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The role of video imagery in predicting daily to monthly coastal evolution

M.W.J Smit [a,*], S.G.J. Aarninkhof [b], K.M. Wijnberg [c], M. González [d], K.S. Kingston [e], H.N. Southgate [a], B.G. Ruessink [f], R.A. Holman [g], E. Siegle [h], M. Davidson [e], R. Medina [d]

[a] *Delft University of Technology, Faculty of Civil Engineering and Geosciences, PO Box 5048, 2600 GA Delft, The Netherlands*
[b] *WL|Delft Hydraulics, Marine and Coastal Management, PO Box 177, 2600 MH Delft, The Netherlands*
[c] *Faculty of Engineering Technology, Water Engineering and Management, University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands*
[d] *Ocean & Coastal Research Group. Departamento de Ciencias y Técnicas del Agua y del Medio Ambiente, Universidad de Cantabria, 39005 Santander, Spain*
[e] *School of Earth Ocean and Environmental Science, University of Plymouth, Drake Circus, Plymouth, Devon, PL4 8AA, UK*
[f] *Institute for Marine and Atmospheric Research Utrecht, Department of Physical Geography, Utrecht University, Heidelberglaan 2, 3584 CS Utrecht, The Netherlands*
[g] *College of Oceanic and Atmospheric Sciences, Oregon State University, 104 COAS Admin Bldg, Corvallis, OR 97331–5503, United States*
[h] *Universidade de São Paulo, Instituto Oceanográfico, Praça do Oceanográfico, 191, Cidade Universitária, 05508–900-São Paulo, Brazil*

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Abstract

Owing to intensified use of the coastal region and the frequent application of small-scale, tailored interventions such as beach nourishments, there is a growing need for coastal state information and knowledge on spatiotemporal scales of meters to kilometers and days to months. The design and implementation of engineering and management measures at these scales is hampered by limited predictability of their impact. Advanced, automated video stations open the door towards the collection of long-term, high-resolution data sets, which offer enhanced opportunities for the prediction of coastal processes at smaller scales. In this paper, the added value of high-resolution data sets for prediction purposes is explored. In particular the application of data-driven approaches as well as process models supported by video data are explored. In the data-driven approach, the inclusion of monthly video-derived data was found to not only improve confidence intervals on the predicted shoreline evolution, but also to facilitate the use of more sophisticated data extrapolation methods. Short-term, operational forecasts of the nearshore flow and sediment transport field were found to benefit from the inclusion of intertidal bathymetric data derived from video imagery. Though in its pioneering stage for video-based research, it is foreseen that significant advancement in prediction skill will be achieved through development of data-assimilation schemes which combine the best of existing process and empirical knowledge on coastal morphodynamics.

Keywords: Argus video monitoring; Coastal state indicator; Data-driven modelling; Data-model integration; Prediction of coastal evolution; High-resolution monitoring; High-resolution modelling

1. Introduction

Coastal managers, engineers and scientists increasingly need coastal state information at small scales of days to weeks and meters to kilometers. This is – amongst other reasons – due to the frequent use of local beach nourishments as a sustainable, tailored intervention to mitigate coastal erosion, the recognition of rip currents as a serious threat for swimmer safety and the demand for year-round exploitation of beaches, driven by the increasing recreational pressure on the coast. The design and evaluation of coastal measures and engineering interventions is hampered by the dynamics of the natural system, which act over a wide range of spatiotemporal scales (e.g. De Vriend, 1997; Stive et al., 2002). Beach and nearshore nourishments, for example, are often found to adapt to the longer-term profile shape in a matter of weeks but may show unexpected behaviour that could pose temporary local erosion problems (e.g. Wijnberg et al., 2006). Rip currents may even develop within days. Effective management of a variety of coastal functions thus

* Corresponding author. Tel.: +31 15 2789457; fax: +31 15 2785124.
E-mail address: M.W.J.Smit@tudelft.nl (M.W.J. Smit).

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demands a sound understanding of the complex morphological behaviour of coastal systems, long-term coastal monitoring strategies with high resolution in time and space and predictive skills to assess the future impact of coastal interventions.

Long-term, high-resolution morphological data sets that enable the investigation of coastal dynamics at time scales of days to months are sparse (Southgate et al., 2003). Traditional, in situ survey methods involving the use of ships, amphibious vehicles or jet skis provide excellent data but require major logistical commitments and often lack spatiotemporal resolution to resolve processes of interest. Besides, in situ hydrodynamic data are often hard to collect owing to the hostile environmental conditions in the surfzone. However, many nearshore processes have a visible signature at the sea surface, which can be monitored remotely. While perhaps of lower accuracy, remote-sensing techniques offer the potential for cost-efficient, long-term data collection with high resolution in time and space. With the advent of digital imaging technology, shore-based video techniques like the advanced Argus system (Holman and Stanley, 2007-this issue) enable the monitoring of coastal processes at spatiotemporal scales of meters to kilometres and days to months.

Whereas accompanying papers (Kroon et al., 2007-this issue; Jiménez et al., 2007-this issue; Medina et al., 2007-this issue) focus on the quantification of coastal state information from video and its interpretation in an end-user context (hence adopting a descriptive approach), this paper adopts a predictive approach by discussing the role of video imagery in predicting daily to monthly coastal evolution. This implies that the high-resolution video monitoring technique will not only be used to nowcast the coastal system, but also to make near-future forecasts of hydrodynamic and morphological developments. It is the aim of this paper to demonstrate the added value of high-resolution video observations for making short-term predictions of nearshore hydrodynamic and morphological processes, at spatiotemporal scales of meters to kilometers and days to seasons.

Coastal scientists and engineers often utilise either data-driven extrapolation techniques or process-based numerical and analytical models to predict nearshore flow fields and the resulting coastal evolution. Both represent classical approaches, with known limitations owing to for instance the lack of long-term high-resolution data sets, poor opportunities for model calibration or inadequate representation of fundamental coastal processes in the model formulations. In this paper, we explore the added value of high-resolution video observation for both approaches. In Section 2, this is done through application of three different data extrapolation techniques to a video-derived dataset of monthly shoreline locations. Results are evaluated against the outcome of a traditional approach, based on annual surveys of bathymetry. Data-driven methods are well suited to trend predictions. However, to predict the impact of a particular event or intervention, the use of process models would prevail. The added value of high-resolution video data in support of process models is evaluated in Section 3. High-resolution video data are used for the updating of the intertidal bed level to improve short-term predictions of the nearshore flow and sediment transport field, as well as for validation and calibration purposes. Despite the distinct added value to both approaches, we anticipate significant advancement in prediction skill by combining the best of the existing process and empirical knowledge, adopting a true data-model integration approach. Though still in its pioneering stage for video-based research, opportunities in this respect are discussed in Section 4.

2. Data-driven prediction of intertidal beach evolution

Prediction of coastal evolution based on morphologic data alone, implicitly assumes that morphologic time series contain information about future developments of the morphology. Since morphologic feedback is an essential element of the coastal morphodynamic system, this seems a valid assumption. That is, provided the statistical properties of the hydrodynamic forcing remain unchanged at the time scale of interest, as are the sediment properties. Measured time series of, for instance, beach volume can thus be used to make predictions over future time periods that are short compared to the data series.

The above notion is applied in current coastal zone management practice in the Netherlands when assessing the need for shore nourishment. This assessment is based on a time series analysis of some aggregated measure of the shoreline location in the previous ten years (Van Koningsveld and Mulder, 2004). This aggregated measure is referred to as the Momentary Coast Line (MCL) and is approximately derived from the sand volume between the dune foot and the seaward end of the surf zone. The analysis consists of a mixture of linear trend extrapolation and expert judgement. Extrapolation of the linear trend yields the predicted future coastline (referred to as TCL), which governs decisions on whether to nourish or not.

In this section we will explore the added value of high-resolution morphologic data sets for data-driven prediction as compared to the present 'data-poor' situation. We will use the intertidal equivalent of the MCL, the Intertidal Momentary Coastline (MICL), as the indicator of coastal evolution (Kroon et al., 2007-this issue). Kroon et al. (2007-this issue) have shown that trends in video-derived MICL evolution correspond well to the ground-truth MICL and MCL evolution as determined from traditional annual beach surveys. In Section 2.1 we explore the effect of increased sampling resolution on the prediction accuracy of linear trend extrapolation to arrive at the future testing intertidal coastline location (TICL location). In Section 2.2 we will focus on the potential merits of applying more advanced statistical models that seek to take advantage of the autocorrelation in the time series.

For the application of the more advanced methods, the original time series were processed (example shown in Fig. 1) in order to remove the immediate effects of large storm events and human intervention, because of the inherent unpredictability of the moment of their occurrence. The processing procedure is aimed at removing these 'extremes' while retaining the underlying trends as much as possible. The processing consisted of three steps. Firstly, linear trend lines and the standard deviations (s.d.) about these lines were calculated for each of the series. Data above trend plus s.d. and below trend minus s.d. were

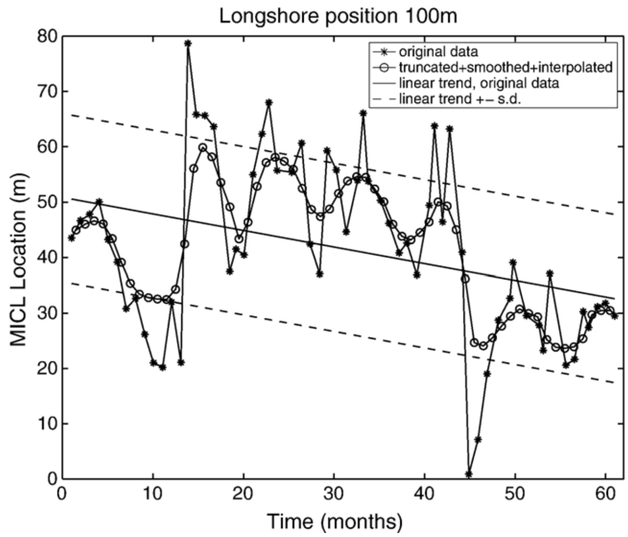

Fig. 1. Example of a MICL time series (longshore index number 41), showing the original beach volume data and the data after truncation, smoothing and interpolation used in the tests.

truncated to the trend plus s.d. and trend minus s.d. values. Secondly, a smoothing algorithm based on Velleman and Hoaglin (1981) was used, which has the effect both of smoothing short-term variations and removing outliers. To fulfill the requirement of fixed time intervals, intervals for the data were linearly interpolated through time so that they corresponded to 30-day intervals. This interval was chosen to be close to the original sampling interval as well as to resolve the seasonal fluctuations. Notice that the analysis presented in Section 2.1 is applied to the original time series.

2.1. Improvements in prediction accuracy due to increased sampling resolution

Prediction accuracy can be quantified by using, for instance, the 95% confidence interval. The width of such an interval is related to the magnitude of the deviations of the observations from the fitted model. These deviations may be purely random (measurement error, inherently random variations) as well as due to lack-of-fit of the chosen model. Assuming an appropriate model is fitted, the width of the confidence interval can generally be reduced by increasing the number of observations, because it improves the accuracy of the estimates of the model parameters (such as the slope, in case of a straight line fit). However, due to the presence of purely random error there will be a limit to this narrowing of the confidence interval of the prediction.

In the presented example we will use the MICL as a proxy for the MCL and compare linear prediction of the MICL one year ahead (TICL) based on 10 year of Jarkus data (annual surveys) to a prediction based on 10 years of Jarkus data with 4.5 year of monthly video data added. We can not compare the conventionally derived TICL to a TICL based on video data alone, because we do not have 10 years of Argus data available yet (see Wijnberg et al., 2004, for a direct comparison on the basis of 4.5 years of video data only). Adding the video data may affect both the prediction itself as well as its 95% confidence interval.

Predictions of the MICL position are made for December 2004 at each of the 250 m-spaced Jarkus survey positions located in the video-surveyed area (9 positions in total).

The predicted value of the TICL changes when the Argus-derived MICL positions are added, because the slope of the linear trend generally changes (e.g. Fig. 2). This is to some extent related to the fact that the additional data are only available for the last 4.5 years of the considered 10-year period. An advantageous effect of adding more weight to the beach evolution in recent years is that it may actually enhance the prediction of coastal changes.

Adding Argus-derived data has a pronounced effect on the width of the confidence interval as it narrows roughly by a third. However, a cautionary note should be added here because some autocorrelation is present in the residuals (i.e. the deviations from the linear trend), both in case of the annual and the monthly sampling. This complicates the estimation of a confidence interval since standard statistical techniques require the residuals to be uncorrelated. In case of positive serial correlation many samples will be effectively redundant which leads to an effective number of degrees of freedom which will be smaller than the sample size would indicate, hence a wider confidence interval. A correction procedure proposed by Nychka et al. (2000), which estimates the effective sample size using the sample autocorrelation, indicates that in the present case, 12 samples per year effectively reduce to only 2 to 4 samples per year. Note that due to autocorrelation at the annual scale the 10 annual samples also reduce to a smaller number of effective samples.

Provided the linear fit is an appropriate model for the MICL time series, increasing the sampling resolution will improve the accuracy of the trend estimate, hence the prediction, since the effective number of samples increases. However, the presence of autocorrelation in the residuals indicates that the linear fit could possibly be replaced by a more appropriate model. More advanced statistical models such as presented in the following sections may be more appropriate.

2.2. Improved prediction accuracy through the use of advanced statistical models

Two prediction methods are applied and compared. The first is a ‘traditional’ time series prediction technique, known as the Holt–Winters method (Chatfield, 1978), that has been used in many fields over the past thirty years, although rarely, if at all, in coastal science. From past data, the method identifies trends at three time scales, local, seasonal and long-term, and determines weighting factors for each scale. Future predictions involve extrapolating and recombining these trends. This technique is related to the ARIMA (or Box–Jenkins) method, but generally requires less expert user intervention, although some intervention is essential to set the three weighting factors (see below). The relation of the Holt–Winters method to ARIMA and other linear methods is discussed in Chatfield and Yar (1988) and references therein. The second method uses a type of neural network model, the feed forward neural network model, which has begun to be used in coastal science over the past five years (Kingston and Davidson, 1999; Kingston et al., 2000). These

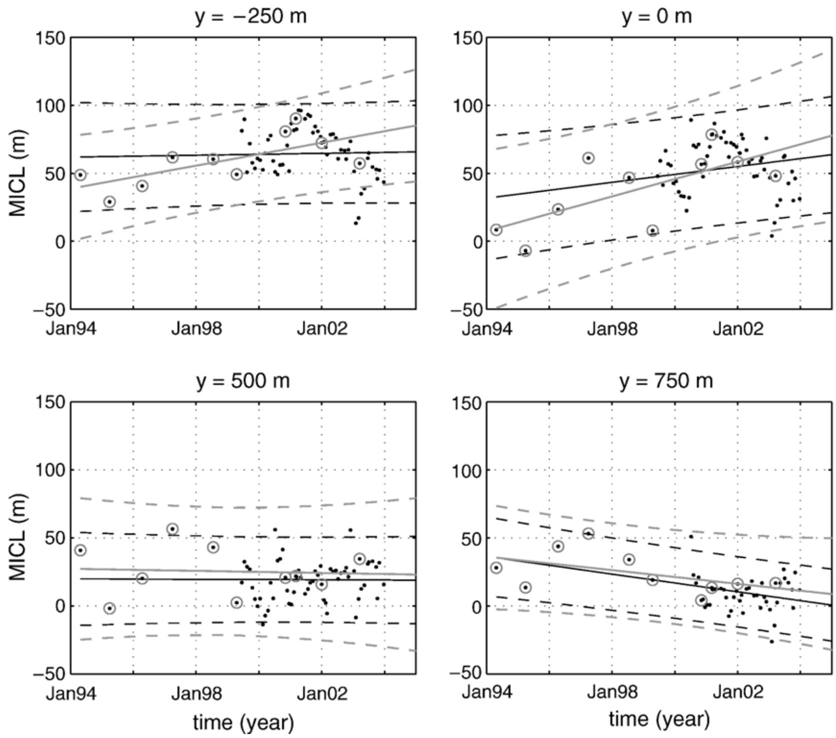

Fig. 2. Ten-year trend in MICL evolution based on Jarkus data only (solid grey line) and ten-year trend in MICL evolution based on Jarkus and Argus data together (solid black line), at 4 longshore locations (y). Circled dots represent the annual traditional surveys (Jarkus), dots the monthly video measurements. Dashed lines represent the confidence intervals for both methods.

Neural Network models have demonstrated their ability to capture complicated system behaviour through recognition of patterns linking system inputs and outputs. Both methods aim to improve on the present method of linear trend extrapolation used by Dutch Authorities for assessing where and when beach renourishment is needed.

Both the Holt–Winters and Neural Network methods require each time series to be split into a 'fitting' period over which model fitting parameters are optimised, and a 'prediction' period over which model predictions are made using the parameter settings derived for the fitting period and are then compared with the data. Given the relatively short time series (60 values) it was decided to treat the first four years as fitting data and the final year as prediction data. Predicting up to a year ahead allows an assessment of the predictive ability of seasonal effects.

The actual approach taken for the Holt-Winters method is as follows. This method determines an overall trend through the data consisting of three components that describe respectively the long-term trend, the seasonal trend, and the local mean. Previous data values are weighted so that their influence on forecast values is greatest for the most recent data and least for the data furthest in the past. Geometric weights are chosen, which decrease by a constant ratio for each of the three trend components. These are the weighting (or fitting) parameters and have values between 0 and 1. Optimum values are determined by repeated running of the model over the fitting period using different combinations of these parameters and choosing the combination that gives the smallest mean-square error.

To train the model using the Neural Network method, short segments are extracted from the fitting period of each time series, which act as input to the network. The data point immediately after each input sequence is the output value used by the network while it is being 'trained'. In this way, a Neural Network allows for experimentation with different input segment lengths to capture trends expected in the data, and, once trained, can be used predictively.

Preliminary tests were done ignoring the first 13 data values of each time series. This was because there was a beach renourishment towards the end of the first year, and it would be unrealistic to calculate trends across such an event. However, because the renourishment occurred near the start of the time series, it had relatively little effect on the trends that are present towards the end of the fitting period, and the main tests were done with the full time series.

After the fitting phase, the models were run predictively using the optimum fitting parameter settings for a further 12 months (i.e. twelve time steps) into the future, corresponding to the final year of data. However, since the aim is to predict underlying trends, instead of actual MICL locations including short-term events, trend-prediction rather than precise agreement with the data was sought. For this reason, comparisons were made with the smoothed data (described above) rather than the raw MICL data.

The full results are presented as a set of twelve plots, one for each time step in the prediction period. Each plot shows the predicted MICL location (y-axis) for all 71 profiles (x-axis), for the two models and for a default prediction in which MICL values at the end of the fitting period are assumed to continue unchanged through the prediction period. Fig. 3 shows a selection of these results at 1, 4, 8 and 12 months into the

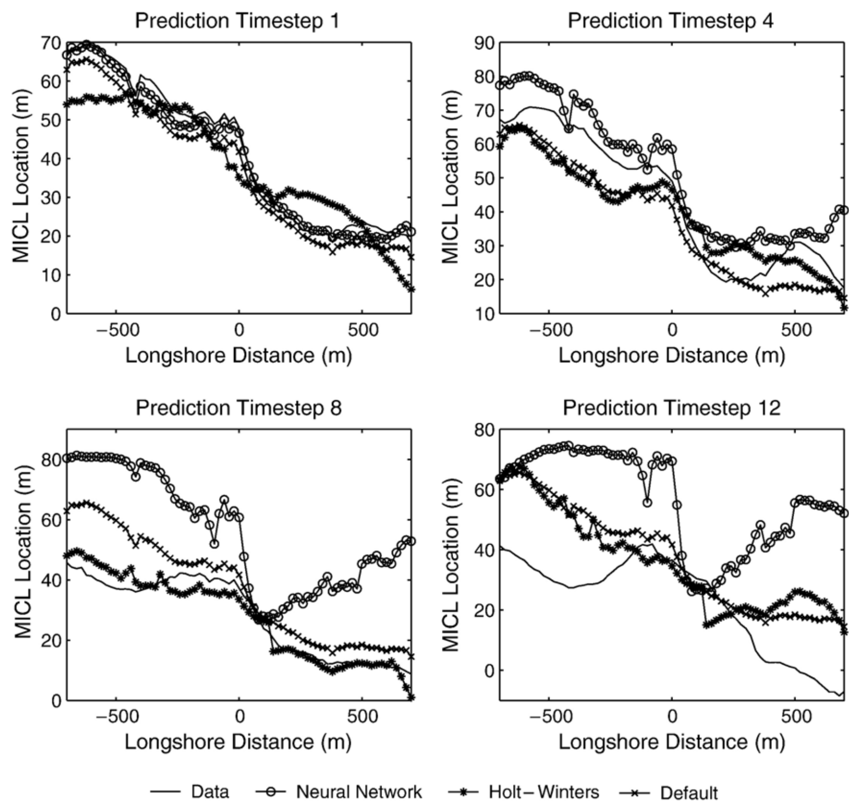

Fig. 3. Predictions of beach volume (MICL) for all longshore locations at four timesteps (1, 4, 8, and 12 months into the prediction period). Holt–Winters, Neural Network and Default predictions.

prediction period. Generally, it is expected that the accuracy of predictions decreases at longer prediction times. Qualitatively, Fig. 3 bears this out, with the Holt–Winters predictions doing well at 1, 4 and 8 months and poorly at 12 months, while the Neural Network does well at 1 and 4 months but much worse at 8 and 12 months.

The uncertainties associated with these results are summarised in the Prediction–Decay plot in Fig. 4. Mean square errors (MSEs) across all the profiles are calculated for each model (and the default) at each time step, and are normalised by the variance of the full smoothed data set (all profiles and times). The quantity $1-\mathrm{MSE}/\mathrm{Variance}$ is plotted against prediction time step for the two models and the default, so that a value of 1 means a perfect prediction, and progressively smaller values represent poorer predictions. The Neural Network outperforms the default for up to 4 months but then decays rapidly. The Holt–Winters method starts with slightly poorer predictions than the default, but then improves, overtaking the default until decaying at Months 11 and 12. It appears the Neural Network is extrapolating local trends at the end of the fitting period, giving rise to good predictions at short times but much poorer at longer times after the local trends change. This may be expected if you consider that short bursts of data were used in the training data set. The Holt–Winters method, however, explicitly incorporates seasonal trends, which helps towards a good performance at longer times (around 5–9 months), at the expense of a slightly poorer performance at shorter times. The performance of the default is largely arbitrary, depending on where the last value in the fitting period appears in relation to the trends and events in the subsequent data.

2.3. Discussion and conclusions

In this section, the added value of high-resolution video observations for the data-driven prediction of coastal evolution at the seasonal time scale has been explored. The inclusion of

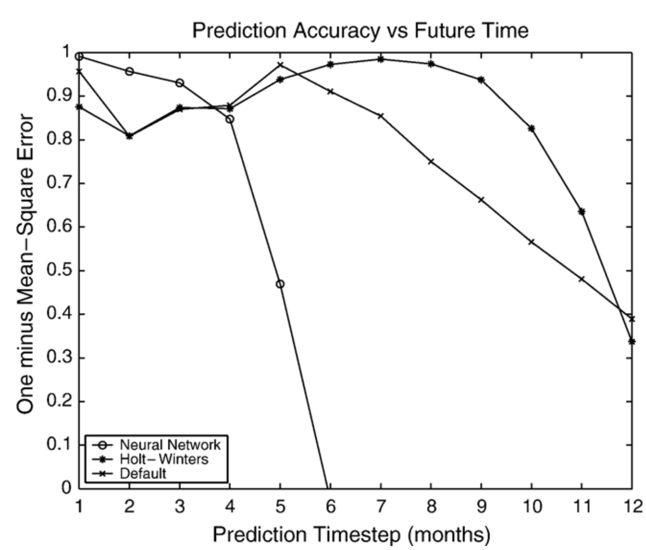

Fig. 4. Prediction–Decay plots using mean-square errors calculated across all longshore locations. Holt–Winters, Neural Network and Default predictions.

monthly video estimates of the momentary intertidal coastline indicator (MICL) was found to narrow the width of the confidence interval for one-year predictions of shoreline evolution on the basis of a simple, linear regression technique. A first order estimate indicates a reduction by about one third, but redundancy in both the monthly and annual observations, as indicated by serial correlation, may change this number. At the same time this serial correlation warrants the use of more advanced statistical methods to forecast MICL evolution. Notice that, as a general limitation, any data-driven approach can only predict the type of behaviour that is included in the dataset.

The large amount of data also allows for the prediction of the future coastline position (TICL position) in terms of probability. At present, the extrapolation of the linear trend provides the most likely position of the TICL (provided that linear evolution is an appropriate model). However, it is very likely that the next year observation of the MICL is located landward or seaward of this TICL position. Confidence intervals of varying width can now be used to predict lines along the beach with a given probability of landward exceedance. For example, the 80% confidence interval around a TICL implies that the next year MICL observation has an 80% probability of being inside this interval. Consequently it has a 20% probability of being outside this interval, with equal chances of being smaller or larger. This implies that the lower boundary of the 80% confidence interval may be regarded as a position on the beach that has a 10% probability of being exceeded in the landward direction by the next year MICL observation. Analogously, using the 98% confidence interval provides the position on the beach that has a 1% probability of being exceeded in the landward direction by the next year MICL observation, etc. Application of this approach on many locations along the beach (e.g. every 20 m, see Fig. 5), enables the mapping of lines along the beach with known probability of landward exceedance by the time of next year's MICL observation.

This example illustrates the concept of making predictions in terms of probability. Here a Gaussian, hence symmetric, distribution of deviations from the trend has been assumed. Although there may be theoretical reasons for asymmetric distributions, such as non-linear beach response to individual storms, no indications for such asymmetry were found in the data. To test this, deviations of the MICL observations from the trends were calculated. The frequency distribution of all these deviations was then calculated and shown to be Gaussian.

Note that Fig. 5 is based on video observations only (covering a period of 4.5 years), in order to illustrate the high spatial resolution that can be derived using video data. It reveals that longshore variation occurs in the cross-shore positions of these lines at a scale that is not well sampled with the current 250 m longshore spacing of the profile surveys. Hence, using video-based surveys also reduces the risk of missing a very localized threat to the coastal defense, e.g. in relation to a stationary pattern in offshore bar morphology.

The availability of monthly MICL observations yields another advantage for coastal management purposes, when assessing the need for shoreface/beach nourishment. Currently, this decision is made through linear extrapolation of the ten-year

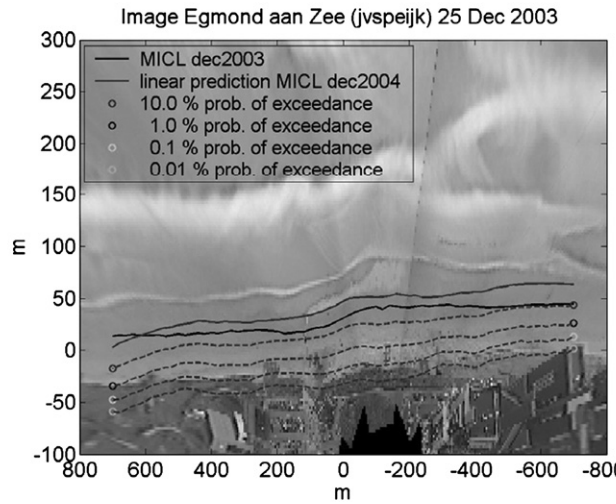

Fig. 5. Prediction next year MICL using probability approach showing probabilities of exceedance.

trend in shoreline evolution, which is derived from annual bathymetrical surveys. In the case of a perturbed (e.g. nourished) coastal system, this approach is replaced by an expert judgement, which involves a subjective component. The availability of weekly to monthly MICL observations would offer more complete information to the experts and at the same time allow for a more objective evaluation by using advanced prediction methods that are tailored to the nourished beach case. Data-driven prediction methods, if sufficiently accurate, would thus be an important tool for coastal management by providing information about the extent to which volumetric changes are a response to storm 'events' or reflect a longer-term 'trend', and about when to implement beach renourishment or other remedial measures.

The results presented in this section show a definite potential for forecasting MICL locations (or beach volumes) up to a year ahead based on previous MICL data derived from video images. Improvements can be expected from refinements to the models themselves, but also from longer time spans and higher temporal resolution of MICL data, which potentially are obtainable from raw Argus data. Furthermore, a more robust coastal state indicator, involving beach volumes calculated over a wider portion of the beach profiles (e.g. the MCL), would increasingly tend to filter out events and noise, possibly making the long-term and seasonal signals proportionately stronger. This tendency to filter the event signal implies loss of information on short-term changes to cross-shore morphology, because such changes mainly occur *within* the wider portion of the beach profile. The data-driven approaches discussed here are complementary to process-based modelling, which is more appropriate to predicting the effects of the immediate aftermath of short-term events, such as storms or renourishment.

3. Process-based prediction of hydro- and morphodynamics, supported by video data

This section discusses the use of high-resolution video data in support of process-based hydrodynamic and morphological models. The predictability of coastal evolution is treated as an inherent characteristic of the model formulations, in combination with the prediction horizon of the forcing conditions. Video observations may improve model predictions by means of iterative updating of the intertidal bed level condition, or through enhanced opportunities for model calibration and validation. As video monitoring systems allow for virtually continuous, synoptic data sampling, video observations embody significant added value as compared to in situ flow meters (few points in space) or beach profile surveys (typically up to a few times per year, at best). With improved communication capabilities and computational power, remote-sensing data are easily collected – without the need to deploy in situ instruments in a hostile environment – and available in real-time. In contrast to the previous section, video data play an indirect role to further the predictability of nearshore coastal evolution at time scales of days to months here. Several case examples of this approach are discussed below.

3.1. Video-based updating of the intertidal bed level condition in process models

Video observations of the nearshore zone easily allow for the quantification of intertidal beach bathymetry on a daily to monthly basis (e.g. Plant and Holman, 1997; Aarninkhof et al., 2003). As in situ surveys of nearshore bathymetry are usually sparse, the availability of video-derived bathymetrical information allows for the frequent updating of intertidal bed levels in process-based hydrodynamic and morphological models. As a result, these models are being applied on the basis of more recent bathymetrical data, which is expected to positively affect the reliability of the model predictions.

The merits of this approach have, as a first example, been explored in the framework of the Spanish Nearshore Operational Forecasting System (NEOFOS). This operational system is used to provide 48-hour forecasts of waves, currents and sea levels along Spanish coastlines, with a 6-hour time interval, in support of naval operations and swimmer safety. Hydrodynamic forecasts are based on short-term predictions of the offshore wave and sea level conditions, using numerical models on oceanic scale. These wave and sea level predictions provide the input boundary condition for a local spectral wave propagation model OLUCA-SP (a parabolic approximation solution to the mild slope equation), followed by wave-induced current forecasting using the MOPLA-SP model (a 2DH nearshore circulation model). The shallow water sea state and the wave-driven current system in the nearshore zone are obtained using the most “recent” nearshore bathymetry data as morphological boundary for the local models. In a previous version of NEOFOS, the offshore and local sea level, waves and currents were usually updated every 6 h, while the coastal morphology rarely was. Consequently, the reliability of the predictions was limited; especially in zones exposed to high energetic wave conditions and zones with an important morphological variability in short time intervals. This is the case at the Cantabria coast (northern Spanish coast).

At El Puntal beach (near Santander, cf. Medina et al., 2007-this issue), the NEOFOS is applied to provide state information on swimmer safety, with a focus on dangerous currents and surf zones, 48 h in advance. Being fully exposed to North-West Cantabrian swell and sea waves with significant wave heights up to 5–6 m during storm events, the beach shows strong variations of morphology (cf. Fig. 6). For this reason, the NEOFOS application is enriched with intertidal bathymetrical data, derived from time-averaged Argus video imagery with the help of the Intertidal Beach Mapper by Aarninkhof et al. (2003). Shorelines are mapped every 30 min along a 1500 m coastal stretch, at different tidal levels. Owing to the large tidal range at Santander (up to 5 m during spring tide), these intertidal bathymetries cover a significant part of the beach profile. Near the tip of the spit, sub-tidal bathymetry was updated on the basis of the observed shoreline changes in combination with the assumption of a constant channel slope. Historical data records confirm the validity of the latter assumption. Further towards the east along the exposed part of the spit, sub-tidal bathymetry was updated on the basis of empirical knowledge on sand bar dynamics in the region, combined with their actual position as observed from video imagery. Throughout the winter season from October to March, the NEOFOS bathymetry is updated on a daily basis; during summer (from April to September) the bathymetry is updated every week.

The added value of updating the intertidal bed level conditions is demonstrated with the help of the example application presented in Fig. 6. It shows the NEOFOS prediction of wave-induced currents during a storm event that occurred on November 15, 2003, with a significant wave height of 4.5 m, a peak period of 16 s and north-north-western direction. The hydrodynamic computations are based on the surveyed bathymetry of October 25, 2003 and the updated bathymetry of October 30, 2003, respectively. The bathymetry at October 30 represents the situation after a severe storm. Updating the intertidal bed level strongly affects the predicted nearshore flow field, changing the current magnitudes as well as directions. This qualitative analysis shows that the incorporation of up-to-date bathymetrical data in the NEOFOS environment may contribute importantly to the reliability of short-term forecasts of the nearshore wave and flow field.

As a second case example, Siegle et al. (2006) utilise a coastal video system to improve the initial bathymetric conditions for a two-dimensional numerical model (MIKE21 — DHI Water & Environment) to study the dominant processes responsible for the evolution of a dynamic estuary and sandbank system at a macro-tidal inlet near Teignmouth, UK (Davidson et al., 2007-this issue). The ultimate goal of the study is to provide enhanced predictions of sediment fluxes and bed evolution for different morphological states of the system. A brief example is given here but more detailed information, including the model calibration parameters, can be found in Siegle (2003), Siegle et al. (2003) and Siegle et al. (2004). Close to the region of interest at the mouth of the Teign Estuary a spit constricts the strong tidal flows (>2 m/s) leading to significant variability in the water surface topography (water surface gradients are of order 10^{-2}). As a result, the common assumption of shoreline detection models (e.g. Plant and Holman, 1997; Davidson et al., 1997; Aarninkhof et al., 2003) mapping a horizontal beach

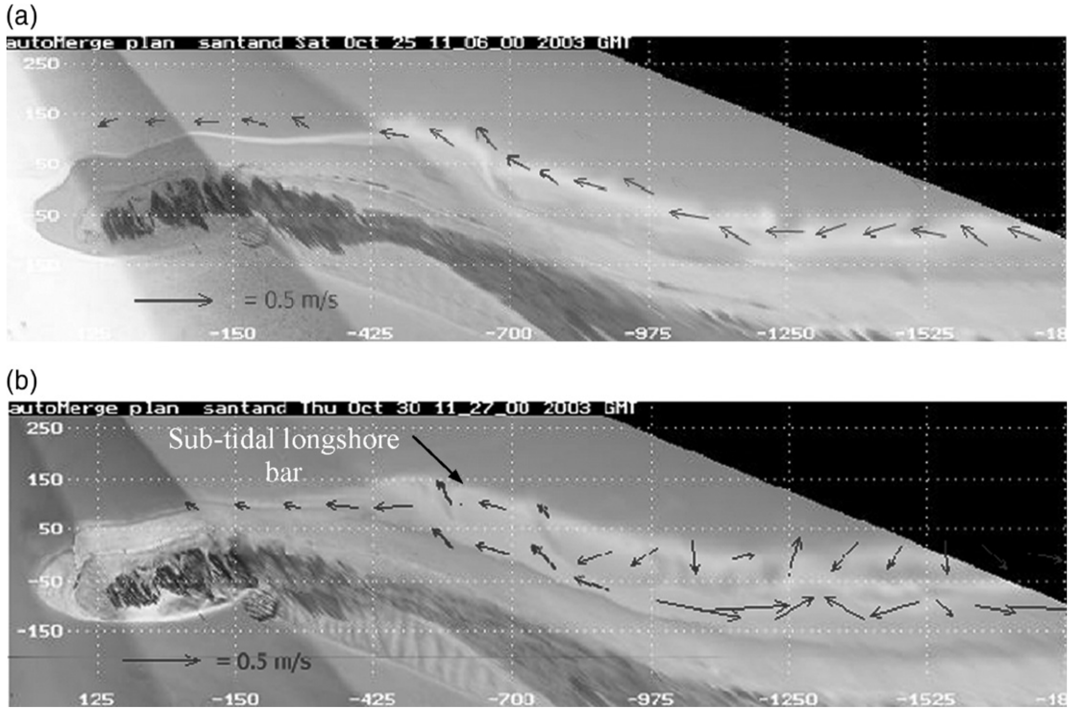

Fig. 6. Wave-induced currents at El Puntal, Santander (Spain) computed from NEOFOS operational forecasting system. Results are obtained by simulating the November 30, 2003, storm conditions across a surveyed bathymetry dated October 25, 2003 (a) and the updated bathymetry dated October 30, 2003 (b). The October 30 bathymetry was enriched with intertidal bathymetric data sampled from video imagery, bathymetry after a severe storm.

contour does not hold, inducing large errors in the order of 0.5–1 m near the tidal inlet (Siegle et al., 2002). Therefore, a two-fold application of the coupled video-model system is required.

In the first instance the numerical model is used to predict the water surface topography using the most recent bathymetric information for its initial conditions. Using the model prediction for the shoreline elevation in place of the horizontal shoreline assumption is seen to improve the accuracy of the intertidal surveys by a factor of two yielding survey accuracies of ±0.15 m (Siegle et al., 2006).

The second stage of the analysis involves carefully merging the video-derived intertidal morphology with the most recently measured sub-tidal bathymetric survey to provide the initial conditions for the hydrodynamic, sediment transport and bed-evolution modules. The assumption here is that the sub-tidal bathymetry evolves over a longer time scale than the intertidal area. In spite of the assumptions involved in the video-survey, integration produces far more accurate initial conditions for the model and permits a good assessment of the dominant processes affecting sediment transport and the morphodynamic evolution of the system. An example of the predicted sediment transport patterns, bed evolution and comparison with the next observed state using video-derived bathymetry can be seen in Fig. 7. At short time scales (days to weeks) the methodology has allowed an assessment of the dominant physical processes affecting the morphodynamic evolution of the system, and how they interact, which was not possible prior to this analysis. At longer time scales (months to years) the combined video-numerical model approach has resulted in qualitatively realistic prediction of the sandbank evolution at each stage of the morphodynamic cycle.

3.2. Video-based calibration and validation of hydrodynamic and morphological models

Video-based nearshore data collection provides suitable information to add to the calibration and validation of both hydrodynamic and morphological models. Several examples of that are treated in this section.

3.2.1. Calibration and validation of hydrodynamic models

Long and Özkan-Haller (2005) examine the efficacy of a nearshore circulation model along regions of complex bathymetry through comparisons with remote-sensing observations. Bathymetry and offshore spectra measured during the Nearshore Canyon Experiment (NCEX) are used to initialize a spectral wave model (e.g. Booij et al., 1999; Ris et al., 1999) extending approximately 10 km offshore and 12.5 km along the coast of Southern California. The resulting wave forcing information is used to drive a nearshore circulation model (Özkan-Haller and Kirby, 1997, 1999), which is nested within the computational domain of the wave model and covers the 6 km coastline of Blacks beach. The flow model solves the depth-integrated time-averaged Navier–Stokes equations and evaluates the temporally and spatially varying circulation patterns.

Model-derived ten-minute average horizontal flow fields are compared to variance images sampled from the Argus video station at Blacks beach. Bright regions in variance images correspond to areas of high optical intensity variability such as the swash zone and the region of initial wave breaking. Rip currents often provide a surface signature through advection of persistent foam. Variance images are thus used to qualitatively

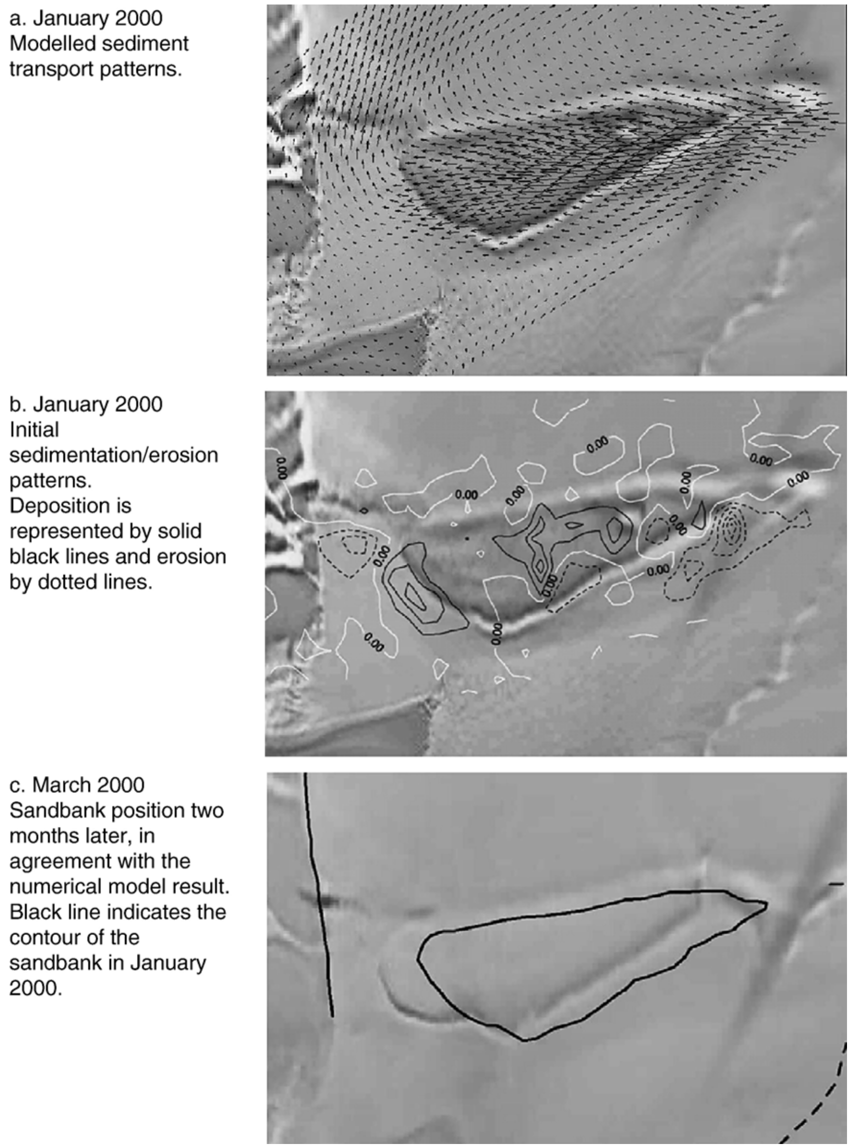

Fig. 7. Modelled sediment transport patterns (a) and associated initial bed level changes (b) over the Teignmouth sandbank for the January 2000 situation. The predicted bar evolution over a two-month period (c) shows good correspondence with the observed evolution.

validate model capabilities in predicting the location of rip currents. Long and Özkan-Haller report good data-model agreement (Fig. 8) in predicting the location of the observed rip currents during two distinct rip events separated by 17 days. This data-model comparison could be extended through inclusion of video-derived estimates of flow velocity and wave characteristics (wave period and direction). Techniques to quantify these hydrodynamic properties are under continuous development (Chickadel et al., 2003; Holman and Chickadel, 2004). Detailed, synoptic information on key characteristics of the wave and flow field is expected to provide enhanced opportunities for the calibration of wave dissipation and bottom friction parameters in present-day models. This will yield an improved representation of the process of wave breaking and associated currents, hence improved morphological predictions.

A second example on the interaction of video observations and hydrodynamic models is taken from Aarninkhof and Ruessink (2004). Aarninkhof and Ruessink investigate the process of depth-induced wave breaking on the basis of intra-wave time series of pixel intensities and compare the time-averaged video registration of wave dissipation (after correction for the effects of background illuminations, noise and persistent foam) to various model-predicted measures of wave breaking. Although Aarninkhof and Ruessink primarily aim to develop and verify a methodology for the quantitative interpretation of time-averaged image intensities in support of their model to map sub-tidal bathymetry from video imagery (Aarninkhof et al., in press), their work provides an interesting side-product. Based on video and bathymetric data collected at the double-barred beach at Egmond (The Netherlands) and a standard wave transformation model containing balance equations for wave and roller energy, Aarninkhof and Ruessink find that the modelled cross-shore distribution of the dissipation of the energy of the surface roller (the white, aerated, turbulent mass of water at the breaking wave face) matches the cross-shore shape of breaking-induced image intensity well. Moreover, they find

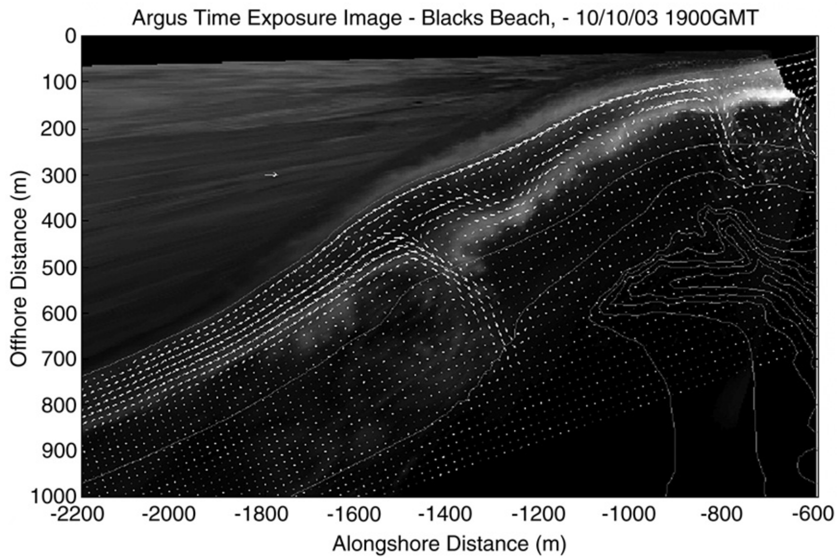

Fig. 8. Ten-minute average flow field overlain on an Argus variance image of: insert location for Oct. 10, 2003 1500 GMT. Bathymetric contours show the submarine canyon that strongly affects the incoming wave field. Bright patterns in the background image represent areas of strong optical intensity variability, including traces of offshore drifting patches of foam associated with rip currents. The vector fields visualize the model-predicted ten-minute average flow field, which shows excellent correspondence to the location of the rip currents observed from video imagery. After: Long and Özkan-Haller (2005).

an optimal match between video-observed and model-predicted dissipation patterns for settings of the roller dissipation parameter β (e.g. Stive and De Vriend, 1994) in the range 0.10–0.125. These values are slightly larger than the default settings recommended in literature (e.g. Stive and De Vriend, 1994; Nairn et al., 1990) based on measurements of wave set-up across the surf zone. As the collection of field measurements of wave set-up comes with considerable logistic and financial demands, Argus video observations of wave breaking provide enhanced opportunities for the calibration of wave models.

3.2.2. Calibration and validation of morphological models

Time-averaged Argus video imagery usually shows one or two alongshore continuous high-intensity (i.e. white) bands, which reflect locations of predominant wave breaking on the crests of nearshore bars. These patterns have been shown to accurately reflect the underlying sand bar topography (Lippmann and Holman, 1989; Van Enckevort and Ruessink, 2001). The spatial evolution of these wave breaking-induced patterns over time can thus be used to characterize the evolution of a sandbar system with high resolution in time and space. This allows for phenomelogical analysis of coastal morphology (Konicki and Holman, 2001; Van Enckevort et al., 2004, among others) and as discussed below with 2 examples, may facilitate the calibration of morphodynamic models.

In a one-dimensional, cross-shore approach, Barreto (2001) adopts a detailed 3.5 year data set of video-derived, daily to weekly sand bar locations at Noordwijk, The Netherlands (Van Enckevort and Ruessink, 2003) to calibrate the morphodynamic behaviour of Delft Hydraulics' coastal profile model Unibest-TC (e.g. Ruessink, 2005). The data set provides alongshore-averaged bar crest positions, which were derived from the locations of

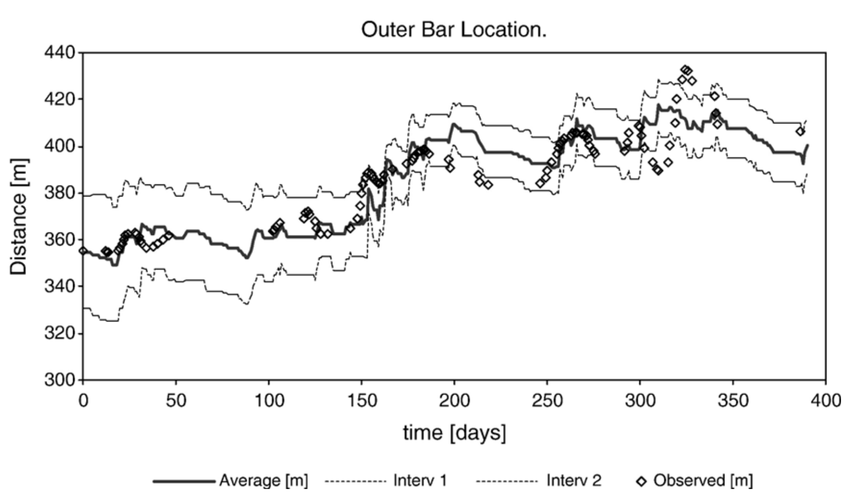

Fig. 9. Measured (◇) and computed (bold line) evolution of the alongshore-averaged location of the outer bar at Noordwijk, The Netherlands (after: Barreto, 2001).

visually observed peaks in wave breaking at the inner and outer bar. The latter, indirect measurements of bar crest position were corrected for contaminating effects induced by water level fluctuations in response to semi-diurnal tides and spring-neap tide variations (see Ruessink et al., 2002a for further details). The resulting time series consists of 391 daily observations for the outer bar within the analysed 3.5-year (1282 days) period and shows strong seasonal and interannual variability in bar position.

Consistent with the nature of the available video observations of sand bar location, Barreto (2001) applied the one-dimensional morphological model to an alongshore-averaged coastal profile, obtained by averaging 5 cross-shore profiles spacing 250 m alongshore. Time series of significant wave height H_{sig} and peak period T_p were taken from the measurement platform 'Meetpost Noordwijk' at 6 km off the coast. Limited by the availability of good quality bathymetrical and wave data, morphodynamic model simulations were carried out for the period May 1996 to December 1997. Model calibration involved the determination of best settings for particularly the wave dissipation parameter γ (Battjes and Janssen, 1978), the roller dissipation parameter β (Stive and De Vriend, 1994), the bottom friction coefficient and an empirical factor on the fraction of breaking wave affecting the onshore sediment transport rate. Barreto (2001) compares the migration of the outer bar as computed from the calibrated model to the measured migration observed from video (Fig. 9). Good agreement was found for both offshore and onshore migration of the outer bar. The model failed to reproduce dramatic changes in bar location as occasionally observed from the video data (e.g. the strong seaward bar migration around day 320 of the period of interest). Moreover, less good results were obtained in the region of the inner bar, where the model results showed a seaward offset in the bar location.

A second case example illustrating the use of Argus video imagery for model calibration and validation purposes is provided by Reniers et al. (2001). Reniers et al. (2001) present a new morphological model to simulate the development and evolution of complex, rhythmic patterns in coastal bathymetry, such as rip currents. The model operates on the time scale of wave groups, accounting for the effects of wave groupiness and associated infragravity waves on the evolution of nearshore morphology. The model was tested against field data sampled at Palm Beach (Australia), a 2.5 km embayed beach that is known for the frequent occurrence of rip channels. Video time exposures of the surf zone were used to calibrate the model dissipation coefficients by comparing the measured image intensity and the computed roller energy. Flow velocities obtained from the calibrated model were found to be in good agreement with in situ flow measurements throughout the eleven day duration of the experiment, showing a strong tidal variation (Fig. 10). In extension of this approach, time series of plan view Palm Beach time exposures were and will be used to directly validate the model-predicted morphological evolution.

3.3. Discussion and conclusions

The case examples treated in this section demonstrate that the use of high-resolution video observations provides a useful aid to the process-based prediction of coastal evolution. The distinct advantage of optical remote-sensing systems is found in the synoptic nature of the data, the ease and safety of operation (only minor logistic and financial commitments as compared to in situ measurements in a hostile surf zone environment) and the capability to serve long-term monitoring programmes with high resolution in time. As a result, time series of nearshore video observations span a wide range of conditions which yields better opportunities for model calibration and validation, thus improving the prediction range of process-based models. These beneficial characteristics enabled, amongst others, the frequent updating of the intertidal bed level condition to improve the performance of hydrodynamic and morphological forecast systems, the evaluation of a nearshore circulation model in predicting the occurrence of rip currents and the calibration of the behaviour of morphological models at time scales of days to seasons. The applications would have been hard to achieve without the availability of high-resolution remotely-sensed data.

The applicability of video imagery in support of the calibration and validation of hydrodynamic and morphological models is closely related to our capabilities to quantify relevant nearshore variables from video. Interestingly, the location of the shoreline is relatively simple to determine from video (e.g. Davidson et al., 1997; Plant and Holman, 1997; Aarninkhof et al., 2003; Turner et al., 2000) but the use of this type of information for the initialization and validation of coastline

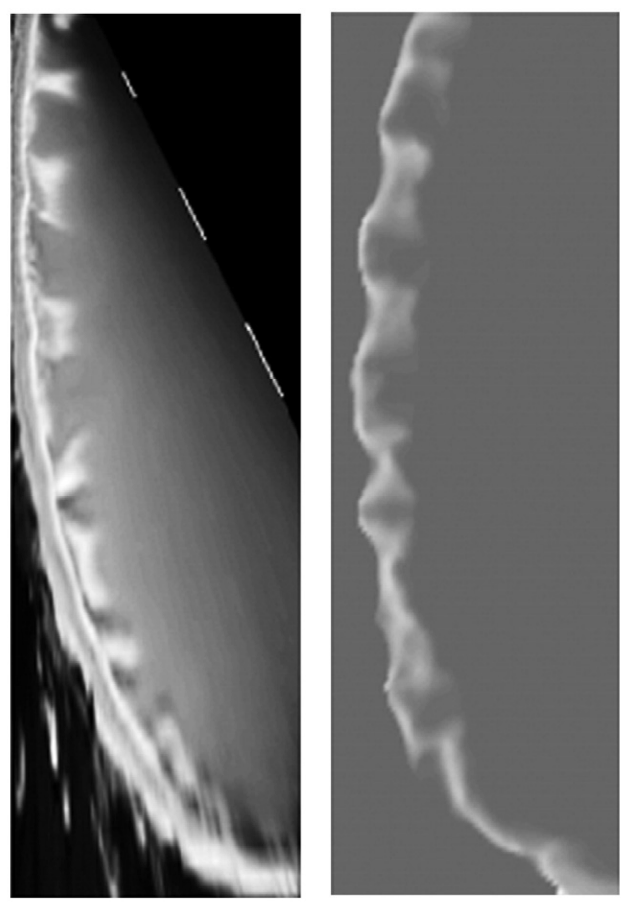

Fig. 10. Plan view video observation (left panel) and the corresponding model prediction of wave dissipation at Palm Beach (after: Reniers et al., 2001).

models (e.g. Szmytkiewicz et al., 2000) is – with the exception of a Narrowneck Reef application at the Australian Goldcoast (Dronkers, 2001) – only in its infancy. The added value of automated video imagery in this context would further benefit from the ongoing development of robust algorithms to quantify coastal state information from video, including sub-tidal bathymetry and cross-shore current velocities.

4. Discussion: integration of video-derived data and process-based models?

In the preceeding two sections two end-members in modelling the nearshore system were encountered, viz. the data-driven approach in Section 2 and the presently more common process-knowledge approach in Section 3. The main advantage of the latter approach is its genericity. As long as the physics of the system under study is as the physics in the model, the model can produce potentially useful predictions. Another aspect of the genericity is the use of process models in scenario applications to answer 'what-if' questions. In many situations, however, process modelling is not as straightforward as it may seem, as each new application will require appropriate external inputs, initial conditions and, very likely, adjustments of the model's free parameters. As advocated in Section 3, video-derived data may play an essential role in calibrating process models.

Process modelling is, however, not always feasible. The studied system may be too complex or too little understood to build a process model. Also, the time scale of interest may be beyond what is practically possible. The typically desired engineering time scale of days to years would require a lengthy forward stepping of a process model (with steps of typically 1 h); because of various simplifications inherent to process modelling, such as the grid and process schematization, computational errors propagate with time and may cause physically impossible results on the long run. In such cases predictions have to increasingly rely on historic input–output relations, leading to data-driven approaches as exemplified in Section 2.

Their strength thus lies in the ability to make hindcasts and, potentially, forecasts in situations where process models cannot be applied or will fail.

However, the potential for predictions is at the expense of genericity and process-knowledge improvement. For instance, it is unlikely that the data-driven models for the temporal evolution of the MICL at Egmond will produce any sensible predictions elsewhere.

Analogous with developments in related disciplines such as hydrology and weather forecasting, significant advancement in prediction skill of nearshore systems can be made by combining the best of the process-knowledge and data-driven approaches. It is the author's belief that this data-model integration is an important future key research topic. Formally, data-model integration can be defined as the combining of models and measurements with the aim to objectively increase the total information of these information sources beyond that of the individual components. The combination of models and measurements involves the mutual replenishment of unknown information and the reduction of the uncertainties in both information sources.

Data-model integration is in its pioneering stage for video-based research and clear examples of its use can, therefore, not yet be given. In the following we present preliminary results of a study that focused on the use of a dynamic neural network in predicting sandbar behaviour and some thoughts and new research initiatives on data assimilation.

Dynamic (or, recurrent) neural networks (DNNs) are neural networks with one or more feedback loops (see Haykin, 1999) for the foundations and terminology of DNNs). This feedback distinguishes DNNs from static neural networks, as used in Section 2, which have no such feedback. The feedback in DNNs implies that they have the same time propagation as a process-based model. Consider, for instance, the Unibest-TC based modelling of sandbar position at Noordwijk discussed in Section 3. The sandbar position at time $t+1$ was, in that case, determined by its position at time t, external system forcing (waves and water levels), the free model parameters, and system knowledge. A DNN employs the same time propagation but uses a fully parameterized model based on previous observations (the NN part) rather than physical principles and system knowledge. Although strictly speaking a DNN is a data-driven model, we consider it as an example of data-model integration because the DNN combines a data-driven modelling approach with the time propagation inherent to process-based modelling. Additional discussion on the similarity of DNNs and process-based models can be found in, among others, Van den Boogaard and Mynett (2004).

Fig. 11 shows an example of a DNN based prediction of sandbar position at Noordwijk (see Section 3) using wave height, period and direction as external input and the predicted position at the previous time step as feedback. Details on the applied DNN structure, and on its training and testing, can be found in Ruessink et al. (2002b,c)) and are not reiterated here. As can be seen, the DNN reproduces the general characteristics in the time series well Fig. 11a). Intriguingly, the DNN has captured the dominant seasonal and interannual variability in outer sandbar position (Fig. 11b and c), despite the fact that the wave forcing varies mainly on daily and weekly scales. Apparently, the applied DNN has the skill to model systems with a long-term memory, that is, systems where the state at time t depends on observations and external forcings at many previous time steps. The results in Fig. 11 were found to be robust to the various choices that can be made to set up the network (Ruessink et al., 2002b). Additional tests showed that the modeled seasonal variability in sandbar position was indeed due to the weak seasonal variability in offshore wave characteristics, as forcing the network with random noise as external wave input failed to reproduce the seasonality in sandbar position (Ruessink et al., 2002b).

A second example of data-model integration is data assimilation, which can be defined as the statistical combination of observations and short-range forecasts (Kalnay, 2003) to make a better prediction of the state and/or the parameters of the system that need to be modelled or to better understand the (relative importance of) uncertainties in the observations and model predictions. In contrast to batch calibration (e.g. in Section 3.2.2), data assimilation continuously updates the states

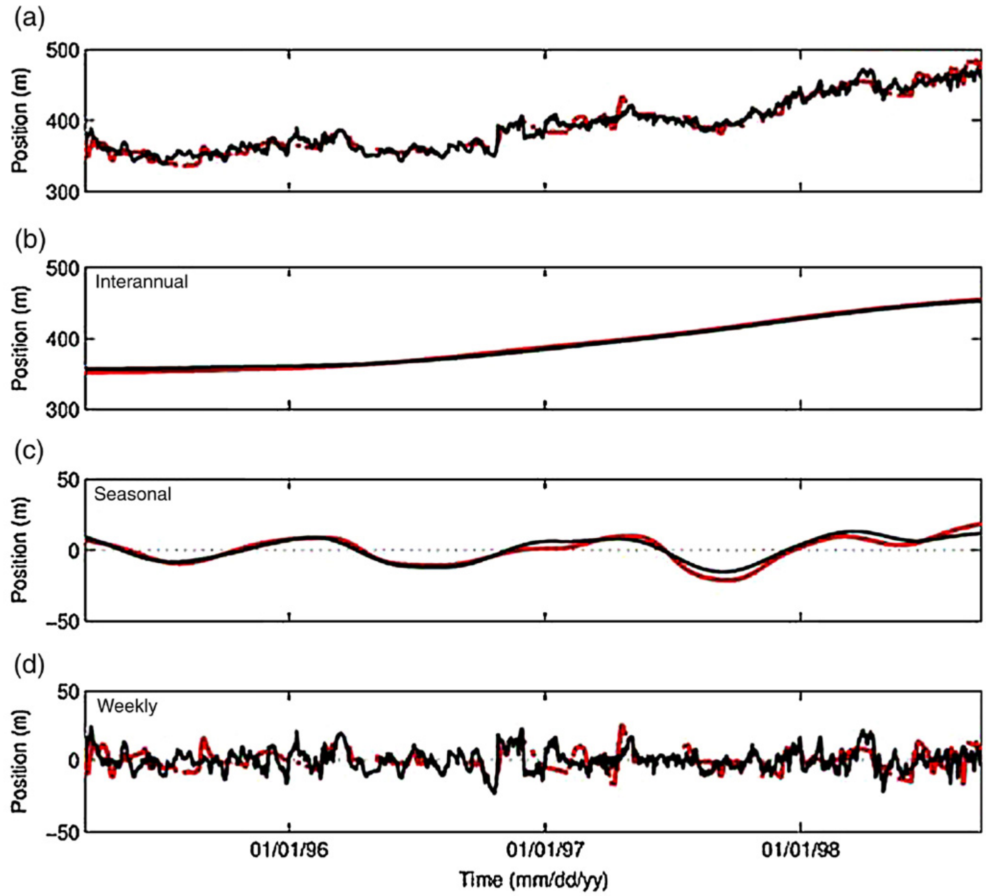

Fig. 11. (a) Observed (red) and DNN predicted (black) position of the outer sandbar at Noordwijk versus time, based on Ruessink et al. (2002b). Panels (b), (c) and (d) show these time series decomposed into their interannual, seasonal and weekly components, respectively. See also Van Enckevort and Ruessink (2003). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

and/or parameters in the model when new observations become available and is, therefore, also referred to as on-line calibration. The expected added value of data assimilation is related to the modelling nature of nearshore predictions: it is an initial/boundary value problem where given an initial state (e.g. bathymetry) and boundary information the model forecasts the next state. Data assimilation helps in making a better guess for the initial state and, in this way, for the next state. A recent modelling study by Smit et al. (2004) suggested that predictions of nearshore bathymetry might indeed be sensitive to initial conditions, as two model simulations with marginally different initial bed levels (in the order of a few centimetres) led to rather different positions of rip channels (in the order of hundreds of metres). This illustrates the chaotic character of the modelled system, indicating that techniques incorporating this character are near future in coastal morphodynamics. For nearshore bar systems it is expected that continuously adjusting the model forecasts with video-based bathymetric information will yield improved model predictions.

There are, to the best of the authors' knowledge, no examples of data assimilation examples involving Argus based data and process-based models at the moment of writing. There are, however, various research initiatives. One example is the BeachWizard project, funded by the Office of Naval Research and involving 9 Australian, US and Dutch partners. The primary idea in BeachWizard is to assimilate dense remotely-sensed field observations of wave dissipation, phase speed, surface currents, water line position, and sand bar morphology into the process-based morphological model Delft3D to provide integrated bathymetric and hydrodynamic nowcasts and short-term (order one week) forecasts. A second example, funded by the Netherlands Organisation for Scientific Research NWO and carried out by Utrecht University, is the project 'Predictability and uncertainty analysis of nearshore sandbar behaviour'. This project aims to (1) study the (limits to the) predictability of nearshore sandbar dynamics by developing and applying novel approaches to quantify uncertainties in nearshore sandbar behaviour associated with parameter and observational errors, and (2) to integrate 2D bed-evolution process models with remote-sensing data of nearshore bathymetry to provide more accurate state descriptions during forecasting and to assess short-term variability in the model's free parameters. Some initial results of the latter project can be found in Ruessink (2005).

On the whole, we envisage that the combination of state-of-the-art process modelling and field data collected for a wide range of conditions will enable a more complete description of nearshore morphological evolution than possible now. This should lead to improved nowcasts and forecasts of the nearshore, including a better prediction of the impact of the design and implementation of nearshore engineering and management measures.

5. Concluding remarks

The prediction of coastal evolution at time scales of days to months is becoming increasingly important for both coastal managers and scientists. In this paper, the value of high-resolution remote video observations for predicting the behaviour of coastal systems has been examined. In a data-driven approach, the inclusion of monthly video-derived data was found to not only improve confidence intervals on the predicted shoreline evolution, but also to facilitate the use of more sophisticated data extrapolation methods. Inclusion of video-derived monthly shoreline observations, for instance, yielded a narrowing of the confidence intervals on one-year shoreline predictions by about one third, in first approximation, as compared to predictions based on the traditional annual observations alone. Short-term predictions based on the use of hydrodynamic and morphological models benefited from the availability of high-resolution video observations through frequent updating of the intertidal bed level and enhanced opportunities for model calibration and validation. Though in its pioneering stage for Argus video-based research, the authors expect that significant advancement in prediction skill will be achieved through development of data-assimilation schemes which combine the best of existing process and empirical knowledge on coastal morphodynamics.

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