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Calibrating and assessing uncertainty in coastal numerical models

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ABSTRACT

Advanced numerical models used to predict coastal change at a variety of time and spatial scales often contain many free parameters that require calibration to the available field data. At present, little guidance (beyond the adoption of the default values provided) is available in the field of coastal engineering to inform the selection of best-fit parameter values. Common calibration techniques can often lack a rigorous quantification of model sensitivity to parameters and parameter-induced model uncertainty. Here we employ the Generalised Likelihood Uncertainty Estimation (GLUE) method to address these issues. The GLUE method uses Monte Carlo sampling to assess the skill of many different combinations of model parameters when compared to observational data. As a rigorous modelling framework, the GLUE method provides a series of standard tools that assist the modeller to analyse model sensitivity, undertake parameter optimisation and quantify parameter-induced uncertainty. In addition, new tools are presented here to identify where unique calibrated parameter sets are required for different observational data (e.g., should the calibrated parameter set differ between alongshore locations at a site) and investigate the convergence of GLUE estimated optimum parameter values over increasing numbers of Monte Carlo samples.

As the methodology and philosophy of GLUE is well established in other fields, this paper presents a practical case study to explore the strengths and weaknesses of the method when applied to a relatively complex coastal numerical model (XBeach). The results obtained are compared to a previously reported and more 'standard' model calibration undertaken within the context of a coastal storm early warning system. While the GLUE method requires orders of magnitude more computational power, it is shown that its use in place of the more common one-at-a-time 'trial-and-error' approach to model calibration, provides: a significant improvement in predictive skill; a more rigorous evaluation of the model sensitivity to parameters; the ability to identify distinct differences in the XBeach model performance dependent on dune impact processes; and additional analysis including the quantification of parameter-induced uncertainty.

1. Introduction

Numerical models underpin a wide range of coastal engineering applications and are increasingly being relied upon to provide precise and detailed predictions as to the timing, location and extent of morphological change at the coast. For example, numerical models to predict beach erosion during storms typically require morphology data consisting of pre-storm elevation data (2D profile or 3D grid) and apply hydrodynamic forcing (i.e., waves and varying water-levels) to estimate beach response. In this context, modelling approaches range from more simple empirical models (e.g., [1–3]), to sophisticated process-based models that can be used to predict both morphological and hydrodynamic conditions including shoreline movement, dune erosion, surfzone circulation and wave run-up (e.g., [4]).

A number of forecasting systems have been developed around the world which utilise coastal erosion models to quantify coastal storm hazards and to inform the management of coastal storm risk [5–7]. For these and other applications, it is imperative that modellers and decision-makers recognise the uncertainties present in the erosion models used, especially when utilising models with imperfect formulations and input data [8–10]. Uncertainty in the modelling process can arise from many sources, including the boundary conditions and input data (e.g., errors arising from the use of imperfect wave transformations from deepwater buoy locations to the modelled inshore profile), model formulation (i.e., if the model equations do not adequately describe the physics of the system) and through the calibration process

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(e.g., individual modellers may prioritise the calibration of different parameters or subjectively judge different values to perform better). Therefore, in order to present accurate representations of uncertainty bounds, modellers in the field of coastal engineering must have access to tools with which to robustly assess and quantify each of these sources of uncertainty, either individually or based on their combined influence on the final model predictions obtained.

A number of studies have approached the specific challenge of explicitly quantifying the prediction uncertainty resulting from imprecise knowledge of forcing conditions (i.e., storm waves, storm duration, and surge) by providing probabilistic estimates of storm erosion (e.g., [11,12]). Monte Carlo (MC) sampling and the use of bootstrapping methods to combine the results of many model runs for varying forcing conditions are used to produce estimates of storm erosion demand and corresponding uncertainty bounds spanning a range of time scales [13,14]. While this approach provides considerable insight, this is effectively limited to one source of prediction uncertainty. Additional uncertainties stemming from the formulation of the model itself as well as calibration errors are effectively neglected once the initial calibration process has been completed [15]. This is a non-trivial assumption that requires careful investigation, particularly given a recent study by Splinter et al. [10] which found that the variability of coastal erosion models can be greater with changes in free parameters than model inputs such as bathymetry.

Bayesian Networks provide the ability to quantify a number of different potential sources of prediction uncertainty. These are probabilistic models used to draw statistically significant correlations between identified variables in the modelled system [16]. This modelling approach has been utilised in coastal engineering applications to estimate storm erosion damage [17], surf zone processes [9,18] and sediment transport [16,19,20] to yield information on specific errors and uncertainty in the values for each output variable and model parameter. Bayesian Networks, however, require large observational datasets for model training and do not incorporate any of the underlying physics that allows model prediction at diverse sites where different processes may dominate [21]. Ideally, a solution is sought whereby a similar level of detail about each potential component of model uncertainty is explicitly identified and quantified; but that the model remains as closely as possible physics-based, minimising the need for extensive historical and site-specific training data.

Parameter-induced uncertainty, resulting from the varying of free parameters during model calibration, is a component of model prediction uncertainty that is rarely quantified [22]. It is common practice to perform manual 'trial and error' selection of parameters to complete the model calibration process, with relatively few examples in the coastal engineering literature where more advanced and rigorous calibration techniques have been applied that guide the choice of free parameter values and reduce parameter uncertainty (e.g., [23]). Algorithms have been applied to simpler models with fewer free parameters, searching through the parameter space to find optimal parameter values by minimising discrepancies between model prediction and observational data (e.g., [24,25]). However, parameter response surfaces (i.e., the multidimensional surface that maps the skill of a model to the value chosen for each free parameter [26]) are often complex due to the non-linear interaction of parameters inherent in many coastal numerical models. As a consequence, depending on the starting parameter values, simple 'hill-climbing' algorithms can be trapped by local optima rather than finding the parameter values that perform best globally. To deal with these issues, complex methods such as genetic algorithms [27] and simulated annealing [28] must be employed which can test random starting points [29].

Advanced process-based models such as XBeach [4], representing the present state-of-the-art in coastal morphodynamic modelling, have tended to be calibrated less rigorously due to the large number of free model parameters present and the practical challenge that individual model runs are time-consuming. XBeach was primarily developed to predict changes in beach and nearshore morphology that occur during extreme storms [4], but the abundance of adjustable model parameters has enabled its adaption to a broad range of applications (e.g., [5,12,30–32]). XBeach may be implemented in both one-dimensional (beach profile) and two-dimensional depth-averaged (coastal area) modes, solving coupled equations for hydrodynamics, sediment transport and evolving bed morphology.

Documented calibrations of XBeach to-date have typically relied upon individual modeller experience and manual one-at-a-time parameter variation to determine the more sensitive parameters to be optimised during calibration. Generally only a few values of these parameters are trialled, and the skill of the model (commonly defined by a Brier Skill Score) is used to judge performance and determine the optimal parameter set. Some recent examples from the published literature of this approach include Harley et al. [33], Splinter and Palmsten [10], Callaghan et al. [13], Pender and Karunarathna [12] and Stockdon et al. [34]. Notably, in each of these five example studies, different subsets of calibration parameters were found to be sensitive. With the exception of a very limited number of published studies (e.g., [35]), there are few examples available that detail the rigorous trial of a much broader range of XBeach parameter combinations and values. Crucially, the present authors have been unable to identify any reports of the use of generalised techniques applied to examine the impact of XBeach model uncertainty due to parameter selection.

Fortunately, researchers in fields outside of the coastal sphere have made considerable advances in this area that can be drawn upon. In this paper we present one such approach, the Generalized Likelihood Uncertainty Estimation (GLUE) method (see [26]), which has the potential to address a number of the potential shortcomings identified above. GLUE is based on MC sampling (i.e., a large number of random samples) of the potential calibration parameter space, and provides tools to separately identify and quantify parameter sensitivity, reliable parameter values and parameter-induced uncertainty.

A fundamental concept underpinning the use of the GLUE method is 'equifinality', whereby it is observed that multiple parameter combinations may produce model runs of equal skill (e.g., the same Brier Skill Score) in estimating observed morphological change in the system [36,37]. Equifinality can occur due to a range of potential sources, including: the complex and often non-linear interaction between model parameters; over-parameterisation without sufficient observational data to inform parameter selection; uncertainty in the observational data; and/or model formulation that does not accurately or adequately encapsulate the full spectrum of processes being numerically simulated.

In this context, the errors in input data and/or model formulation are termed 'epistemic', referring to a lack of knowledge of the system within the model [38,39]. For instance: the complex three-dimensional morphology observed at beaches may not be adequately captured in two-dimensional beach profile surveys; observational data may not have been obtained immediately before/after the particular storm event being used for calibration, such that sediment transport is likely to have occurred outside of the modelled simulation period; and/or the model may be formulated in such a way that it overly simplifies the physics of the system [28]. Recognising that these errors cause equifinality to occur, the modeller's focus is then shifted to finding the most reliable parameter combination across a range of sites and/or hydrodynamic boundary conditions, while also assessing the validity of the model in truly representing the physics responsible for the observed change [38,40].

The two studies of Ruessink [23] and Ruessink [22], that used the cross-shore hydrodynamic-morphodynamic model UNIBEST-TC [41] and a nearshore alongshore current model [42] respectively, together pioneered the use of GLUE in the field of coastal engineering. These two applications of GLUE to coastal numerical models focused on comparing the method to other automated optimisation algorithms, noting that GLUE was particularly effective where parameter interdependence and complex response surfaces were present ([27] dis-