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The Effect of Temporal Wave Averaging on the Performance of an Empirical Shoreline Evolution Model

M.A. Davidson, I.L. Turner and R.T. Guza

Abstract

The effect of using time-averaged wave statistics in a simple empirical model for shoreline change is investigated. The model was first calibrated with a six-year time series of hourly wave conditions and weekly shoreline position at the Gold Coast, Australia. The model was then recalibrated with the hourly waves averaged over intervals up to 1 year. With wave averaging up to 2 days, model performance was approximately constant (squared correlation r^2~0.61-0.62), with only small changes in the values of empirical model parameters (e.g. the beach response coefficient c varied by less than 4%). With between 2 and 40 day averaging, individual storms are not resolved; model skill decreased only modestly (r^2~ 0.55), but c varied erratically by up to 40% of the original value. That is, optimal model coefficients depend on wave averaging, an undesirable result. With increased averaging (>40 days) seasonal variability in the wave field is not resolved well and model skill declined markedly. Thus, temporal averaging of wave conditions increases numerical efficiency, but over-averaging degrades model performance and distorts best-fit values of model free parameters.

1. Introduction

Coastal management would benefit from realistic prediction of long-term (multi-year) coastal variability and change. However, such predictions are beyond the capability of processed-based, coastal evolution models [De Vriend et al., 1993; Van Rijn et al., 2003]. Process models based on detailed physics of hydrodynamic and sediment transport processes (e.g., Mike21, Delft 3D and Telemac) are hindered at long time-scales by both excessive computation time and poor model accuracy.

To bypass these difficulties, empirical models with reduced computation loads have been developed recently for shoreline position [e.g., Miller and Dean, 2004, Yates et al., 2009], sandbar location [e.g., Plant et al. 2006, Pape et al 2010] and beach gradient [e.g., Madsen and Plant, 2001]. Computational speed is obtained through both drastic simplification of the underlying equations, and through larger model time steps.

Accuracy is (hopefully) provided by extensive model calibration. However, the impact of using time-averaged wave parameters on shoreline model skill is unclear. Here, a six-year, highly temporally resolved (hourly waves and weekly shoreline position) data set is used to investigate the impact of wave-averaging on the performance of a simple empirical model for shoreline evolution [Davidson, Lewis and Turner (2010), hereafter DLT10].

Yates et al. (2009) developed a shoreline model similar to DLT10, based on wave energy disequilibrium, and presented preliminary evidence that excessive wave averaging degrades model performance by blurring the time history of storm waves.

For example, averaging wave parameters over the time period between sand level surveys (weekly to monthly) vastly simplified the numerics of calculating optimal values of model free parameter compared with hourly wave measurements, but model performance was reduced substantially. Owing to the numerical complexity of finding optimal free parameters of this model, the tipping points for model degradation as functions of the degree of wave averaging were not established. This illustrates the need to ascertain limits on wave averaging, even with simple empirical models for coastal change. The DLT10 numerics for optimal free parameters are much simpler, and therefore allow straightforward investigation of the impact of wave averaging on model performance over a broad range of time-scales. DL10 is viewed here as a generic, fast, empirical model for shoreline evolution.

The transfer functions for linear running average filters are well known. The cut-off characteristics are notoriously broad and are described well using the Dirichlet function. The (-3bB) cut-off frequency may be approximated by 0.433/*Mdt*, where *dt* is the sampling interval and *M* in the number of points in the averaging window. Thus, the impact of the filter stretches to frequencies that are considerably lower than the reciprocal averaging window duration (1/*Mdt*).

The field site and observations are described in Section 2. Although the shoreline model itself is not the topic of the present paper, the model is briefly reviewed in section 3 for clarity, and the reader is referred to DLT10 for further information. The effect on model performance of increased temporal averaging of the wave field is presented in Section 4. Conclusions and implications for further model development and application are summarised in Section 5.

2. Observations

A six-year record of wave and shoreline data from the Gold Coast, located on the SE Australian coastline is used (see Davidson and Turner, 2009, for details.) Wave parameters are reported hourly from a wave-rider buoy located approximately 2 km offshore of the study site in 16 m of water. Mean sea level shoreline locations are extracted weekly from a coastal video system. The shoreline data are averaged over 500 m of the coastline to remove small-scale variability. Waves are energetic with significant offshore wave heights exceeding 7 m, and annual shoreline displacements exceed 50 m. The comparative spectral distribution of variance in the shoreline and hydrodynamic (dimensionless fall velocity) time-series are shown in Figure 1. Here spectral estimates have been computed after de-trending the data and application of a Hanning window. The spectral estimates have 19 degrees of freedom and a bandwidth of 0.0028 Hz. Both the shoreline and hydrodynamic spectra are red in form, dominated by a seasonal peak at 0.0028 cycles/d. Variance of the shoreline displacement is roughly divided between seasonal/interannual, trend and storm as 55%, 35% and 10% respectively (DLT10). Note that the hydrodynamic spectrum of dimensionless fall velocity has significantly more high frequency (0.01 cycles/d to 0.1

cycles/d) content than the shoreline series. There is a small diurnal peak in the fall velocity spectrum at 1 cycle/d, but very little variance above this point.

The tidal range is microtidal with spring tidal ranges of 1.8 m. The beach sediments have a median grain size and mean fall velocity of 0.25 mm and 0.03 m/s respectively.

3. Model

The 1-D scheme of DLT10 (building upon the earlier 2-D 'behavioural-template' scheme of Davidson and Turner, 2009) was used to investigate the impact of temporal wave-averaging on empirical shoreline evolution models. The cross-shore shoreline position *x* at time *t* is:

$$\frac{dx}{dt} = b + c\left(\Omega_0 - \Omega\right)\Omega \qquad (1)$$

where Ω is the time-varying dimensionless fall velocity $\left(= H/\omega T\right)$, ω is the sediment fall velocity, T is the peak wave period and H is the significant offshore wave height. Ω_0 is the time-averaged, equilibrium dimensionless fall velocity that causes no net shoreline change in equation 1, (DLT10). A linear shoreline trend (if present) is given by b. The rate of shoreline change in response to time-varying wave forcing is governed by the reciprocal response time coefficient (c), wave steepness (H/T), and the disequilibrium magnitude $\left(\Omega_0 - \Omega\right)$. Although other empirical schemes (refer Section 1) could have been chosen here, the model represented by Equation 1 is simple and transparent, computationally efficient, stable over long (decadal) model runs, and most importantly, skilfully hindcasts seasonal and multi-year shoreline change at the test case site (DLT10).

Temporal analytical integration of Equation 1 includes antecedent conditions and enables an analytic solution for the least squares calibration of the three unknown coefficients; a constant shoreline offset a (units of m), a linear trend b (ms^{-1}) and the shoreline response parameter c (ms^{-1}) (DLT10).

To isolate the affect of using different wave averaging times, the model time-step (*dt*) was held constant at 1 hour. The averaging period (Δ) for the forcing wave data (*T* and *H*) was progressively increased from hourly (as observed) up to 1 year. For each Δ, the model was re-calibrated yielding values for model coefficients a, b and c, and a hindcast of the 6-year shoreline position. Model performance relative to the observed weekly shoreline measurements was quantified by the squared correlation (r^2). The transfer function for a 2 and 40 day moving average filter function is also included in Figure 1, so that the influence of the filter on model forcing parameters may be fully appreciated. Notice that the impact of the filter function encompasses much lower frequencies than one might intuitively expect. The temporal integration of ordinary differential equation (1) leads to downshifting of the frequency response, thus propagating the impact of time-averaging forcing parameters to still lower frequencies. Thus, it is unclear, without numerical experimentation such as this, what the impacts of frequency averaging on predictions of shoreline response will be.

4. Results

Using hourly waves and optimal values for free parameters, the model captures both the seasonal variability and the rapid shoreline retreat associated with energetic storms at the start of 2001, 2004 and 2006 (Figure 2). However, the model fails to reproduce all the high frequency variability in the observed shoreline location and the squared model-data correlation $r^2 \sim 0.62$.

Model performance, and the value of optimal model free parameters, varies as wave averaging is increased from 1 hour to 1 year (Figure 3). With wave averaging up to 2 days, model performance is approximately constant (squared correlation $r^2 \sim 0.6$), with only small changes (< 4%) in the reciprocal response time, c. Thus, the time step can be increased (from hourly) by a factor 50, without degrading model performance or substantially distorting free parameter values. With between 2 and 10 day averaging individual storms are not resolved; model skill decreased only modestly ($r^2 \sim 0.55$), but c varies erratically by up to 45% of the hourly value. With further increases in averaging (> 40 days), seasonal variability in the wave field is not resolved and model skill declines markedly. Brier skill scores, using the linear trend as the base prediction (not shown), are very similar to r^2.

Pape et al (2010) showed that a model for sand bar location, with structure similar to the present shoreline model (1), is sensitive to wave averaging that blurs storms. For both shoreline and sandbar location models, temporal averaging of wave conditions increases numerical efficiency, but over-averaging degrades model performance and/or distorts best-fit values of model free parameters (e.g. response time).

5. Conclusion

Time-averaging of the waves forcing morphologic change models must be done carefully. For the wave climate at the Gold Coast test site, model performance deteriorates with averaging between 2-10 days, as short-duration storm events become poorly resolved. The model skill again degrades with wave averaging greater than about 40 days, as seasonal variations are progressively smoothed.

Declining model hindcast skill and variation in model optimal free parameter values resulting from time-averaging of the seasonal wave component is more significant than the impact of averaging over individual storms. This is consistent with the distribution of shoreline variance in this dataset: seasonal/interannual band (55%) with relatively small contributions at storm frequency (10%).

Another likely contributing factor was that, although the model when forced with hourly wave parameters successfully predicts the larger shoreline recession events associated with the major storms in this time-series (start of 2001, 2004 and 2006 - Figure 2), it does not reproduce all of the observed high frequency variability. With an alternative model that better predicts high-frequency shoreline variability; the impact of averaging over storm times-scales will be more significant. Similarly, smoothing over storms may be more detrimental at other coastal sites where storm frequency variance contributes a higher percentage of the total shoreline variance. Storms and seasonality are the two most important drivers of wave-forced shoreline change, so it is anticipated that the two key time-average thresholds (≥2 days and ≥40 days) corresponding to the initial and further degradation of model skill and fluctuation in free parameter values, are likely more generically applicable to other models and sites. This assertion warrants further investigation.

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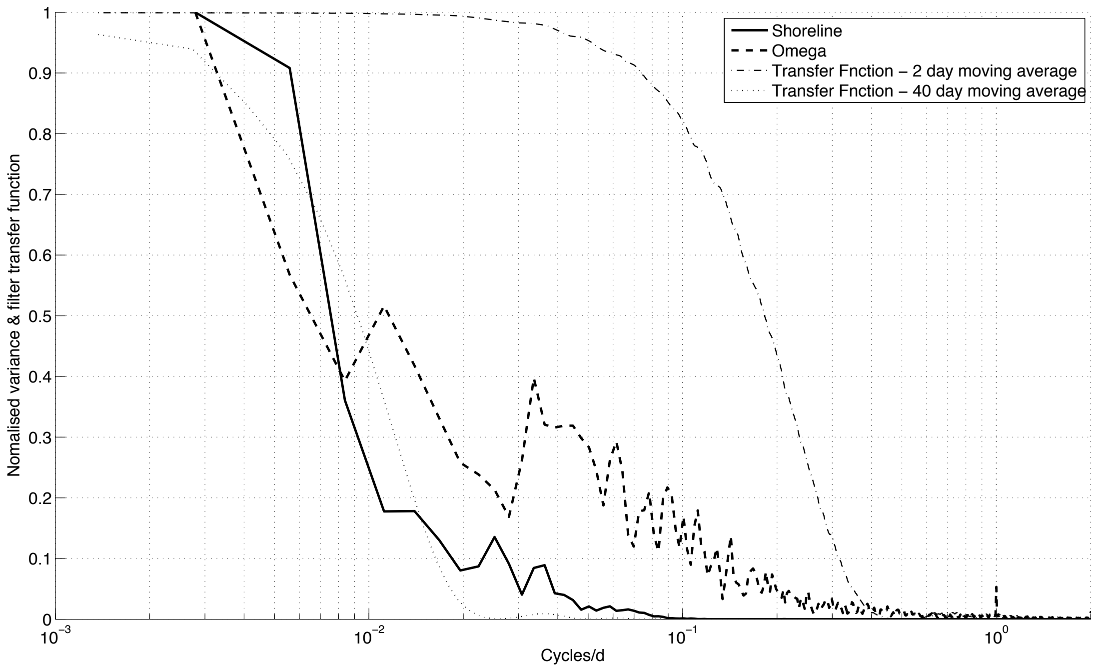

Figure 1. Spectral estimates of shoreline position and dimensionless fall velocity (omega) plotted together with moving average filter transfer functions with windows of 2 and 40 days.

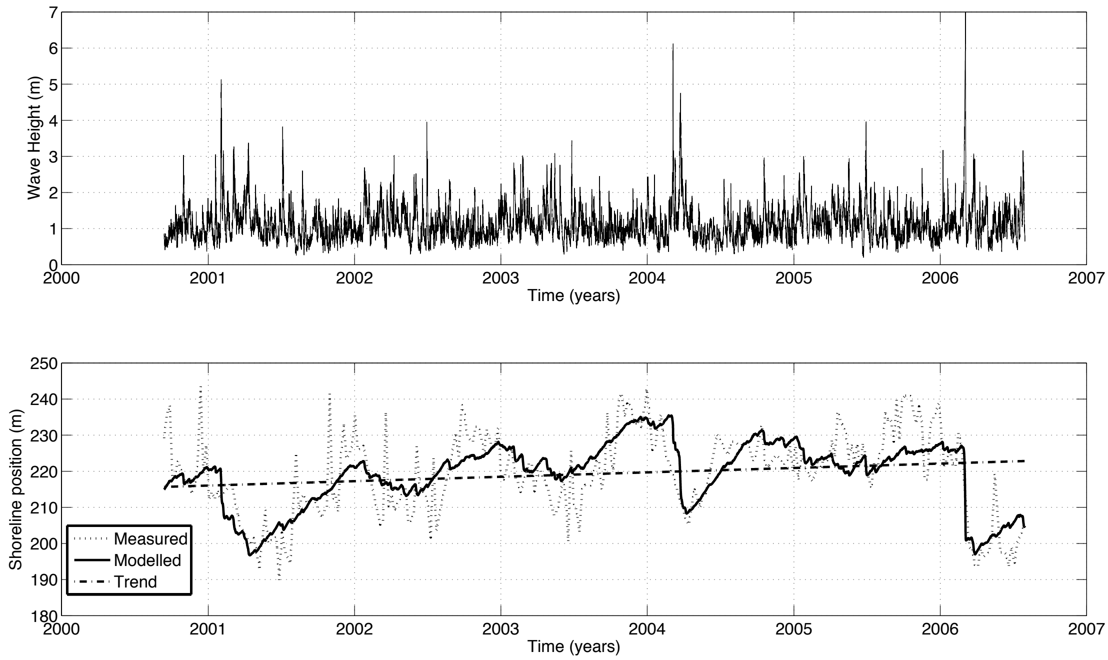

Figure 2. (top) Observed hourly significant offshore wave height, and (bottom) shoreline positions observed (dotted) and modelled (solid). The dashed broken line is a linear trend.

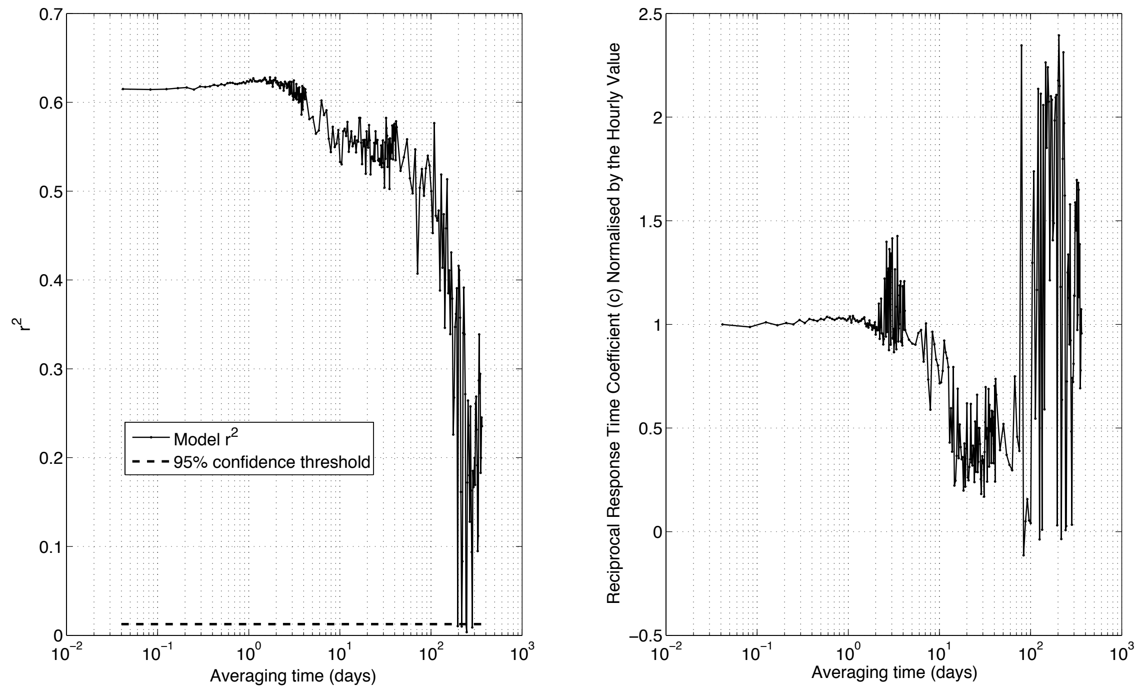

Figure 3. (left) Squared correlation (r^2) between model and observed shoreline position and 95% confidence threshold (dotted). (right) Reciprocal response coefficient c, normalised by the value for no wave averaging (hourly sampled wave parameters), versus wave averaging time (days) used in the model.