### **CHAPTER 151**

# HOW MUCH VELOCITY INFORMATION IS NECESSARY TO PREDICT SEDIMENT SUSPENSION IN THE SURF ZONE?

### Bruce E. Jaffe<sup>1</sup>, David M. Rubin<sup>1</sup>, and Asbury Sallenger, Jr.<sup>2</sup>

## ABSTRACT

The time-dependent response of sediment suspension to water velocity was explored by modeling field measurements collected in the surf zone during a large storm. Both linear and nonlinear input-output models were formulated with water velocity as input and suspended-sediment concentration as output. A sequence of past velocities (velocity history), in addition to velocity from the same instant as the measurement of suspended-sediment concentration, were used as input. The velocity-history length was allowed to vary. The models also incorporated a lag between input (instantaneous velocity or velocity history) and output (suspendedsediment concentration).

Instantaneous horizontal water velocity, or velocity to a power, does not contain enough information to predict suspension in the surf zone. Unlike steady uniform flow, more than one velocity is necessary to parameterize pick-up and mixing of sediment into the water column. Using a velocity history improves predictions of suspension by more fully specifying flow conditions (including accelerations and changes in accelerations) responsible for suspension.

Suspension in the future is better predicted than suspension at the same instant as velocity measurements. Incorporating such a lag between velocity and concentration improved predictions, with optimum lag time increasing with elevation above the sea bed (from 1.5 seconds at 13 cm to 8.5 seconds at 60 cm for linear models). These lags are largely due to the time for an observed flow event to effect the bed and mix sediment upward.

Nonlinear models relating suspension to velocity do better than linear models using the same velocity history. Nonlinear models are able to exploit changing relationships between suspension and velocity history for different wave shapes. For the environmental conditions of our study, the optimal model (correlation coefficient of 0.58) used 3 seconds of velocity history (approximately one-quarter wave period) and a 1.5 second lag to predict suspension.

<sup>&</sup>lt;sup>1</sup>U. S. Geological Survey, 345 Middlefield Rd., Menlo Park, CA 94025

<sup>&</sup>lt;sup>2</sup> US Geological Survey, Center for Coastal Geology, 600 4th St. South, St. Petersburg, FL 33701

### INTRODUCTION

Models for sediment suspension in the surf zone are based on models developed for streams and the continental shelf. Additions of time-varying pick-up and mixing of sediment into the water have been the major changes to fluvial or continental shelf models to make them usable in the surf zone. For stream flow, a mean velocity (raised to a power) is used to determine the steady driving force for suspension. Two velocities, a mean velocity and a maximum orbital velocity, are used to determine the forcing for suspension in continental shelf sediment transport models (Smith, 1977; Grant and Madsen, 1979; Glenn and Grant, 1987). It is not obvious how much velocity information is necessary to predict suspension in the surf zone or if velocity alone is a good predictor for suspension.

There are many complexities that make it difficult to use first principles of physics to formulate models for sediment suspension. For example, it is not obvious how to model suspension in a reversing flow with velocity asymmetries caused by irregular waves. In this paper, we use a method dcveloped by researchers studying nonlinear systems, input-output modeling, to determine which velocity information is important to predict sediment suspension. The goal of this study is to guide us in formulation of improved models.

#### METHODS

The ability to predict sediment suspension from flow velocity was evaluated using input-output modeling of field measurements. Input-output modeling, employing one time series of forcing input and a simultaneous series of output response, has been described by Hunter and Theiler (1992). In this study, input is a single near-bed flow velocity or a sequence of velocities (velocity history) and output is suspended-sediment concentration.

The techniques applied in this paper are based on techniques that have been developed recently for forecasting nonlinear, nonperiodic, time series and spatial patterns (Livezey and A. G. Barnston, 1988; Farmer and Sidorowich, 1989; Sugihara and May, 1990; Casdagli, 1991; Casdagli et al., 1992; Rubin, 1992). The procedure requires splitting a time series into two parts. One part, the learning set, is used to learn the relations between input and output variables. The other part of the time series, the testing set, is used to test the predictive ability of relations determined from the learning set. Predictions are made by searching the learning set for conditions where the recent velocity history approximates the velocity history of a predictee from the testing set, and then using the concentration of the predictee. The general approach is outlined below; details of the computational algorithm are given by Casdagli (1991) and Rubin (1992).

The approach in this study is to relate concentration C to a sequence of velocities  $(U_t^n \text{ through } U_{t+1-m}^n)$  in the learning set by solving

$$C_{t} = a_{0} + \sum_{i=1}^{m} a_{i} U_{t+1-i}^{n}$$
(1)

where m is the number of velocity measurements that are used to predict each C, n is an integer, and t is time.

Eq (1) can be used for both linear and nonlinear modeling. For linear models,  $a_0$  through  $a_m$  are evaluated a single time for the entire learning set. The values of  $a_0$  through  $a_m$  are then substituted in eq (1), and each predicte velocity sequence from the testing set is substituted in eq (1) to predict concentration. The resulting model is a global, linear, multiple regression.

For nonlinear models,  $a_0$  through  $a_m$  are re-evaluated for each prediction using a subset of observations in the learning set. To solve eq (1) requires a minimum of m+1 observations from the learning set, but any greater number of observations can be used. For each solution, the k observations that are most similar to each predictee sequence are used to solve eq (1). For example, if concentration is being related to a sequence of 2 successive velocity measurements, then to make a single nonlinear prediction, the entire learning set is searched to find the 3 sequences of 2 successive velocities that are closest to the predictee sequence. Eq (1) is used to solve for  $a_0$  through  $a_2$  using these 3 nearest-neighbor velocity sequences and the 3 corresponding observed concentrations in the learning set. Those values of  $a_0 \dots a_2$ and the velocities of the predictee sequence are then substituted in eq (1) to predict concentration.

Closeness of sequences is measured using least squares, and those sequences that are most similar to the predictee sequence are known as nearest neighbors. Ranking of neighbors can be visualized in two ways: (1) similarity of velocity sequences in a time series or (2) distance in velocity space. Determination of nearest neighbors can be visualized as matching a segment of velocity time series by sliding a m-point window through the time series (Fig. 1a). The most similar velocity sequences (evaluated by the squared differences between individual points in the two sequences) are defined to be the nearest neighbors. Alternately, nearest neighbors can be visualized by plotting each velocity sequences as a single point in velocity space. For a two-point sequence, the axes of velocity space are the two successive velocities (Fig. 1b). The nearest neighbor to a velocity sequence (represented as a single point) is the nearest point. Note this is computationally equivalent to the squared difference in individual dimensions. The three nearest neighbors to point A in Figure 1b are points B, C, and D.

Because  $a_0$  through  $a_m$  are re-evaluated for each prediction in nonlinear modeling, nonlinear relations between concentration and velocity can be learned and exploited for forecasting, even though eq (1) is purely linear. The advantage of using a small subset of observations (or small neighborhood) in the learning set is that the nonlinear structure of the data can be approximated most precisely using small linear pieces; the resulting model (called a local linear model) is thus more sensitive to the specific flow conditions (Fig. 2a). In contrast, the advantage of using all the observations in the learning set (a global model) is that noise reduction is greater (Fig. 2b). In the present study, we know that sediment response to forcing by velocity is nonlinear but are using the forecasting technique to learn if the system is noise-free enough that nonlinear models outperform linear models and if the nonlinearity is more complicated than U<sup>n</sup> or |U|<sup>n</sup>.

In addition to varying the number of nearest neighbors used to make forecasts, we can vary the number of velocity measurements (velocity history) used to predict each concentration. This velocity history can be as low as 1 point (where instantaneous concentration is related only to the simultaneously observed velocity), but increasing the velocity history to values greater than 1 can improve modeling accuracy in several ways. First, additional dynamic properties of the forcing flow can be identified. For example, with a single velocity observation, only velocity is known; with a second sequential velocity observation, acceleration can also be determined; and with a longer sequence of velocity measurements, wave shape can be identified.



Figure 1. Two methods of visualizing selection of nearest neighbors. (a) Sliding a window the width of the velocity sequence through a time series to select similar sequences. (b) Distance in velocity space. In this case a two point sequence can be represented by a single point having coordinates given by velocity and velocity from the previous time step. The nearest neighbors to point A are points B, C, D. In both cases, the difference between sequences (a) or the distance between neighbors (b) is

defined by  $\sum_{i=1}^{m} (U_{t+1-i} - U_{l_{ts+1-i}})^2$ , where m is the number of points in the velocity

sequence, U is the velocity in the testing set,  $U_l$  is the velocity is the learning set, and t and ts are the times of the last point in the velocity sequences in the testing and learning set, respectively.



Figure 2. Comparison of modeling results for hypothetical steady flow transport data. Dots are data points; light lines are global linear model predictions; dark lines are local linear model predictions. For noise-free data (a), local linear models can learn the nonlinear relation between concentration, C, and velocity, U, by looking at local pieces of the curve, thereby outperforming a global linear model. For example, a threshold velocity for suspension can be predicted by a local linear model. For noisy data (b), the global linear model outperforms local linear models because of the greater noise reducing capability of the global model. These examples are based on one-dimensional models (concentration is predicted from a single value of velocity). In the case of surf-zone transport, concentration is predicted from a sequence of velocities, and the relations can not be displayed as easily. Instead, the capability of each model is quantified by the correlation coefficient for the predictions.

Second, because of the time required for settling to occur, concentration in a decelerating flow depends on previous velocities (those that caused suspension of sediment that has not yet had time to fall to the bed). If the velocity history used to predict concentration is extended too far into the past, however, forecasts become degraded because the early velocities have increasingly little relevance to the later concentration.

In applying these forecasting techniques, a large number of models are evaluated, each employing a different number of nearest neighbors k, a different number of velocity measurements m used for each forecast, a different exponent of the velocity n, or a different time from the end of the velocity sequence to the time for which concentration is forecast (lag). The models are evaluated by the correlation coefficient between predicted and observed concentrations.

### FIELD EXPERIMENT

Sediment suspension was measured during a large cooperative field experiment investigating the morphologic response of the nearshore to storms conducted at the U. S. Army Corps of Engineers Field Research Facility (FRF) at Duck, North Carolina (see Mason et al., 1984, for a description of the experiment). The FRF is located on a long straight beach with well-sorted fine sand (~0.15 mm median diameter) in the offshore.

As part of this experiment, the U. S. Geological Survey deployed an underwater sea sled (Sallenger et al., 1983) equipped with instruments to measure waves, currents, sediment suspension, and profile change. Waves were measured using a pressure sensor and horizontal currents were measured at 3 elevations (0.5, 1.0, and 1.75 m above the bed) using 2.5-cm-diameter electromagnetic current meters. Suspended-sediment concentration was measured at 5 elevations (0.10, 0.13, 0.19, 0.31, and 0.61 m above the bed) using optical backscatter sensors (OBS, Downing et al., 1981). The nearshore profile was measured using an infrared range-finder sighting on prisms mounted on a 10 m mast as the sled was pulled offshore and onshore by a winch and lines and a system of blocks. The sled was moved to measurement locations where 34.1 minutes of data were collected at 2 Hz from each sensor.

### RESULTS AND DISCUSSION

Data reported in this paper were collected at one mid-surf-zone station, 100 m offshore, during the waning stages of a large extra-tropical cyclone on October 13, 1982. Offshore significant wave height was 1.6 m, and peak period was 12 s during data collection. Significant wave height at the measurement location was 1.7 m (water depth of 3.6 m). Mean currents at 0.5 m above the sea bed were directed obliquely offshore, with a 0.11 m/s cross-shore component and a 0.12 m/s longshore component. Significant orbital velocities at 0.5 m above the bed were 0.85 m/s in the cross-shore direction and 0.36 in the longshore direction. Waves were asymmetrical, with stronger, short-duration onshore flows and weaker, longer-duration offshore flows. Maximum cross-shore velocity was 2.12 m/s, directed onshore. The bed configuration was calculated to be within the planar-bed regime of Komar and Miller (1975).

### Using instantaneous velocity to predict suspension

A time series of suspension and horizontal water velocity (Fig. 3) shows intense suspension (referred to as suspension events by Downing, 1983; Jaffe and Sallenger, 1992) occurs irregularly. A scatter plot of concentration 19 cm above the sea bed versus cross-shore velocity (squared, to remove the sign and to make the relation between flow and concentration more in agreement with what is known for steady flow) 50 cm above the sea bed shows a lack of correlation between suspended sediment concentration and instantaneous velocity (Fig. 4). High concentrations can occur at zero velocity because sediment suspended earlier has not yet settled. Low concentrations can occur at high velocities because sediment suspended at the bed has not yet mixed high enough into the water column to reach the elevation of the sensor. The correlation between instantaneous concentration and cross-shore velocity squared is very poor, with a correlation coefficient of -0.02. Correlations between the instantaneous concentration and velocity to a higher power are also poor (Fig. 5). Other instantaneous velocity measures, longshore velocity or speed, are also poor predictors of suspension (Jaffe and Rubin, in preparation; Jaffe, 1993). More than instantaneous velocity is needed to predict sediment suspension.

#### Acceleration as a Predictor for Suspension

Acceleration/deceleration effects on bottom turbulence have been observed by other researchers. Increased turbulence during flow deceleration was observed by Schubauer and Skramstad (1947) in the laboratory. Gordon (1975) found increased Reynolds stresses during deceleration in tidal flow (Fig. 6). Hanes and Huntley (1986) and Osborne and Greenwood (1993) measured increasing suspension during



Figure 3. Time series of cross-shore velocity (U) and longshore velocity (V) at 50 cm above the sea bed, and suspended sediment concentrations (C) at 4 elevations above the sea bed (13, 19, 31, and 61 cm above the sea bed). For this time series, the testing set used in the modeling is the first 6.66 minutes (800 points) of the time series. The learning set is the measurements from 6.66 minutes to 34.1 minutes (3295 points). Intensity of suspension decreases with elevation above the bed. Note the short-lived periods of intense suspension (suspension events) throughout the record.



Figure 4. Scatter plot of concentration at 19 cm above the sea bed versus the crossshore velocity squared at 50 cm above the sea bed. The correlation coefficient for a linear regression (global model) is -0.02. Note the high concentrations occurring at low velocities.



Figure 5. Correlation coefficient versus exponent of velocity. Correlation coefficients are for a linear model using instantaneous velocity raised to a power to predict concentration at 19 cm above the bed. The velocity and absolute value of velocity raised to a power are plotted for odd powers. Linear models using instantaneous velocity as input are not able to predict concentration well.



Figure 6. Reynolds stress versus flow speed for flood tidal flows. Note that stresses are greater during decelerating flow than accelerating flow for the same speed. Figure from Gordon, 1975.

flow deceleration over bedforms. Conley and Inman (1992) found sediment pluming events (in which sediment was lifted on the order of 10 cm into the water column) occurred during the decelerating phase of some waves over plane beds (Fig. 7).

We tested to determine if suspension was correlated with instantaneous acceleration. Sediment concentration was not well correlated (r=0.12) with acceleration at the same instant (Fig. 8). Higher concentrations tended to occur during decelerating flow than accelerating flow. Onshore accelerating flows tended to have higher concentrations than offshore accelerating flows. Highest concentrations occurred during decelerating onshore flows under the wave crest. High concentrations also occurred at low accelerations and after flow reversals. Similar to instantaneous velocity, instantaneous accelerations during flow deceleration in the input for a model of sediment suspension.

#### Using a Sequence of Velocities to Predict Suspension

A velocity history contains more information about the state of the flow (and possibly about forces causing suspension) than a single velocity. In the previous two sections, instantaneous velocity and aceeleration were found to be poorly correlated with suspension. More information is contained if two velocity points are used to define the flow (Fig. 1b). For example, a two-point velocity sequence contains information about magnitude and direction of instantaneous velocity and magnitude and sign of acceleration. Seven different flow regimes can be delineated by regions in a velocity space plot of a two-point velocity sequence (Fig. 9a). The diagonal line in Figures 1b and 9a indicate no accelerations; points off this line indicate either accelerating or decelerating flow. Contours of concentration plotted in two-point velocity space (instantaneous velocity and velocity 0.5 seconds earlier) are ordered and show that high concentrations occurred for some sequences of two velocities (Fig. 9b). For example, high concentrations occurred for decelerating strong onshore flows (A in Fig. 9b).

Longer velocity histories give information about persistence of strong flows, acceleration history, flow reversals, and wave shape, all of which could be important in predicting suspension. A representative time series of cross-shore velocity (Fig. 10) illustrates how irregular waves have different velocity sequences even where instantaneous velocities and accelerations are similar.

To test whether more information about suspension is contained in earlier flows, differing lengths of velocity histories were used as input to models. Correlations increased as more velocity history was included to relate velocity to suspension until reaching a maximum of 0.42 at a velocity history length of about one wave period. Correlation coefficients for nonlinear models were maximum (0.48) at about one-half wave period of velocity history (Jaffe and Rubin, in preparation; Jaffe, 1993). The increase in predictability primarily results from a more complete description of flow conditions causing suspension. Improved predictions were also the result, in part, of including a lag effect.

### Lag between Velocity and Suspension

Because modeled concentration was measured 19 cm above the sea bed, a lag between the flow inducing suspension and the concentration response would be expected (to allow time for sediment to be carried up into the water column). Models incorporating such a lag performed better than models that did not. For a linear



Figure 7. Sediment plume rising above the bed during decelerating flow under a wave crest. Figure from Conley and Inman, 1992.



Figure 8. Concentration at 19 cm above the bed versus cross-shore flow acceleration. Triangles are onshore flows; squares are offshore flows; crosses are for periods where flow reversed. Highest concentrations occurred during decelerating (negative sign) onshore flows.



Figure 9. (a) Seven different flow regimes in a velocity space plot of a two-point velocity sequence (b) Concentration contours plotted in velocity space (instantaneous velocity and velocity from the previous time step). See Figure 1b for data density. High concentrations occurred for decelerating strong onshore flows (e.g., point A).

model with instantaneous cross-shore velocity squared as input, peak performance was obtained using velocity to predict concentration 1.5 seconds later (Fig. 11). This lag increased with elevation above the bed, increasing to 8.5 seconds at 61 cm above the bed (Jaffe and Rubin, in preparation; Jaffe, 1993). Nonlinear models and models using a velocity history also performed better when including a lag. An additional cause for a lag would be a sediment pick-up response lagging the velocity. This could occur if turbulence at the sea bed took time to build or its structure changed with time (e.g., response to flow reversal).



Figure 10. Time series of cross-shore velocity at about 300 s into the record (Fig. 3) illustrating why a velocity history is necessary to fully specify flow conditions. Points A, B, and C have similar instantaneous velocities, but different accelerations and are preceded by different velocities.



Figure 11. Correlation coefficient versus lag time between input (a single crossshore velocity squared) and output (concentration 19 cm above the sea bed). A positive lag is concentration later than velocity. Models perform better when a lag time is included primarily because they account for the time it takes to mix sediment up into the water column.

## Best model

Incorporating lag and velocity history into a nonlinear model gave the best predictions for suspension. Addition of nonlinearity allows differing relationships between velocity and concentrations for different velocity sequences (e.g., flow under differing wave shapes). The optimal model (correlation coefficient of 0.58) used 3 seconds of velocity history (approximately one-quarter wave period) and a 1.5 second lag to predict suspension. This nonlinear model was able to predict the suspension event at 312 seconds (Fig. 12). Just as important, suspension events were not predicted for waves between 320 and 350 seconds.

Mean concentration and cross-shore suspended sediment flux were well predicted by this model. Observed and predicted mean concentration was 1.12 and 1.11 gm/l, respectively. Observed and predicted cross-shore flux at 19 cm above the bed was 37.1 and 34.3 gm/m<sup>2</sup>/s onshore, respectively. The good agreement between predicted and observed flux was largely due to good predictions for high concentration. Low concentrations were not predicted as well; but, because their phasing relative to the wave orbital velocity is more random than high concentrations (Jaffe and Sallenger, 1992), errors in predictions were diminished by fluxes in opposite directions canceling resulting in a low contribution to net flux.



Figure 12. Time series of cross-shore velocity 50 cm above the sea bed and predicted and observed suspended sediment concentration 19 cm above the sea bed. Concentrations were predicted using the best model found through exploratory modeling, a local linear model with an input of 3 seconds of velocity squared, decimated to one point every 1.5 seconds, and a time lag of 1.5 seconds. This nonlinear model was able to predict high concentrations that occurred at 310 seconds into the record. Intermediate concentrations before and after highest concentrations are not well predicted. Correlation coefficient for 794 predicted/observed values is 0.58.

# CONCLUSIONS

(1) Instantaneous horizontal water velocity, or velocity to a power, does not contain enough information to predict suspension in the surf zone. Unlike steady uniform flow, more than one velocity is necessary to parameterize the pick-up and mixing of sediment into the water column.

(2) Instantaneous acceleration predicts suspension better than instantaneous velocity, but neither of the instantaneous models performs as well as models using a sequence of velocities. A sequence of past velocities (a velocity history) improves predictions of suspension by more fully specifying flow conditions (including accelerations and changes in accelerations) responsible for suspension.

(3) Suspension in the future is better predicted than suspension at the same instant as velocity measurements. These lags are largely due to the time for an observed flow event to effect the bed and mix sediment upward.

(4) Nonlinear models relating suspension to velocity do better than linear models using the same velocity history. Nonlinear models are able to exploit relationships between suspension and velocity history that change for different wave shapes. For the environmental conditions of this study, the optimal model used 3 seconds of velocity history (approximately 1/4 wave period) and a 1.5 second lag to predict suspension.

## ACKNOWLEDGMENTS

BEJ would like to thank his Thesis committee, Gary Griggs (Chair), Bob Anderson, and Ed Thornton for their help during the early stages of this work. This manuscript was improved by the reviews of Guy Gelfenbaum and John Dingler. We wish to thank the personnel at the Army Corps of Engineers Field Research Facility in Duck, North Carolina for their excellent help with the experiment.

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