_k is the frequentist probability of occurrence of the cluster k in the region, and complies with the conditions outlined in section ?? that $w_k \geq 0$ and $\sum w_k = 1$.

Remember that the mixture of the *GLDs* can be written as:

$$f(x) = \sum_{k=1}^K w_k GLD(\lambda_1, \lambda_2, \lambda_3, \lambda_4) \quad (6.11)$$

So, if we have the weights and a representative GLD for each cluster, we have the mixture of GLD that characterizes the uncertainty in the spatio-temporal region $(\mathcal{S}_i \times \mathcal{T}_j)$.

The GLD mixture process is summarized in algorithm 3.

Algorithm 3 GLD mixture in a region $(\mathcal{S}_i \times \mathcal{T}_j)$

```

1: function GLDMIXTURE( $\mathcal{S}_i \times \mathcal{T}_j, C_{\mathcal{S}_i \times \mathcal{T}_j}$ )
2:   for each  $p_i$  in  $(\mathcal{S}_i \times \mathcal{T}_j)$  do
3:      $c \leftarrow \text{cluster}(p_i)$ 
4:      $w_c = w_c + 1$ 
5:      $N = N + 1$ 
6:   end for
7:   return  $\frac{1}{N} \sum_c^{C_{\mathcal{S}_i \times \mathcal{T}_j}} w_c * c.\text{getGLD}()$ 

```

6.4 Information entropy as a measure of the uncertainty in an spatio-temporal region

Now, what happen if we want to measure the uncertainty quantitatively? As we mention in subsection 2.2.3.2 the information entropy is useful in this context. The limitation we mention in that section is solved here, because we can use the different clusters we got in section 6.2 as the different outcomes of the system. The equation 2.2 can be rewritten as follow:

$$H(s, t) = - \sum_{c=1}^C p_c(s, t) \log p_c(s, t) \quad (6.12)$$

where c represent a particular cluster of the total number of clusters C , and $p_c(s, t)$ represent the probability of occurrence of the cluster c in the spatio-temporal region (s, t) .

Algorithm 4 Information Entropy in a region $(\mathcal{S}_i \times \mathcal{T}_j)$

```

1: function GLDMIXTURE( $\mathcal{S}_i \times \mathcal{T}_j, C_{\mathcal{S}_i \times \mathcal{T}_j}$ )
2:   for each  $p_i$  in  $(\mathcal{S}_i \times \mathcal{T}_j)$  do
3:      $c \leftarrow \text{cluster}(p_i)$ 
4:      $w_c = w_c + 1$ 
5:      $N = N + 1$ 
6:   end for
7:    $p_c(s, t) = \frac{w_c}{N}$ 
8:    $H(s, t) \leftarrow - \sum_{c=1}^C p_c(s, t) \log p_c(s, t)$ 
9:   return  $H(s, t)$ 

```

Algorithm 4 computes the Information Entropy in a region $C_{(\mathcal{S}_i \times \mathcal{T}_j)}$. In lines 2 to 7, we compute the probability of each cluster in the region. Using this probability we compute the information entropy $H(s, t)$, line 8, and finally we return the result in line 9.

6.5 Information entropy and model selection

6.6 UQ Proposed Dataflow

Summarizing, we proposed a workflow to quantify the uncertainty in large-scale spatio-temporal models, figure 3. The workflow is divided into three main steps, the fitting process, the clustering and the queries. We illustrate the use of the workflow with two queries, sections 6.3 and 6.4.

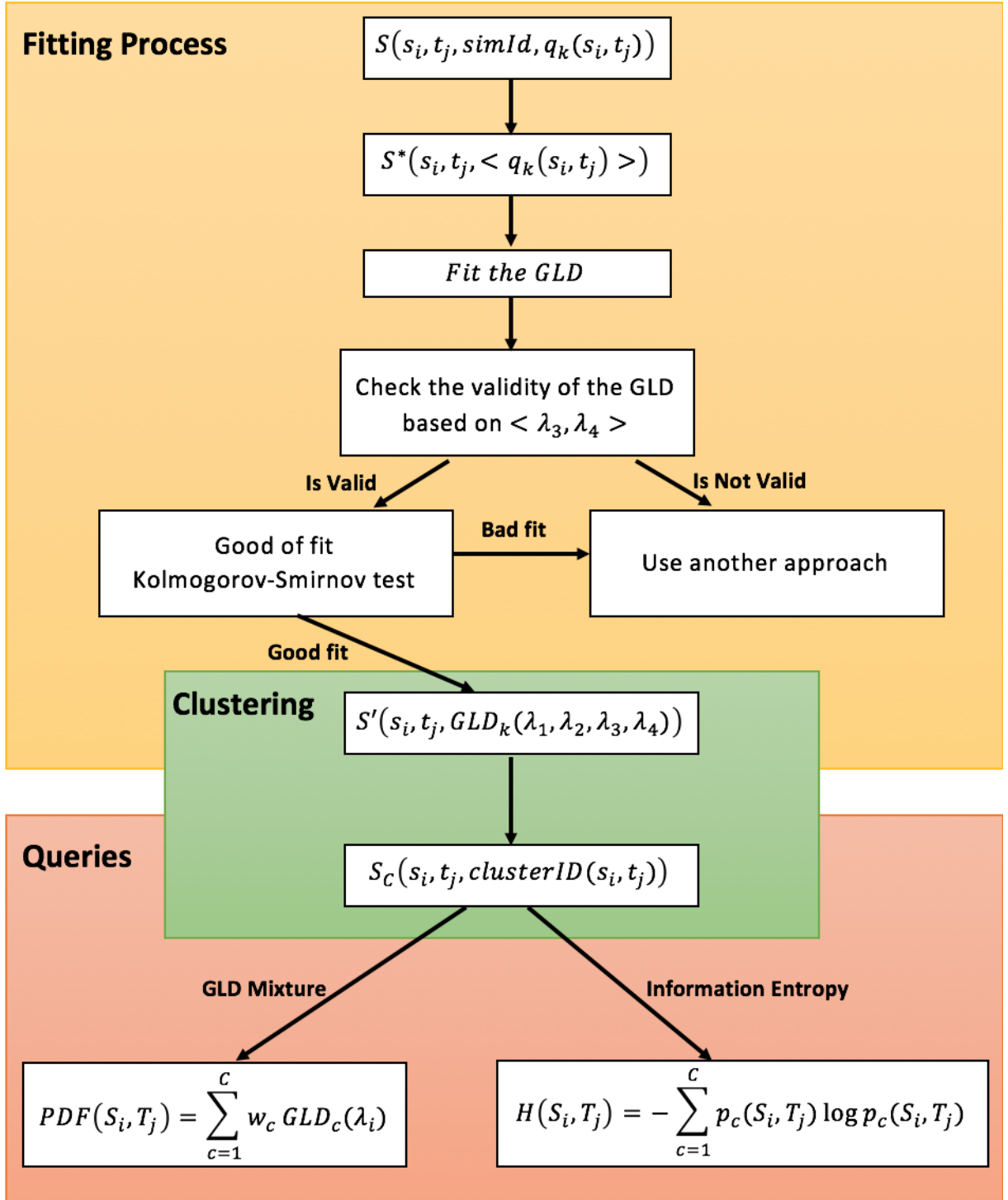


Figure 3 – Proposed workflow. The workflow was divided in three steps, (a) the fitting process, (b) the clustering of the GLDs and, (c) the queries over the results of the clustering process.

6.7 LaSST-UQ R package

6.8 Conclusions

7 Use Cases

In the present chapter we are going to test the UQMS in three different scenarios, spatial only domain, section 7.1, spatio-temporal domain, section 7.2, and finally a multidisciplinary system, section 7.3.

7.1 Case Study: Wave Propagation Problem

The first one is a geophysical tests for wave propagation problems

As a first case study we use the “HPC4E Seismic Test Suite”, a collection of four 3D models and sixteen associated tests that can be downloaded freely at the project’s website (<https://hpc4e.eu/downloads/datasets-and-software>). The models include simple cases that can be used in the development stage of any geophysical imaging practitioner (developer, tester ...) as well as extremely large cases that can only be solved in a reasonable time using ExaFLOPS supercomputers. The models are generated to the required size by means of a Matlab/Octave script and hence can be used by users of any OS or computing platform. The tests can be used to benchmark and compare the capabilities of different and innovative seismic modelling approaches, hence simplifying the task of assessing the algorithmic and computational advantages that they pose.

In our case, we are going to use the “HPC4E Seismic Test Suite” as a case study of the proposed UQMS. As we mention in the introduction of this chapter this model is a spatial only domain problem, because we are going to consider a multidimensional array as an Input and a multidimensional array as an output, but of them time independent.

7.1.1 Mathematical Formulation

7.1.2 Model and Dataset Description

The models have been designed as a set of 16 layers with constant physical properties. The top layer delineates the topography and the other 15 different layer interface surfaces or horizons. In the following, an interface horizon is associated with properties that apply to the layer that exists between itself and the immediately next layer horizon. The model covers an area of 10 x 10 x 5 km, with maximum topography at about 500 m and maximum depth at about 4500 m. The layer horizons have been sampled very finely with 1.6667 m spacing so that a highly accurate representation can be honored at high frequencies. For simulation schemes based on unstructured grids, the layer horizons can be used easily to constrain model blocks. For simulation schemes based upon Cartesian grids, a simple

Table 2 – Layer constant properties and their depth range. “Star” layers are only used in the flat case, in substitution of their non-star equivalents

Layer Id	Vp (m/s)	Vs (m/s)	Density (Kg/m3)	Max. depth (m)	Min. depth (m)
1	1618.92	500.00	1966.38	-135.55	-476.35
2	1684.08	765.49	1985.88	41.50	-394.90
3					
4					
5					
6					
7					
8					
9					
10					
11					
12					
13					
14					
15					
16					
2*					
3*					

script is provided that can generate 3D grids for any desired spatial sampling. Table 2 shows the properties of each of the layers included in the models.

7.1.3 Adding uncertainty into the model

The “HPC4E Seismic Test Suite” does not provide uncertainty sources, because all the input parameters of the model have fixed values. Then, to the purpose of our work we need to add some uncertainties into the inputs. Let’s suppose the variable V_p is uncertain. As this variable have 16 different values, one for each layer, we can consider it as a random vector, equation 7.1. We associate to each of the V_{p_i} a Normal distribution with μ_i equal to the value reported in Table 2 and $\sigma = 2$.

$$V_p = \langle V_{p_i}, \mathcal{N}(\mu_i, \sigma_i) \rangle \quad (7.1)$$

7.2 Case Study: Austin, queso library

7.3 Case Study: Multidisciplinary System (NASA)

7.4 Case Study: Spatio-temporal Nicholson-Bailey model

Este esta en el software uqlab, en la carpeta Doc Manuals

8 Conclusions and Future Works

8.1 Revisiting the Research Questions

8.2 Significance and Limitations

8.3 Open Problems and Future Work

8.4 Final Considerations

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Appendix

APPENDIX A – uqms R package

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A.1 Título da seção

Aqui temos uma seção dentro do Apêndice.

Figure 4 – Legenda para a figura.

APPENDIX B – Ideas

B.0.1 Variance, Information and Entropy

Variance.

Information and Entropy.

B.0.2 Information Gain, Distances and Divergences

B.1 Sensitivity Analysis

Sensitivity analysis is the systematic study of how model inputs—parameters, initial and boundary conditions—affect key model outputs. Depending on the application, one might use local derivatives or global descriptors such as Sobol’s functional decomposition or variance decomposition. Also, the needs of the application may range from simple ranking of the importance of inputs to a response surface model that predicts the output given the input settings. Such sensitivity studies are complicated by a number of factors, including the dimensionality of the input space, the complexity of the computational model, limited forward model runs due to the computational demands of the model, the availability of adjoint solvers or derivative information, stochastic simulation output, and high-dimensional output. Challenges in sensitivity analysis include dealing with these factors while addressing the needs of the application. (??)

$$E = mc^2 \tag{B.1}$$

Nunc velit. Nullam elit sapien, eleifend eu, commodo nec, semper sit amet, elit. Nulla lectus risus, condimentum ut, laoreet eget, viverra nec, odio. Proin lobortis. Curabitur dictum arcu vel wisi. Cras id nulla venenatis tortor congue ultrices. Pellentesque eget pede. Sed eleifend sagittis elit. Nam sed tellus sit amet lectus ullamcorper tristique. Mauris enim sem, tristique eu, accumsan at, scelerisque vulputate, neque. Quisque lacus. Donec et ipsum sit amet elit nonummy aliquet. Sed viverra nisl at sem. Nam diam. Mauris ut dolor. Curabitur ornare tortor cursus velit.

Morbi tincidunt posuere arcu. Cras venenatis est vitae dolor. Vivamus scelerisque semper mi. Donec ipsum arcu, consequat scelerisque, viverra id, dictum at, metus. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Ut pede sem, tempus ut, porttitor bibendum, molestie eu, elit. Suspendisse potenti. Sed id lectus sit amet purus faucibus vehicula. Praesent sed sem non dui pharetra interdum. Nam viverra ultrices magna.

Aenean laoreet aliquam orci. Nunc interdum elementum urna. Quisque erat. Nullam tempor neque. Maecenas velit nibh, scelerisque a, consequat ut, viverra in, enim. Duis magna. Donec odio neque, tristique et, tincidunt eu, rhoncus ac, nunc. Mauris malesuada malesuada elit. Etiam lacus mauris, pretium vel, blandit in, ultricies id, libero. Phasellus bibendum erat ut diam. In congue imperdiet lectus.

APPENDIX C – Título do apêndice C

Morbi luctus, wisi viverra faucibus pretium, nibh est placerat odio, nec commodo wisi enim eget quam. Quisque libero justo, consectetur a, feugiat vitae, porttitor eu, libero. Suspendisse sed mauris vitae elit sollicitudin malesuada. Maecenas ultricies eros sit amet ante. Ut venenatis velit. Maecenas sed mi eget dui varius euismod. Phasellus aliquet volutpat odio. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Pellentesque sit amet pede ac sem eleifend consectetur. Nullam elementum, urna vel imperdiet sodales, elit ipsum pharetra ligula, ac pretium ante justo a nulla. Curabitur tristique arcu eu metus. Vestibulum lectus. Proin mauris. Proin eu nunc eu urna hendrerit faucibus. Aliquam auctor, pede consequat laoreet varius, eros tellus scelerisque quam, pellentesque hendrerit ipsum dolor sed augue. Nulla nec lacus.

Annex

ANNEX A – Título do anexo A

Donec et nisl id sapien blandit mattis. Aenean dictum odio sit amet risus. Morbi purus. Nulla a est sit amet purus venenatis iaculis. Vivamus viverra purus vel magna. Donec in justo sed odio malesuada dapibus. Nunc ultrices aliquam nunc. Vivamus facilisis pellentesque velit. Nulla nunc velit, vulputate dapibus, vulputate id, mattis ac, justo. Nam mattis elit dapibus purus. Quisque enim risus, congue non, elementum ut, mattis quis, sem. Quisque elit.

Maecenas non massa. Vestibulum pharetra nulla at lorem. Duis quis quam id lacus dapibus interdum. Nulla lorem. Donec ut ante quis dolor bibendum condimentum. Etiam egestas tortor vitae lacus. Praesent cursus. Mauris bibendum pede at elit. Morbi et felis a lectus interdum facilisis. Sed suscipit gravida turpis. Nulla at lectus. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Praesent nonummy luctus nibh. Proin turpis nunc, congue eu, egestas ut, fringilla at, tellus. In hac habitasse platea dictumst.

A.1 Título da seção

Aqui temos uma seção dentro do Anexo.

Vivamus eu tellus sed tellus consequat suscipit. Nam orci orci, malesuada id, gravida nec, ultricies vitae, erat. Donec risus turpis, luctus sit amet, interdum quis, porta sed, ipsum. Suspendisse condimentum, tortor at egestas posuere, neque metus tempor orci, et tincidunt urna nunc a purus. Sed facilisis blandit tellus. Nunc risus sem, suscipit nec, eleifend quis, cursus quis, libero. Curabitur et dolor. Sed vitae sem. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Maecenas ante. Duis ullamcorper enim. Donec tristique enim eu leo. Nullam molestie elit eu dolor. Nullam bibendum, turpis vitae tristique gravida, quam sapien tempor lectus, quis pretium tellus purus ac quam. Nulla facilisi.

ANNEX B – Título do anexo B

Curabitur nunc magna, posuere eget, venenatis eu, vehicula ac, velit. Aenean ornare, massa a accumsan pulvinar, quam lorem laoreet purus, eu sodales magna risus molestie lorem. Nunc erat velit, hendrerit quis, malesuada ut, aliquam vitae, wisi. Sed posuere. Suspendisse ipsum arcu, scelerisque nec, aliquam eu, molestie tincidunt, justo. Phasellus iaculis. Sed posuere lorem non ipsum. Pellentesque dapibus. Suspendisse quam libero, laoreet a, tincidunt eget, consequat at, est. Nullam ut lectus non enim consequat facilisis. Mauris leo. Quisque pede ligula, auctor vel, pellentesque vel, posuere id, turpis. Cras ipsum sem, cursus et, facilisis ut, tempus euismod, quam. Suspendisse tristique dolor eu orci. Mauris mattis. Aenean semper. Vivamus tortor magna, facilisis id, varius mattis, hendrerit in, justo. Integer purus.

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ANNEX C – Título do anexo C

Nunc velit. Nullam elit sapien, eleifend eu, commodo nec, semper sit amet, elit. Nulla lectus risus, condimentum ut, laoreet eget, viverra nec, odio. Proin lobortis. Curabitur dictum arcu vel wisi. Cras id nulla venenatis tortor congue ultrices. Pellentesque eget pede. Sed eleifend sagittis elit. Nam sed tellus sit amet lectus ullamcorper tristique. Mauris enim sem, tristique eu, accumsan at, scelerisque vulputate, neque. Quisque lacus. Donec et ipsum sit amet elit nonummy aliquet. Sed viverra nisl at sem. Nam diam. Mauris ut dolor. Curabitur ornare tortor cursus velit.

Morbi tincidunt posuere arcu. Cras venenatis est vitae dolor. Vivamus scelerisque semper mi. Donec ipsum arcu, consequat scelerisque, viverra id, dictum at, metus. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Ut pede sem, tempus ut, porttitor bibendum, molestie eu, elit. Suspendisse potenti. Sed id lectus sit amet purus faucibus vehicula. Praesent sed sem non dui pharetra interdum. Nam viverra ultrices magna.

Aenean laoreet aliquam orci. Nunc interdum elementum urna. Quisque erat. Nullam tempor neque. Maecenas velit nibh, scelerisque a, consequat ut, viverra in, enim. Duis magna. Donec odio neque, tristique et, tincidunt eu, rhoncus ac, nunc. Mauris malesuada malesuada elit. Etiam lacus mauris, pretium vel, blandit in, ultricies id, libero. Phasellus bibendum erat ut diam. In congue imperdiet lectus.