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Confidence in real-time forecasting of morphological storm impacts

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ABSTRACT

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Previous studies have expanded warning systems for coastal predictions with information on coastal morphology. Here we present the methodological choices for creating confidence intervals around the morphological forecasts. Three different methods (based on ensembles, hydrodynamic forecast errors and morphodynamic forecast errors) are compared based on required computation time, assumptions and data requirement for the operational forecasting system at the study site of Egmond, the Netherlands. The assumptions on the stochastic nature of the processes and the assumptions about error sources determine the practical applicability of a method.

ADDITIONAL INDEX WORDS: *Morphodynamic, operational forecast, warning system, methodology, coastal*

INTRODUCTION

Worldwide, numerous approaches have been developed to deal with extreme events. Dealing with safety can be separated into different phases: pro-action and prevention, preparation, response and mitigation and relief.

While the focus used to be on strategic phases, the operational phases have received increased attention. One of the projects that focus on the operational phases is the EU FP7 Project MICORE. This project analyses current storm response approaches in 9 European countries and concluded that the study sites could be improved by implementing operational, quasi real-time, coastal risk assessment methods.

While a few European countries have operational systems available predicting storm surge levels, none had real-time systems taking into account morphodynamics. Within the MICORE project countries develop real time erosion forecast systems. The aim of these systems is to assist local authorities and the population in their response to extreme events with timely access to relevant information of sufficient reliability and validity regarding impending natural threats. Current real-time systems are extended with relevant physics e.g. with morphodynamic response (Baart, 2009).

Adding morphological responses to the list of physical phenomena about which we have real time forecasts is a step forward. However any model prediction has to be accompanied by information about the precision of the prediction. The usefulness of knowing the precision can be seen in weather reports and typhoon path predictions. These forecasts are presented to the general public together with the confidence intervals (Demeritt, 2010 Fisher, 1956). The next step after generating real time morphological forecasts is to extent the morphological forecasts with confidence intervals.

Most methods that take uncertainty of forecasts into account do this with the aim to make a better estimate. Van Dongeren (2008) showed how numerical model results can be combined with a statistical model (data assimilation). Plant (2011) showed how multiple numerical model runs can be used for training a Bayesian network, with the aim of getting better estimate and obtaining optimal parameter settings.

In this paper, we present different choices to determine confidence bounds around morphological forecasts. The aim here is not to find a method that can give an optimal forecast but to find a method that, given the limited availability of computer resources and data, gives the most accurate confidence interval. As an example, we determine methods for creating confidence intervals for morphological forecasts at the beach of the Dutch coastal town of Egmond and compare the effect of the choices on data requirements, assumptions and computation effort.

METHODS: CONFIDENCE IN MORPHOLOGICAL FORECASTS

The confidence interval is an interval estimate (in contrary to a point estimate) that reflects the reliability of a parameter. The reliability represents the consistency of measurements or random error as opposed to validity, which reflects the constant error. In this paper the parameter of interest is a forecast of some morphological aspect, for example the mean high waterline. The prediction of a mean high waterline a few days ahead can already

be made, now the goal is to examine methods that give an estimate of the expected error of this prediction.

There are three choices that define the confidence band around a morphological forecast.

- Where in the chain of models do we introduce the error?
- What is the source of the error?
- What are the statistical characteristics of our error?

To be able to better explain the nature of the variation represented in the confidence bounds, we follow the categorization of uncertainties by (van Gelder, 2000). It is also important to define the terminology used for uncertainty. Reliability and validity are the terms mostly used in statistics (Wilkinson, 2005) they correspond to precision and accuracy as used in measurement literature (ISO, 2008), but in coastal research the terms accuracy (used for precision) and bias (referred to as reliability, but used as validity) are also used (Sutherland, 2004). Because of this mix up we do not use the term accuracy nor bias in this paper.

Introducing uncertainties

The forecast system to predict morphological changes during storms consists of a chain of nested models. A meteorological forecast model generates wind fields and pressure fields. These fields are used as input for a hydrodynamic model that computes waves, tides and surge levels. These are used as input for the morphodynamic model that computes near shore waves and erosion. Each of these models could be used as a starting point for the variation in the morphodynamics. The errors resulting from using a chain of numerical models is called model uncertainty.

meteorology The first model in the chain is the weather prediction model by the European Centre for Medium-Range Weather Forecasts (ECMWF). Due to the great dependency of the pressure and wind predictions on the initial conditions there is a large expected error in the forecasted pressure and wind, especially if multiday forecasts are made.

hydrodynamic The second model in the setup is the hydrodynamic model. In contrary to the weather model, the output of the hydrodynamic model (waves and water level) is less sensitive to variations in the initial conditions. The main error to be expected is the error of its source, the weather model.

morphodynamic The initial bathymetry might be uncertain. A bathymetry of a sandy coast shows quite a lot of variation during the year. Because of the wave bathymetry interaction the morphodynamic model is more sensitive to its initial bathymetry than the hydrodynamic model, with regards to the quantities and scales of interest during storm surges. For example the surge level is mainly a function of the magnitude of the wind and pressure and the tide is largely deterministic, while the exact position of dune breaching can be quite chaotic.

It is hard to argue that introducing the errors in one part of the model train over the other is better. As we will see it depends very much on the assumptions and availability of data.

Error sources

The next step is to determine the source of the error that should be represented in the confidence interval. The intrinsic uncertainty, as caused by the chaotic nature of the models. If we consider the approaches used most often than we can basically choose one of two approaches.

ensemble One approach, used in numerical weather forecasting, is ensembles forecasting. This is a method that started to become common in the early 1990's when enough computer power became available (Toth, 1993). The term ensemble comes from the field of statistical mechanics, which Gibbs and others contributed to the laws of thermodynamics (Lewis, 2005). An ensemble represents a sample of the unknown state of the input of model. The ensemble approach deals with the chaotic nature of a model.

The ensembles with varying inputs are used to do multiple runs of the same model. The resulting confidence interval does not necessarily relate to the confidence interval of the mean forecast. This relationship, in the numerical weather world called the spread-skill relationship, does often exist but can vary depending on the nature of the forecast (Whitaker, 1998). To determine the confidence based on skill, we would have to compare the forecasted pressure and wind fields with the observed ones.

expected error This skill based approach comes down to the assumption that errors made in the past are representative for the errors that we will make tomorrow. This application is in line with the application used in the pure statistical approach to generating confidence intervals as described by for example (Fisher, 1956). This method is used in many fields such as hydrology (Weerts, 2010).

Error model

After the sources of variation have been introduced in the chain of models, the final choice to make is the statistical model to be used to represent the error. This last step relates to the statistical uncertainty. The choices to make are what distribution should be assumed and what kind of autocorrelations (spatial or temporal) is expected to exist.

distribution If we choose the distribution of our error we can choose from a wide variety of parametric distributions. If the distribution is computed in the middle of the model chain, a Monte Carlo approach can be used to generate samples for the next model in the chain.

If we do not want to or cannot make an assumption about the distribution we can choose a non parametric approach. A popular non parametric method is the bootstrap (Efron, 1993). This method is widely used, for example in social sciences, biology (Felsenstein, 1985) and numerical weather predictions (Hamill, 2008). The bootstrap uses a dataset of observations as a basis to draw resamples from. The function of interest is applied to each resample. In our case the dataset would be a sample of previous differences between forecasts and observed values. This method is not much different from the ensemble approach, the main difference is that ensembles are created from “breeding ground” and bootstrap is drawn from an empirical probability distribution function of errors.

autocorrelation It is not unlikely that the errors are correlated in time or space. If errors are correlated in time the proper way to deal with it is to use a model out of the autoregressive family of time series models, commonly used in econometrics (for example Cryer, 2008). The confidence interval is then based on the time series of the quantity of interest and one or more extraneous variables.

If errors are correlated in space the spatial autocorrelation should be modelled. The models used for spatial autocorrelation are different from temporal correlation because temporal correlation goes only in one direction whereas spatial correlation is usually two-dimensional and in two directions (Ripley, 2004).

As an example of how to the aforementioned choices can be made for the coast, we look at the operational forecast model for Egmond Beach. The forecasts are based on a series of nested numerical models. For sake of simplicity, we only consider the forecast of the coastline during a storm.

Egmond beach

The Egmond beach is located in the northern part of the Holland Coast. The coast consists of a dune area, sandy beach and multiple-barred nearshore zone. On average, the beaches are approximately 60m wide with a 1 to 40 slope. Two directional wave buoys, located approximately 15 km to the south and approximately 75 km to the north, measure offshore wave conditions. Offshore tidal levels are found from interpolation in water level data collected at tidal stations located 15 km north and south of Egmond. Since the implementation of the Dynamic Preservation policy, in the early 90's, this coastal stretch has been nourished regularly and is among the most frequently nourished areas in the Netherlands. The Egmond beach is 5 Km long and the area is mesotidal. Two Argus video-stations have been active at the site for about 10 years, making the location a popular research location (for example Aagaard, 2005).

Model setup

The hydrodynamic model is based on the Dutch Continental Shelf Model (DCSM) model (Gebraad, 1998; Gerritsen, 1995) that makes use of the open source numerical model Delft3D (Lesser, 2004). The morphodynamic part and near shore beach processes are modelled using the open source model XBeach (Roelvink, 2009). The same model setup is used as in (Baart, 2009a). In this study however XBeach is used as a 1D (profile) model.

RESULTS: CONFIDENCE INTERVALS AT EGMOND BEACH

Introducing uncertainties

If we consider the position of the coastline at Egmond beach, where do we expect the errors we make to originate from? Does the error in a weather prediction lead to a too high surge that causes the coastline to shift or does the numerical error in the calculation of the bathymetry cause a slightly different beach angle that can also cause the coastline to shift? This choice seems quite impossible to make. Therefore the errors should be preferably propagated throughout the model chain, starting at the weather model. This however leads to practical problems for the computation power. The total set of models takes about 6 hours to run for a 72 hour forecast. If multiple runs need to be made that will result in huge computational effort.

Error sources

The ensemble method is the common approach for the weather model. This is due to the chaotic nature of weather models. These ensembles are usually calculated on a lower resolution than the deterministic forecast because of the computation time. For the ECMWF model there are 52 runs available, 1 deterministic run, and 1 deterministic run at coarser resolution and 50 ensembles also at a coarse resolution (Buizza, 1998). These ensembles can be used as boundary conditions for the hydrodynamic model. This gives 50 hydrodynamic boundary conditions for the morphological model. The 50 morphological runs result in a variation of the morphological forecast and a dramatic increase in total computation time.

The alternative would be to use ensembles only for the hydrodynamic model or for the morphodynamic model. However the hydrodynamic model ensembles are not the logical option because it is expected to be less chaotic, thus the model uncertainty is relatively high compared to the intrinsic uncertainty. The morphodynamic model would seem like a good option to introduce ensembles, especially with regards to the bathymetry, but this requires some more advanced insights into how to generate proper ensembles for morphodynamic models.

The expected error approach can be a way to introduce the uncertainties in the model chain without much computational effort. There is not much computational effort because this approach involves using the previous observed forecast errors as a prediction for future errors and this does not require extra model runs for the models up to the source of the forecast errors. This does however require a history of valid measurements and a history of forecasts. In the case for Egmond there are measurements available of waves and surges 30km north and south of Egmond. These measurements are done at a temporal resolution of 10min. The errors at these stations can be used as expected wave and water level errors for the Egmond model.

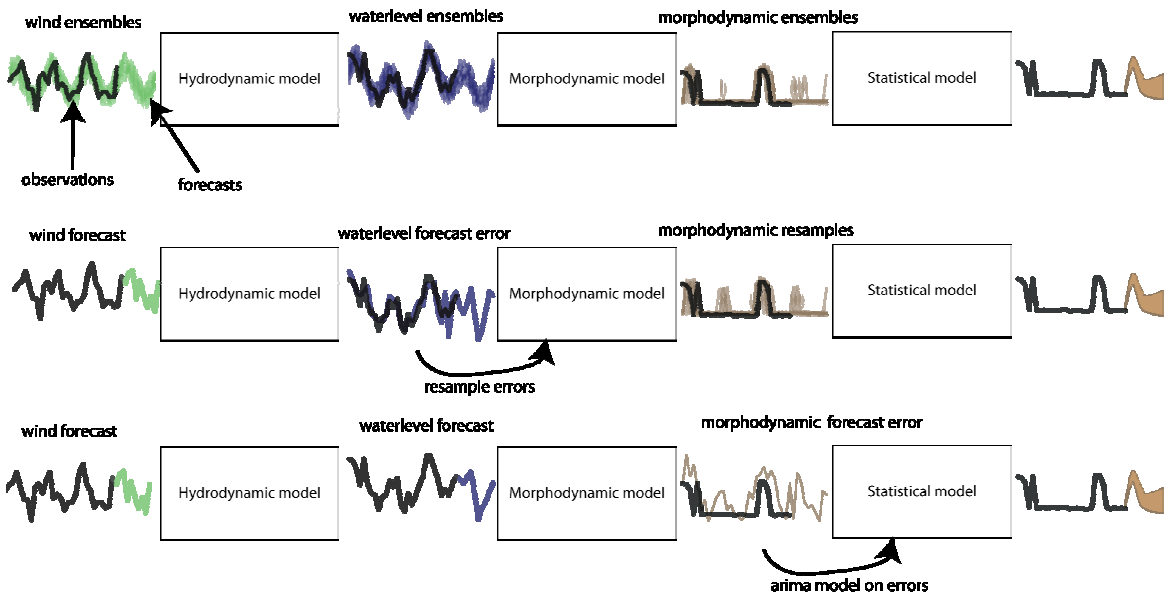

Figure 1: Three different methods to compute the confidence bounds around morphological forecasts (*top*: Ensemble, *middle*: bootstrap, *lower*: autoregression)

There are also measurements available for the morphodynamics. The ARGUS video system (Holman, 2007) together with the shoreline mapper (Aagaard, 2005) gives measurements of the shoreline. A problem does occur if these measurements would be used to estimate the forecast error, as it is then not possible to use them as verification of our confidence intervals, at least not without possibly introducing spuriosities or making extra assumptions.

Error model

Choosing the error model is not required if the EMCWF ensembles are propagated through the chain of models.

If errors are introduced in the hydrodynamic model by using the expected error approach assumptions about the distribution of the error do have to be made. Because we only use a profile model the coastline is only a point, so spatial correlations are not present. There can be a temporal correlation for which can be tested using the Dickey Fuller test (Dickey, 1979). It is possible to use either a parametric distribution or the bootstrap approach. In this case the bootstrap method will be used. If autocorrelations are present block resamples from the distribution of differences between forecasted water levels and observed water levels from the past. These differences are added to the forecasted water level sample, resulting in a distribution of water levels. These resampled water levels are used as input for the morphodynamic model.

If the errors are introduced in the morphodynamic part of the model, it is likely that errors are temporal correlated. An error with a high temporal correlation can occur for example if a small foredune exists on the beach. If the water comes just up to this foredune in the observations and the water level is a bit higher in the forecast then there is an error which is likely to be high until both forecast and observations end up on the same side of this foredune again. The time-series is therefore fitted using an autoregressive approach.

Three approaches

After applying all the possible choices for creating a confidence interval three different methods for computing confidence bounds for morphological forecasts emerge. They are summarized in figure 1. The first method (a) is to compute the EMCWF ensembles all the way through the model train, using a non parametric confidence interval. The second method (b) is to use bootstrap resampling on the average forecast error of the hydrodynamic model and the final option (c) is to fit an autoregressive model through the morphological forecast error.

DISCUSSION: EVALUATING THE THREE APPROACHES

Several aspects make the three approaches different, i.e. required data, required computation time and assumptions. Table 1 summarizes the differences between the three methods. As is the case in most forecast system design choices, the computation time will probably be leading. Computation time is so important because it is strictly limited. Forecasts are not so useful when given as hindsight. In the setup for the Egmond beach the forecast is made for three days ahead. The time for running the hydrodynamic model and the morphodynamic model is limited to 4+2=6 hours. Luckily all the ensembles and resample models can run in parallel, so only the amount of required available computer nodes grows. The total amount of run time required for the ensemble approach is 6x 50=300 hours. This can be reduced if the approach used in ECMWF of running ensembles on coarser grids is used. For the bootstrap approach it is 4+2x50=104 hours and for the autoregressive approach it is 4+2 hours.

The assumptions for the approaches are also quite different. For method a these are based on the assumption that the sample of initial states provides a realistic estimate of the probability distribution of analysis errors and that the phase-space trajectories computed by the numerical model are good approximations of atmospheric trajectories (Molteni, 1996). The same type of assumption should hold all the way through the model train, the ensemble of wind fields should provide a realistic distribution of water levels and the ensemble of wind fields should provide a realistic estimate of the probability distribution of intertidal beach volume. It is easy to challenge these assumptions because the morphology is influenced, not only by water level, but also by setup, long waves and grain size. But for simplicity we'll stick to these assumptions for now. The assumptions for the other two methods are that the skill in the past is representative for the skill in the future.

CONCLUSION

Several aspects have been discussed that can be used to choose a method for computing a confidence interval. Because the morphological forecast is dependent on several other models the introduction of error determines the amount of computation required for the forecast of the interval. The error source is dependent on the availability of data. The computational effort of the error model is small relative to the computation effort of the numerical model.

The aspects discussed in this paper relate to the practical

Table 1: Comparison of the three different methods to compute confidence bounds

Method	Error introduction	Error source	Error model	Data required	Computation time	Assumptions
(a)	Meteorological	Ensembles	Non parametric	Ensemble breeding	(4 +2) hours x 50	Ensemble variation propagated through model chain is representative for the error made in morphological forecast.
(b)	Hydrodynamic	Expected error	Bootstrap	History of hydrodynamic observations and forecasts	4 hours + 2 hours x 50	Previous hydrodynamic forecast errors are representative and the main source for errors in the morphological forecast
(c)	Morphodynamic	Expected error	Arima	History of morphodynamic observations and forecasts	4+2 hours	Previous morphodynamic forecast errors are representative for future forecast errors

applicability of the method. To determine if a forecast confidence interval is actually valid it needs to have a skill. That is if we create a 95% prediction interval, one would expect that 95% of the observations would lie within those ranges. The skill of the confidence intervals will be addressed in a future paper.

LITERATURE CITED

Aagaard, T., Kroon, A., Andersen, S., Møller Sørensen, R., Quartel, S., and Vinther, N. 2005. Intertidal beach change during storm conditions; Egmond, The Netherlands. *Marine geology*, 218(1-4), 65–80.

Baart, F., van der Kaaij, T., van Ormondt, M., van Dongeren, A., van Koningsveld, M., and Roelvink, J. A. 2009. Real-time forecasting of morphological storm impacts: a case study in the netherlands. *Journal of coastal research*, 2, 1617–1621.

Buizza, R., Petroliagis, T., Palmer, T., Barkmeijer, J., Hamrud, M., Hollingsworth, A., Simmons, A., and Wedi, N. 1998. Impact of model resolution and ensemble size on the performance of an ensemble prediction system. *Quarterly journal of the royal meteorological society*, 124(550), 1935–1960.

Cryer, J.D. and Chan, K. 2008. *Time series analysis: with applications in r*. New York: Springer.

Demeritt, D., Nobert, S., Cloke, H., and Pappenberger, F. 2010. Challenges in communicating and using ensembles in operational flood forecasting. *Meteorological applications*, 17(2), 209–222.

Dickey, D.A. and Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the american statistical association*, 427–431.

Efron, B., Tibshirani, R., and Tibshirani, R.J. 1993. *An introduction to the bootstrap*. Chapman and Hall/CRC.

Felsenstein, J. 1985. Confidence limits on phylogenies: an approach using the bootstrap. *Evolution*, 39(4), 783–791.

Fisher, R.A. 1956. *Statistical methods and scientific inference*. Oliver and Boyd London.

Gebraad, A. W. and Philippart, M. E.. 1998. *The Dutch Continental Shelf Model, DCSM98: calibration using altimeter data*. Werkdocument RIKZ/OS- 98.121x. RIKZ. in Dutch.

Gerritsen, H, de Vries, J W, and Philippart, M. 1995. *Quantitative Skill Assessment for Coastal Ocean Models*. American Geophysical Union. Chap. The Dutch Continental Shelf Model.

Hamill, T.M., Hagedorn, R., and Whitaker, J.S. 2008. Probabilistic forecast calibration using ECMWF and GFS ensemble reforecasts. Part II: precipitation. *Monthly weather review*, 136(7), 2620–2632.

Hapke, C. and Plant, N. 2010. Predicting coastal cliff erosion using a bayesian probabilistic model. *Marine geology*.

Holman, R.A. and Stanley, J. 2007. The history and technical capabilities of Argus. *Coastal engineering*, 54(6-7), 477–491. The CoastView Project: Developing coastal video monitoring systems in support of coastal zone management.

International Organization for Standardization. 2008. *Guide to the expression of uncertainty in measurement*. Tech. rept. ISO.

Lesser, G.R., Roelvink, J.A., van Kester, J.A.T.M., and Stelling, G.S. 2004. Development and validation of a three-dimensional morphological model. *Coastal engineering*, 51(8-9), 883–915. Coastal Morphodynamic Modeling.

Lewis, J.M.. 2005. Roots of ensemble forecasting. *Monthly weather review*, 133(July), 1865–1885.

Molteni, F., Buizza, R., Palmer, TN, and Petroliagis, T. 1996. The ECMWF ensemble prediction system: Methodology and validation. *Quarterly journal of the royal meteorological society*, 122(529), 73–119.

Plant, N.G., & Holland, K.T. 2011. Prediction and assimilation of surf-zone processes using a Bayesian network part I: Forward models. *Coastal engineering*, 58(1), 119–130.

Ripley, B.D. 2004. *Spatial statistics*. Wiley-Blackwell.

Roelvink, D., Reniers, A., van Dongeren, A., van Thiel de Vries, J., McCall, R., and Lescinski, J. 2009. Modelling storm impacts on beaches, dunes and barrier islands. *Coastal engineering*, 56(11-12), 1133–1152.

Sutherland, J, Peet, AH, and Soulsby, RL. 2004. Evaluating the performance of morphological models. *Coastal engineering*, 51(8-9), 917–939.

Toth, Z., and Kalnay, E. 1993. Ensemble forecasting at NMC: The generation of perturbations. *Bulletin of the american meteorological society*, 74, 2317–2330.

van Dongeren, A. R., Plant, N., Cohen, A. B., Roelvink, J A, Haller, M.C., and Catalán, P. 2008. Beach Wizard: Nearshore bathymetry estimation through assimilation of model computations and remote observations. *Coastal engineering*, 55(12), 1016–1027.

van Gelder, P H A J M. 2000 (January). *Statistical methods for the risk-based design of civil structures*. Ph.D. thesis, Delft University of Technology.

Weerts, A.H., Winsemius, H.C., and Verkade, J.S.. 2010. Estimation of predictive hydrological uncertainty using quantile regression: examples from the national flood forecasting system (england and wales). *Hydrology and earth system sciences discussions*, 7.

Whitaker, J.S. and Loughe, A.F. 1998. The relationship between ensemble spread and ensemble mean skill. *Monthly weather review*, 126(12), 3292–3302.

Wilkinson, L. 2005. *The grammar of graphics*. Springer Verlag.

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