

CHAPTER 83

STOCHASTIC ANALYSIS OF BEACH PROFILE DATA

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ABSTRACT

Stochastic prediction of beach changes by means of a linear least-squares transfer function requires a knowledge of power spectra. Since most field data are too short to ensure stable analysis, an attempt was made to generate data artificially by a Monte Carlo simulation. A beach profile transition model which considers the beach profile as a dynamic system allows beach width, sediment storage, and surface configuration to be determined in successive profiles and simulates beach cycles associated with random waves which are in sufficient agreement with the actual observation. The simulated data are amenable to standard stochastic analysis to yield power spectra, cross spectra, coherence functions, and phase lags. Comparison of the results with those derived from actual data shows reasonable agreement. It appears that the process of beach sediment storage involves a combination of classes of Markov Gaussian random processes, whereas that of beach width resembles a white noise. Coupling between these two parameters occurs in the lower frequency range with periodicities longer than about 8 days. Moreover, the beach width shows phase advance before sediment storage. Although the beach profile transition model requires further refinement, especially in regard to quantitative response to waves of various magnitudes and characteristics, the basic concept of the model is sound and will probably explain beach changes in various types of world coasts.

INTRODUCTION

The process of beach change is stochastic in nature. It is also a Markovian process in the sense that the resulting beach profile is partly a function of the preceding profile. Stochastic analysis is a well-established method in many areas of geophysics (see, e.g., Blackman and Tukey, 1958) but has seldom been applied to the study of beach changes. An attractive feature of this approach is the possible design of an optimum transfer kernel function which will allow linear prediction of beach changes as extrapolated time series (Wiener, 1956; Lee, 1960).

A difficulty in the application of stochastic analysis to the process of beach change is the need for data with sufficient length. To illustrate the length of time required to gather a meaningful data set, consider semidiurnal sampling intervals and let the normalized standard error in a power spectrum be ϵ . This is calculated by (see,

e g , Bendat and Piersol, 1966)

$$\epsilon = \sqrt{m/N} \quad (1)$$

in which m is the maximum correlation lag value and N is the total sample size. The relationship between the sampling interval, Δt , the maximum correlation lag, m , and the equivalent resolution band width, B_e , is

$$\Delta t = 1/(B_e \quad m) \quad (2)$$

Assuming a modest 20 percent for ϵ and 2×10^{-3} cycles per hour (CPH) for B_e , the required total sample length is

$$\begin{aligned} \Delta t \times N &= 12 \times 10^3 \text{ hours} \\ &= 500 \text{ days} \\ &= 1 \text{ year } 4 \text{ months} \end{aligned} \quad (3)$$

A continuous field operation requiring such a long period of time is impractical, if not impossible.

To the writers' knowledge, the longest available beach profile data set is one representing 180 days of successive measurements by the Coastal Studies Institute, Louisiana State University, on an Outer Banks beach, North Carolina (Dolan et al , 1969). However, it is evident that the data are still far short of the desired length.

The purpose of this paper is to explore the possibility of generating beach profile data of desired length by means of stochastic simulation. In the first step, a beach profile transition model is established which describes the sequence of profile changes under accretive or erosional wave excitation. The beach profile is defined as a system which essentially incorporates three parameters: beach width, sediment storage (or profile cross section), and surface configuration. The pathways of transition of the surface configuration are dictated by the accretive and erosional wave actions, which are simulated by random numbers. The actual values for the remaining two variables to assume are determined by the Monte Carlo method. Time series of beach profiles thus generated are subjected to stochastic analysis. The resulting power spectrum, cross spectrum, coherence function, and phase lag between the beach width and the sediment storage are then compared with the results obtained with actual data.

DATA ACQUISITION

The field site was located at Nags Head, the Outer Banks, North Carolina (Fig. 1). The coastline was relatively smooth, trended in the north-south direction, and faced the Atlantic Ocean on the east. Rhythmic

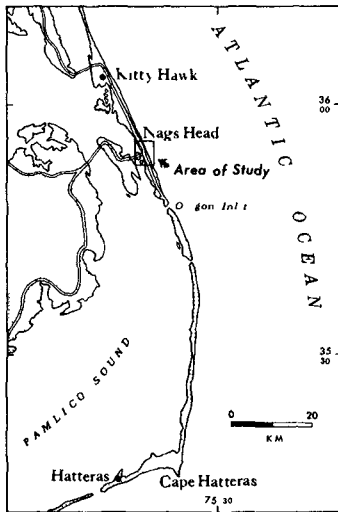


Fig 1 Location of Nags Head, site of field investigation

beach features such as lunate bars and cusped shorelines occurring on this coast have already been discussed (Sonu and Russell, 1966, Sonu *et al*, 1966)

Five traverses perpendicular to the shoreline were set up 30 feet apart. Stakes were set at 10-foot intervals on each traverse over the entire length of approximately 200 feet between the dune and the shoreline. The crests of the stakes were initially surveyed in reference to a permanent datum, so that the successive profile surveys read in rapid sequence the exposed lengths of the stakes. The accuracy of measurement of beach elevation was on the order of 0.01 foot.

The field investigation was conducted between October 1963 and May 1964. The profiles were measured at successive semidiurnal low tides at intervals of approximately 12 hours 25 minutes. A step-resistance wave gage of the Coastal Engineering Research Center, placed 400 feet from the shore alongside a fishing pier, provided data.

Figure 2 shows the cumulative distribution of these wave data, which were processed from 2-minute strip chart records at 4-hour intervals for about 6 months. Waves higher than about 4.5 feet, representing a 25 percent probability of occurrence, broke over the outer bar, while those higher than about 2.5 feet, representing a 65 percent probability of occurrence, broke only over the inner bar. The median wave height was slightly above 3 feet, and the standard deviation was 1.8 feet. Wave periods occurred in a wide range, between 4 and 20 seconds.

Figure 3 shows the mean profile and histograms of semidiurnal elevation changes. Though there was an indication of net erosion on the upper beach level and of net accretion on the lower beach level, net equilibrium of sediment load was maintained over the entire profile. The higher intensity of elevation changes closer to the shoreline is indicated by the increase in the standard deviation with proximity to the shoreline. Elevation changes were particularly active in an 80-foot width immediately next to the shoreline where the beach was washed by most of the ordinary waves. Only storm waves coinciding with the flood tides sent swashes beyond this limit.

DERIVATION OF PROFILE TRANSITION MODEL

In many of the past studies on beach change, it was customary to represent the beach profile by single parameters. Thus, such parameters as beach width (or shoreline position relative to a fixed base line), beach face slope, and elevations at selected stations were singled out

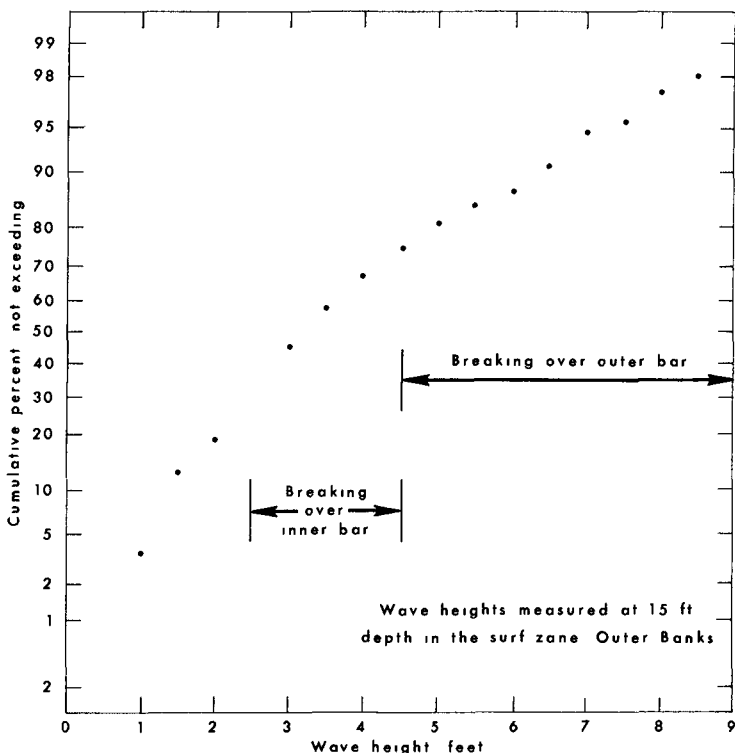


Fig 2 Cumulative distribution of wave heights from 6-month records between December 1963 and May 1964 at Jennette's Pier, Nags Head, North Carolina

and dealt with independently. However, such an approach fails to treat the beach profile as a dynamic system.

Sonu and van Beek (in press) introduced the idea that the beach profile may be represented as a system in which varying amounts of sediment would assume varying distribution patterns within the varying subaerial spaces. To describe this system, obviously, three parameters were needed: the beach width (X), which represented the subaerial space in a two-dimensional profile, the profile cross section (Q), which represented the amount of sediment accommodated in the subaerial beach space, and the surface configuration (Ω), which represented the manner by which the sediment was distributed. For brevity, Q may be referred to as "sediment storage."

The predominant occurrence of six major profile configurations (Ω) was noted, as follows (see Fig 4):

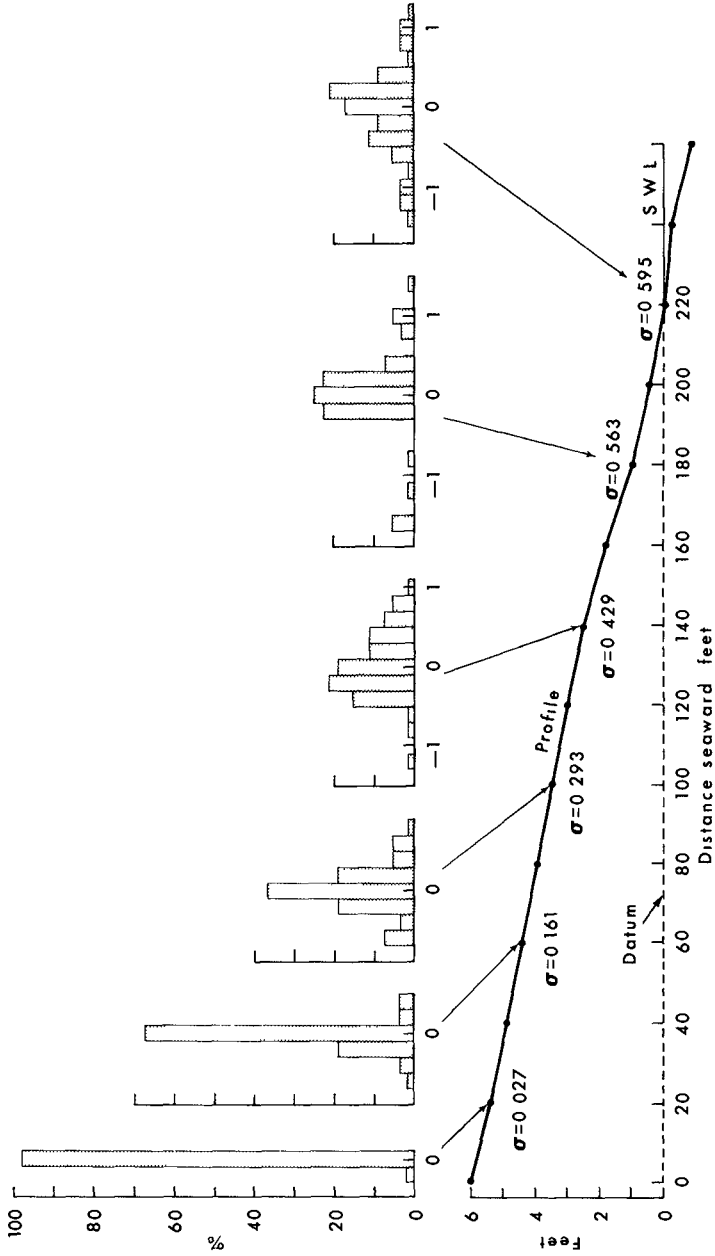


Fig 3 Histograms and standard deviations of semidiurnal elevation changes in the profile, shown relative to mean profile

- A smooth concave profile,
- A' concave profile having a berm at the lower beach elevation,
- B smooth linear profile,
- B' linear profile having a berm at the intermediate beach elevation,
- C smooth convex profile,
- C' convex profile having a berm at the upper beach elevation

The relationship among the three beach profile parameters is illustrated schematically in Figure 4. According to this diagram, accretion of the profile (e.g., increase in sediment storage Q) is accomplished through either growth in beach width (X) or transformation of surface configuration from concave to linear or from linear to convex profiles, in either case involving a profile with a berm. The pathways of profile transition are indicated by arrows. Since the profile C' represents the maximum state of accretion, no further climb of a berm, hence no further accretion, would occur once this profile was realized.

On the other hand, erosion of the profile (e.g., decrease in sediment storage Q) is accomplished through either decrease in beach width (X) or transformation of surface configurations from C to B or from B to A, the process involving only the smooth profiles. Note that profile A represents the maximum state of erosion, therefore, no further erosion would occur once this profile was formed.

Another interesting characteristic of the profile transition model herein described is that it explains the occurrence of beach cycles by random wave excitation, e.g., without considering cyclic energy input such as tides. Because of the unidirectional accretive transitions through A', B', C', and also because of the unidirectional erosional transitions through

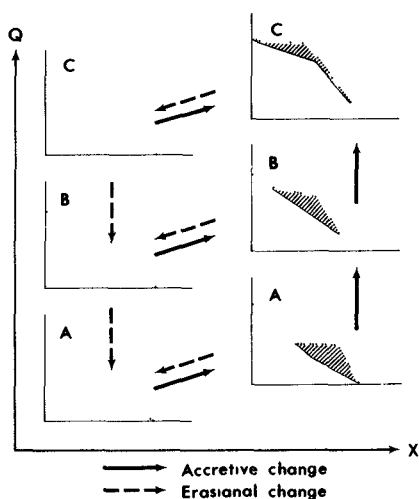


Fig 4 Beach profile transition model

C, B, and A, the beach changes in the long run are bound to produce a net loop of pathways connecting A, A', B', C', C, B, and back to A. A simulated analysis to test this cyclic characteristic was performed. Uniformly distributed random numbers were used to simulate random wave excitation, and the number of transition steps needed to complete a cycle at each trial was counted. Random numbers between 0 and 0.5 were considered to represent accretive excitation, those between 0.5 and 1 were considered to represent erosional excitation. A total of 3,000,000 trials were carried out on an IBM 360 Model 65 computer, and the result is presented as a histogram in Figure 5. The mode, which represented the most frequent number of steps required to complete a cycle, was located at 18. The actual observed cycle had 20 steps, showing close agreement with the experiment.

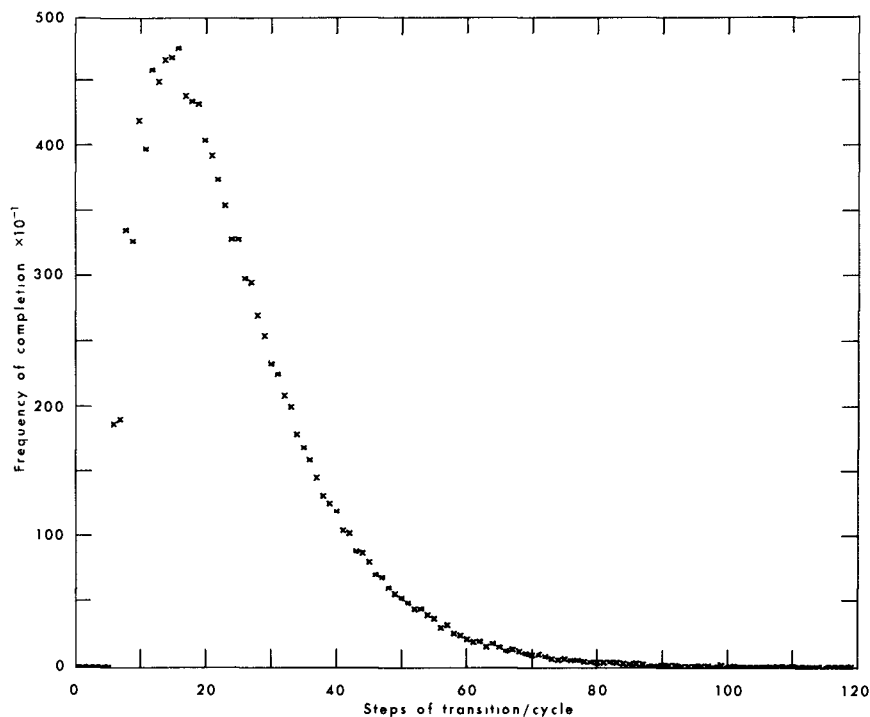


Fig 5 Histogram of the number of transition steps to complete a beach cycle upon 3,000,000 trials

DATA GENERATION

Each of the surface configurations, A, A', B, B', C, and C', was represented by a linear regression relationship between Q and X, as follows (see Fig 6)

For profiles A and A'

$$Q = 0.45 X$$

$$A \quad 32 < X < 46, \quad 29 < Q < 41 \quad (4)$$

$$A' \quad 46 < X < 55, \quad 41 < Q < 49$$

For profiles B and B'

$$Q = 1.00 X$$

$$B \quad 32 < X < 43, \quad 32 < Q < 43 \quad (5)$$

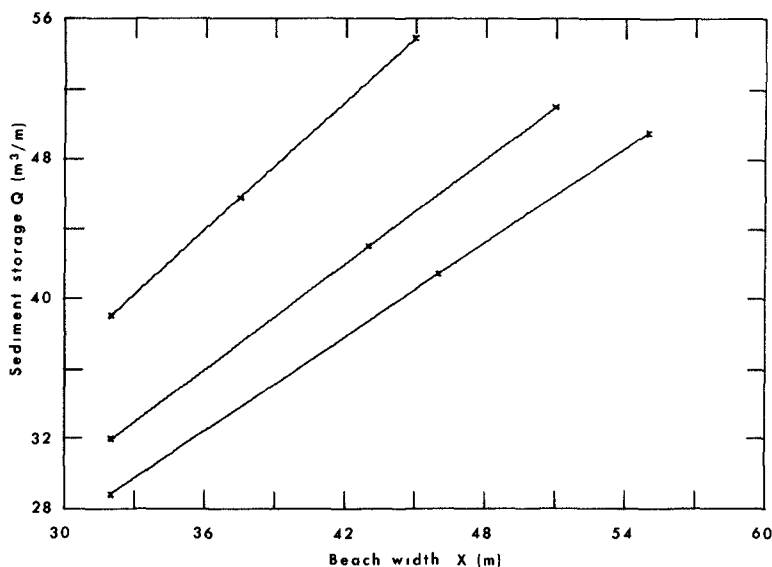


Fig 6 Representation of the beach profile transition model through linear regression relationships

$$B' \quad 43 < X < 51, \quad 43 < Q < 51$$

For profiles C and C'

$$Q = 1.22 X$$

$$C \quad 32 < X < 37, \quad 39 < Q < 46$$

$$C' \quad 37 < X < 45, \quad 46 < Q < 55$$

The derivation of these relationships has been given elsewhere (Sonu and van Beek, in press)

The first step of data generation by the Monte Carlo technique is to draw a random number to induce a profile transition. A number less than 0.5 meant accretive transition, and those larger than 0.5, erosional transition. In the next step, another random number was drawn to determine quantitative measures of the resulting profile, e.g., beach width X and sediment storage Q .

The quantitative profile was determined by using a random number as the proportional length in the corresponding regressive curve. A point thus located in the curve yielded a beach width (X) and sediment storage (Q) pair in accordance with Figure 6. The random number generator was provided by the "RANDU" subroutine of the IBM scientific sub-

routine package A uniform distribution-type generator was used in view of the nature of the problem These steps were repeated to generate a succession of data in regard to X and Q The total sample size was 6,000, it was limited by the computer storage capacity when spectral analysis was performed at the same time Figures 7 and 8 show part of the generated data

It was necessary to filter out low-frequency oscillations in order to eliminate the underlying trend This was done by smoothing with weighted running means

$$\hat{X}(k) = \sum_{i=-n}^n X(k+i) W_{k+1} \quad (7)$$

in which $i = -n, -n+1, \dots, n-1, n$

$$\{X(j)\}, j = k+1 = 1, 2, \dots, N \quad (8)$$

are the original data, and

$$\{\hat{X}(k)\}, k = n+1, n+2, \dots, N-n \quad (9)$$

are the smoothed data The weighting function W_j serves as a low-pass filter Therefore, the desired time series after removal of low frequencies is obtained as

$$X'(k) = X(k) - \hat{X}(k) \quad (10)$$

$$k = n+1, n+2, \dots, N-n$$

Note that the sample size has now reduced to $N - 2n$

Figure 9 shows the response characteristics of the weighting functions An equal-weight smoothing function is a constant for all j 's, e g ,

$$W_j = 1/(2n+1) \quad (11)$$

$$j = n+1, n+2, \dots, N-n$$

However, the range of summing, n , may vary, e g , $n = 10$ and 30 As shown in Figure 9, the equal-weight filter with a larger range of summation $n = 30$ gives a cutoff at lower frequencies, thus saving a greater portion of the higher frequencies for analysis than the filter using $n = 10$ This advantage is gained only at the expense of a larger amount of data, lost because the data length is reduced to $N - 2n$ ($N - 60$) Note also the prominent peaks, which exceed unity, followed by rippling effects, which

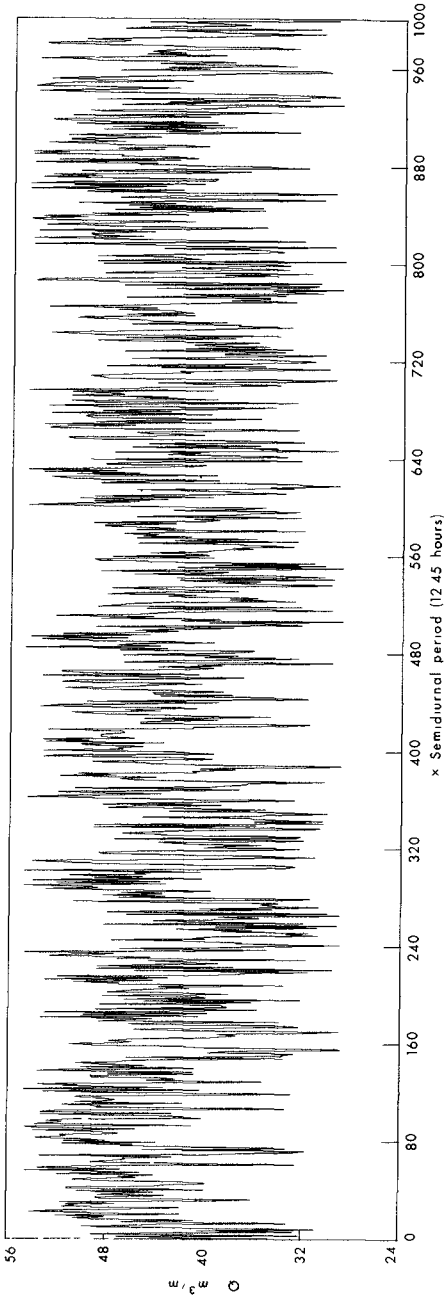
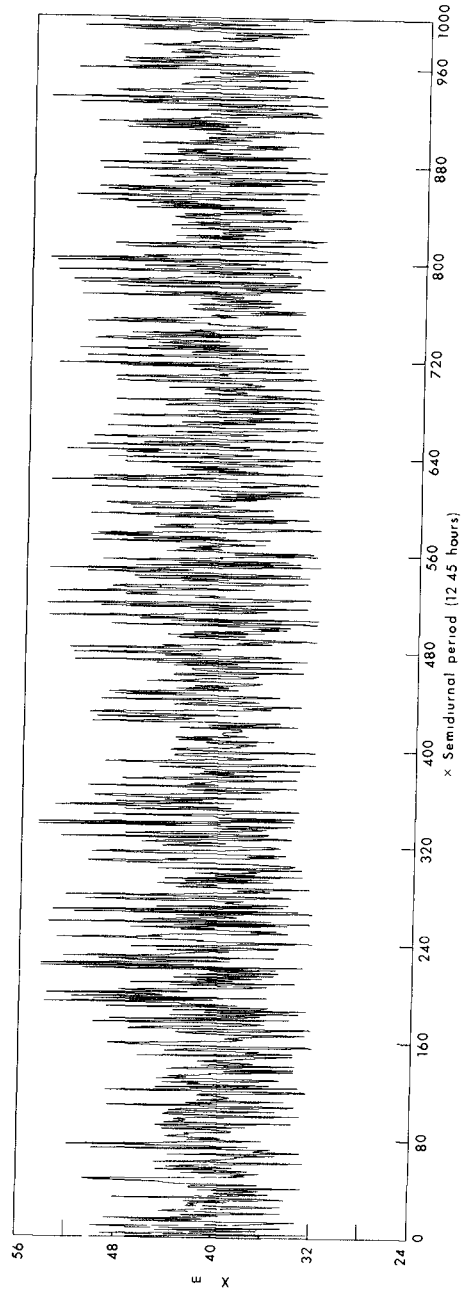


Fig 7 Artificially generated data, the beach sediment storage Q



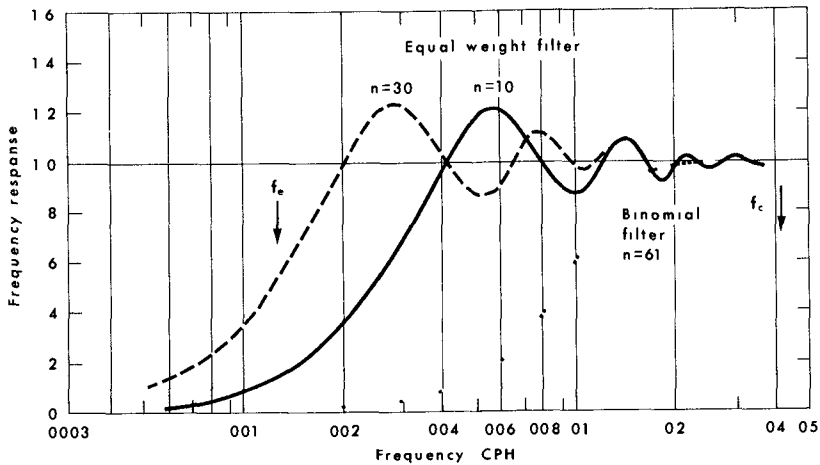


Fig 9 Frequency response characteristics of various high-pass (smoothing) filters

may produce corresponding false peaks in the power spectrum. It is also known that the equal-weight function produces polarity reversal in the filtered data (Holloway, 1958). These problems may be overcome by using a binomial weighting function. But, as seen in Figure 9, a cutoff at a sufficiently low frequency cannot be expected without a large n , hence a considerable reduction in the data size. After repeated trial-and-error calculations it was decided to use an equal-weight filter with $n = 10$ and a binomial filter with $n = 61$. Figures 10 and 11 show the real data and the filtered data, respectively, using the binomial filter for sediment storage.

DATA ANALYSIS

Table 1 shows the frequency resolution f_e and the Nyquist frequency f_c for the real and the simulated data.

Table 1 Frequency Resolution F_e and Nyquist Frequency f_c for the Real and Simulated Data

	f_e	f_c
Real data	0.0156	0.0402
Simulated data	0.0003	0.0402

The power spectrum, cross spectrum, coherence function, and phase

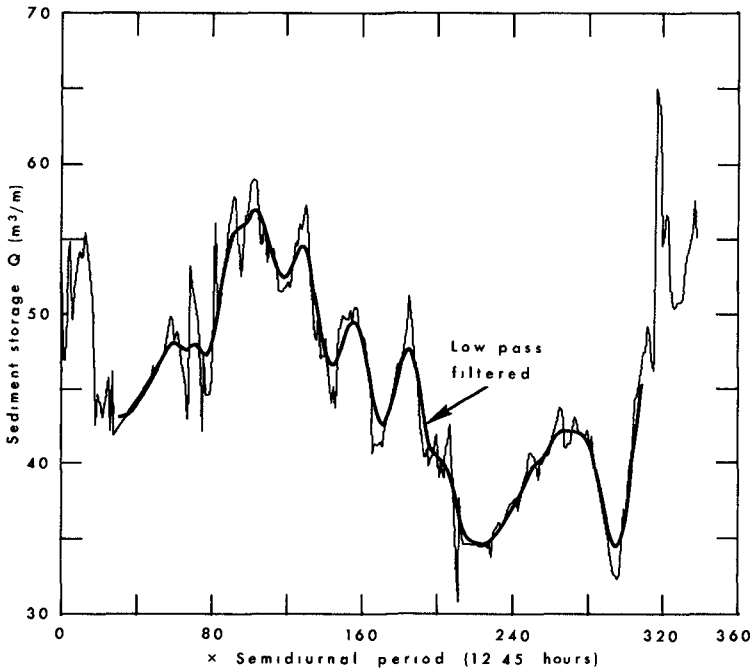


Fig 10 Original real data, the beach sediment storage Q , shown with the binomial low-pass filtered data in thick line

lag calculations in the present study are essentially the same as described by Blackman and Tukey (1958) and Bendat and Piersol (1966). However, the Fast Fourier Transform (FFT) program by Cooley and Tukey (1965) is used to improve the accuracy of calculation as well as to reduce computational time (see also Rothman, 1968).

The autocovariance function at the k -th lag is given as

$$R(k) = \frac{1}{N-k} \sum_{i=1}^{N-k} X(i) X(i+k) / R(0) \quad (12)$$

The one-side power spectrum can be calculated as a Fourier transform of the autocovariance function,

$$G\left(\frac{kf}{m}\right) = 2 \Delta t \left[R(0) + 2 \sum_{i=1}^{m-1} R(k) \cos\left(\frac{\pi i k}{m}\right) - (-1)^k R(m) \right] \quad (13)$$

The FFT subroutine computes the values within the brackets For

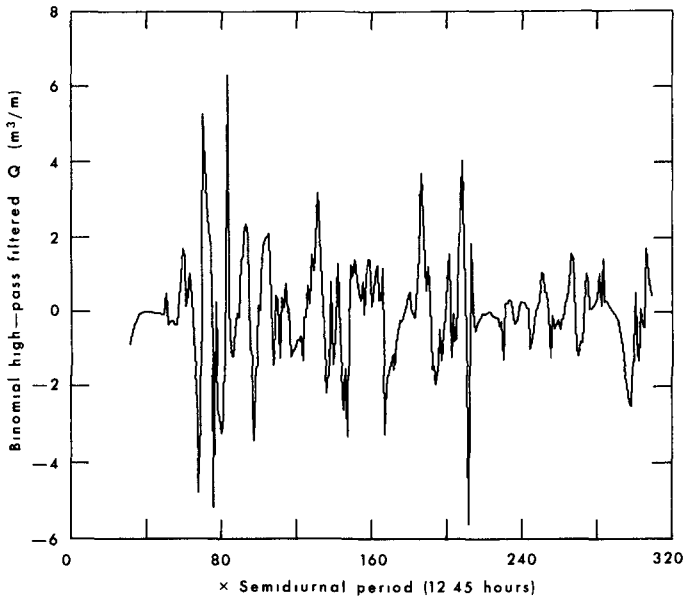


Fig 11 Real data upon subtraction of the binomial low-pass filtered data from the original data ($n = 61$)

stochastic representation, the final estimates are smoothed by Hanning's equation (see Blackman and Tukey, 1958)

The coherence function and phase lag of beach width and sediment storage are calculated by first obtaining the cross covariance functions between the time series data of X and Q

$$R_{XQ}(k, \Delta t) = \frac{1}{N - k} \sum_{n=1}^{N-k} X_n Q_{n+k} \quad (14)$$

$$R_{QX}(k, \Delta t) = \frac{1}{N - k} \sum_{n=1}^{N-k} Q_n X_{n+k} \quad (15)$$

The cross spectral function $G_{XQ}(f)$ is then obtained from the cospectrum and quadrature spectrum, which are the Fourier transform of the modified functions of the above cross covariance functions R_{XQ} and R_{QX} . These relations are given in equations (18) through (22)

$$G_{XQ}(f) = C_{XQ}(f) - jD_{XQ}(f) \quad (16)$$

in which $C_{XQ}(f)$ is the cospectrum, $D_{XQ}(f)$ is the quadrature spectrum, and $j = \sqrt{-1}$. They are related to the cross covariance functions as

$$C_{XQ}\left(\frac{k f}{m}\right) = 2 \Delta t \left[A_0 + 2 \sum_{i=1}^{m-1} A_i \cos\left(\frac{\pi i k}{m}\right) + (-1)^k A_m \right] \quad (17)$$

$$D_{XQ}\left(\frac{k f}{m}\right) = 4 \Delta t \sum_{i=1}^{m-1} B_i \sin\left(\frac{\pi i k}{m}\right) \quad (18)$$

where A_1 and B_1 are the modified cross covariance functions

$$A_1 = 1/2 (R_{XQ}(1 \Delta t) + R_{QX}(1 \Delta t)) \quad (19)$$

$$B_1 = 1/2 (R_{XQ}(1 \Delta t) - R_{QX}(1 \Delta t)) \quad (20)$$

Finally, the coherence function γ_k^2 and the phase angle ϕ_k can be obtained

$$\gamma_k^2 = \frac{C_{XQ}^2\left(\frac{k f}{m}\right) + D_{XQ}^2\left(\frac{k f}{m}\right)}{G_X\left(\frac{k f}{m}\right) G_Q\left(\frac{k f}{m}\right)} \quad (21)$$

$$\phi_k = \tan^{-1} \left(\frac{D_{XQ}\left(\frac{k f}{m}\right)}{C_{XQ}\left(\frac{k f}{m}\right)} \right) \quad (22)$$

The Monte Carlo method requires repeated trials of data generation and analysis so that the end product may be evaluated through the central limit theorem. In the present study, the results of the initial several trials were so similar to each other that no further calculation was pursued.

INTERPRETATION

Figure 12 shows the power spectrum for Q. The real-data spectrum using an equal-weight filter and one using a binomial filter show peaks in the spectral density at 0.003 and 0.008 CPH, respectively. A gross peak is also located near 0.010 CPH in the simulated power spectrum using a binomial filter. However, all these peaks are spurious since

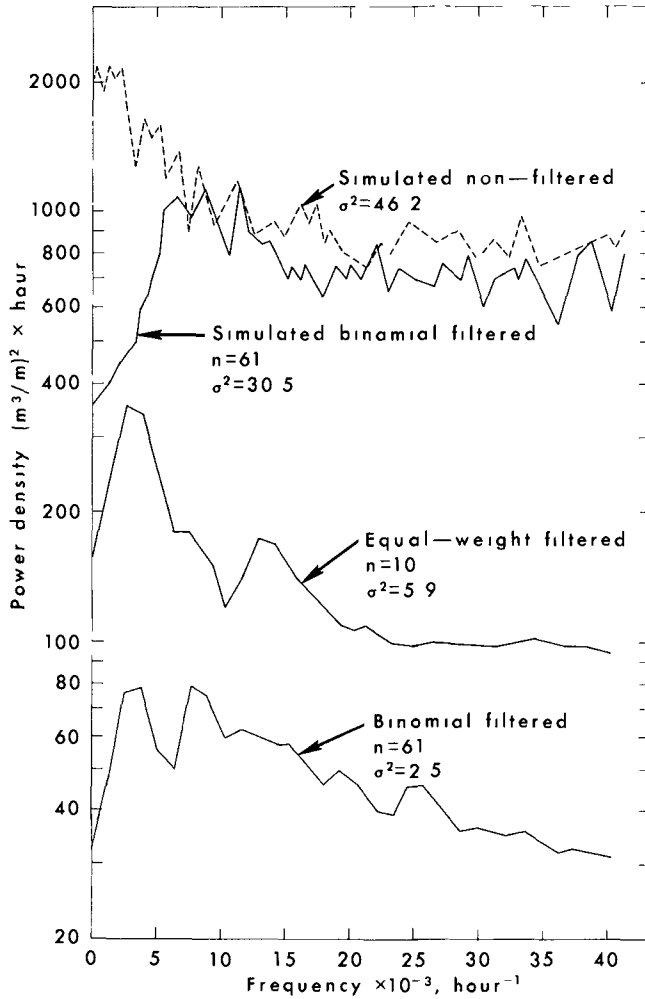


Fig 12 Power spectrum of Q (sediment storage)
 Data smoothed with equal-weight filter ($n = 10$),
 with binomial filter ($n = 61$), simulated data using
 binomial filter, and simulated data with no smoothing

they represent the effect of low-frequency cutoff by the high-pass filter used (see Fig 9). The true spectrum for the actual sediment storage Q is very likely to be a smooth curve which has no prominent peak but attenuates monotonically toward high frequencies (see Fig 17, case 1). This type power spectrum was indeed obtained from the simulated data in

which no high-pass filter was applied (The ripples are probably the result of intrinsic noise in the simulation process)

The minimum number of transition steps necessary to complete a beach cycle is six, representing a frequency of 0 013 CPH The majority of beach cycles take more steps than six, which corresponds to frequencies shorter than 0 013 CPH The most probable number of steps is 18, which gives a frequency of 0 0067 CPH In Figure 12 beach cycles shorter than 0 013 CPH indeed constitute the major part of the simulated power density Note particularly that a peak appears at 0 005 CPH, which is equivalent to a 16-step simulated beach cycle and hence approximates the observed 20-step beach cycle of the real data reasonably well This peak is especially noteworthy because of its occurrence in the frequency range where the response has been considerably reduced by the high-pass filter

There are smaller beach cycles in the analysis For example, the four-step cycles through A, A', B', B, and A or through B, B', C', C, and B represent a frequency of 0 0201 CPH The two-step cycles through A, A', and A, through B, B', and B, or through C, C', and C represent a frequency of 0 040 CPH However, they fail to comprise a significant level of power spectral density

The discrepancy between the actual and the simulated power spectra of Q is due mainly to the fact that in the simulation the profile transition was only allowed to take either erosional or accretive pathways, disregarding the third possibility, in which the profiles would remain unchanged As a result, the variability was exaggerated in the simulation, leading to a larger value of power density (σ^2) This discrepancy may be adjusted as the interaction between the profile and wave characteristics is better established

Power spectra for the real-data beach width X are shown in Figure 13 Both an equal-weight filter and a binomial filter are used in the analysis The density concentration is found in the frequencies below 0 015 CPH, which corresponds to a period of 60 hours or a five-step transition period Although the binomial filter allows only 40 percent or less response for this frequency range, the filtered spectra reveal peaks at 0 012 CPH as well as at 0 005 CPH The 0 012 CPH frequency corresponds to a period of about 83 hours or a 6 7-step transition period

The simulated power spectrum for X, on the other hand, is quite inconsistent Repeated calculations using different random numbers showed that individual peaks in this power spectrum were fortuitous Therefore, they may average out only if a long record can be simulated in the analysis The general trend of the simulated power spectrum for X strongly suggests a similarity to a white noise spectrum, which characterizes a consistent power density level for all frequencies It is not immediately clear why the beach width should behave so differently from the sediment storage

Figure 14 shows coherence functions between the beach width X and the sediment storage Q The real-data coherence functions are obtained by using both equal-weight filter and binomial filter Both curves show a high level of coherence About 50 percent coherence is found for

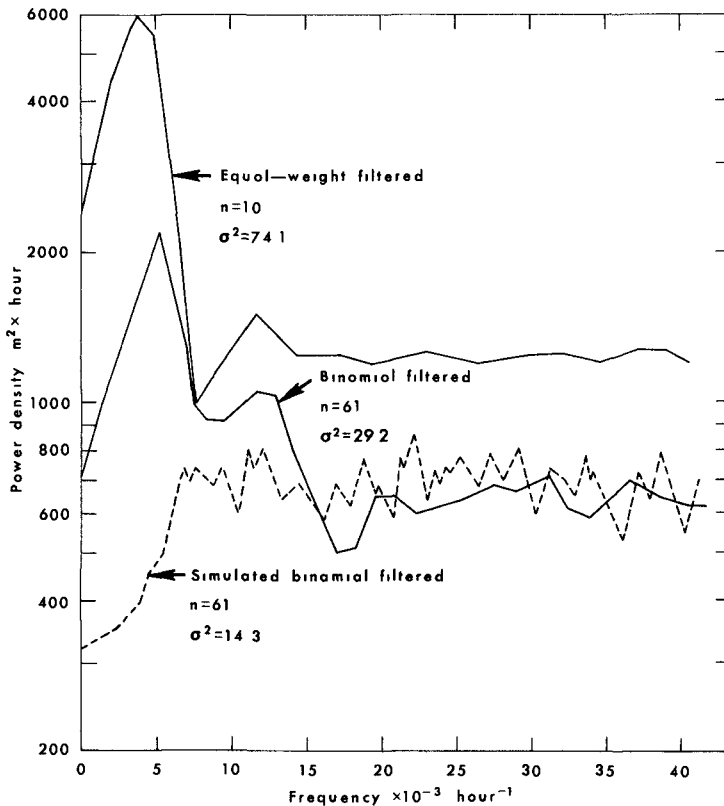


Fig 13 Power spectrum of X (beach width) Data smoothed with equal-weight filter ($n = 10$), data smoothed with binomial filter ($n = 61$), and simulated data

frequencies below about 0.005 CPH, which is a region where the beach width power spectrum displays a peak density. The coherence drops sharply to less than 20 percent at higher frequencies, which means that the coupling between the beach width and the sediment storage is basically a low-frequency phenomenon with periodicities of 8 days or longer.

A discrepancy with the above results is noted in the simulated coherence function. Here, the coherence is low at low frequencies and high at high frequencies. A probable explanation for this may be revealed from the following considerations. The beach process is basically a response to a weather regime which will change gradually with periodicities of several days. Consequently, following "persistence" in natural processes, the beach width change will essentially be a gradual process in which the effect of the preceding profiles

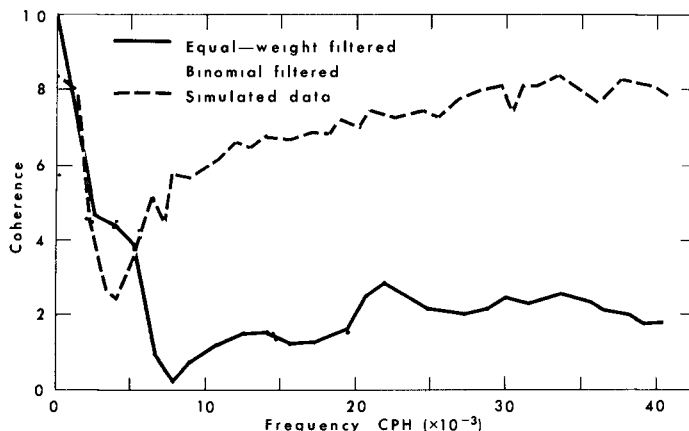


Fig 14 Coherence function for X and Q Data smoothed with equal-weight filter ($n = 10$), smoothed with binomial filter ($n = 61$), and simulated data

will persist for some time. In the data simulation, the effect of persistence was taken into consideration in the transition of surface configurations but not in the successive values of beach width and sediment storage. These parameters were determined by random numbers not influenced by their preceding values. Consequently, the coupling effect with periodicities on the order of the weather influence may not be expected. The high coherence at high frequencies in the simulated coherence function is not important because the power density in the corresponding frequency range is extremely low.

Figure 15 shows phase lags in the correlation between the beach width and the sediment storage. In the real data, the sediment storage lags behind the beach width in the low-frequency region, where a coherence coupling between the two parameters exists. At somewhat higher frequencies, however, this relationship is reversed, and eventually the phase difference disappears at frequencies higher than about 0.020 CPH, which corresponds to 2 days or less in period. In the simulated data, the phase lag of the sediment storage also lags behind the beach width. However, it appears at a much lower frequency than that of the real data. It is then followed by a reversed relationship and eventually reduces to a zero phase difference at frequencies higher than 0.020 CPH.

DISCUSSION

Dynamic beach transitions are Gaussian processes in nature. Therefore, these random processes deserve special attention for two reasons:

1. They approximate reasonably well a number of experimental data involving noise and random phenomena.

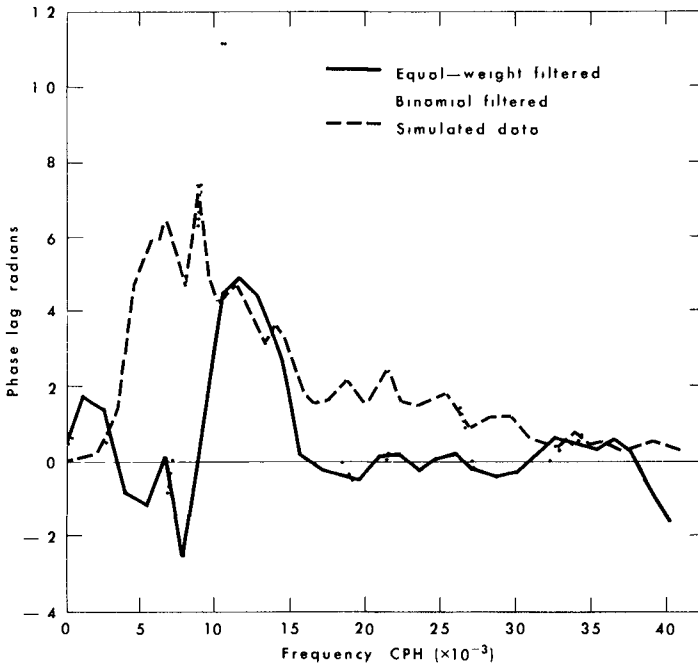


Fig 15 Phase lag for X and Q Data smoothed with equal-weight filter ($n = 10$), smoothed with binomial filter ($n = 61$), and simulated data

- 2 They arise from "multidimensional central limit theorem and, therefore, [are] of theoretical significance as an idealization of the superposition of small effects" (Bendat, 1958)

In the present case, a Markovian feature must also be considered, since according to the profile transition model the successive profiles are products not only of either accretive or erosional wave excitation but also of the preceding profile. Thus, a Markov Gaussian random process may possibly explain beach profile changes. According to Doob (1953), the stationary Markov Gaussian random process requires an exponential autocovariance function and hence necessarily a power spectrum of the form

$$G(f) = \frac{2k}{\pi} \frac{f^2 + (k^2 + c^2)}{f^4 + 2(k^2 - c^2)f^2 + (k^2 + c^2)^2} \quad (23)$$

in which parameters k and c are obtained by a curve fitting the autocovariance function in the low lag region, $e g$,

$$R(\tau) = e^{-k|\tau|} \cos c \tau \quad (24)$$

Figure 16 shows the approximation of the real data autocovariance function fitted by equation (24), in which $c = 0.048$ CPH and $k = 0.024$ CPH. According to Bendat (1958), two types of power spectrum may result, depending on the relative size of $3c^2$ and k^2 (see Fig. 17). With the above values for c and k , it is obvious that $3c^2 > k^2$ for the sediment storage, hence the power spectrum of Q must have a peak density, contrary to the actual case. Moreover, for the theoretical power spectrum the power density is inversely proportional to f^2 , e.g.,

$$G(f) \propto f^{-2} \quad (25)$$

whereas in the present case

$$G(f) \propto f^{-1/3} \quad (26)$$

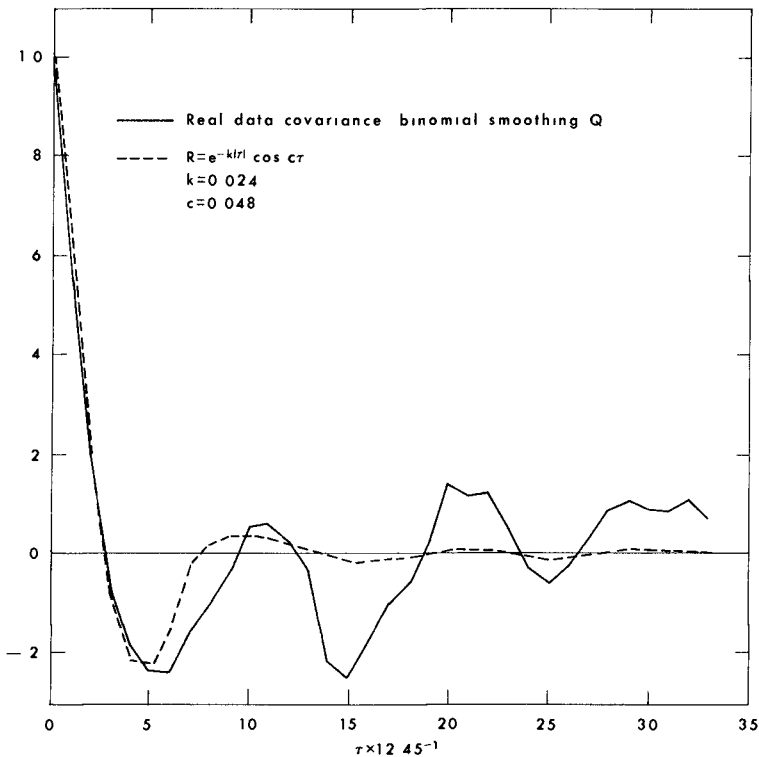


Fig. 16 Autocovariance function of the real data Q compared with the theoretical covariance function for Markov Gaussian random process

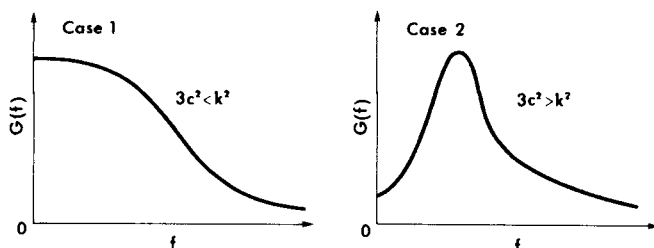


Fig 17 Two cases of power spectrum for Markov Gaussian random process (after Bendat, 1958)

The reason for this discrepancy is not immediately clear, but it seems possible that the actual example represents the superposition of two or more case 1 and/or case 2 situations

The time series simulation by means of a Monte Carlo technique, as demonstrated in this paper, appears to be reasonably successful. Areas of needed improvement are the interactions between waves and beach profiles. "Accretive" and "erosional" wave excitations, which are simulated by random numbers in the present study, need further clarification. According to Sonu and van Beek (in press), erosion of the beach profile is associated with a period of growth of waves, while accretion is associated with a period of wave decay. This relationship is more pronounced than the generally acknowledged effect of wave steepness. In fact, it is noted that waves of the same steepness could cause either erosion or accretion, depending on whether they occurred during growth or decay of a wave field. The basic mechanism controlling this relationship is not known. Also unknown is the extent of beach change as a function of wave energy. In the simulation study, it is assumed that each wave excitation would cause only one step of profile transition. More precisely, the number of steps per semidiurnal period (the speed of beach change) should vary by types of profiles as well as by waves.

The beach profile transition model, while requiring further refinement, appears to be basically sound. It is likely that various regional coasts may be represented by different regression areas in the Q-X plane. As indicated schematically in Figure 18, a type I coast may be found in an embayed coastline with a flat slope receiving little lateral supply of sediment, a small change in sediment balance may seriously affect the shoreline positions. A type III coast may be, on the other hand, a steep beach sufficiently close to the source of sediment supply so that it requires a large amount of sediment movement to cause appreciable dislocation of the shoreline. A type II coast is a typical ocean-exposed sandy coast, while type II' is exposed to limited fetch, such as on a lake or an inland sea. With accumulation of data, it is hoped that a generalized picture of beach profile transition model for various regions may be constructed in the entire Q-X plane.

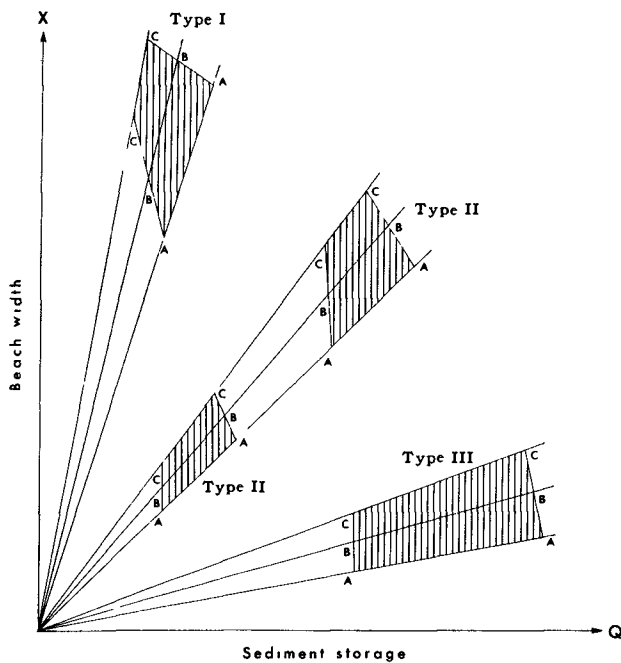


Fig 18 Suggestion for a generalized beach profile transition model for different types of coasts

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