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Analysis and Modeling of Field Data on Coastal Morphological Evolution over Yearly and Decadal Time Scales. Part 1: Background and Linear Techniques

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ABSTRACT

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A number of statistical techniques to analyze and model coastal morphological evolution over yearly and decadal (*i.e.,* long-term) time scales based on field data are presented. After a general introduction to long-term morphological modeling, mainly linear methods are discussed, whereas nonlinear methods are treated in a companion paper (SOUTHGATE *et al.,* 2001). The theoretical background to the methods introduced is summarized and examples of field applications are given to illustrate each method. High-quality field data sets from different sites in the world, including Germany, The Netherlands, and United States, were employed in these examples. The analysis and modeling techniques used encompassed bulk statistics (mean, standard deviation, correlation *etc*), random sine functions, empirical orthogonal functions, canonical correlation analysis, and principal oscillation pattern analysis. Besides an evaluation of how suitable respective technique is for analyzing and modeling long-term morphological evolution, some general observations are presented regarding scales of morphological response as derived from the field applications. Data describing the evolution of both natural and anthropogenically affected coastal systems were studied. All methods investigated proved their usefulness for extracting characteristics of long-term morphological evolution, as well as for modeling this evolution, when applied under the right circumstances. However, more sophisticated techniques rely on more data in time and space, which is typically the limiting factor in the application of statistical methods as those presented here.

ADDITIONAL INDEX WORDS: *Data analysis, modeling, bulk statistics, principal component analysis, empirical orthogonal functions, canonical correlation analysis, principal oscillation patterns, long-term morphological evolution.*

INTRODUCTION

The coastal areas constitute complex physical systems of high dimensionality where the forcing acts at many scales in time and space, often through complicated interactions and feedback mechanisms between the forcing and the system response (DE VRIEND, 1991a; LARSON and KRAUS, 1995). Thus, predicting sediment transport and evolution of beach morphology in these areas are difficult tasks, especially over longer time periods when the scale range is wide. Physically based prediction models have their inherent limitations due to insufficient knowledge of the governing processes as well as how these processes are described in equation form (DE VRIEND, 1991b). In a more basic context there are limits to the predictability of morphological variables that are related to the issue of scale (CAPOBIANCO *et al.,* 2003), but possibly also due to the nonlinearity of many coastal systems that may induce chaotic behavior (SOUTHGATE *et al.,* 2003).

A useful alternative to models of long-term beach evolution developed based on physics (see HANSON *et al.,* 2003) might be data-based models, where the components as well as the entire structure of the model could be constructed from anal-

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ysis of available data on beach morphology. The fundamental assumption in data-based modeling is that the sampled data sufficiently well reflect the essential properties of the process under study in time and space. If this is not the case, model predictions will fail to capture the system behavior and prediction results will be poor. The strength of a data-based model, that is, it may reproduce the main features of the beach behavior observed at a particular site without any special physical insight, could also be the primary weakness of the model since the general applicability is not ensured. Using a data-based model developed for one site requires careful considerations before it is used at other sites.

A natural step prior to data-based model development is analysis of the data to establish basic properties and the degree of association between these properties. Such analysis typically aims at detecting and quantifying dominant patterns in the data and their evolution in time and space, as well as how different patterns are related to each other. Thus, it is possible to obtain valuable information on the long-term behavior of beaches that may be used not only for developing data-based models, but also for increasing the understanding of the factors governing the morphological evolution. The use of a limited set of basic patterns to represent the data is often an effective way of distinguishing between signal and noise (VON STORCH and NAVARRA, 1995). The signal is associated with the morphological processes at the scale of interest, whereas the noise includes the effects of processes operating at smaller scales not sufficiently resolved by the data as well as inaccuracies in the measurements. Distinguishing between signal and noise is often non-trivial and depends on the specific application as well as the required accuracy of the data representation.

The main objective of this paper is to introduce a number of data analysis and modeling techniques that are potentially useful in predicting the long-term evolution of beaches. The emphasis is on presenting examples from the field where the techniques have been applied to understand and predict the behavior of the coastal system, although a brief theoretical background is provided for each technique discussed and appropriate references are given. By discussing the techniques through practical examples it may be easier to assess the usefulness and limitations of respective technique for application to a specific data set. The focus on practical examples stresses the need for high-quality data sets and at present this remains one of the major obstacles for understanding long-term beach evolution (DE VRIEND *et al.*, 2003). In the PACE project a number of such long-term data sets were compiled and the examples provided here constitute a part of the research work performed within PACE.

Another important aspect of the data analysis and modeling discussed in this paper, besides evaluating the applicability of the techniques in predicting long-term beach evolution, was to determine characteristic time and space scales of long-term beach response in order to extract some general properties of these response scales. The response of a coastal system is associated with changes in the forcing or the system itself, which could be naturally or anthropogenically induced (*e.g.*, beach nourishment or the construction of a groin or jetty). Finally, a third motivation for employing the present analysis techniques is data reduction where the original data are too extensive to be efficiently managed. Instead, the data are represented through a limited set a functions obtained by using some predefined statistical measure. An example of such functions that are discussed extensively here are empirical orthogonal functions (EOFs) which concentrate the variance in an optimal manner.

Data sets on long-term beach evolution typically encompass time series of topographic surveys (one- or two-dimensional in space), possibly with some simultaneous measurements of the forcing (*e.g.*, wind, waves, and currents). Detailed, high-quality data sets tend to be relatively limited in time extending from a few years up to a few decades, which limits the possibilities of understanding the coastal behavior and making predictions of this behavior. Geologically reconstructed data sets on beach evolution are much longer and could encompass many thousands of years (STIVE *et al.*, 2003). In the examples given here no such long-term data set is included, although the present techniques might be highly useful to explore and model beach evolution also on geological scales.

A majority of the techniques introduced in this paper are related to principal component analysis (PCA). PCA methods have been employed for quite some time in meteorology and oceanography to resolve the spatial and temporal variability of physical fields (PREISENDORFER, 1988; VON STORCH and NAVARRA, 1995). However, PCA was originally developed by researchers in the field of experimental psychology (HOTELLING, 1933) and later utilized by geologists (KRUMBEIN and GRAYBILL, 1965; DAVIS, 1971). The PCA methods have shown great promise in terms of representing complex fields through a limited number of basic patterns in space (principal components or spatial EOFs) combined with multiplicative time functions (principal component scores or temporal EOFs). Even though the patterns do not necessarily have any physical relevance, it is often possible to give an interpretation that is physically based when beach topographies are analyzed. This is probably due to the fact that topographies are geometric constructs made up of different features, and the patterns extracted through PCA often happen to match these features. PCA has previously been employed in analysis of coastal data, typically to determine the shape of the EOFs for time series of beach profiles surveyed at a particular location (*e.g.*, WINANT *et al.*, 1975; AUBREY, 1979). However, several of the other PCA-related methods discussed here have not been applied to coastal morphological data before.

In the following, a selected number of methods, judged to be especially suitable for investigating long-term beach evolution, are introduced and examples are discussed to highlight the characteristics of these methods. Mainly linear methods are presented in this paper, whereas nonlinear methods are the topic of a companion paper (SOUTHGATE *et al.*, 2003). As pointed out above, most of the techniques discussed here are related to PCA, but also simple, bulk statistical methods are included. The paper concludes with a section summarizing the applicability of the presented techniques for predicting long-term beach evolution. Some general observations regarding the long-term response of beaches based on the data analysis performed within the PACE project are also given.

BULK STATISTICAL ANALYSIS

Background and Theory

Traditionally, simple bulk statistical measures such as the mean, standard deviation, range, and correlation have been employed to characterize beach response. A time series of, for example, profile surveys is used as input data and the statistics of the profile elevation is computed at selected cross-shore locations. Such statistics may be used for predicting the probability that a certain variation in the elevation will occur and provide a basis for design of structures and activities in the nearshore (INMAN and RUSNAK, 1956; DEWALL and CHRISTENSON, 1984). Another common application related to the variability in profile elevation is determining the depth of closure (HALLERMEIER, 1981), which corresponds to the seaward limit of significant sediment transport. In practice, significant transport is related to profile variability given by the local standard deviation in elevation (KRAUS and HARIKAI, 1983) or a predefined depth change between individual profile measurements (NICHOLLS *et al.,* 1998a). Recently, probability-based approaches have been developed for determining the depth of closure where a range of depth changes are investigated and their probability of exceedance (CAPOBIANCO *et al.,* 1997; NICHOLLS *et al.,* 1998b).

Bulk statistical analysis has also been employed to derived quantities, that is, morphological variables computed from topographic measurements. An example of this is analysis of morphological features and forms, for example nearshore bars and berms (HANDS, 1976; LARSON and KRAUS, 1992; RUESSINK and KROON, 1994), dunes (STIVE *et al.,* 1996), and overall profile shape (DEAN, 1977; PRUSZAK, 1993), where the temporal and spatial variations of the quantity are investigated. In the case of morphological features, an objective definition must be found that correctly represents the properties associated with the feature and the variation in these properties. Investigating the behavior of morphological features typically requires fairly detailed information about the bottom topography that could be difficult to obtain for long time periods. An alternative to topographic surveys might be image data collected using video cameras, where changes in the topography could be directly or indirectly inferred through image analysis (WIJNBERG and HOLMAN, 1997).

Correlation analysis provides a measure of the linear relationship between two quantities for which simultaneous measurement time series are available. If a strong correlation is observed between two quantities, models can be developed (empirical or physically based) to predict one quantity from the other. Establishing relationships between different quantities could also be of interest from an analysis perspective, where insights into the behavior of a beach and how it responds to the forcing might be gained. Waves are the primary forcing for beach change in many cases and time series of measured (or hindcasted) statistical wave properties are often available. Although marked correlation between the waves and profile change might be noted, it is in general difficult to establish predictive relationships between, for example, bar movement and offshore wave characteristics without data censoring (LARSON and KRAUS, 1992). Thus, significant relationships may only be derived for certain classes of events (*e.g.,* extreme storms) which display a distinct response with respect to the scales resolved in the measurements. A remedy for this situation might be advanced statistical models that can describe more complex input-output systems as well as include the time history of the morphological evolution, which often is of major importance for the beach response.

Different types of Fourier methods, which represent physical features in time and space through sinusoidal functions, have also been employed in analysis of coastal morphology (PRUSZAK and RÓŻYŃSKI, 1998). Such analysis may provide an efficient way of deriving characteristic scales for cyclic phenomena in the coastal areas, for example, seasonal shoreline fluctuations, material exchange between the bar and berm region, and spatial properties of rhythmic features. One disadvantage of the Fourier analysis is the a priori assumed sinusoidal shape of the applied functions, which restricts the identified patterns in time and space. In general, selecting a specific shape for the functions in the analysis may provide a certain robustness in the estimates and allow for introducing process knowledge into the analysis. However, the representation of the data is typically not optimal in the sense that the applied patterns are fixed and not derived from the data properties. A particular technique applied here that may be classified as a Fourier method is Random Sine Functions (RSFs). In RSF analysis residuals around a certain reference shape (*e.g.,* an equilibrium beach profile) are treated as sine functions with random amplitude (envelope), wave number, and phase. The derived sine functions reflect the variability in the data and may be suitable for characterizing spatial and temporal properties of different features and forms.

Field Application

Data on waves and profiles have been collected at the U.S. Army Field Research Facility at Duck, North Carolina, since the beginning of the 1980s (HOWD and BIRKEMEIER, 1987; LEE and BIRKEMEIER, 1993). This data set is unique with respect to the spatial and temporal resolution of beach profile change as well as the accuracy of the measurements. Thus, in several applications discussed in this paper the Duck data set was employed to evaluate analysis and modeling techniques. The beach profile has been surveyed approximately biweekly along four lines at Duck (Line 58, 62, 188, and 190; see HOWD and BIRKEMEIER, 1987), from the dune region out to about 8 m water depth, and at present about 13 years of data are available.

A commonly used measure of beach profile variability is the standard deviation in elevation, which may be computed at selected cross-shore locations from a time series of profile measurements. Figure 1 illustrates the standard deviation in elevation (s_e) as a function of mean profile elevation calculated for the four survey lines at Duck using 13 years of data. The main features of the cross-shore variation in s_e are quite similar at different beaches, although the magnitude differs (KRAUS and HARIKAI, 1983). A maximum in s_e is typically

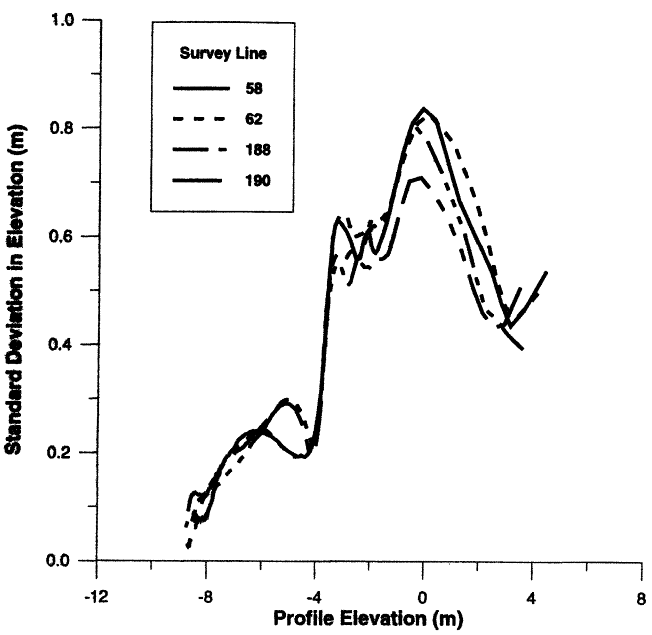

Figure 1. Standard deviation in elevation as a function of mean profile elevation for four survey lines at Duck (1981–1993).

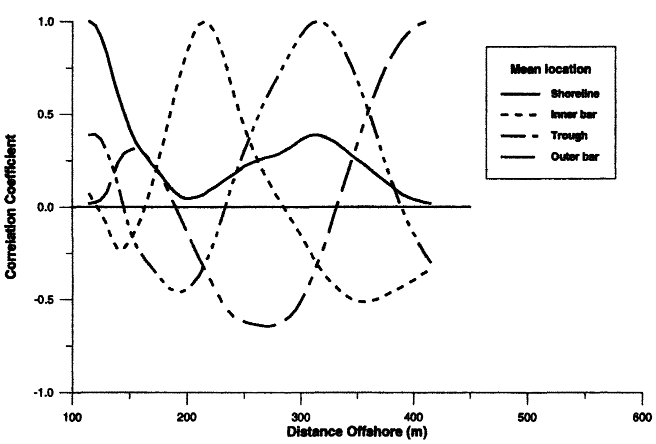

Figure 2. Correlation between time series of elevation at selected locations representing main morphological features and neighboring profile regions (data from Duck, 1981–1993).

found around the shoreline, and, going offshore, s_e decreases first at a low rate after which it drops drastically at a certain depth (about 4 m in Figure 1). This marked drop in s_e has often been used to define a depth of closure. It is also clear from the figure that s_e attains small but non-zero values at greater depth, indicating that, although these events are rare, profile change of significance occasionally occurs at these depths (another factor affecting s_e at greater depths is the survey accuracy). By introducing probability considerations into designs involving the depth of closure, a more realistic description of profile variability and its effect on the activity or structure to be designed is obtained.

Even though simple bulk statistics are quite useful in characterizing long-term beach dynamics, more sophisticated measures may provide additional insights to how the beach responds. For example, correlation analysis yields information about whether different quantities tend to display interrelated behavior. If such behavior is established, it could be a starting point for identifying physical mechanisms to explain the response or for deriving empirical predictive relationships. Figure 2 shows the correlation coefficient (c_e) calculated between time series of measured profile elevations at selected cross-shore locations. The variability associated with four main profile morphological features was investigated, namely shoreline, inner bar, outer trough (between inner and outer bar), and outer bar (two bars are commonly present at Duck). Elevation time series at the mean locations for these features were correlated with corresponding series measured at other locations.

The c_e-values for the mean inner and outer bar locations exhibit the same basic spatial correlation pattern (most seaward part of the profile not shown): there are strong positive correlations around the mean bar location and marked negative correlations with points located further away (on both sides of the positive maximum). This pattern is probably caused by the fact that the bars are built over a certain distance by material from both the shoreward and seaward side. The outer bar has a broader positive correlation area than the inner bar reflecting the typical greater horizontal extent of the former bar. Around the mean outer trough location the same basic pattern is observed as for the bars. For the mean shoreline location, c_e shows a sharp drop going offshore, most likely because coarser material often found in this region produces a beach response that often display little covariability with locations further seaward. However, in the outer trough region there is a positive peak in c_e indicating that erosion at the shoreline is connected with deepening of the outer trough. The correlation between what is happening at the shoreline and the mean inner and outer bar locations is weak, although slightly negative as expected.

Correlation analysis may be less well-suited for resolving morphological forms and features. Instead, different Fourier methods may be applied that more readily identify the presence of such features and quantify their properties. Here, RSFs were developed to study the behavior of multi-barred beaches. A certain degree of integrity (regular sampling) should be retained, however, the method is much less computer-intensive than traditional Fourier transformation techniques or different types of PCA. RSF was first applied to the Lubiatowo beach (PRUSZAK and RÓŻYŃSKI, 1998), which is gently sloping with fine sand (D_{50}=0.22mm) having multiple bars and a marked dune typical of the South Baltic coast. Measurements were performed at 27 cross-shore survey lines regularly spaced at 100 m. Three of the lines located in the middle of the study site were chosen for the RSF analysis, because their records had the best integrity and contained measurements of all surveys between 1964 and 1994, usually taken once or twice per year. This measurement time span allowed for determining bar behavior at time scale of decades.

The analysis started by computing the reference Dean pro-

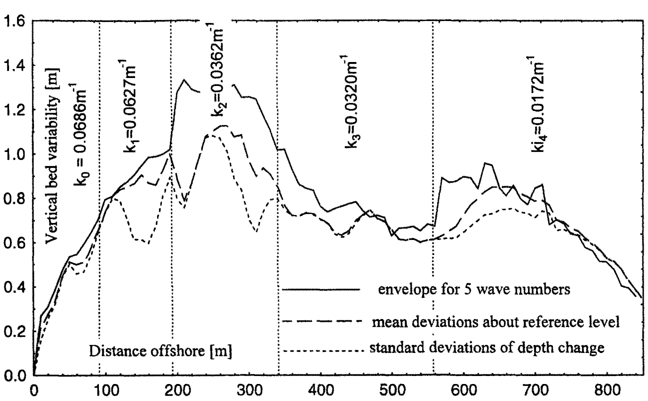

Figure 3. Profile envelope resulting from RSF analysis employing five fixed bar wave numbers.

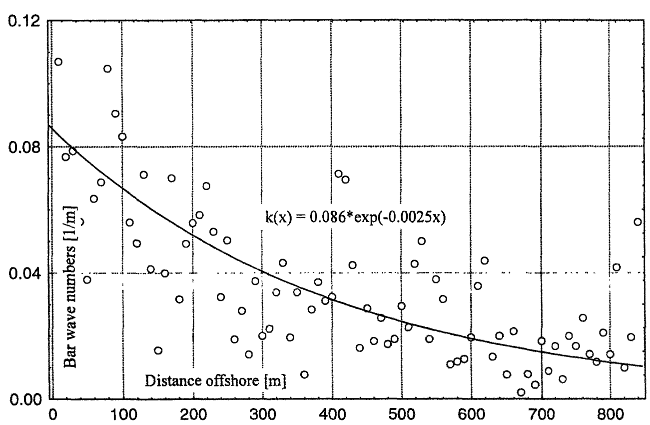

Figure 4. Exponentially decaying bar wave number pattern.

file, which was determined through a least-square fit against all surveys lumped together. Then the residuals were computed around the reference profile. In the RSF analysis a sine function is drawn along three such consecutive residuals and a bar wave number $k(x)$, envelope $A(x)$, and phase $\phi(x)$ are obtained for the middle residual according to the following formulas: $k(x)\cdot\Delta x = \arccos[(r(x+\Delta x)+r(x-\Delta x))/2r(x)]$; $A(x) = [r^2(x)+((r(x+\Delta x)-r(x-\Delta x))/2k(x)\Delta x)^2]^{1/2}$; and $r(x)/A(x) = \sin[k(x)x+\varphi(x)]$, where $r(x-\Delta x)$, $r(x)$ and $r(x+\Delta x)$ are consecutive residuals and Δx is the sampling interval. The first formula yields $-1 \leq \cos[k(x)\Delta x] = (r(x+\Delta x)+r(x-\Delta x))/2r(x) \leq 1$ and this criterion determines whether a sine function can be drawn through three given residuals. Apart from a few cases this criterion was satisfied for the present data, so the analysis could be applied successfully. Thus, the RSF analysis produces three functional parameters, where the bar wave number and the envelope express bed variability. The phase can not be given any physical interpretation and it is discarded in the following discussion.

The envelope reflects the intensity of the bed variation. Standard deviation or mean deviation about the reference profile play a similar role, so the line of the envelope should closely resemble these two measures, especially the latter one. Since the envelope depends on the bar wave number pattern, the RSF model is usually calibrated so that the envelope becomes close to the mean deviations about the reference profile. Initially, the bar pattern was characterized by five constant parameters k_0 to k_4, each one associated with typically observed bar configurations (subscript '*0*' corresponding to the ephemeral innermost bar located 0–90 m offshore and '*4*' to the outermost bar located 580–800 m offshore). The k_i-parameters were obtained as the mean values for locations where the bars were typically observed. Such an approach seemed to slightly overestimate the most intensive bed variability (Figure 3), so it had to be modified. The computation of average bar wave numbers for every location revealed an exponentially decaying trend, and the expression $k(x) = 0.086\exp(-0.0025x)$ was obtained through a least square fit against the data points (Figure 4). As a result a better agreement between the mean deviations and the envelope was achieved (Figure 5).

RSF is especially useful for description of local geometrical bar properties. The main idea is that bar length and height can be associated with the location across the beach profile, so the variability of large rhythmic bed forms can be studied in relation to their position on the profile. Thus, it permits for quasi-dynamic analysis as bar properties can be related to their cross-shore locations. The exponential pattern for the bar wave numbers corresponds to the observation that onshore bars are short and high, whereas offshore bars are long and flat. Another point is that bar behavior is described by only two functional parameters, which combine profile variability with bar length.

EMPIRICAL ORTHOGONAL FUNCTION (EOF) ANALYSIS

Background and Theory

Eigenvector techniques encompass the mapping of the observed data onto a set of shape functions (the EOFs) that is

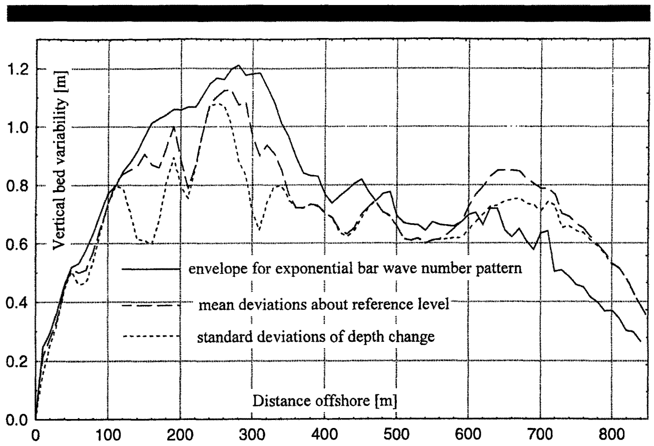

Figure 5. Profile envelope resulting from RSF analysis employing exponentially decaying bar wave number.

extracted from the data itself (PREISENDORFER, 1988; JACKSON, 1991). The EOFs correspond to a statistically optimal description of the data with respect to how the variance is concentrated in the modes, where the variance explained decreases monotonically with the mode number. Thus, since the explained variance typically drops at a high rate with the mode number, only a limited number of modes is needed to explain most of the variance in the data. This property is often the motivation for using EOFs as a data reduction technique or a method to separate between signal and noise. As previously discussed, although the EOFs are optimal in a statistical sense there is no reason that the eigenfunctions should have a physical background, even though such interpretations are possible in many cases as will be shown below.

A data matrix X containing, for example, morphological quantities sampled in space (columns) at specific times (rows), may be represented using matrices involving the spatial EOFs (E), the eigenvalues (L), and the temporal EOFs (A):

$$X = ELA^T \tag{1}$$

The column vectors in E and A are orthonormal and corresponds to the eigenmodes, and the variance associated with respective mode is given by the eigenvalue in L. The EOFs are normally obtained by solving an eigenvalue problem involving the covariance or correlation matrix based on X, but in some applications the sum-of-square matrix is used instead. In the former approach the arithmetical mean is removed, which is the most common method in applications to morphologic data since the mean tends to dominate the signal. Using the sum-of-squares matrix might be more useful in cases where the EOFs are rotated (*i.e.,* are replaced with another pattern to achieve a "simpler" description according to some criterion) to allow for a more physical interpretation of the eigenvectors (PREISENDORFER, 1988; VON STORCH and NAVARRA, 1995).

A disadvantage of traditional EOF analysis is the inability to resolve fixed patterns in the data that propagate with time. Thus, progressive wave-like motions are represented as combinations of standing waves and the characteristics of propagating patterns can not be quantified by the technique (*e.g.,* wave speed and wavelength). However, modifications of the EOF analysis have been developed to remedy this deficiency, namely extended EOF analysis (EEOF) and complex PCA (CPCA). In EEOF analysis the original data set is extended by adding lagged observations in time after which traditional EOF analysis is performed (WEARE and NASSTROM, 1982). A disadvantage with EEOF is that the approach becomes computer-intensive as the number of time lags increases. In CPCA a new data set is formed from the original set and its Hilbert transform (HOREL, 1984). Then, complex eigenvectors are determined by applying EOF analysis to the derived complex data set. CPCA has a good potential for identifying traveling patterns in the data, although the interpretation is more difficult than EOF analysis since both amplitude and phase relationships must be considered. Further, CPCA, or any modification of the EOF technique involving time-lagged data, requires the data to be sampled with a constant time interval, which is often not the case for coastal morphology data.

EOF analysis was originally applied in coastal morphology in the middle of the 1970s to investigate variations in the beach profile shape in space and time (HAYDEN *et al.,* 1975; WINANT *et al.,* 1975). Theses studies showed that distinct morphological characteristics could be associated with the lower EOF modes. For example, AUBREY (1979) related the mean profile shape, bar and berm features, and the low-tide terrace to the first, second, and third EOF modes, respectively (the mean was not subtracted in the analysis). After these pioneering studies, EOF analysis has become a fairly commonly applied technique in morphological research to investigate beach response over time scales of several years. More advanced techniques have also been applied to beach topography data in a few cases, for example CPCA (LIANG and SEYMOUR, 1991; LIANG *et al.,* 1992) and three-mode PCA (MEDINA *et al.,* 1992). For revealing patterns in data sets on nearshore topography that are spatially extensive but temporally sparse, a combination of the EOF technique with a moving window approach can prove useful (WIJNBERG, 1995; WIJNBERG and TERWINDT, 1995) (see application in the following). EOFs may also be used for modeling purposes if the time functions (A) can be predicted over the simulation period. AUBREY *et al.* (1980) tried to predict daily and weekly beach changes over a five-year period from offshore wave properties using linear statistical predictor techniques to obtain A (see also HSU *et al.,* 1986 and HSU *et al.,* 1994).

Field Application

EOF analysis was applied to two different data sets on nearshore beach topography, one from Terschelling off the Dutch coast and the other from Sylt off the German coast. The Terschelling data encompass a longer time period and a greater spatial area than the Sylt data. Also, the beach at Terschelling basically represents a natural beach unaffected by human intervention, whereas major beach nourishments have been carried out at Sylt. Thus, application to these two data sets will illustrate what the EOF analysis can reveal regarding natural variations as well as anthropogenic effects. Also, two slightly different analysis techniques were used for the two data sets, one involving direct analysis of the topographic data with the spatial EOFs representing two-dimensional maps (Sylt data), and the other involving spatial filtering and separate analysis of individual profile lines (Terschelling data).

The Terschelling data set consists of annual surveys of the nearshore bathymetry over the period 1965–1995 (31 years) along 20 km of coastline. Surveys were carried out along fixed cross-shore transects (profiles) every 200 m alongshore. In the example discussed here, profiles of 750 m length were analyzed, starting at the +1m contour. The cross-shore spacing of the surveyed elevations was 15 m. In the analysis, the EOF technique was applied to spatial subsets of the profile data using a moving window (see WIJNBERG and TERWINDT, 1995). The applied window size was 1 km with a temporal extent of 31 years. The main advantage of the spatial subdivision compared to the traditional approach of including the

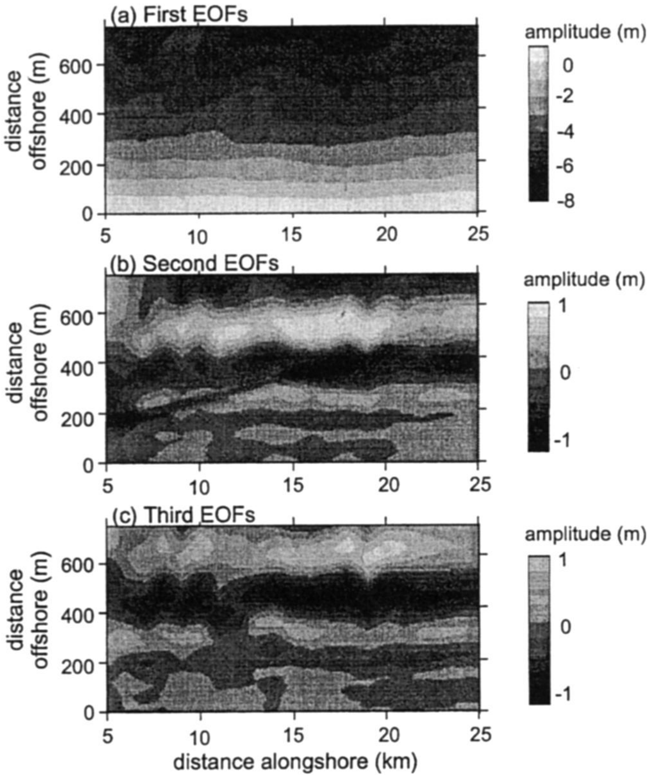

Figure 6. Spatial EOFs for profile lines along the Terschelling coast: (a) first mode, (b) second mode, and (c) third mode.

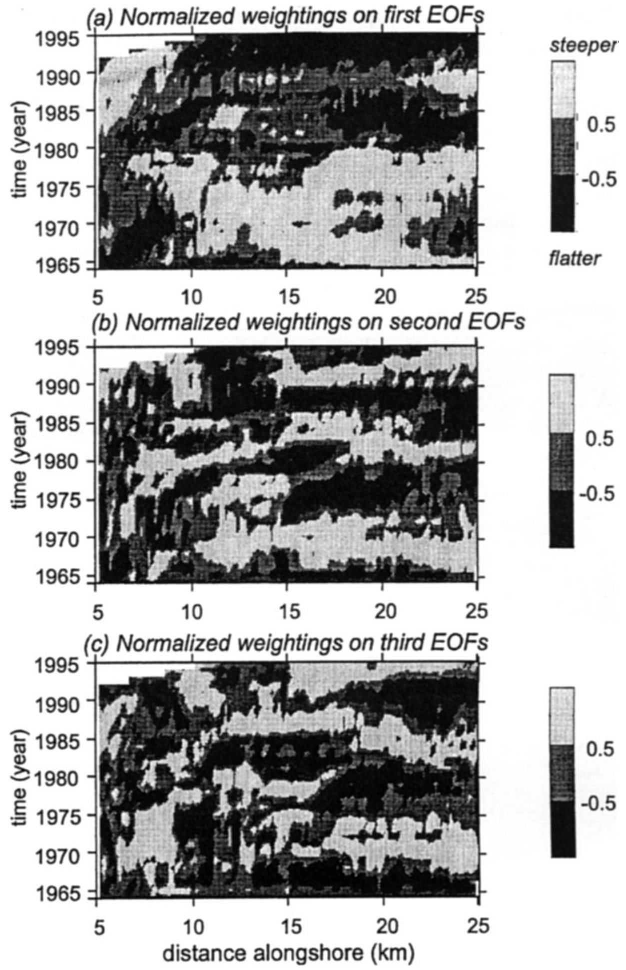

Figure 7. Temporal EOFs for profile lines along the Terschelling coast: (a) first mode, (b) second mode, and (c) third mode.

entire surface (compare with the following example) is that it allows for the possibility of having longshore varying temporal evolutions for similar cross-shore EOF patterns. Also, alongshore variation in the character of large amplitude bed level fluctuations may appear more clearly, because there is no constraints regarding longshore correlations. Note that these arguments are most relevant for cases where large stretches of coast are analyzed (10 to 100 km or more). An additional advantage of the window approach is that the spatial averaging over a 1 km section improves the robustness of the EOF estimate, because instead of using only 31 profile observations (or 31 'surfaces'), $6 \times 31 = 186$ observations were used.

The first EOF modes describe the mean profiles (Figure 6a; the mean was not removed from the data before the analysis). The related temporal functions (Figure 7a) describe fluctuations in mean steepness. Positive (negative) values imply a steeper (flatter) than average profile. The second EOF modes generally describe nearshore bar topography, except in subsets km 5–6 and km 6–7 (Figure 6b). In these windows the second EOF mode relates to the concavity of the profile. The third EOFs also characterize bar topographies (Figure 6c). It appears that the second and third EOF bar functions are often about 90 degree phase shifted (like sine and cosine), such that they appear to be mapping the cross-shore migration of bars. The temporal functions of the second and third EOFs show rather regular behavior to the right of km 17 and more complex behavior to the left, though it is still coherent (Figures 7b and 7c). Note that the spatial EOF's are more or less similar across this whole reach. The regular behavior appears to describe net offshore propagation of all bars, out of the monitored area, while at some point in time a new bar is formed near the shoreline.

Placement of material in the nearshore to nourish beaches typically causes changes in the natural conditions that modify the sediment transport patterns and associated beach changes. Such modifications of the transport patterns may have both short-term (*e.g.*, initial profile adjustment and response to severe storms) and long-term effects (*e.g.*, adjustment towards long-term dynamic equilibrium, the natural state or a new state induced by the fill). Here, fill response at different time and space scales was investigated by analyzing a high-quality data sets from the Island of Sylt, Germany, on the topographic evolution in connection with fill placements. The Island of Sylt is a well-known beach resort on the German North Sea coast that has suffered severe erosion at least since the middle of the last century (DETTE and

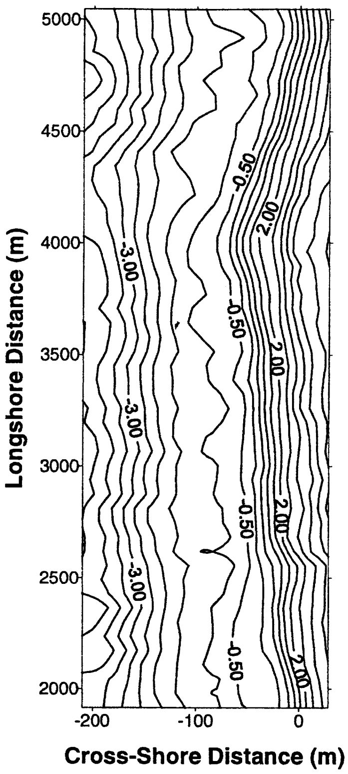

Figure 8. Mean topography for the beach at Rantum, Sylt.

NEWE, 1997). In the beginning of the 1980's it was decided to halt further erosion of the dunes and high cliffs, and in order to implement this policy beach fills have been placed along selected stretches of the island. As an example, the evolution of the fill placed at Rantum in the southern part of the island was investigated using EOF analysis. The beach at Rantum was nourished in 1987 with 1.44 10^6 m^3 of sand put along 3 km of the coast. Here, a subset of 63 profile lines surveyed 8 times during approximately four years were analyzed. In order to obtain a good data coverage in time and space for the analysis only survey data out to about 5 m water depth were included.

Figure 8 displays the mean topography for Rantum indicating the presence of rhythmic features (see wavy depth contours), which are frequently observed along the Island of Sylt (LARSON *et al.,* 1999a). The first spatial EOF map (E_1; Figure 9a) essentially shows an increase in the elevation over the entire area that reflects the addition of the fill material. The associated temporal function A_1 (see Figure 10) displays a similar behavior to what EOF analysis have shown at other nourishment sites (LARSON *et al.,* 1997): a rapid change when the fill was placed followed by a gradual decay towards the natural equilibrium state. For beach fills placed at Ocean City and Silver Strand (LARSON *et al.,* 1999a), for which similar EOF analysis was performed, this adjustment took about one year (a complete seasonal cycle). At Sylt it seemed to take considerably longer time, possibly because the material was placed above mean sea level making it less accessible for cross-shore adjustment, except during major storms. The spatial EOFs E_1, E_2, and E_3 explained 47.7, 24.4, and 10.7%,

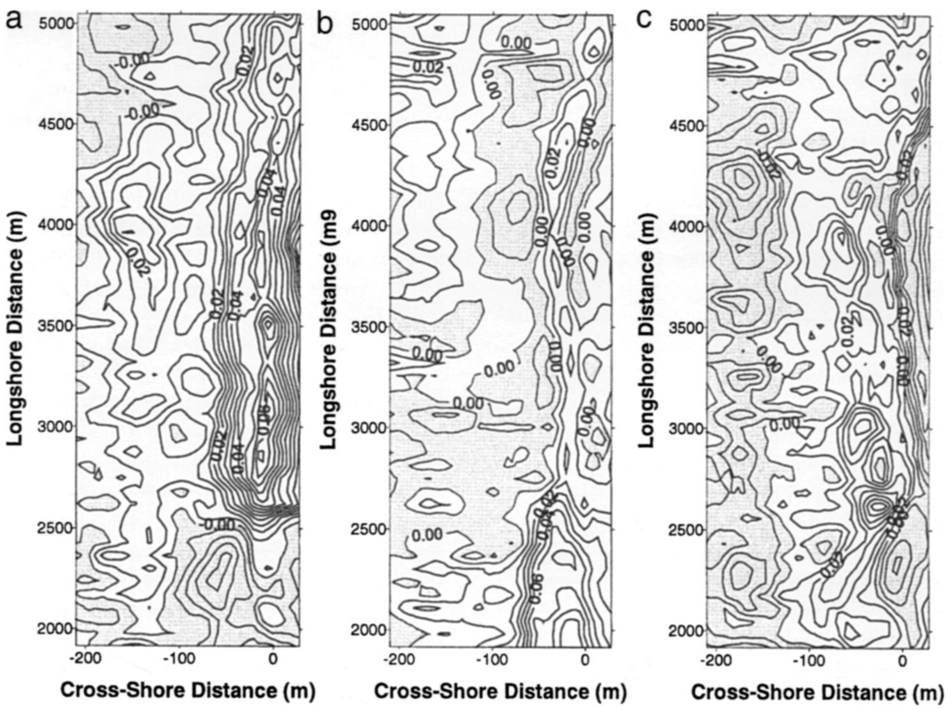

Figure 9. Spatial EOF maps for the beach at Rantum, Sylt: (a) first mode, (b) second mode, and (c) third mode.

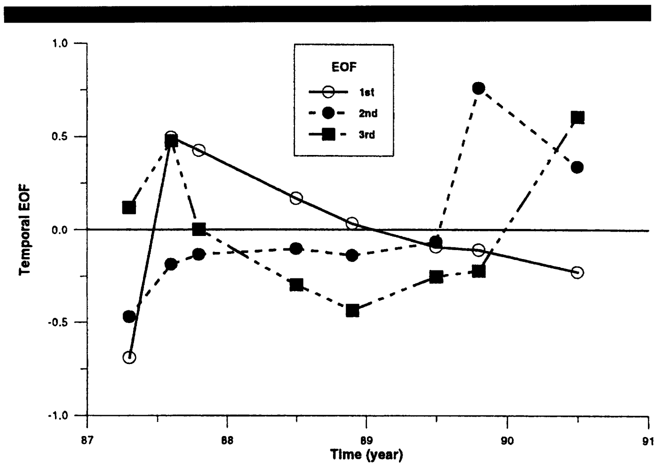

Figure 10. Temporal EOFs for the beach at Rantum, Sylt.

respectively, of the variation in the data. Figure 9b shows the spatial map E_2 and Figure 9c the map E_3. The map E_2 is most likely also related to the fill placement modifying the shape given by E_1, whereas E_3 characterizes the effect of some major storms occurring during the study period (*i.e.*, erosion of material on the foreshore and in the dunes and deposition in the bar region). Such storms appeared in the end of March 1987 and during January/February 1990 (DETTE and NEWE, 1997; compare with the peaks for E_3 in Figure 10).

CANONICAL CORRELATION ANALYSIS (CCA)

Background and Theory

CCA may be used to investigate if there are any patterns that tend to occur simultaneously in two different data sets and what the correlation is between associated patterns (BARNETT and PREISENDORFER, 1987; GRAHAM *et al.*, 1987a). The main idea is to form a new set of variables from the original two data sets so that the new variables are linear combinations of the old ones and maximally correlated. Thus, if the two original data sets are denoted Y and Z, the new transformed variables in matrices U and V have maximally correlated column vectors for the same index and zero correlation for differing indices. Furthermore, the column vectors in U and V are orthonormal. The desired weights for transforming Y into U are given by the solution to the eigenvalue problem (GRAHAM *et al.*, 1987a),

$$[(Y^TY)^{-1}(Y^TZ)(Z^TZ)^{-1}(Z^TY - \mu^2 I] = 0 \qquad (2)$$

where μ^2 denotes the eigenvalues and the subscript T is transpose. The eigenvalue gives the squared correlation between the corresponding temporal amplitudes of the canonical modes (the column vectors in U and V), and the associated eigenvectors R yield the transformation $U=YR$. A similar eigenvalue problem as given by Eq. 2 defines the transformation of Z into V having the same μ^2-values and eigenvectors Q, which produces the other transformation $V=ZQ$. The spatial amplitudes (G and H) of the canonical modes are obtained as $G=Y^TU$ and $H=Z^TV$. Thus, the original data sets are expressed as $Y=UG$ and $Z=VH$.

EOF analysis is often used in a pre-processing step to CCA in order to reduce the noise in the data and to become familiar with the general structure of the data. The data sets (Y and Z) are developed in terms of their EOFs and a certain number of modes are selected to represent the data before the CCA is carried out. Thus, the data sets maybe expanded as $Y=AE^T$ and $Z=BF^T$, where A and B contains the temporal EOFs and E and F the spatial EOFs for Y and Z, respectively. A limited number of EOF modes are then selected to represent Y and Z when performing the CCA.

Based on the correlation between the dominant patterns in Y and Z established through the CCA, a regression matrix may be derived that relates the two matrixes to each other. Thus, if Y is known, Z may be predicted by employing the regression matrix. Having an input data matrix Y_p (measured or simulated), the associated output data matrix Z_p is given by,

$$Z_p = Y_p\Psi \qquad (3)$$

where,

$$\Psi = GSF^T \qquad (4)$$

and $S=U^TB$. CCA has not been previously used in applications to coastal morphology, but several examples exist from the fields of meteorology and oceanography (BARNETT and PREISENDORFER, 1987; GRAHAM *et al.*, 1987b; BRETHERTON *et al.*, 1992; BARNSTON and HE, 1996).

Singular Value Decomposition (SVD) is sometimes used as an alternative to CCA for finding coupled patterns in two data sets (WALLACE *et al.*, 1992; CHENG and DUNKERTON, 1995). In SVD are the patterns derived by maximizing the cross-covariance between Y and Z, whereas in CCA the cross-correlation is maximized instead. Since correlation is a better measure of linear association than covariance, CCA is often more appropriate to apply, although this is not always the case (CHERRY, 1996).

Field Application

The measurement time series of waves and profiles from Duck were analyzed using CCA in order to determine the covariability between waves and profile response (LARSON *et al.*, 1999b). The profile shape itself as well as the change between consecutively surveyed profiles were correlated with both the offshore (deep-water) and nearshore wave conditions. In the offshore, the waves were described by composite probability density functions (pdf) derived based on the measured wave conditions prior to a profile survey. Nearshore wave conditions were calculated using a random breaker decay model (LARSON, 1995) and averaged local wave properties were used as input to the CCA. The profile response displayed significantly higher correlation with the nearshore wave properties as compared to the offshore waves, and the highest correlation was found between the profile shape and the mean ratio of breaking waves for the time period preceding the profile survey. The CCA using nearshore wave properties indicated a potential for predicting the profile response with an acceptable degree of accuracy once a regression matrix relating the profiles to the waves have been established that represents the typical variability at the site.

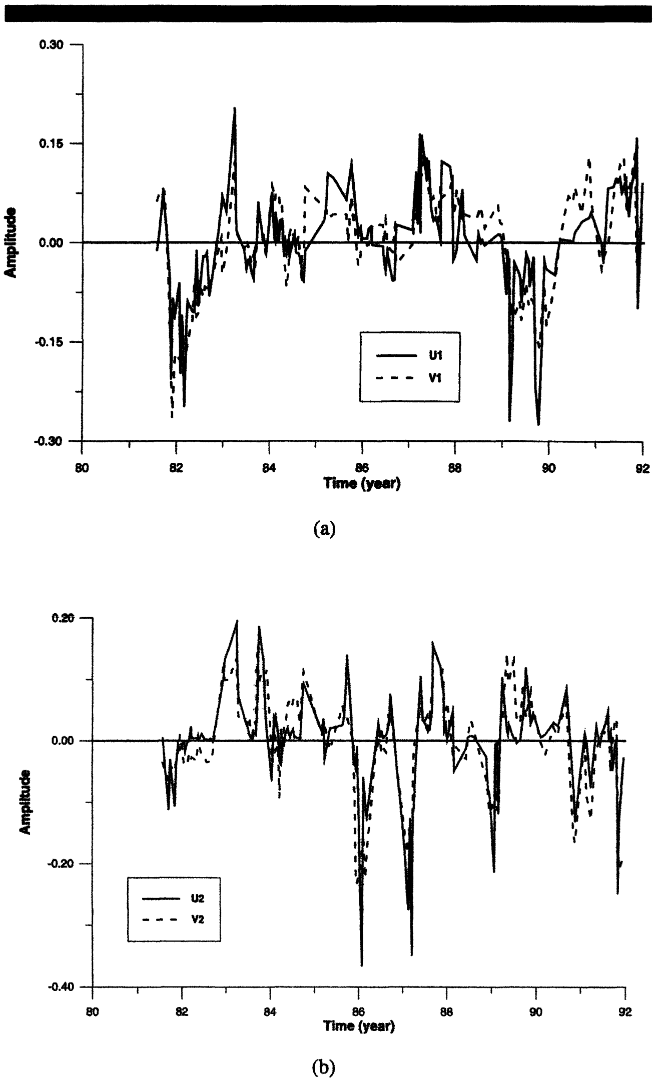

Figure 11. Temporal amplitudes of CCA modes for mean wave energy dissipation and beach profile shape: (a) first modes (U_1 and V_1), and (b) second modes (U_2 and V_2).

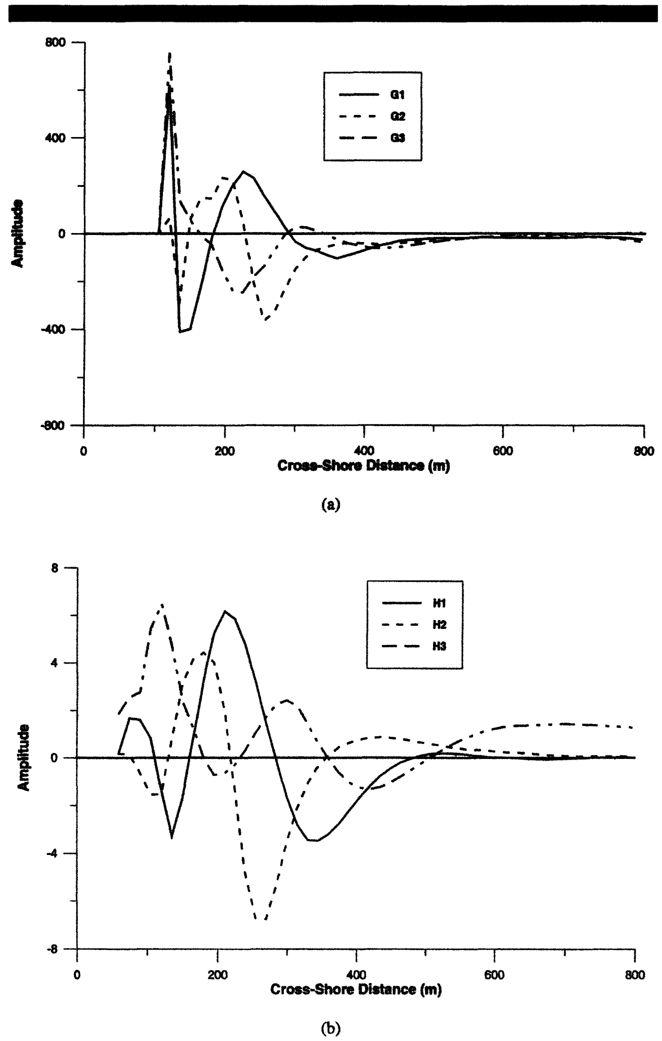

Figure 12. Spatial amplitudes of the CCA modes: (a) lowest three modes for mean wave energy dissipation (G_1–G_3), and (b) lowest three modes for beach profile shape (H_1–H_3).

Applying CCA between the deepwater wave height pdf and the profile shape produced a maximum correlation of 0.41 between U_1 and V_1 (temporal amplitudes of the first CCA modes). These modes showed that the shift of material between the foreshore and the bar area is related to an increase in the probability of higher waves in the pdf (and vice versa). If the change in elevation between consecutive profiles was used instead of the profile shape itself, the correlation between U_1 and V_1 dropped to 0.37. However, taking the absolute elevation change yielded an increase in the correlation to 0.63. This marked increase indicates that the magnitude of elevation change (quantified by the absolute values) is much easier to relate to the waves than the change itself, which is because the latter also includes the direction of the change (positive or negative). The pdfs derived for other quantities (wave energy flux, dimensionless fall speed, and wave steepness) did not produce notably higher correlations than the wave height pdf and are not discussed here. The highest correlation (0.70) between the temporal amplitudes of the first CCA modes was obtained when the absolute elevation change per unit time was correlated with the wave height pdf.

The relationship between the profiles and nearshore waves was also investigated with CCA. First, the profile shape was correlated with the mean energy dissipation due to wave breaking calculated based on the waves measured during the period preceding a specific profile survey. The correlation was 0.77, 0.74, and 0.65 between the first, second, and third CCA temporal modes, respectively. Figures 11a and 11b display the temporal amplitudes of the first and second modes, respectively, for the profile elevation and dissipation. The high correlation between associated modes is clearly visible as well as the variability at many different temporal scales. In Figure 12a the spatial amplitudes of first three modes are shown for the energy dissipation, while corresponding modes are displayed in Figure 12b for the profile elevation. The mean was subtracted out from the data before the analysis, implying that the modes associated with the dissipation can attain negative values. It is difficult to give any physical interpretations to the mode shapes; however, the modes associated with the profile elevation reflects the presence of longshore bars at Duck.

The profile elevation was also correlated with the mean ratio of breaking waves. This analysis resulted in somewhat higher correlation values with 0.80, 0.76, and 0.60 for the temporal amplitudes of the first three modes. The spatial amplitudes of the first mode for the breaking wave ratio showed that more wave breaking close to shore was associated with more material in the profile here. Thus, higher waves with more wave breaking in the offshore implies that more material is typically found in the outer part of the profile. Analysis of profile elevation and root-mean-squre wave height produced correlation values similar to the analysis between elevation and ratio of breaking waves. Correlating elevation change with nearshore wave properties produced somewhat lower values. For example, the mean energy dissipation gave correlation values of 0.65, 0.53, and 0.40 for the temporal amplitudes of the three first modes.

In order to further investigate the predictive capability of CCA, regression matrices derived from the data sets on profiles and waves were used to reconstruct the time series of profiles using a limited number of CCA modes (to calculate the profiles 10 CCA modes were employed). Here, some results from the analysis of profile elevation and breaking wave ratio will be discussed. For these quantities, satisfactory agreement between calculated and measured profiles was achieved in the area where the profile exhibited a lot of change, whereas in the offshore the discrepancy was relatively larger. The wave properties selected for the CCA are mainly related to wave breaking which means that areas where this process dominates the sediment transport and profile response, such as in the nearshore, show better agreement. As a total measure of how well the profiles could be predicted from the breaking wave ratio using the regression matrix obtained from the CCA, the squared deviation between predicted and measured profile elevation was calculated across the profile for all surveys (see Figure 13). Also, the total variation in the data was quantified by computing the squared deviation between the measured profiles and the mean of the profiles at the same locations. The difference between the two curves in Figure 13 indicates how much of the variation that is explained by the CCA model. Thus, the model is explaining a large part of the variation (around 50%) in the nearshore out to about 400 m, but further offshore is the predictive capability more limited.

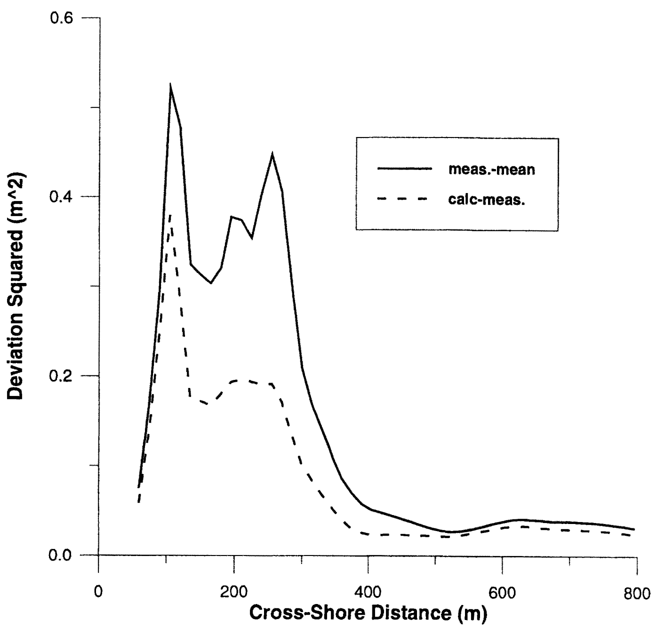

Figure 13. Deviation squared between calculated and measured profile elevations together with deviation squared between measured elevation and the mean of the elevation.

PRINCIPAL OSCILLATION PATTERN (POP) ANALYSIS

Background and Theory

In POP analysis the patterns used to characterize the data set under study are derived based on approximate forms of certain dynamical equations. This is in contrast to, for example, EOF analysis where the patterns are determined from an optimal description of the variance in the data. The POP technique may be used to identify coherent migrating, standing, and otherwise changing patterns without prior knowledge of the system dynamics forcing (VON STORCH *et al.*, 1988). The POPs are defined as the normal modes of a linear dynamical representation of the data in terms of a first-order autoregressive vector process with residual noise. POPs associated with real eigenvalues represent non-propagating, non-oscillatory patterns that decay exponentially, whereas the complex eigenvalues can represent propagating waves. POP analysis is a linearized form of the more general Principal Interaction Pattern (PIP) analysis, which involve non-linear dynamical equations (HASSELMANN, 1988; JANSEN, 1997a).

The analysis encompasses the representation of the data set X (*i.e.*, a time series of morphological variables) through the POPs P and the corresponding time functions W, which are governed by linear dynamical equations. Thus, the prediction model may be written,

$$X = PW \qquad \frac{dW}{dt} = CW + \eta \tag{5}$$

where C is a constant matrix and η a noise matrix (in the optimal case this is white noise implying that no dynamics have been left unmodeled). Typically, most of the dynamics is concentrated in the lower-order POPs allowing for a considerable data reduction as well as distinction between signal and noise for the particular application. Thus, the POP model is normally restricted to include a limited number of modes that explain most of the dynamics in the data. In applications to data, the differential equation in Eq. 5 is written in differ-

Table 1. *Loss of information due to model reduction (EOF model) and additional dynamic constraints (POP model).*

Number of EOF	EOF Data (%)	POP D/D (%)*
4	62	58/53
6	74	70/64
8	79	76/71
10	84	81/77
12	88	85/80
15	92	90/86
20	97	94/91

* Data/change-of-data

Table 2. *POP characteristics (8 modes included).*

POP	D.FAC (E^{-1} yr)	Per (yr)
1R	4.0	6.0
1I	4.0	6.0
2R	3.5	5.0
2I	3.5	5.0
3R	10.0	53.4
3I	10.0	53.4
4	0.6	
5	1.7	

ence form and the POPs are determined from the eigenvectors of C, which in turn is derived from the data by defining two new data sets separated by a time step (that is, C is obtained from solving the equation $X_{t+\Delta t}=CX_t$, where Δt denotes the time step). EOF analysis often proceeds the POP analysis to reduce the computational effort to obtain the POPs.

Since C is non-symmetric in general, the eigenvalues will be complex valued. As mentioned previously, the eigenvalues characterize the dynamics of the system, where the real and imaginary parts represent the damping and frequency of the oscillation for the corresponding POPs, respectively. The predictive power of a POP model depends on the characteristics of its POPs, for example, the damping or the e-folding time (the time by which a particular POP has damped out to 1/e of the original value) and the cycle period. The POP modes are not orthogonal which may be a drawback in some applications. POP analysis has not been previously employed to study long-term beach evolution, but some practical applications to geophysical data exist (VON STORCH *et al.,* 1988; PENLAND, 1989; XU and VON STORCH, 1990).

Field Application

A POP analysis was applied to a section of the Dutch coast (see JANSEN, 1997b and JANSEN, 1998), which has been monitored for over 35 years (the JARKUS data; 33 years of data were available at the time of the analysis). The measurements include the first row of dunes and the morphodynamic bed at a longshore spacing of approximately 800 to 1000 m. Reduced POP models with, respectively, 4, 6, 8, 10, 12, 15, and 20 EOFs (and corresponding POPs) were identified from the first 32 years of the data (1965–1996). Table 1 shows the loss of information due to model reduction (EOF models) and additional dynamic constraints (POP model), expressed in the percentage of the variance that is captured when the 32-year data is reconstructed from the reduced EOF and POP models. Because of the dynamic constraints, the POP models systematically lose 4 to 8 percent more than the EOF models.

The results for a model based on 8 POPs will be discussed in detail here. Comparison between measured and reconstructed data displayed good agreement for all years within the data range used for identification (provided a sufficient number of EOF/POPs were included). The prediction for 1996, however, shows significantly larger differences. Theoretically, this can be explained by the 'quality' of the POP model, or better, the 'quality' of each individual complex POP characterized by the relationship between its period and amount of damping (real POPs have no period and are merely damped). Severely damped POPs give a limited contribution to the first prediction step and consequently have little utility for prediction purposes. Table 2 shows these characteristics for the 8-POP model (a damping factor of 4 years means that the amplitude of the particular POP in 4 years time is reduced to 1/*e* of its original value). Optimally, the periods of the complex POPs are significantly larger than their corresponding damping factors. It can be concluded that this is not the case for any of the POPs identified.

The unsatisfactory prediction results obtained for the data set employed may be caused by (1) poor data quality (*i.e.,* the accuracy of the topographic measurements); (2) measurements not performed at equally spaced time intervals; (3) lack of dominant rhythmic (*i.e.,* quasi-periodic), features in the morphodynamic system indicating that the driving force (wave climate) may be more important than expected; and (4) inadequacy of the linear POP model (the dynamics may be dominated by nonlinear interactions, including the possibility of chaos). In the POP analysis, the identification of dynamic features is based on the assumption of a fixed sampling interval. This assumption should probably not be maintained in view of the sampling of the employed data. In order to correctly identify a dynamic model one first has to slice the sample vectors according to their sample date. This will generate a longer time series with non-equally sampled measurements. Taking care of the exact sample dates, a continuous-time dynamic model can then be identified. Finally, it was also found that the prediction quality is not necessarily improved when more POPs are included. In Figure 14 the quality of the prediction is schematically shown as a function of the number of POPs used. In the present application, the best prediction was obtained for 8 POPs. With a smaller number of POPs not all of the identifiable dynamics in the time series was captured by the model. Inclusion of more POPs only lead to capturing more of the noise rather than identification of additional rhythmic features. Such inclusions will improve the reconstruction but, in general, have a negative effect on the prediction.

APPLICABILITY OF TECHNIQUES AND GENERAL OBSERVATIONS

Selecting methods for analyzing and modeling long-term morphological evolution is intimately connected to the avail-

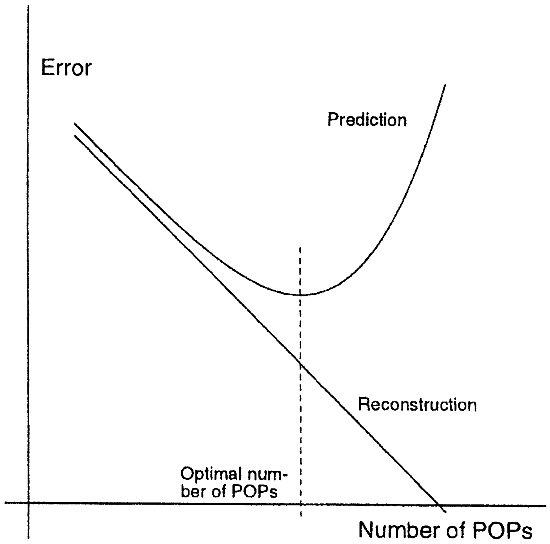

Figure 14. Accuracy as a function of the number of POPs included.

ability and quality of the data under study. In general, a more sophisticated method needs a larger amount of data as well as special requirements regarding the data sampling (*e.g.*, at even intervals in time and space). Unfortunately, in the practical case, long-term data is often scarce and restricted to a few variables, so that more advanced methods might be unsuitable or not possible to apply. Thus, bulk statistics is still very useful for analyzing beach evolution and for deriving simple empirical relationships to be used for predictive purposes. For example, time series of beach level measurements may be used for quantifying the variability, which in turn could be a basis for the design of structures and activities at the site in question. Formulas for the depth of closure arise from such analysis and they have a wide range of applications in engineering studies. Scales of beach response in time and space may be extracted through correlation and Fourier analysis techniques, forming a basis for assessing the impact of various types of forcing or disturbances.

However, simple bulk statistics can typically not adequately resolve shapes or forms of morphological features and other methods are needed. Different types of Fourier techniques might be useful for describing such features, although predefined functions are used to match the features that may limit the applicability of these techniques. EOFs are more general in the sense that the shape is not a priori given but derived from the properties of the data. For example, longshore bars are common and persistent features in many nearshore areas. Bars actively participate in the material exchange across the profile, often acting as temporary storage for sediment eroded from the foreshore. Knowledge of the properties of bars can yield insight to placement of sediment for nourishment purposes. Fourier methods or EOF analysis could provide valuable information on the temporal and spatial variability of bars improving the design of offshore nourishment schemes, especially regarding the long-term nourishment response. Furthermore, many coastal areas have alongshore rhythmic features at spatial scales ranging from hundreds of meters up to many kilometers, with characteristic time responses over decades and centuries (compare DODD *et al.*, 2003). The properties of these features are often crucial to understand in connection with engineering activities in the nearshore zone. Again, methods involving data representation through special functions could yield information on such properties.

EOFs are derived based on an optimum description of the variance (*i.e.*, a purely statistical criterion), but the shapes can often be given physical interpretations. Applications have shown that signals from different types of forcing and disturbances, for example, signals generated by the impact of beach nourishment, the effect of extreme events, and the influence of large-scale features in the offshore on nearshore morphological evolution, may be detected and quantified in an objective way using EOFs (LARSON *et al.*, 1997). Although EOF analysis requires larger amounts of data than determining bulk statistics, such data sets are often available including long time series of profile surveys at a particular location or complete topographies surveyed for a relative modest number of times. Again, the characteristic time and space scale of the sampling underlying a particular data set determine the scales of morphodynamic behavior possible to extract from the data. The data sets employed in the PACE project were selected for their quality as well as spatial and temporal extent, and typically it would be difficult to obtain comparable data sets in engineering applications.

Most of the methods discussed here can be applied for predictions, ranging from calculations of depth of closure through empirical formulas to forecasting large-scale morphological evolution using POP analysis. In several of the methods some physics may be introduced, thus improving the generality of the predictive model both regarding applications to other sites and for other forcing conditions. Simple empirical equations, as well as sophisticated multi-regression methods (*e.g.*, CCA), introduce leading parameters based on physical considerations, whereas other methods employ constrains that are intimately linked to the dynamics of the process (*e.g.*, POP analysis). Applications of more sophisticated data-based models (CCA and POP analysis) clearly showed the potential for these techniques, although the data requirements for their application are quite extensive. If a strong correlation is observed between two data fields, CCA is an effective way of developing a predictive model and the need for data from each individual field might not be much larger than for EOF analysis. Concerning POPs, larger amounts of data is typically needed, possibly with other requirements on the accuracy and sampling of the data.

The analysis and modeling of different data sets carried out within PACE led to some general observations regarding the long-term behavior of coastal morphological system. A few of these observations were discussed in connection with the application examples for the various methods introduced here, whereas other results have been presented elsewhere. In brief, the analysis and modeling revealed the following general long-term characteristics of the morphological systems studied:

- The more advanced methods applied allowed for a separation between morphological responses at different scales and some of these responses could be directly related to the forcing or to specific disturbances in the coastal system. The possibility to distinguish such responses indicates a potential for analyzing and modeling the evolution at a particular scale fairly independently of processes at other scales. Thus, in describing long-term morphological evolution model formulations could be successfully made directly at the scale of interest instead of formal derivations from a smaller scale.
- Using EOF techniques, it was possible to show that the disturbances generated by a beach nourishment placed in the nearshore area basically disappear after a complete seasonal cycle of waves, if the material is available for transport by the waves. In the case the material is placed in the upper part of the profile (or in deeper water) where waves only attack during extreme events, the adjustment back towards an equilibrium state takes considerably longer time (depending on the characteristics of the extreme events).
- On most beaches the seasonal signal in the profile variability is quite strong because of the material exchange between the foreshore and bar region. Although this exchange is important for many engineering activities in the nearshore, the coastal system exhibits a certain stability and the statistical properties of the profile variation indicate predictability. However, the seasonal signal is typically superimposed by extreme events that could change the fundamental state of the system. The effects on the morphological system of these events are difficult to predict and only limited data are available. Thus, long-term data from coastal systems should be studied on the premises that the collected data originated from different populations.
- Beach profile evolution displayed a distinct correlation with the offshore wave climate, but modeling efforts indicated that this relationship was not dominant enough to yield predictions explaining a large part of the profile variation. Calculating nearshore wave properties with a theoretical model and using some antecedent profile shape significantly improved the correlation and models could be derived that explained a satisfactory portion of the variation in the data. This indicates the importance of the preceding topography for the morphological evolution and the close interaction between the profile and the waves (forcing). Thus, the coastal morphological system have some of the basic characteristics of chaotic systems, namely strong feedback and nonlinear couplings between the variables.

CONCLUDING REMARKS

This paper provides a summary of statistical techniques for analysis and prediction of coastal morphological evolution at yearly and decadal time scales. A wide range of primarily linear methods was reviewed and field applications of the various techniques were presented to illustrate their usefulness and limitations. The methods included bulk statistics (*e.g.,* mean, standard deviation, correlation, and Fourier analysis), random sine functions, empirical orthogonal functions (EOFs), canonical correlation analysis (CCA), and principal oscillation patterns (POPs). High-quality data sets from Germany, The Netherlands, and United States encompassing time series of profile surveys and complete topographies were employed in the applications to evaluate the techniques. These specific applications also yielded some general information on the response scales of both natural and anthropogenically affected coastal systems over yearly and decadal time periods. Furthermore, several of the techniques investigated are highly useful for data reduction as well as signal/noise distinction, which are increasingly important applications in coastal morphology where large data sets often have to be managed.

Some major, overall conclusions that emerged from the review and application of the techniques presented here are:

- sophisticated methods (*e.g.,* CCA and POP analysis) require large amounts of data often in combination with special requirements on the data sampling and quality that at present restrict their use in field applications
- linear methods are highly useful for analyzing and modeling coastal morphological systems, although these system often display characteristics that tend to promote nonlinear behavior (*e.g.,* high-dimensionality and strong interaction between forcing and response)
- the need for high-quality data encompassing coastal evolution from yearly to decadal scales is significant and the present lack of data is one major obstacle for understanding and predicting the beach response at these scales
- the characteristic scale (in time and space) of the process governing the coastal evolution of interest provides the key to analyzing and modeling the evolution
- statistically based models might perform as good or better than physically based models in terms of predictive skill, although the possibility of applying a statistical model to a site different from where it was developed is limited (similar problems arise if fundamental changes in a coastal system is going to be simulated)
- there is a need to introduce probabilistic considerations when modeling coastal morphological evolution, even in the case of physically based models, in order to obtain a quantitative estimate of the uncertainty in predictions made
- data collection and monitoring should be designed based on clear objectives regarding data usage, analysis, and modeling in order to maximize the added value of the data

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