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Morphological impact of a storm can be predicted three days ahead

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Abstract

People living behind coastal dunes depend on the strength and resilience of dunes for their safety. Forecasts of hydrodynamic conditions and morphological change on a timescale of several days can provide essential information to protect lives and property. In order for forecasts to protect they need be relevant, accurate, provide lead time, and information on confidence.

Here we show how confident one can be in morphological predictions of several days ahead. The question is answered by assessing the forecast skill as a function of lead time. The study site in the town of Egmond, the Netherlands, where people depend on the dunes for their safety, is used because it is such a rich data source, with a history of forecasts, tide gauges and bathymetry measurements collected by video cameras. Even though the forecasts are on a local scale, the methods are generally applicable. It is shown that the intertidal beach volume change can be predicted up to three days ahead.

Keywords: Forecasts, Skill, Morphology

1. Introduction

Coastal areas are exposed to extreme natural conditions, such as storm surges, waves, tsunamis, and erosion. Providing warnings is one of the ways to reduce the risk to human life and to allow for property to be protected (Day et al., 1969). Although warnings are not always effective (Normile, 2012), when a disaster is imminent, people expect to be warned (Arceneaux and Stein, 2006).

The need for an improved coastal warning system arose from the disasters that impacted the United States (Katrina, Sandy) and Europe (Xynthia) (Ciavola et al., 2011b). Improving coastal warning systems has become possible due to the improved weather forecasts. Even hard to predict variables like precipitation have seen a strong improvement. The lead time has improved from 2 days ahead in 2001 to 6.5 days ahead in 2014 (European Centre for Medium-Range Weather Forecasts, 2014). The skill has improved due to higher resolution measurements and models and integration of physical and statistical models (data assimilation).

In order for a coastal warning to be helpful it needs to be relevant, accurate, provide lead time, (Baart et al., 2009) and confidence estimates. Previous studies have worked on providing relevant warnings by extending operational hydrodynamic forecast models with forecasts of morphological change (Baart et al., 2009; Plant and Stockdon, 2012; den Heijer et al., 2012b; Vousdoukas et al., 2012). Adding morphodynamic processes to a coastal warning system is relevant because the failure modes of coastal dunes depend on morphological change (Sallenger, 2000; Mai et al., 2007). Most of these studies incorporate confidence (Plant and Stockdon, 2012; den Heijer et al., 2012b; Baart et al., 2011) and accuracy estimates (Plant and Stockdon, 2012; Vousdoukas et al., 2012), but lack information about lead time (the time between the dissemination of a forecast and the onset of an event (Verkade and Werner, 2011)).

Here we expand on previous efforts by showing how many days of lead time a forecast of coastal change provides during a storm surge. The amount

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of lead time is evaluated by how much the predictive skill of forecasts improve in the days up to an imminent storm. We add information about the confidence by including confidence intervals around the forecast variables. The extensions to the warning system described in this paper are part of a collective European effort to improve the warning systems (the Morphological Impacts and COastal Risks induced by Extreme storm events (MICORE) project).

Morphological effects of a storm occur at the end of a chain of processes, which can be represented by a chain of numerical models. The last four parts of the chain, which are commonly used to forecast the coastal morphology, are shown in Figure 1. Each of these models is based on assumptions, schematizations and reductions of the real world (Oreskes et al., 1994) and can only explain a certain proportion of variance of the quantity for the next link.

The amount of explained variance at the end of the chain is essential in the response phase. More specifically the explained variance as a function of lead time determines the feasibility of different response actions. Given hours, one can close down a beach, but one needs a lead time of days to evacuate a city. In the case of imminent dune failure the morphological forecasts describe the relevant (Morris et al., 2008) process of dune erosion. This raises the question “How many days ahead can we still rely on local morphological forecasts during a storm?”.

For weather and ocean dynamic forecasts it is already common practice to study the forecast skill as a function of lead time (European Centre for Medium-Range Weather Forecasts, 2010). Figure 2 shows that the forecast skill for the ocean waves are lower than the pressure fields, 60% versus 70% for the 7 days ahead forecast and 92% versus 98% for the 3 days ahead forecast. The skill for pressure fields and ocean waves eventually determines at least part of the skill for coastal morphological forecasts. Pressure anomalies generate wind and surge. During a storm, the local wind generated sea waves and the propagated ocean waves in combination with a surge and high tide can cause severe coastal erosion.

In this paper we extend Figure 2 with information about forecasting skill for water levels and morphodynamic change. The coastal hydrodynamic and morphological skill as a function of lead time is most relevant under storm conditions. A local field study is appropriate as no morphological forecast or measurement system exists with a global coverage

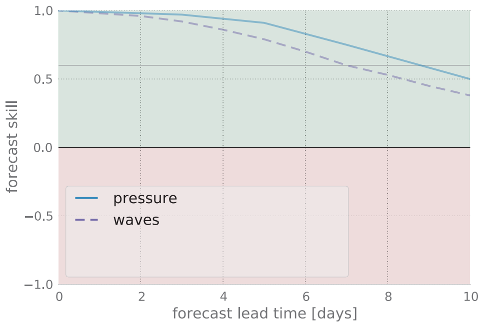


Figure 2: Skills for pressure, and waves as a function of forecast lead time. Pressures are anomaly correlation (Wilks, 2011) (AC) for the ECMWF 500 hPa forecasts (European Centre for Medium-Range Weather Forecasts, 2010), waves are AC for the ECMWF significant wave height forecasts (European Centre for Medium-Range Weather Forecasts, 2010).

2. Methods

2.1. Study site Egmond (the Netherlands)

The requirements of availability of dune erosion events, measurement data and existing near shore models has resulted in the selection of the Egmond study site. The Egmond study site, located on the Dutch coast (Figure 1), has been used in numerous publications (for example Aagaard et al., 2005). The video measurement stations have generated before- and after storm bathymetry measurements over the last decade. The video system was setup in the CoastView project (Davidson et al., 2007), based on the Argus system (Holman and Stanley, 2007). The morphodynamic forecasts are relevant for the town of Egmond, as it is an area with a high risk of dune erosion (den Heijer et al., 2012a).

2.2. Model setup

The model chain used to forecast coastal change (Figure 1) is described in detail in Baart et al. (2009). The model chain consists of a global wave model (schematisation: Wave Watch, processes: waves, model: Wave Watch 3 (WW3)), with a nested regional (Dutch Continental Shelf Model (DCSM), hydrodynamic and waves, Delft3D, (Gebraad and Philippart, 1998)) and coastal model (Dutch “Kuststrook Fijn”, hydrodynamic and

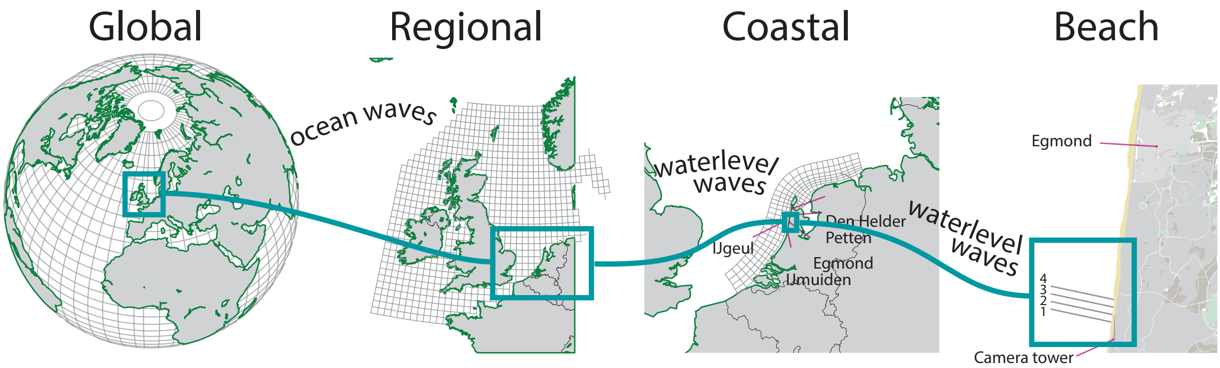


Figure 1: Nested schematization of an operational morphological model. Applied to Egmond, the Netherlands as described by Baart et al. (2009), extensions described in subsection 2.2.

waves, Delft3D). For this study we replaced the water level forecasts by the setup as described by De Vries (2009) (Delft3D replaced by the similar SIMONA model engine), which provides a history of ensemble forecasts. The model chain consists of solely open source models, making the chain verifiable (Kettner and Syvitski, 2013) and reproducible. Other researchers can check and reuse the source code and model schematisations. Replacing model engines by similar components has become easier due to the combined effort of the integrated modeling community (for example Peckham et al., 2013; Voinov et al., 2010).

The last link is the beach model. Four 1D profile models describe the topography and bathymetry of the dunes at the Egmond study site. The model uses the hydrodynamics (water levels, wave energy and direction) of the previous step as input. The numerical model XBeach (Roelvink et al., 2009) is used to describe the nearshore hydrodynamics and coastal erosion. The beach model is schematised using 1D profiles instead of a 2DH bathymetry. The main reason for this is to reduce calculation time. It is believed that for this part of the coast a 1D approach is sufficient (den Heijer et al., 2012a). For areas with more complex foreshores a 2D approach is thought to be more appropriate (van Geer and Boers, 2012).

2.3. Storm selection

To answer the question how many days ahead the morphological effect of a storm can be forecast, multiple storms are considered. The forecast system is setup to predict extreme events. For a representative sample, one would prefer a large number of extreme storms (return period $\geq$ 10 yr). But as only a decade of data is available, this is not possible. The water level records from the Petten tide gauge (20 km north of Egmond) give a good selection criterion, as it is the closest tide gauge to the Egmond study site. A search for the highest water levels, with a window of three days, results in the selection of five storm events (see Table 1).

Besides a high water level, availability of morphologic and hydrodynamic data is important. No intertidal morphologic estimates have been made for the 2007-01-18 storm, due to unavailability of the video camera system. Therefore, this storm is only used to determine the hydrodynamic forecast error and skill as a function of forecast lead time. This gives a total of four storms, used for the morphodynamic skill evaluation.

2.4. Boundary conditions and validation data

Water level forecasts, including ensembles, are available for two nearby stations, at IJmuiden and Den Helder. Water level observations are also available for these two sites and for the location Petten (locations in Figure 1). The weighting of the ensemble forecasts and measurements of the IJmuiden and Den Helder stations are used to create boundary conditions and validation data for the area of interest. We use the high and low tide estimates and ignore any errors in forecast time.

There is no archive of the wave ensemble forecasts. The wave time series, as observed at the IJgeul (13km offshore), provide us with a reasonable alternative to use as a boundary for the beach model. Using the observed waves instead ensemble forecasts of waves could lead to overconfident confidence intervals around the morphological forecasts, since the same wave time series is used for

Date	Pre	Post
2007-11-09	2007-01-01 – 2007-01-06	2007-11-10 – 2007-11-14
2006-11-01	2006-10-26 – 2006-10-30	2006-11-02 – 2006-11-07
2007-01-18	No data	No data
2008-03-01	2008-02-27 – 2008-02-29	2008-03-02 – 2008-03-07
2007-03-18	2007-03-14 – 2007-03-17	2007-03-19 – 2007-03-24

Table 1: Selection of pre and post storm profiles for the five storms that resulted in the highest water level at Petten, the Netherlands.

each ensemble.

Two datasets provide information for the bathymetry and topography. The Dutch Annual Coastal Measurement (JARKUS) dataset (Rijkswaterstaat, 2008) provides the base bathymetry and topography. Pre- and post storm intertidal bathymetry is obtained from the Automated Shoreline Mapper (ASM) archive (Uunk et al., 2010), a process for extracting shorelines from the Argus video camera system.

The ASM measurements cover the intertidal zone. Along the Dutch coast, the sand that erodes from the dune is transported through the intertidal zone towards the sea. After a storm, part of the sand that eroded remains in the intertidal zone, causing the volume of the intertidal zone to temporarily increase. Thus the intertidal shoreline is a proxy for the storm impact above the dune foot. As it is the only available pre- and post storm measurement source it is the best available information of dune erosion. The implied geometric relation between the intertidal zone and dune erosion is the basis of dune erosion models such as DUne eROSion model (DUROS) (Vellinga, 1986).

Adjustments were made to the process described by Uunk et al. (2010). The shorelines generated by the ASM showed intra-day inconsistencies, which required an extra manual selection step. In the context of an operational system, a manual selection step is unsatisfying because it requires human intervention. The overview of selected days for each storm event can be found in Table 1. As an estimate of the vertical error (Root Mean Squared Error (RMSE) in m) Uunk et al. (2010) gives an estimate of this measurement source is in the range of 0.28 m for supervised applications such as applied here.

2.5. Forecast skill

We are assessing the forecast skill as a function of lead time for two quantities, water level (Equation 5) and morphodynamic change (Equation 4). The equations show that the skill of a forecast is computed from a forecast, a reference forecast, and a measurement.

The statistical measures that are used in this paper are listed in Equations 1 through 5. These include anomaly correlation (Wilks, 2011) (AC) based on forecast y, observations o and climate c, a number of n forecasts, observation pairs with index k, Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), the Forecast Skill Score (SS). Detailed explanations about the forecast skill SS (Equation 3) and how it relates to MSE can be found in Murphy and Epstein (1989) and Wilks (2011).

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2 : o \in \mathbb{R} \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

$$SS = 1 - \frac{MSE_{\text{model}}}{MSE_{\text{reference}}} \tag{3}$$

$$SS_{bathy} = 1 - \frac{MSE_{\text{model}}}{MSE_{\text{initial bathymetry}}} \tag{4}$$

$$SS_{wl} = 1 - \frac{MSE_{\text{model}}}{MSE_{\text{astronomical tide}}} \tag{5}$$

$$\tag{6}$$

Deterministic model runs of the chain in Figure 1 provide the forecasts for the four storm periods. The forecasts have a lead time from 10 days down to 1 day.

For a reference forecast we use astronomic tide and for the morphological forecast we use the initial bathymetry (initial Jarkus profile). The competition between the reference forecast and the model forecast determine the sign of the skill score. If the SS goes below 0, the reference (tide, initial bathymetry) is a better forecast than the model forecast.

Verification calculations were done using the National Center for Atmospheric Research (NCAR)

R Project for Statistical Computing (R) verification package (Gilleland, 2010). In coastal research a Skill of over 0.6 is often used as a criterion for a good forecast(van Rijn et al., 2003), we'll use this even though it's an over simplified approach (Bosboom et al., 2014).

The above provides information about lead time and accuracy. To also provide information about the confidence, we include confidence intervals around the morphological forecasts as described in (Baart et al., 2011).

3. Results

3.1. Hydrodynamics

The amount of lead time of the hydrodynamic forecasts of the November 2007 storm is seen as a time series in Figure 3. As the number of days to the storm decreases the ensemble spread in forecasts converges to a narrow yellow band.

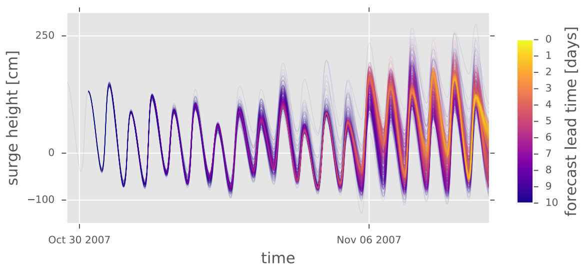


Figure 3: Hydrodynamic ensemble (n=52) forecasts as a function of forecast lead time for the storm in November 2007.

These timeseries are combined with measurements into Figure 4a which shows the errors of the forecasts as a function of lead time. As one would expect the forecast for one to a few days ahead has less errors than a forecast several days ahead.

As can be seen from the white line , when a storm is about to occur, longer forecast lead times result in a positive forecast errors. An observed positive surge minus a near zero surge forecast give a positive forecast error, as seen in Figure 3.

The hydrodynamic ensemble forecast errors are shown in Figure 5a. These are comparable to the deterministic forecast errors, only with more spread. The ensemble forecasts are based on boundary conditions with coarser resolution.

3.2. Morphology

The results from the determinstic model runs are shown in Figure 6. The first thing to note is that, in the forecast bathymetries, the sand is deposited closer to the dunes than observed. This can be seen in the brown patches that are higher than the green patches near the dunes and the green patches that are higher than the brown patches near the intertidal area −1.5 m to 1.5 m, representing forecast and observed bathymetry changes. The intertidal volume change is not very sensitive to errors in beach angles.

The morphological errors are shown in Figure 4b. Comparable to the hydrodynamic forecast errors, the deterministic morphological forecast errors show an increased average error (white line going up in Figure 4b) for longer forecast times. As the storm approaches the inter tidal volume change forecasts are more close to the observed volume changes. The ensemble errors, shown in Figure 5b, are computed for the profile closest to the camera. The errors for this profile are larger than for the average of the four deterministic profile runs in Figure 4b.

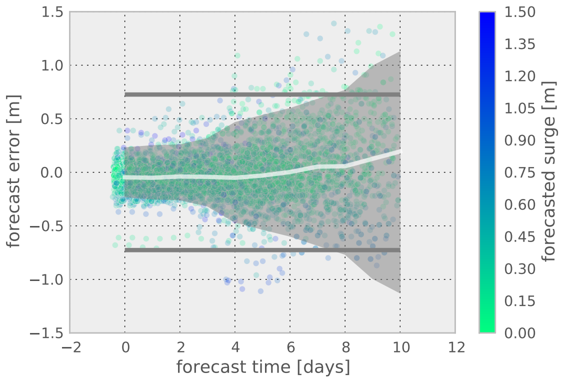
3.3. Skill and lead time

The forecast skills for the hydrodynamic and morphodynamic forecasts are presented in Figure 7, combined with the lines from Figure 2. This figure show that even for forecasts 10 days ahead the hydrodynamic skill is positive. The skill is above 0.6 for a water level forecast with a lead time of seven days.

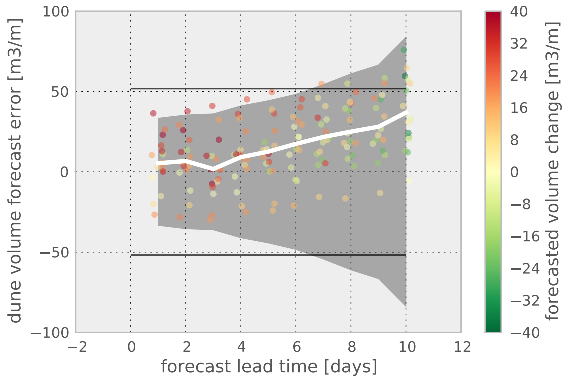
Based on the deterministic water level forecast, the observed waves and the interpolated bathymetry, we hindcast the morphological model starting from 10 days down to 1 day before the storm. The morphological forecast skill (Figure 7) shows that the forecast skill is positive up to five days ahead and over 0.6 for lead times up to three days.

4. Discussion

We have seen that the nested hydrodynamic and morphological models can predict water levels up to ten days ahead and volume changes in the intertidal zone with a skill over 0.6 up to three days ahead at the Egmond location under storm conditions. This analysis was possible because an archive was collected of all previous forecasts. This allows to make

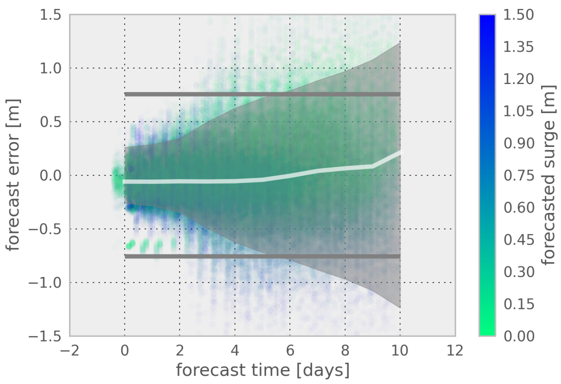


(a) Hydrodynamic deterministic forecast errors as a function of forecast lead time.

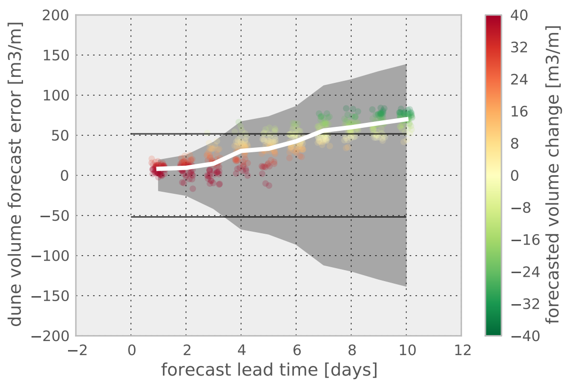


(b) Morphological deterministic forecast errors (intertidal volume change) as a function of forecast lead time.

Figure 4: Errors for deterministic hydrodynamic and morphological forecasts as a function of forecast lead time for the 10 days before the storm surge peaks. White line shows the mean forecast error for surge (4a) and for intertidal volume change (4b). Gray area shows the $1.96 * RMS_{error}$ interval. The grey lines show $1.96 * \sigma_{\text{observed}}$ for intertidal volume change and surge.



(a) Hydrodynamic ensemble forecasts errors as a function of forecast lead time.



(b) Morphological ensemble forecast errors (intertidal volume change) as a function of forecast lead time for ensemble forecasts.

Figure 5: Errors for hydrodynamic and morphological ensemble forecasts as a function of forecast lead time for the 10 days before the storm surge peaks. White line shows the mean forecast error for surge (5a) and for intertidal volume change (5b). Gray area shows the $1.96 * RMS_{error}$ interval. The grey lines show $1.96 * \sigma_{\text{observed}}$ for intertidal volume change and surge.

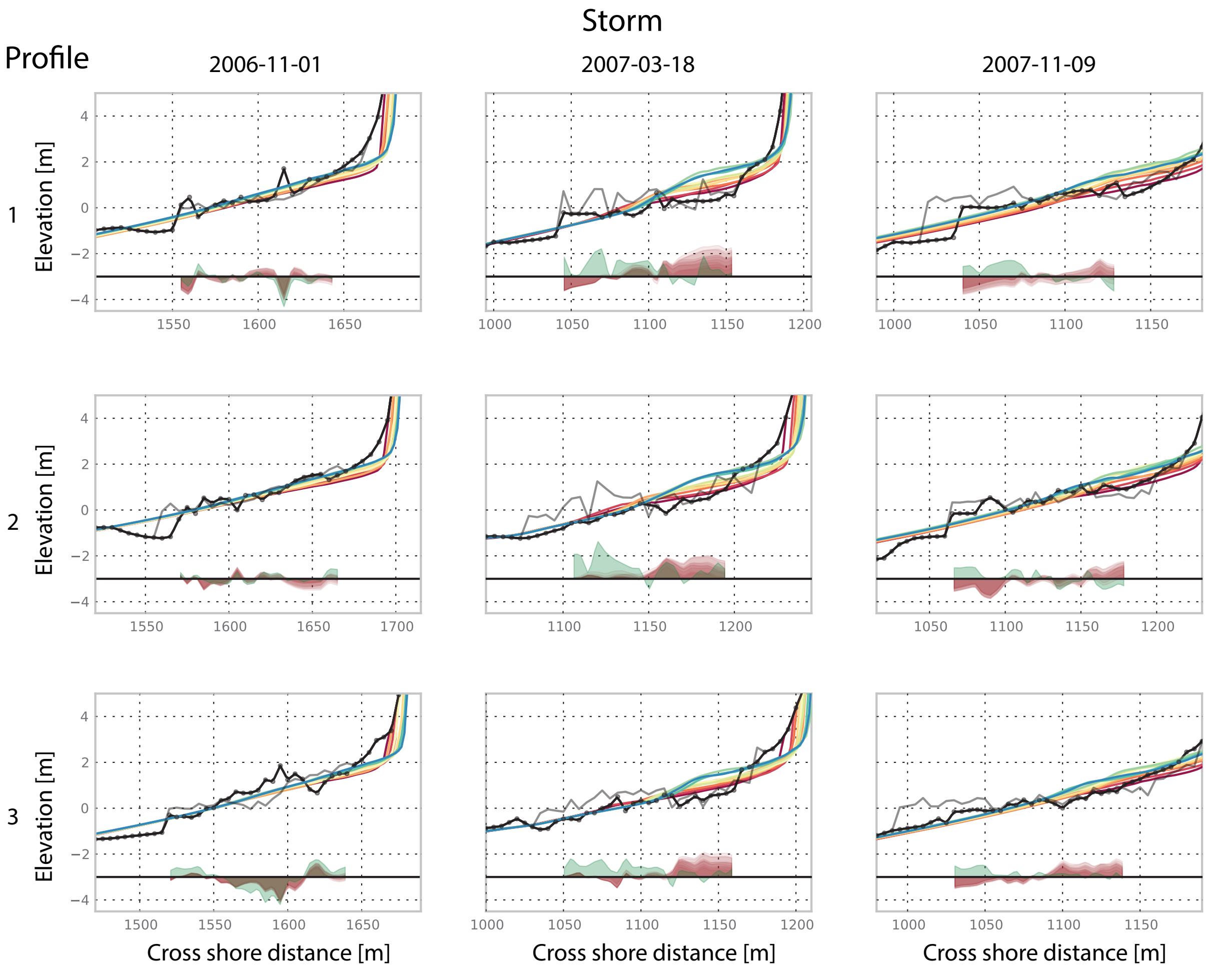


Figure 6: Observed and modelled pre and post storm profiles for three different profiles and three different storms (1 storm and profile left out to save space). Black dots: observed pre storm profile. Black solid line: initial model bathymetry. Gray line: observed post storm profile. Colored lines: forecasts from 10 days ahead (red) to 1 day ahead (blue). Green area with origin at -3: observed bathymetry change. Brown area with origin at -3: forecast bathymetry changes.

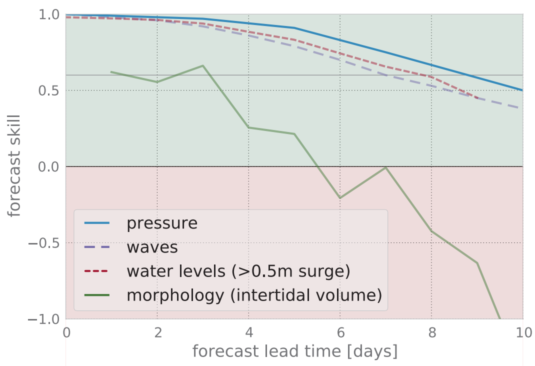


Figure 7: Skills for pressure, waves, waterlevels and morphology as a function of forecast lead time. Pressures are AC for the ECMWF 500 hPa forecasts (European Centre for Medium-Range Weather Forecasts, 2010), waves are AC for the ECMWF significant wave height forecasts (European Centre for Medium-Range Weather Forecasts, 2010). Water levels are the SS for the water levels for the regional model, data de Vries (2009), skill computed in this paper. Morphology SS for the intertidal beach volume, this paper.

the meta-forecast, "How do you forecast the quality of your forecast?", which is an essential question in the confidence in forecasts. The preferred way, if data storage is limited, is to store output of the models at locations where measurements are also available. An alternative, and in itself advisable, is to keep track of the exact versions of the software, input data, schematizations with which the model was run. This allows the recreation of old forecasts.

The system is nearing the skill level needed to predict coastal breaches with enough lead time to act. A lead time of three days can be enough for a warning of possible breaching to trigger a preparation effort. From the three days the calculation time of several hours needs to be subtracted. An extra margin (over the 0.6 SS level) should be included to account for the negative effect of providing false warnings (Breznitz, 1984). The exact time needed to respond depends on the local conditions and measures. Property can be quickly moved but evacuation can take days to prepare.

The lower skill for the morphological forecasts is in line with what one would expect from a basic error propagation theory, where the explainable variance reduces when one makes longer chains of models. This can be countered by assimilating at multiple steps along the chain.

Several approaches can be used to improve on these results. The error (MSE) and model performance measures (SS) used here all assume that the measurements represent a true value. The measurement errors of the hydrodynamic measurements are often an order of magnitude smaller than the forecast errors. Then this is a safe assumption to make. The morphodynamic measurement errors (estimated in the order of 0.3 m) are smaller but in the same order of magnitude as the forecast elevation changes (around 1 m, see Figure 6). One could define performance and error measures that take measurement error into account (only computing skill if there is noteworthy morphological change).

Another alternative is to replace the morphological model by a statistical model (Plant and Holland, 2011a; den Heijer et al., 2012b) trained on numerical simulations. This would have the advantages of the greatly reduced computation times and it would make the separation between the statistical model and the numerical model more explicit. One of the current disadvantages of the Bayesian Network approach (as used by Plant and Holland, 2011a,b) is that continuous variables are treated as nominal variables resulting in a large number of parameters. By moving to a probabilistic graphical model that allows for the inclusion of continuous variables, for example a Markov Chain Monte Carlo (MCMC) model (Gelman et al., 2004), the number of parameters can be reduced, allowing for a greater generalizability. To generalize from mild storms, for which the model can be trained, to large storms, for which the model should predict, requires a parsimonious statistical model.

There are also efforts to improve the numerical models and schematisations used. As a result of these efforts, over the last years the water level forecasts skill increased (Verlaan et al., 2005). Operational models, similar to the one discussed here, have been setup accross Europe (Ciavola et al., 2011a) and the United States of America (Barnard et al., 2014), also resulting in a better set of default parameters for the XBeach model. In this study we have used four year old bathymetry measurement techniques and four year old hydrodynamic forecasts. As our knowledge, measurement and modeling skills have progressed over the last four years, a logical step would be to repeat this activity for the later and coming storms in order to assess our progression.

5. Conclusion

This study shows a first estimate of morphological forecast skill as function of lead time. Based on the forecast system for the case study of Egmond we estimate that the morphological forecast system gives a lead time of 3 days for dune erosion and 7 days for water levels under storm conditions.

The lead time is an important measure of the relevance of the forecast system. The usability of the system depends on its lead time, as it determines the feasibility of response measures. When confident forecasts are given several days ahead it allows for emergency measures and planned evacuation.

Setting a benchmark is the first step towards improving it. As seen in the progress made in numerical weather prediction, trying to beat the benchmark every year, by making full use of available computer power, by assimilating to data (van Dongeren et al., 2008; Smith et al., 2012) and by improving model formulations, is the way forward.

Acronyms

NCAR	National Center for Atmospheric Research
R	R Project for Statistical Computing
SS	Forecast Skill Score
AC	anomaly correlation (Wilks, 2011)
ASM	Automated Shoreline Mapper
JARKUS	Dutch Annual Coastal Measurement
ECMWF	European Centre for Medium-Range Weather Forecasts
DCSM	Dutch Continental Shelf Model
WW3	Wave Watch 3
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MCMC	Markov Chain Monte Carlo
MICORE	Morphological Impacts and COastal Risks induced by Extreme storm events
DUROS	DUne eROSion model

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