ON THE GENERIC UTILIZATION OF PROBABILISTIC METHODS FOR QUANTIFICATION OF UNCERTAINTY IN PROCESS-BASED MORPHODYNAMIC MODEL APPLICATIONS

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A variety of uncertainty sources are inherent in process-based morphodynamic modelling applications. There is an increasing demand for the quantification of these uncertainties. This contribution introduces a probabilistic-morphodynamic (PM) modelling framework that enables this quantification. The PM modelling framework provides a systematic approach, while also lowering the required effort for inclusion of uncertainty quantification in morphodynamic model studies. Applicability and added value is shown using a pilot application to the Holland coast.

Keywords: morphodynamics; process-based morphodynamic models; uncertainties; probabilistics; uncertainty quantification; probabilistic-morphodynamic modelling framework; Unibest CL+; Holland coast;

INTRODUCTION

Coastal morphodynamic models are used to predict the short- and long-term behaviour of the sea bed, including the dynamics of bed forms. The behaviour of the sea bed is relevant for a wide range of engineering applications such as coastline dynamics in relation to coastal safety, beach design, land reclamations and structures, and siltation of harbours and channels. The imperfect description of physics in the model, the inability to accurately define model input parameters (e.g. friction coefficient, eddy viscosity, wave breaking index, sediment transport coefficients, morphological acceleration) and natural variations in the model forcing (e.g. wind, waves, storm surge, sea level rise) introduce uncertainty in morphodynamic model predictions. Identification and quantification of these uncertainties not only supports an improved understanding of the studied morphological system, but is also imperative for the implementation of risk informed management measures and strategies.

Uncertainty quantification essentially requires multiple simulations and subsequent statistical analysis of model results. This ideally requires a structural function (e.g. coastal area model, coastal profile model, coastline model, etc.) embedded within a Monte Carlo simulation. However, as morphodynamic models tend to be computationally demanding and a Monte Carlo approach may require thousands of simulations, this is often not feasible within the timespan/budget of regular engineering projects.

In current engineering practice, uncertainty ranges are often derived (or estimated) from scenario based modelling. In this approach experts define a limited number of (critical) scenarios resulting in a range of model outcomes that indicate the uncertainty in the model prediction. A drawback of this approach is that the uncertainties are not yet quantified, as the likelihood of the scenarios is not taken into account. Without this information it is hard for decision makers and stakeholders to make risk informed decisions.

In between scenario based modelling and Monte Carlo approaches, there is a wide range of probabilistic methods (such as numerical integration, Monte Carlo, directional sampling, stratified sampling, Latin Hypercube sampling and Importance sampling) that assign likelihoods to model outcomes, but require fewer simulations than a full blown Monte Carlo approach. Some of these approaches may be appropriate at engineering time scales. To make engineers familiar with the wide range of probabilistic methods and lower the require effort for application in engineering projects, a generic probabilistic-morphodynamic (PM) modelling framework is developed.

This contribution describes how uncertainties in morphodynamic model predictions can be quantified using this PM modelling framework. To this end, we discuss the origin of uncertainties, different quantification methods, the PM modelling framework and, finally, an application of the framework to the Holland Coast as a pilot application. The ultimate aim is to embed the PM framework in the standard workflow for morphological predictions with engineering time-scales, using state-of-the-art process-based area models, such as Delft3D, at acceptable computational cost.

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ORIGIN OF UNCERTAINTY IN MORPHODYNAMIC MODELS

Sources of uncertainty can be classified as inherent- or epistemological. Inherent (or intrinsic) uncertainty represents variation in nature (both in space and time), whereas epistemological uncertainty is related to both the imperfect representation of reality by a (numerical) model and the inevitable finite amount of data and knowledge (Van Gelder, 2000).

When focusing on these uncertainty sources in relation to morphodynamic models, this labeling can be specified further, owing to their origin:

- Forcing uncertainty:
  - Typical inherent uncertainty in the forcing conditions, originating from natural variation in both space and time, such as storms, disasters, (unknown) trends, climate change, inherent uncertainty from the use of hindcast models for model input, etc.
- Parameter uncertainty:
  - Uncertainty in (physical) model parameters due to the lack of data and knowledge (epistemological uncertainty) such as empirical formula, parameter concepts in relation to actual physics, measurements techniques and –errors, finite data availability, initial conditions, future state uncertainty, etc.
- Model uncertainty:
  - Part of the epistemological uncertainty related to the incompleteness of conceptualizing a real system into a (numerical) model. Reflected in translation of noise & -errors in numerical methods (e.g. numerical diffusion, approximation techniques), underlying assumptions, limited processes, accuracy, etc.
- Unknown uncertainty sources:
  - The uncertainty originating from unknown and unpredictable sources (both natural and operational), such as human errors, erroneous measurements, unknown bugs/faults, wrong assumptions, unknown relations between quantities, unforeseen processes, etc.

A visual representation of this list is provided in Fig. 1.

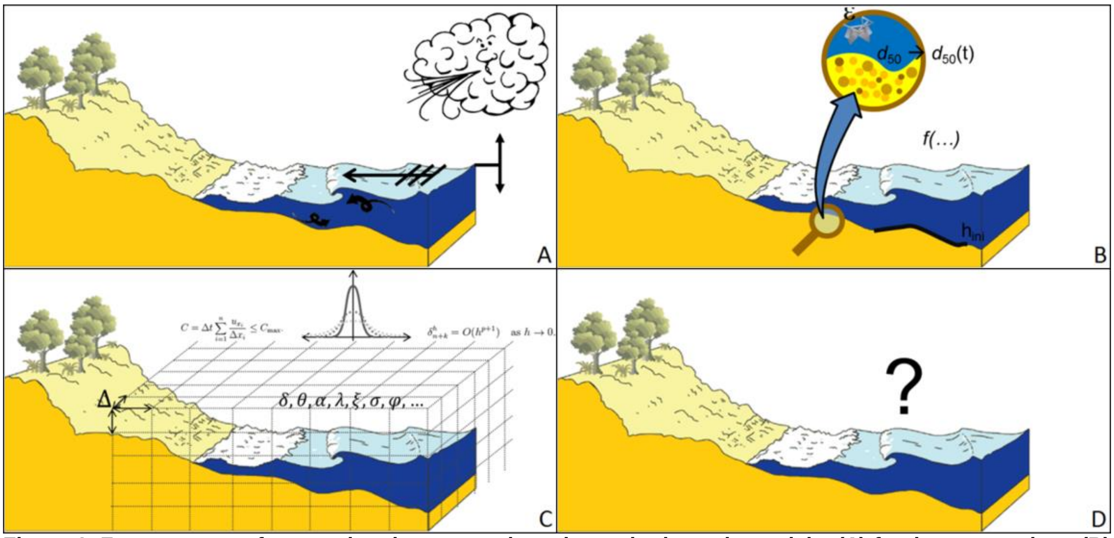

Figure 1. Four sources of uncertainty in process-based morphodynamic models, (A) forcing uncertainty, (B) parameter uncertainty, (C) model (numerical) uncertainty and (D) unknown uncertainty sources.

Given the nature of these different sources of uncertainty, one must immediately conclude that removing or overcoming any of the uncertainty sources is practically impossible, as they are related to the very fundamental properties of predictive process-based morphodynamic modelling.

Therefore, all that can realistically be done is to at least quantify uncertainties associated with morphodynamic modelling, as removing or overcoming the uncertainty is not feasible. Ignoring the uncertainty will lead to an incomplete assessment and potentially dangerous outcomes, when dealing with typical engineering applications (Van Der Klis, 2003).

QUANTIFYING UNCERTAINTY IN MORPHODYNAMIC MODELS

There is now an increasing demand for uncertainty quantification in engineering/management projects. In general, this can be related to the increased involvement of stakeholders such as decision makers, investors and even the general public, and their increasing awareness of uncertainties and their implications (risks). Furthermore, increasing requirements regarding uncertainty quantification are now being incorporated in legislation throughout the world, driving this demand.

When looking at the process towards uncertainty quantification, a typical workflow can be as follows:

- Identification of uncertainty sources:
    - Identifying uncertainty sources is required to assess their influence on the goal variable (i.e. primary diagnostic). Commonly, expert judgement is combined with data analysis (if data is available) to construct a broad overview and sense of the uncertainty sources.
- Performing a sensitivity analysis:
    - Performing a sensitivity analysis provides insight in the actual relevance of the different identified uncertainty sources for the goal variable. This way, a-priori knowledge is generated, which can be used to optimize the inclusion of uncertainty sources (i.e. eliminate insignificant uncertainty sources) in the final uncertainty quantification method.
- Characterizing (relevant) uncertainty sources:
    - Expert judgement can be combined with data analysis (if data is available) to characterize the above shortlist of uncertainty sources by assigning appropriate probability density distributions (such as uniform-, normal-, log-normal-, Rayleigh-, Poisson-, triangular-, Gumbel- or Weibull distributions) associated with relevant uncertainty sources.
- Selecting uncertainty quantification method:
    - Different quantification methods can be considered, appropriate for a specific model application, such as crude Monte Carlo, Importance Sampling, Latin Hypercube, Numerical Integration, Directional Sampling, a First-Order-Reliability-Method (FORM) or a First-Order-Second-Moment (FOSM).
- Performing simulations
    - At this stage, simulations required for the selected quantification method are performed.
- Uncertainty quantification (and presentation):
    - Combining the results from the model simulations (scenarios) and their probability using the selected uncertainty quantification method. Given the nature and focus of the application, this results in a band width and/or (system) failure probability, and in turn should include clear representation of the consequences of the (translated) uncertainty.

To date, various studies have attempted the development and application of methods for quantification of the uncertainties associated with morphodynamic modelling for a large variety of applications (while laying emphasis on different aspects), such as Vrijling and Meijer (1992), Cooke and Van Noortwijk (1999), Dong and Chen (1999), Van Der Klis (2003), Maskey (2004), Reeve and Spivack (2004), Van Vuren (2005), Ruggiero et al. (2006), Vreugdenhil (2006), Fortunato et al. (2009), Reeve et al. (2009), Van Der Wegen et al. (2013), Callaghan et al. (2013) and Baart (2013).

Commonly, focus is laid upon the input- (forcing-) and parameter uncertainty, while omitting model- and unknown uncertainty sources (Maskey, 2004). Obviously, this is related to the impossibility to quantify (any) unknown uncertainty, though model uncertainty may be addressed by comparing results from different models (Radwan et al., 2002), but available formal methods are limited.

Providing a generic approach for uncertainty quantification in morphodynamic modelling applications is challenging, given the diverse nature of both the different morphodynamic applications (differences in models, -relevant processes, -uncertainty sources, -study objectives, etc.) and the probabilistic techniques suitable for each type of application (applicability, computational demand, etc.

Here we present, a probabilistic-morphodynamic (PM) modelling framework, with the aim of addressing the above issues by facilitating straightforward incorporation of well-established probabilistic techniques in morphodynamic modelling studies.

THE PROBABILISTIC-MORPHODYNAMIC MODELLING FRAMEWORK

The probabilistic-morphodynamic (PM) modelling framework developed here aids in the quantification of uncertainties in morphodynamic model predictions by coupling any morphodynamic model to a generic probabilistic toolkit. This toolkit consists of a probabilistic toolbox (probabilistic mathematical routines), a user interface (UI) and standardized connection interfaces, which enable the coupling between the toolkit and morphodynamic models (see Fig. 2).

Functionality offered within the probabilistic-morphodynamic modelling toolkit is in line with the earlier mentioned typical workflow for uncertainty quantification and includes (but is not limited to) automated random variable definition (based on data analysis), sensitivity analysis, automated setup of model proxies, quantification of (system) failure probability (using methods such as numerical integration, Monte Carlo sampling, importance sampling, directional sampling or a First-Order-Reliability-Method, FORM) and quantification of (translated) uncertainties (band widths) in goal variables using different probabilistic sampling techniques such as Monte Carlo, First-Order-Second-Moment (FOSM) and Importance Sampling (e.g. Maskey, 2004).

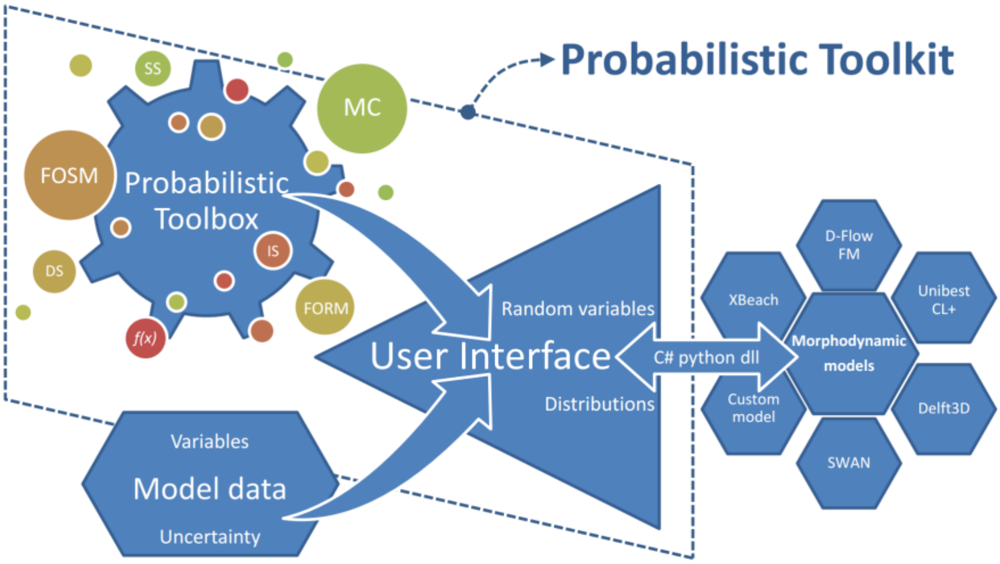

Figure 2. Schematic overview of the probabilistic-morphodynamic (PM) modelling framework components.

The resemblance to the typical workflow, introduced in the previous section, is shown in Fig. 3, which displays screenshots of some components in the PM modelling framework.

The combination of a large amount of supported functionality, flexibility regarding the workflow and the ability to couple with any morphodynamic model makes the platform highly applicable for a large variety of morphodynamic modelling studies, while the user interface contributes to lowering the efforts required for including uncertainty quantification within a morphodynamic modelling study or project.

Figure 3. Overview (screenshots) of some components embedded in the PM modelling framework, with (A) a description of uncertainty sources, with or without data analysis, (B) sensitivity analysis and (C) uncertainty quantification, either focusing on failure probability or bandwidth quantification.

PILOT APPLICATION FOR THE HOLLAND COAST

To generate a typical application of the PM modelling framework, a first step of coupling the framework with the (one-line) coastline model Unibest-CL+ was undertaken. The fundamental concepts regarding this coastline model are shown in Fig. 4, additional in-depth information can be found in Deltares (2011).

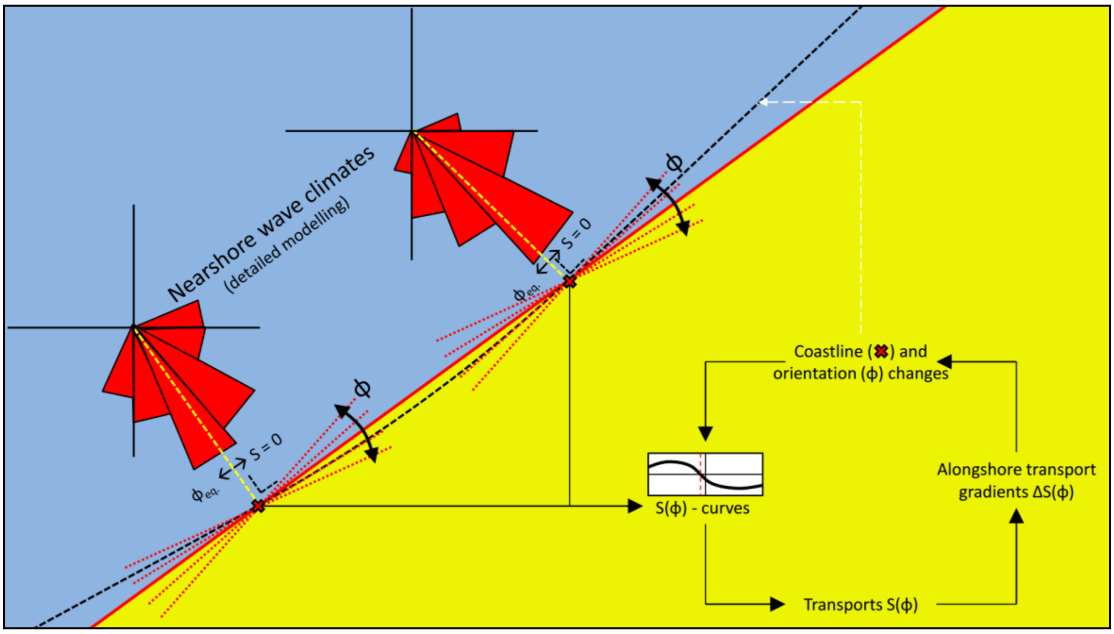

Figure 4. Schematic overview of the Unibest CL+ model.

Unibest CL+ utilizes identical sediment transport formulations to those used in a coastal area model (such as Delft3D), but is computationally very efficient. This allows exploration and testing of different probabilistic techniques in order to obtain uncertainty ranges with sufficient accuracy.

The pilot application focusses on 100 year predictions of the shoreline position of the Holland coast. The Holland coast stretches from the Rotterdam harbour in the south, up to Den Helder in the North (Fig. 5). Following this coastline from south to north (Rotterdam to Den Helder), features such as the harbours of Scheveningen & IJmuiden (‘g’ indicates groynes) and an alongshore revetment at Petten (‘r’ indicates revetment) are found.

The pilot application only focusses to a limited degree on actual uncertainties and can be regarded as a synthetic application to present the workflow while also examining and assessing the PM modelling framework. To that end, a number of variables (by no means adequate in relation to the total uncertainty) were defined as uncertain, and given a probability distribution (assumed to be all normal distributed, not elaborated upon here in detail). The variables water density (ρ_w), sediment porosity, the breaker index (γ_{cfe}) and median grain size (d_{50}) are considered, while the p_{90} value of the grain size (d_{90}) and fall velocity (w_s) are assumed to be linearly related to the median grain size (d_{50}). Furthermore, as future nourishments and coastal development are unknown, only an average amount of dredging and dumping activity at the up- and downdrift side of the indicated harbours, respectively, is imposed on the model.

After defining the sources of uncertainty a crude Monte Carlo approach was implemented, in which the model was run N times (N=1000). For each of these computations, values associated with the random variables were drawn from the defined cumulative distributions using a random value between 0 and 1 (uniformly distributed). The translation of the stochastic variables' uncertainties into model variables is depicted in Fig. 6, which forms the basis for the variation in the N model runs.

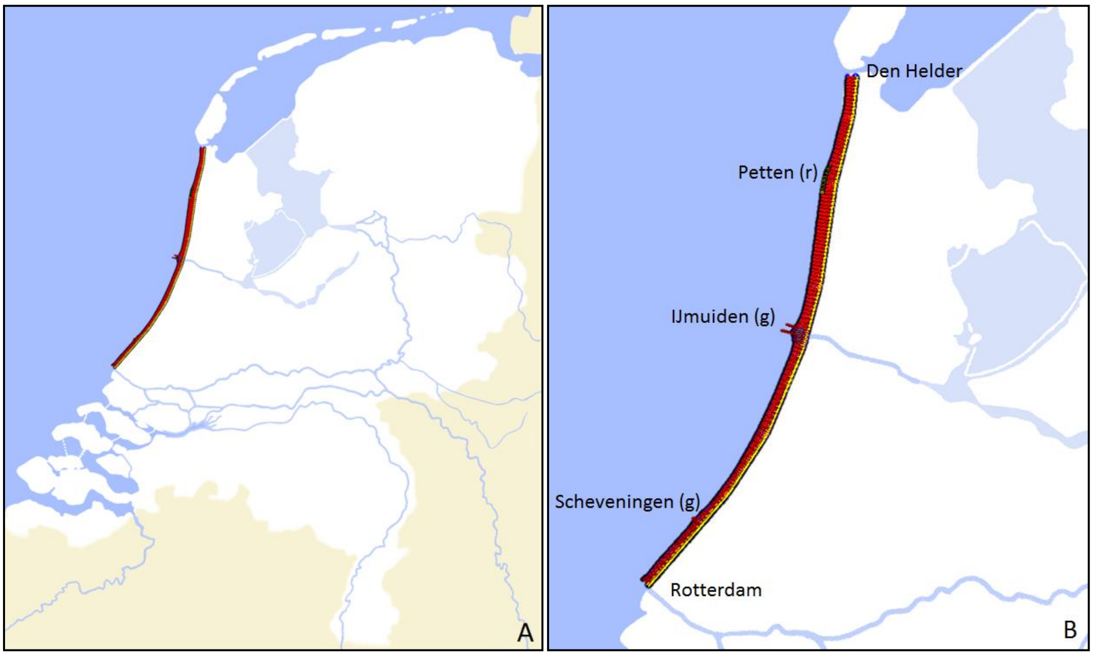

Figure 5. Schematic overview of (A) the Holland coast in relation to the Netherlands and (B) a zoom of the Unibest CL+ model of the Holland coast incl. groynes (Scheveningen & IJmuiden) and revetment (Petten).

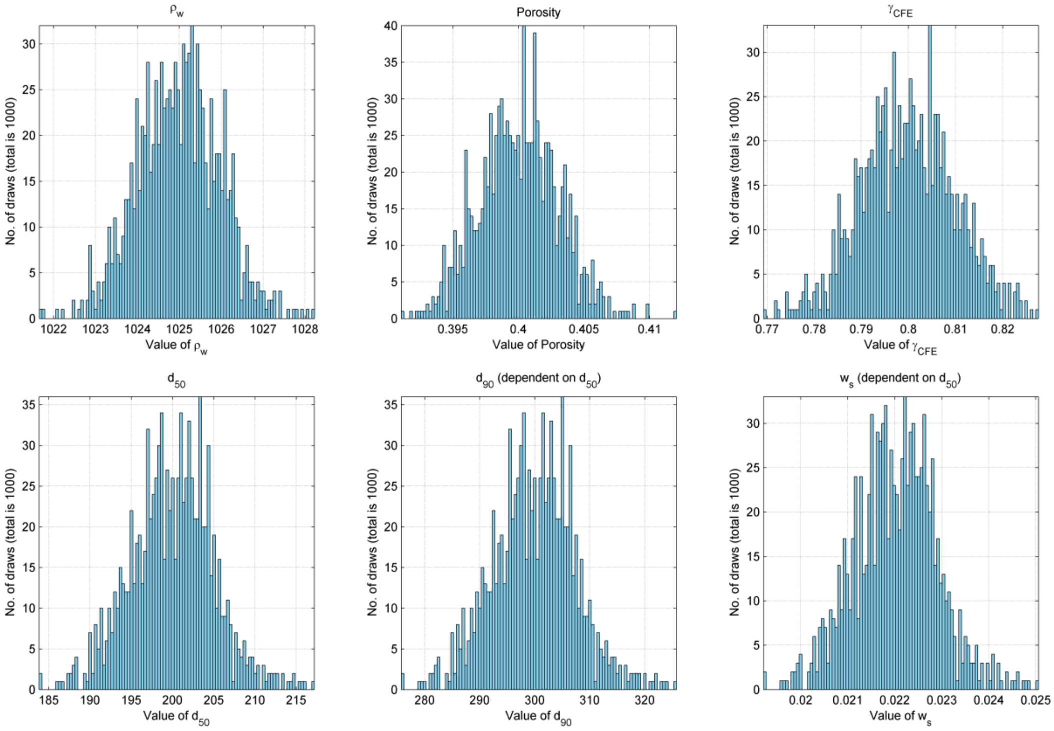

Figure 6. Translation of variable uncertainties (random variables) into different model input distributions (number of computations and draws per random variable is 1000).

After execution of the Monte Carlo analysis (or any sampling technique alike), the next step in the workflow governs the actual uncertainty quantification (in this case using band widths). Fig. 7 depicts some results from this analysis. Both panels of the figure relate the alongshore axis to cross-shore coastline change, the horizontal axis depicts the coastline from Rotterdam (0 km) to Den Helder (~120 km), while the erosion/accretion of the coastline is shown by the vertical axis (negative values depict erosion, positive values indicate accretion).

In the upper panel of Fig. 7, the total band with (or degree of uncertainty/range of outcomes) is provided for the coastline erosion/accretion (zero represents the original shoreline position), along with the associated 5%, 50% and 95% percentiles. Given the provided parameter uncertainty, 90% of the model outcomes are between these upper (95%) and lower (5%) dashed lines.

In the lower panel of Fig. 7 identical information can be found, though here the range of outcomes is sorted against the drawn distribution of the median grain size (d_{50}). This can be regarded as an analysis towards relative parameter importance, as it indicates the influence of the median grain size on the coastline erosion/accretion. Less dominant random variables would show a subordinate role on the outcomes by returning a chaotic distribution (not shown).

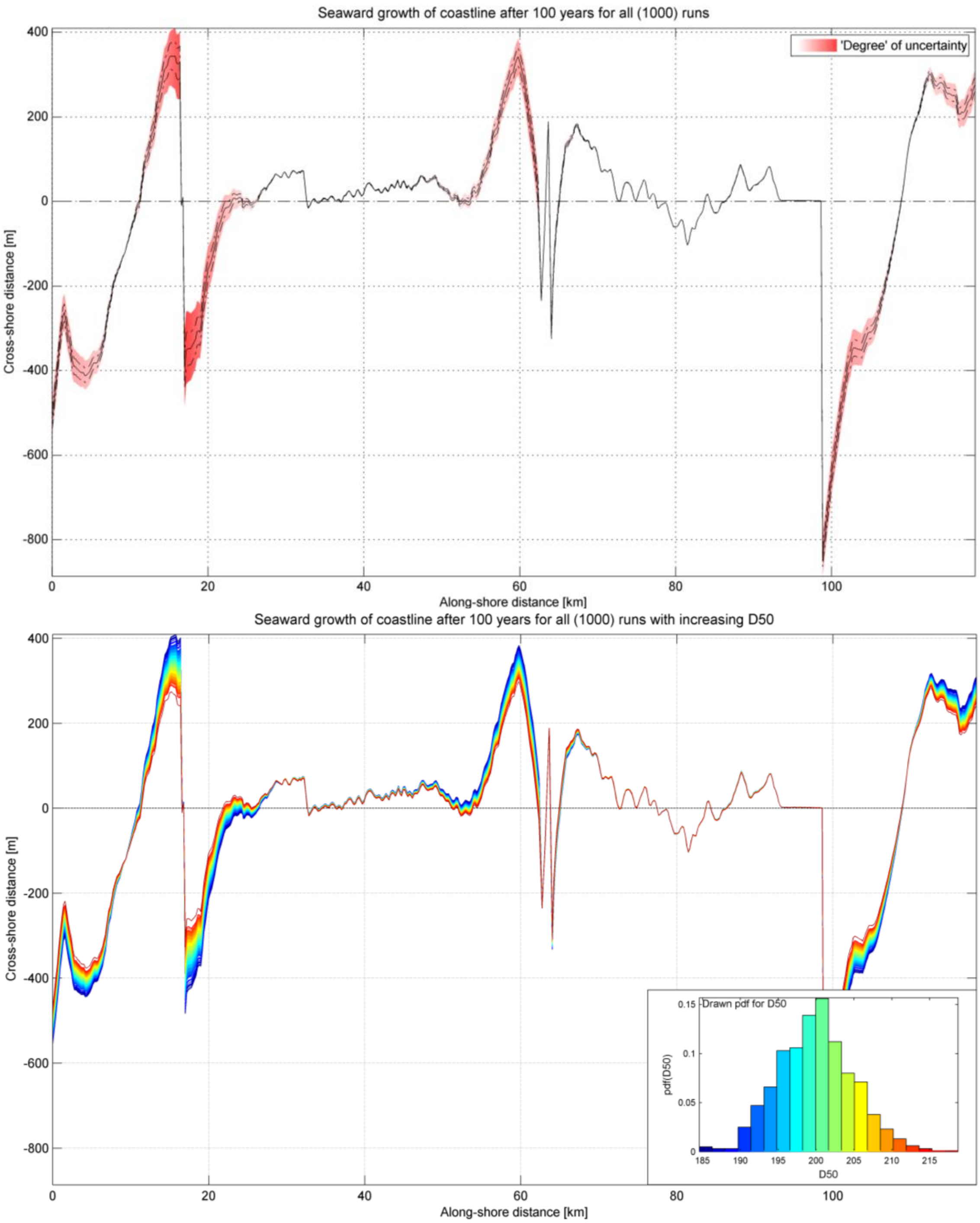

Figure 7. Combined uncertainty band width for coastline development at the Holland coast (upper panel) while also indicating the relative distribution/importance of the median sediment grain size (d_{50}) variation.

CONCLUSIONS

Uncertainties are inherent in morphological model predictions due to the nature of the approach (the finite amount of data and knowledge, the inevitable use of a model representing reality and natural variations associated with the model input). These uncertainties can be classified according to their source, either from forcing conditions, model parameters, (numerical) model uncertainty and unknown uncertainty sources. The latter two sources are hard to quantify, but numerous techniques exist for the quantification of the first two. Nevertheless, uncertainties in morphodynamic models are often only quantified to a limited degree, generally using a scenario based modelling approach, in which the representation of uncertainty within the scenarios is often based upon expert judgement and/or data analysis.

In this study a generic probabilistic morphodynamic (PM) modelling framework is developed. In this framework, users are guided through the following steps: identification of uncertainty sources, performing a sensitivity analysis, characterizing relevant uncertainty sources, selecting an appropriate uncertainty quantification method, performing the required simulations and finally quantify the implication of the uncertainty on the goal variable(s), including proper (re)presentation.

A pilot application of the PM approach to the Holland coast shows that uncertainty quantification methods have an added value, for instance in steering measurements and indicating relevant risks. This provides valuable information for better risk informed decision making in the design, operation and maintenance of coastal interventions.

WAY FORWARD/RECOMMENDATIONS

With the setup of the probabilistic morphodynamic (PM) modelling framework a flexible platform for uncertainty quantification in morphodynamic models is established. The PM modelling framework can be coupled to different (morphodynamic) models. In this contribution, the 1D-coastline model Unibest CL+ is considered, though as a next step 2D/3D coastal area models (such as Delft3D) are considered. Although, these area models are computationally demanding, the PM modelling framework offers the opportunity to investigate which uncertainty quantification methods are computationally feasible within project timespan/budget while remaining sufficiently accurate. Finally, usage and interpretation of uncertainty information by end-users is very important for proper communication and understanding of conclusions. Therefore, exploring ways of how to present the information properly (both in numbers and visualization) is also of great importance.

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