THE EFFECTS OF STORM CLUSTERING ON STORM DEMAND AND DUNE RECESSION AT OLD BAR, NSW.

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Abstract

Numerical and probabilistic modelling are combined to investigate the influence of storm clustering on sand (storm) demand and dune recession at Old Bar on the NSW mid-north coast. Wave and water level data are hindcast to provide long duration synthetic time series for input to a nested nearshore hydrodynamic SWAN model that provides wave conditions at the 12m depth contour. The EVO open-source shoreline evolution model is used to model cross-shore and longshore beach profile evolution, forced by the synthetic time series via the SWAN generated look-up tables. Storm demand and shoreline position are simulated over 50 years, from which the largest 5 events are ranked to form natural estimators of the 50, 25, 16, 12.5 and 10 year return period. The expected storm demand and dune position for those return periods are estimated, together with confidence limits. An exposure analysis is then performed using the dune recession return periods, highlighting proximity of all infrastructure in relation to estimated hazard lines. The storm demand analysis is then repeated by considering the morphological response to clusters of storm events, defined here in a new way by considering the response of the beach, rather than the forcing. The analysis provides a storm demand versus return period curve for the combined population of clustered and non-clustered events, as well as a curve for the total population of individual events. The expected storm demand for 50 year return period including clustering is 25% greater than that excluding clustering. Alternatively, the same storm demand for an expected return period of 50 years for individual events occurs with an expected return period of 17 years when including clustering. The expected storm demand for the population of non-clustered events is similar to that of the clustered events, although the population is much smaller. Hence, while less likely, individual storms can generate the same storm demand as clustered events.

Introduction

It has long been recognised that storms may arrive in sequences, but statistical modelling of beach response and storm demand does not generally consider whether the storm sequencing affects the return period of given morphological response. This paper considers this issue and uses numerical and probabilistic modelling to investigate the influence of storm clustering on storm demand and dune recession at Old Bar, an erosion hotspot on the NSW mid-north coast. The EVO open-source shoreline evolution model is used to model cross-shore and longshore beach profile evolution at that location, using hindcast waves, water levels and bathymetry data, combined with a nested nearshore hydrodynamic SWAN model. This study forms part of the Bushfire and Natural Hazards CRC Project “Resilience to clustered disaster events at the coast: storm surge”.

Beaches undergo continuous cyclic evolution in the form of erosion and accretion processes, and the beach profile at any given instant has an effect on the impact of subsequent storms. A morphological storm cluster occurs when the beach is unable to recover from a storm event before the next one commences. This needs to be distinguished from storm clustering in the wave climate, since the morphology may not respond to a given storm if it is already heavily eroded (e.g. Yates et al., 2009). Further, beach response depends on more than the conventional measure of storm severity (i.e., wave height), with wave direction and water level particularly important. Hence, the erosive potential of a storm is determined by multiple environmental parameters such as wave height, antecedent beach morphology, and variations in water level due to storm surge and tide (Cox, J., & Pirrello, M. ,2001).

Usually, the largest measured historical event is applied as a reference to assess beach erosion for design purposes. This method tends to overlook the effects of storm clusters, which can be more erosive than individual events (Callaghan et al., 2008). In some instances, the cumulative impact of smaller storms may outweigh the erosion potential of a single much larger storm. The effect of clustering in the population is automatically considered through the probabilistic approach of Callaghan et al. (2008), through simulating all storm events and ranking the resulting beach volume change (storm demand). However, the storm demand due to clusters themselves cannot be isolated.

While it is clear that design of coastal protection, setback lines etc., should consider storm clustering, a precise definition of how the storm sequences should be combined has not been found (Coco et al., 2014). Morton (2002) suggests that the sequencing or chronology might be a critical factor in determining the erosive potential of a storm cluster. The cumulative effect of storms is also important and has been investigated recently by a number of studies (Dissanayake et al., 2015; Karunarathna, et al., 2014; Splinter et al., 2015). The expected behaviour is dependent both on the wave conditions and the antecedent beach morphology (e.g. Yates et al., 2009; Splinter et al., 2015).

Old Bar Beach on the NSW mid-coast is an erosion hotspot with chronic dune recession rates averaging nearly 1 m/yr over the last 50 years (Figure 1). With resultant property loss, Old Bar is a focus for active shoreline management by the Midcoast Council and a site requiring further research. Numerical models could be used to help understand the morphological evolution of Old Bar where only sparse historical field data exists. Furthermore, models can also be used in probabilistic applications to quantify uncertainty (Wainwright et al., 2014) and to investigate clustering.

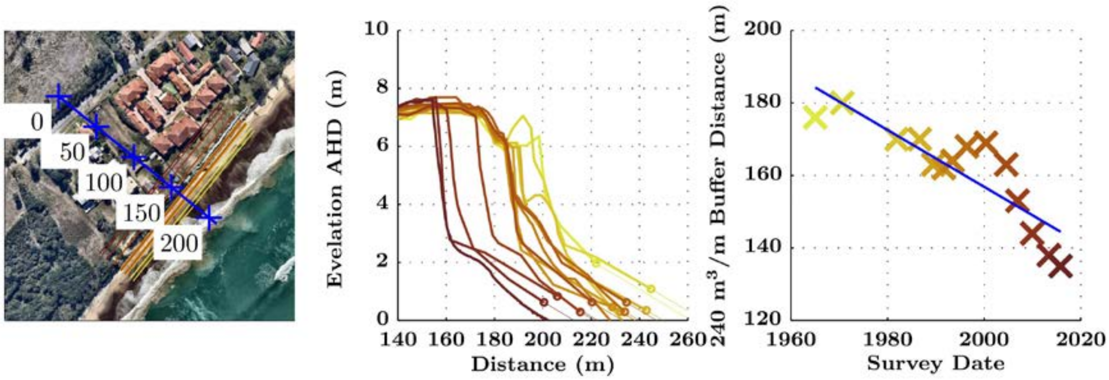

Figure 1. Foredune erosion at Old Bar, NSW, with to fit position of 240 square meter 'dune buffer'. Trend line indicates 0.8 m/yr erosion using data derived from photogrammetry (Harrison 2017) block X profile 6.

Here we apply the hybrid cross-shore (equilibrium type) longshore morphodynamic Shoreline Evolution (EVO) model developed by WBM BMT to model the sediment transport inside the Old Bar coastal compartment. A suite of probabilistic synthetic time series of waves and tides were used to force the model and make robust statistical assessments of the modelled dune recession (erosion) and storm demand. Next, dune recession values at a range of annual return intervals were offset from the current dune toe location as estimated hazard lines. These were then used to generate exposure maps that identify the proximity of infrastructure to the dune erosion.

Next we demonstrate a new approach to distinguish the erosional effects of individual storms versus clusters of storms. In the subsequent analysis, individual storm events are merged into a population of "clustered" events, which might consist of a number of erosive events and beach recovery periods. A clustered event is defined as a sequence of events where the accretionary beach recovery between storms is less than 50 percent of the maximum erosion, as defined by the maximum range of storm demand during the sequence. The conventional statistical analysis to determine the expected storm demand for clusters with given return periods was then repeated. This is an improvement over simply interpolating the return period expected from clustered events from the individual event curve as was done by Ferreira 2005.

Methodology

Waves and water levels

The wave and water level analysis is summarized in Davies et al. (2017). The methodology accounts for non-stationarities in the storm properties and event frequency, including the impacts of seasonal and ENSO related non-stationarities on the storm climate. The primary sources for this modelling were Crowdy Head waverider buoy (Oct 1985 - Jan 2016), Coffs Harbour buoy (1985-2016 with direction since 2011), the Sydney directional waverider buoy (1992-2016) and non-directional Sydney waverider buoy (1987-2000). The Tomaree tidal gauge (1985-2014) provided ocean surface levels. Storms are defined as events where H_{sig} exceeds 3m.

The analysis had the following steps:

1. Perform an exploratory data analysis to determine the dependence of storm summary statistics on time and/or on relevant climate indices.
2. Model the storm event timings as a non-homogeneous Poisson process.
3. Model the cumulative distribution functions of all storm summary statistics (H_{sig}, D, R, T, θ) separately, accounting for any dependence on time and/or climate indices that was identified in the exploratory analysis.
4. Model the joint distribution of all storm summary statistics using a vine-copula.
5. Simulate a long synthetic storm time-series from the fitted model. Arbitrary storm exceedance rates can be determined empirically from this time-series.

Typically, 20-25 storms occur per year, with a few more storms in La-Nina years, and with the highest frequency of storms in July (winter), Figure 2. The wave climate has a 50 year return period storm has a significant wave height of about 7m, and is dominated by southerly waves, Figure 3. Hence the SWAN modelling is important to account for refraction, and events with more Easterly waves but smaller wave can have a much larger impact than the high return period events from the south. Davies et al. (2017) show no additional short-time-scale clustering beyond that expected from the underlying seasonal changes in the storm rate.

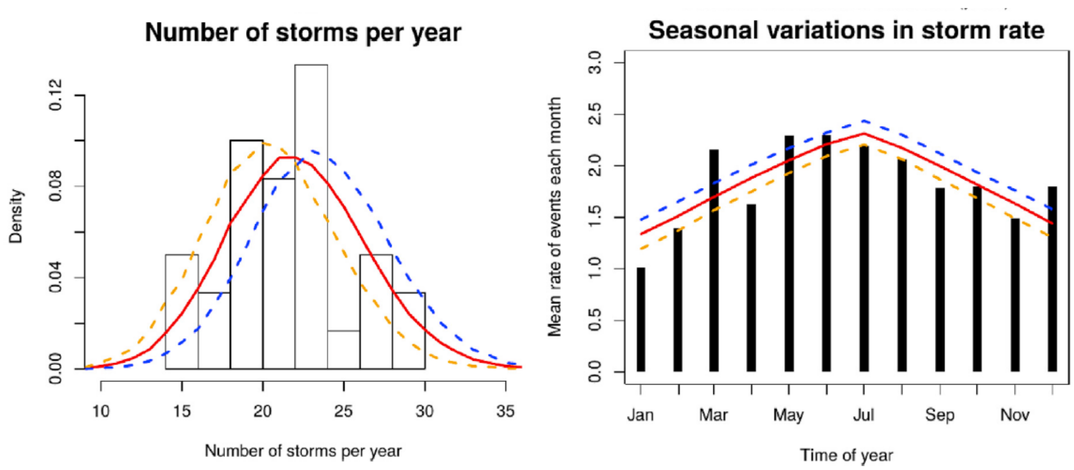

Figure 2. The number of storms per year (left) and the seasonal distribution of storms (right). From Davies et al., (2017).

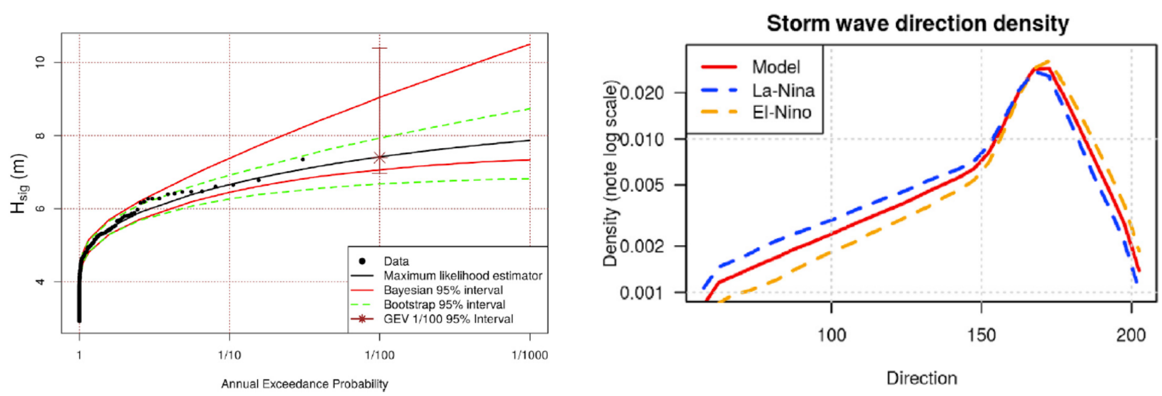

Figure 3. Annual exceedance probability plot for Old Bar, with 95% confidence limits (left) and storm wave direction density (right). From Davies et al., (2017).

Swan modelling and wave transformation "lookup table" approach

The EVO modelling framework handles the transformation of offshore waves to the near-shore by using the so called "lookup table" approach, which is pre-calculated and independent of both the beach morphological change and wave input forcing conditions. In practice, the lookup table is a 4-dimensional matrix (wave height, wave period, wave direction and model chainage) built from a suite of stationary Swan simulations and written to a NetCDF file. The EVO model computes nearshore wave parameters by interpolating the input wave parameters, imposed at the site of the Crowdy Heads waverider buoy, from the lookup table matrix.

The Swan model grids used for the Old Bar simulations consisted of 3 nested grids with 1 km, 250 m and 100 m resolution respectively. The only forcing applied is at the outer grid offshore and two lateral boundaries. This forcing is specified by a range of homogeneous wave heights (1-11 m), periods (4 – 17 s) and directions (20 to 190 degrees). These bulk wave parameters are specified in the form of a Gaussian frequency spectral distribution with width of .025 and directional spreading of 15 degrees. The Gaussian distribution was adopted to help eliminate the potential ambiguity between use of the peak or mean wave directions and their various definitions, given these are all similar for the symmetric Gaussian distribution used, compared to the PM or JONSWAP spectral shapes. At the lateral Swan grid boundaries, refraction and shoaling of each wave condition is first calculated using Matlab scripts as an initial step before building the boundary condition input files, such that results should be valid over the full domain even with very high wave incidence angles.

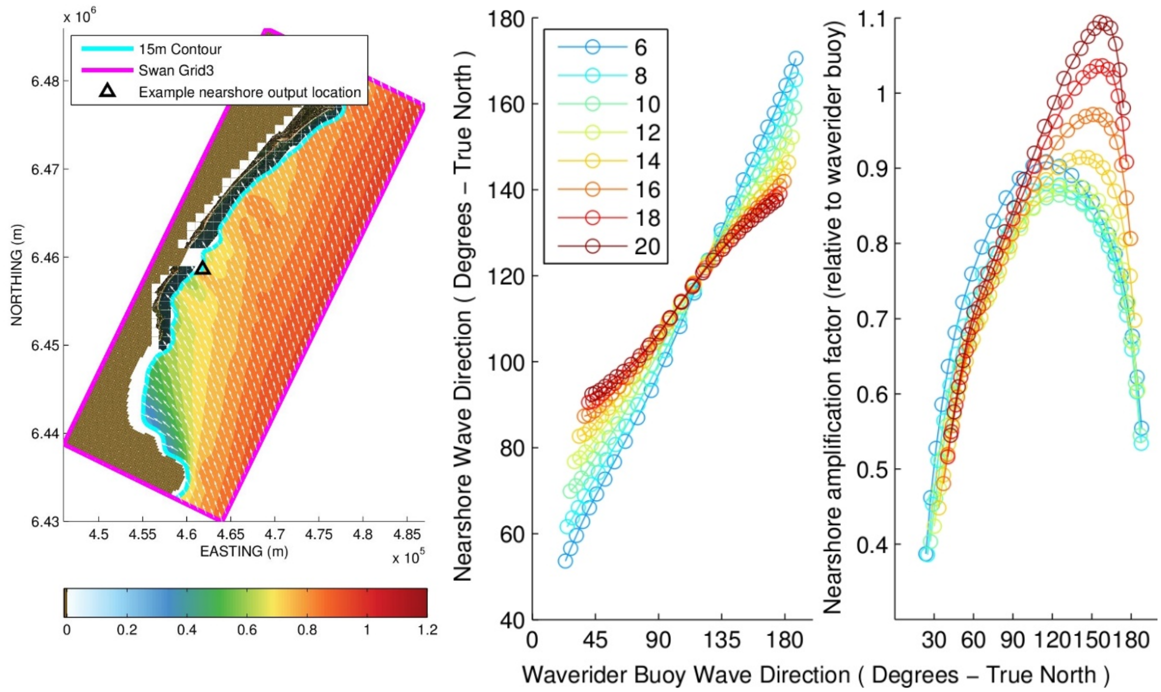

Figure 4. SWAN model nearshore domain, normalised wave height and direction (left) and nearshore wave angle and amplification (right).

A final step in building the wave transformation wave lookup tables is to post process the results from a structured range of Swan wave height and direction inputs at the outer grid boundaries to a structured range at the wave buoy. This is achieved by first interpolating direction and then height for each simulated wave period. Nearshore waves, taken here as 8-15 meters depth, are then known for any given wave buoy input to be used in the EVO model.

This lookup table approach is similar to the NSW wave matrix toolbox (http://nearshore.waves.nsw.gov.au/, Baird Australia 2016) developed for the entire NSW coast with two major exceptions. First, the NSW toolbox uses a single wave height and scales all transforms linearly. Compared to the Swan modelling done here, there is a discrepancy at the extreme wave heights where breaking is important and not represented by the linear wave height scaling. A comparison between the two methods at NSW forecast point 1004800 at approximately 12 m depth is shown in Figure 5. Second, the boundary forcing for NSW toolbox simulations is specified at the wave buoy depth contour. Although assumed relatively minor, long period wave may have already began refraction making the assumption of homogeneous offshore waves less valid.

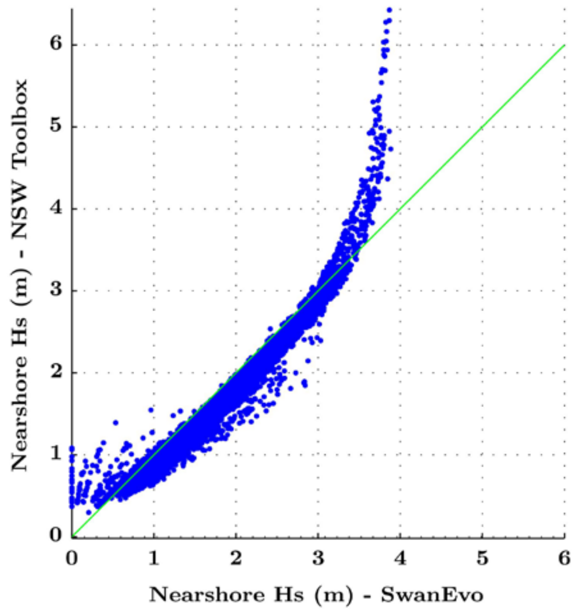

Figure 5. Comparison of nearshore wave heights at 10m contour between SWAN model for Old Bar, NSW and The NSW Nearshore Wave Toolbox (Baird Australia 2016)

Morphodynamic modelling – EVO Model

The shoreline Evolution model or 'EVO' model is a synthesis of pre-existing model theory from both longshore and cross-shore equilibrium type models combined into a hybrid model (Teakle 2013). EVO is open source and with Fortran and Matlab pro-post processing codes available online (https://github.com/UQ-CoastalEngineering/shoreline-Evolution-model). EVO is also well suited for applications within statistical frameworks, Gravois et al. (2016). The model is intended for use as a research tool to study the effects of waves and storm surges on beach erosion from both storm demand and long term shoreline/dune recession. This is achieved by calculating both the longshore sand transport gradients and cross-shore redistribution of sand from large waves or elevated tides that dominate the recession and storm demand processes respectively. The model also allows beach recovery caused by small accretionary waves and by artificial means (i.e. addition of sand from dredging). Seawalls and groyne structures can be included in the modelling, and also modified, to quantify the effects of coastal structures on beach evolution. The recommended spatial and temporal scales for EVO are beach lengths up to 100 km and simulation duration's up to 100 years.

The EVO model cross-shore formulation defines a steady state profile shape for a given constant wave condition and mean water level. This 'active profile' will retain its shape until the wave condition or water level is changed. The underlying assumption in this formulation is a conservation of total volume of sand in the cross-shore. A schematic diagram of the profile shape is given in Figure 6. The potential change depends on both the antecedent beach state and the equilibrium profile.

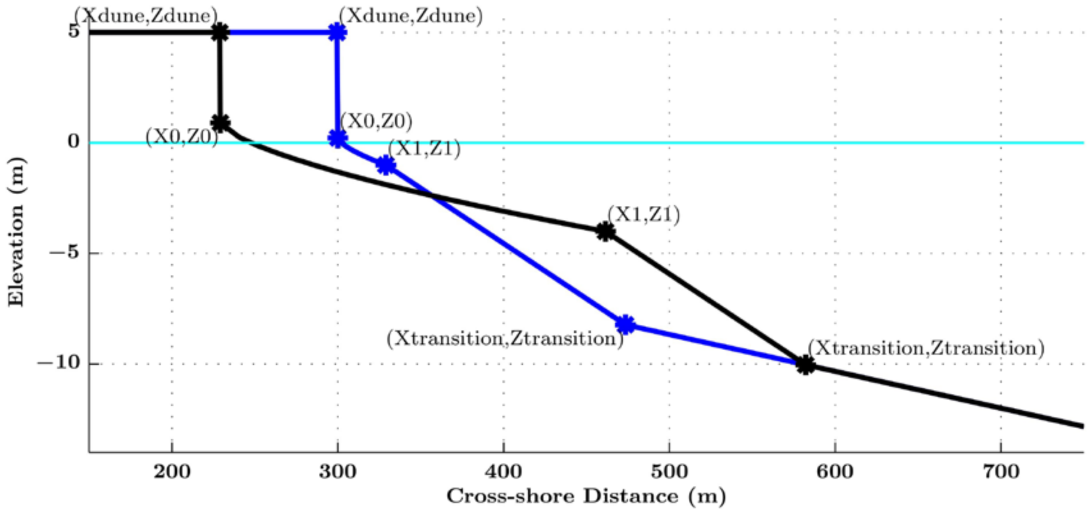

Figure 6. Schematic of EVO model equilibrium profile response to increase from 1 m (blue) to 3 m (black) breaking wave height. Corresponds to 70 m dune recession and 300 square meter storm demand (above 0 AHD).

In reality, the equilibrium profile is never fully realized because the profile is always evolving towards a new equilibrium redefined by the changing wave conditions. Erosion is a much quicker process compared to accretion, and these are modeled using exponential decay rate time constants of approximately 2.5 days and 3 years respectively. The dune recovery scale is similar to those documented by Morton et al. (1994) and are show in Figure 7.

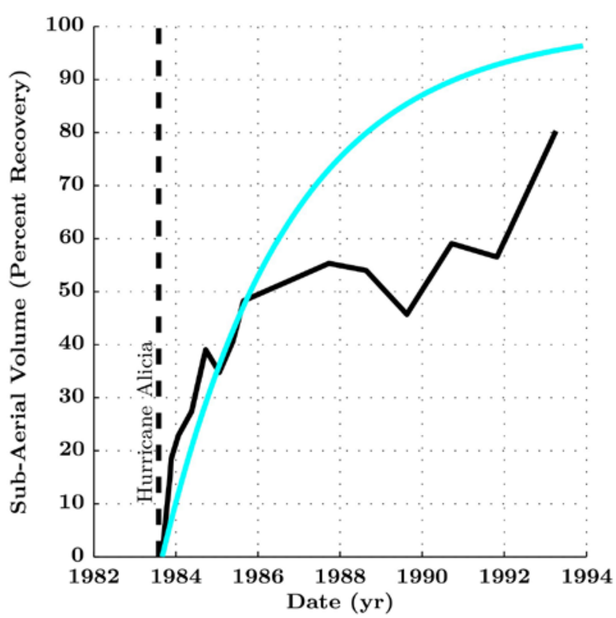

Figure 7. Percentage of dune recovery at Galveston Island over time after Hurricane Alice (black line) and EVO timescale (cyan). Replotted from Morton et al. (1994).

Sediment budget and model boundary conditions

The model boundary conditions were based on analysis of the sediment budget within the Old Bar littoral cell. To the south, the model boundary consists of a groyne, representing the Saltwater and Wallabi Point headlands. A steady sediment supply of 30K m^3/yr was adopted at this boundary. It is not known if sand waves propagate along this section of coast, which could lead to periods of erosion and accretion as the sand wave passes fixed points. Sensitivity testing was performed to investigate if a time-varying supply, triggered by storms, led to significant differences in the statistical description of shoreline response at Old Bar. No major influence was identified, indicating the model domain was sufficiently large for the varying supply to diffuse. To the north the model boundary was a groyne, representing Crowdy Head. The sediment supply condition at this location was zero transport. Finally, aerial images and the overall sand budget were used to identify other sediment sources or sinks. While the morphology of Harrington Inlet (Ruprecht 2011) is highly complex (Figure 8), sinks were identified at Harrington and Farquhar inlets, with adopted sink rates of 15K m^3/yr each in the modelling.

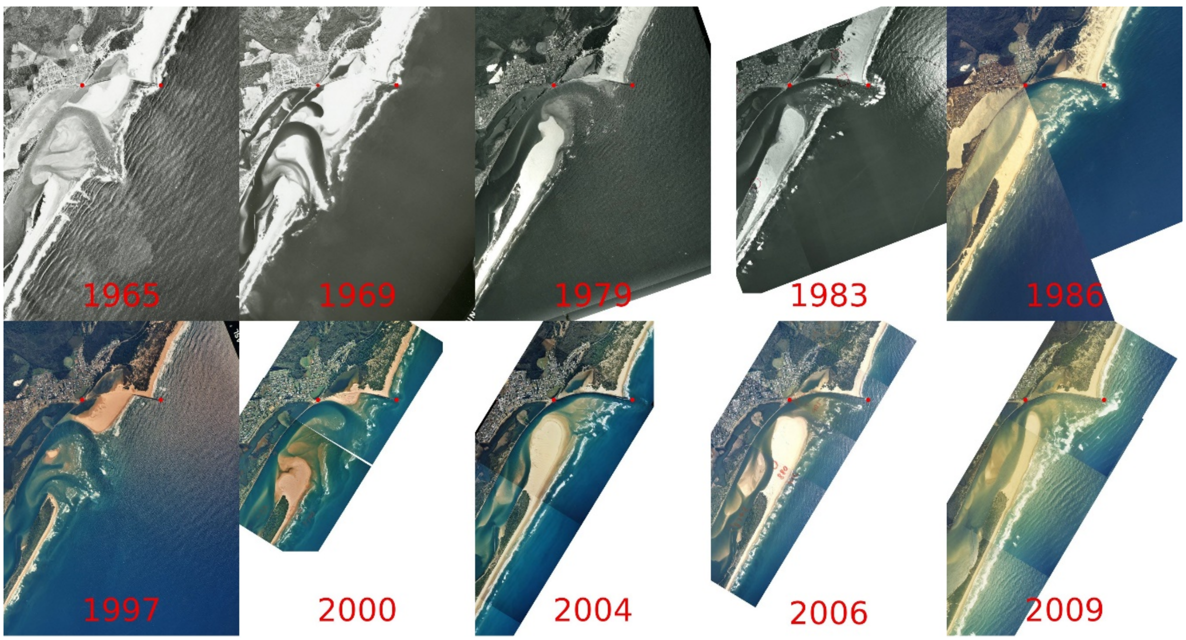

Figure 8. Aerial images of Harrington Inlet north of Old Bar, georectified and rescaled. Red dots indicate the same locations in each image. Data from Office of Environmental Heritage, NSW archives.

EVO model calibration.

The EVO model calibration for Old Bar was done considering both the cross-shore and longshore sediment transport components. The cross-shore calibration procedure entailed running the model with approximate profile shape parameters and then re-initialising the profile initial conditions for the production runs based on the quasi-steady values. This procedure helped to ensure that the initialised profile shape parameters were representative of the equilibrium profile for the mean wave conditions. Additionally, the approximate values for the vertical extent of the 'active profile' were used to estimate the profile shape parameter in the vicinity of Old Bar. This resulted in a value of a=0.13. The longshore calibration objective was to reproduce the approximate observed dune recession near and around Old

Bar through the adjustment of a) southern BC and inlet sinks b) extent of the model groyne lengths representing headlands and training walls c) rotation of the intermediate depth contours around headlands and over complex reef geometry. The southern BC was selected to be 30K m^3/yr, 0 m^3/yr at Crowdy Head and 15K m^3/yr sinks at both Farquhar and Harrington inlets. While these are approximate steady values for transient processes, the net conservation of sediment along the full model domain allows the redistribution of sediment in the Old Bar cell, and no net gain or loss. Groyne lengths in the model were set based on aerial imagery with EVO grid overlain. The procedure to calibrate the intermediate contour rotation involved inspection of the littoral drift rose (Walton 1985) with respect to the contour rotation at the output from the Swan lookup table. Overall the longshore calibration procedure was similar to the cross-shore profile calibration, in the sense that after running an initial simulation, observed net transport was analysed and around the headlands and reefs salient contour angles were modified to avoid unrealistic recession or accretion rates.

Analysis and Results

The model results indicate that the general behaviour of sediment transport at Old Bar is characterized by an average positive net transport (northward) around ~40 K m^3/yr resulting from the difference between very large north and south gross transport rates. This indicates that both the wave direction and the associated transport gradients are important for the balance of sediment transport near Old Bar. The average transport rates from *one EVO model realisation* forced with synthetic waves and times is shown in figure 9.

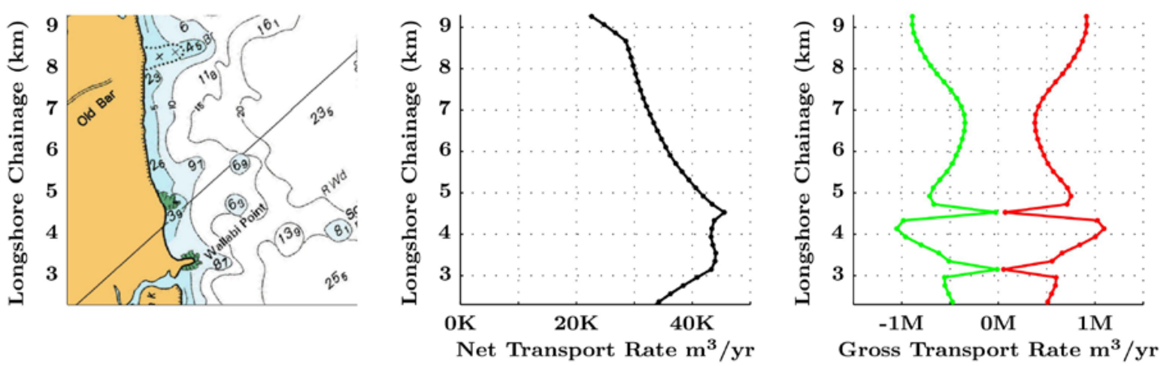

Figure 9. Simulated 50 year average net and gross longshore transport at Old Bar from one synthetic model realisation.

Recession Analysis

The dune recession analysis applied the so-called peaks-over-threshold approach. To prepare the sub-aerial volume time series (Figure 10), movement due to longshore transport gradients (Figure 11) is removed, as well as any offset based on a two monthly mean at the beginning of the time series. Once prepared, events are defined using the resultant time series (Figure 12) based on a 95% exceedance threshold. The longshore component of erosion is then added to the minimum value of these defined events and ranked for natural estimators for annual recurrence intervals. If the 95% exceedance threshold fails to identify at least 10 events, the procedure was then repeated with 90% exceedance threshold. The dune toes oscillates through typical range of about 40m over 50 years (fig. 10), which includes a contribution from both longshore (fig. 11) and cross-shore transport (fig. 12).

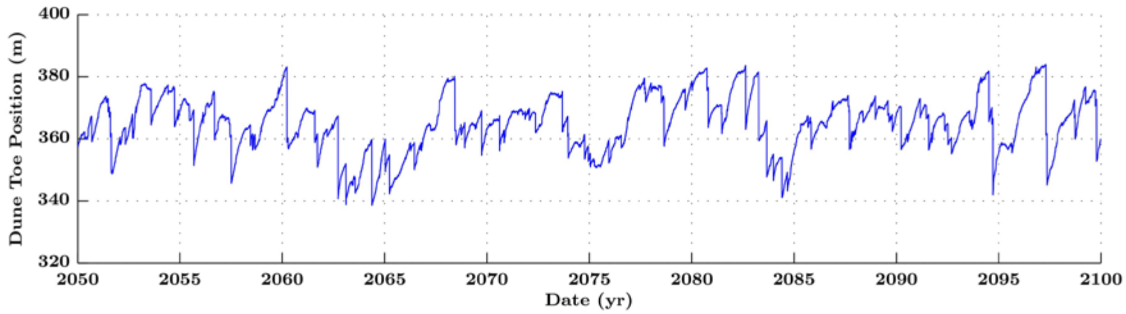

Figure 10. Simulated dune toe position at Old Bar for one realisation of the synthetic wave and tide forcing. Note the model cross-shore datum is not the same as the photogrammetry datum shown in figure 1.

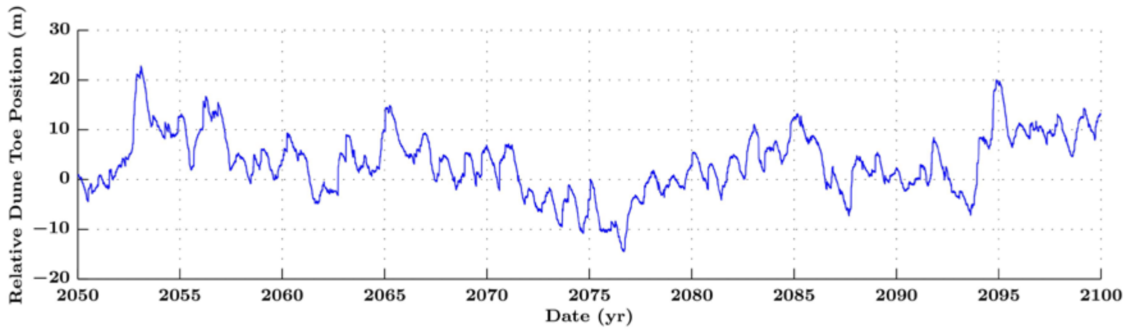

Figure 11. Simulated dune toe position at Old Bar for one realisation of the synthetic wave and tide forcing for the longshore contribution only.

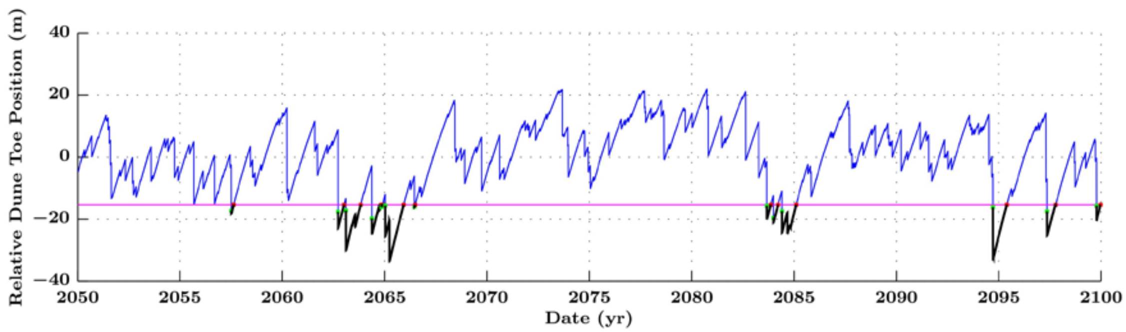

Figure 12. Simulated dune toe position at Old Bar for one realisation of the synthetic wave and tide forcing with longshore contribution and mean removed (blue line). Variable threshold (magenta) value set here at 90% exceedance to identify at least 10 events (thick black lines) showing recession event definitions.

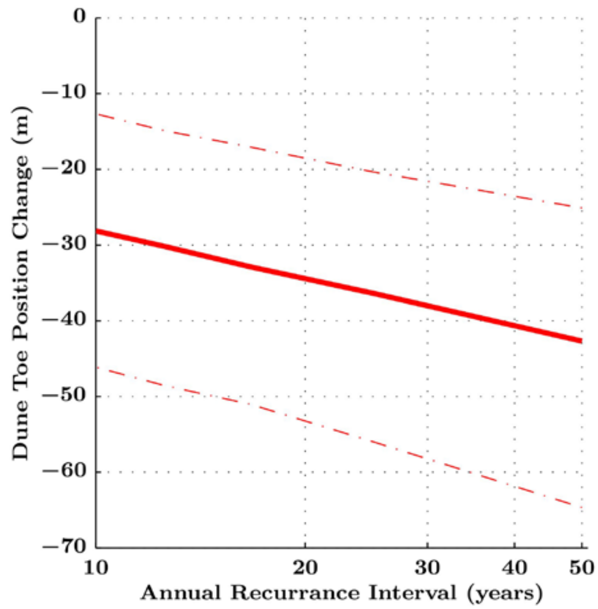

Figure 13. Estimated change in dune position for different return periods at Old Bar, showing the expected value (thick) and 90% confidence limits (dot-dashed). Dune height in EVO modelling is 7m.

Exposure analysis based on dune recession annual exceedance intervals

After the statistical expectation value for dune toe recession corresponding to 10, 25, and 50 year annual recurrence intervals has been determined, these values were used for exposure analysis. Dune recession values were offset from the current dune toe location (figure 14) to estimate hazard lines, with highlighting the proximity of all infrastructure in relation to estimated hazard lines. The change in dune position is consistent with the expected storm demand for the different populations identified in the clustering analysis, see figure 16 below.

Clustering analysis

The methodology for detecting clustering in the morphology was developed for analysing the relative changes in the sub-aerial beach volume. This is a practical measure for coastal management since the dune and beach volume “buffering” coastal infrastructure can be easily estimated at any given instance (figure 1). The method developed here involves three steps. 1) Find all local minimum and maximum values of the sub-aerial beach volume time series. *Individual events* (population A) are then defined as the change in volume between consecutive maximum/minimum pairs. 2) Consecutive morphological events are then combined until half of the volume eroded in the initial event is recovered (figure 15). Finally, the difference between the maximum and minimum sub-aerial volume within that cluster defines the storm demand for those *clustered events* (population B). 3) The remaining events that are not combined into clusters are *non-clustered events* (population C). Populations B and C combined includes the whole time-series, *clustered and non-clustered events*, which has a duration of 50 years.

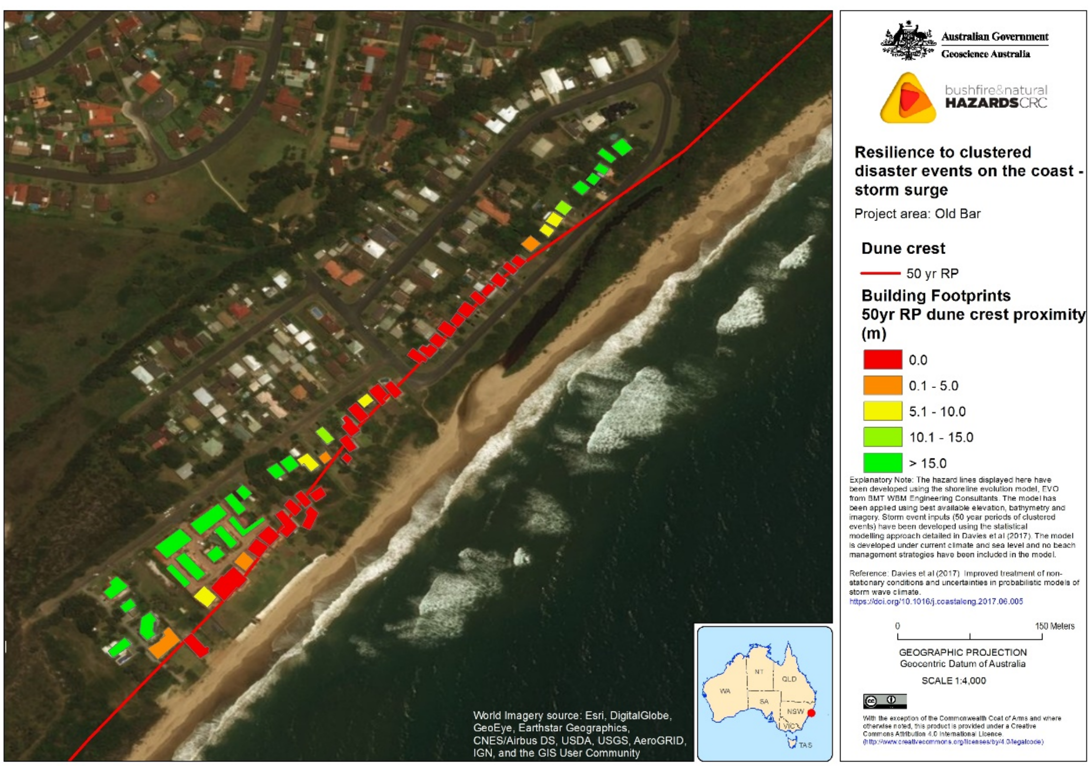

Figure 14. Current (top) and expected 50 year return period (bottom) dune crest at Old Bar, with property colour coded by proximity to the dune crest.

Ranking of the largest five events in each population produces the estimators for annual recurrence intervals (figure16). The expected 50 year ARI for *clustered and non-clustered events* (pop. B&C) is 25% greater than that for *individual events* (pop. A). The same storm demand occurs at a 50yr ARI for *individual* events (pop. A) and at a 17yr ARI for *clustered and non-clustered events* (pop. B&C). A histogram of the rank 1 events, from all realisations, for *clustered events* (pop. B) and *non-clustered events* (pop. C) is given in figure 17, which indicates that those two populations have a very similar median value, but that *clustered events* are much more likely to be the largest event in any given 50 year realisation.

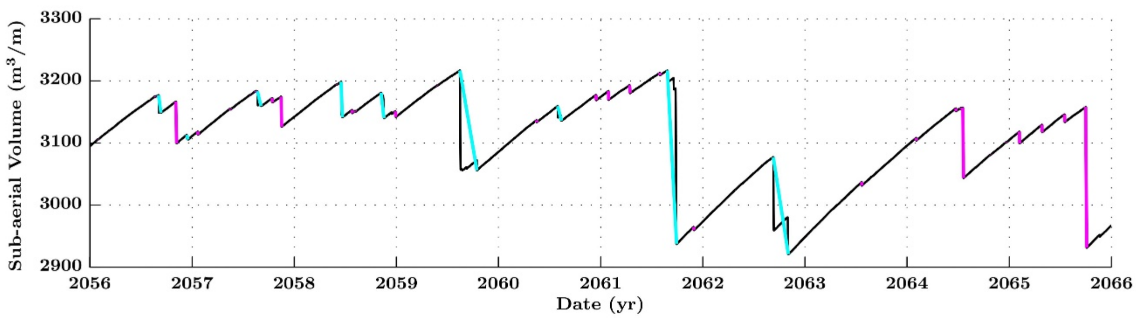

Figure 15. Definition of clustering using the morphological response (change in sub-aerial volume or storm demand). Black line – sub-aerial volume, cyan line – *clustered events*, magenta line – *non-clustered events*.

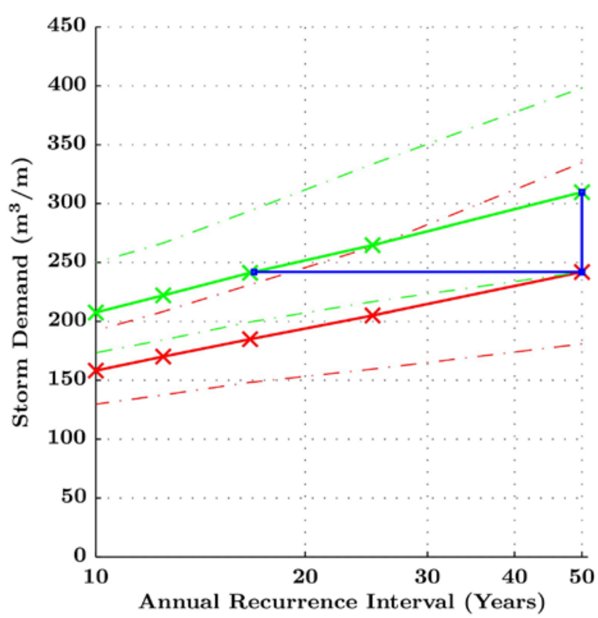

Figure 16. Annual recurrence interval storm demand for *individual events* (population A, red) and *clustered and non-clustered events* (pop. B&C), green). Dot-dashed lines represent 90% confidence limits. Projection of the 50 yr ARI for *individual events* to the ARI for *clustered and non-clustered events* with the same storm demand (blue).

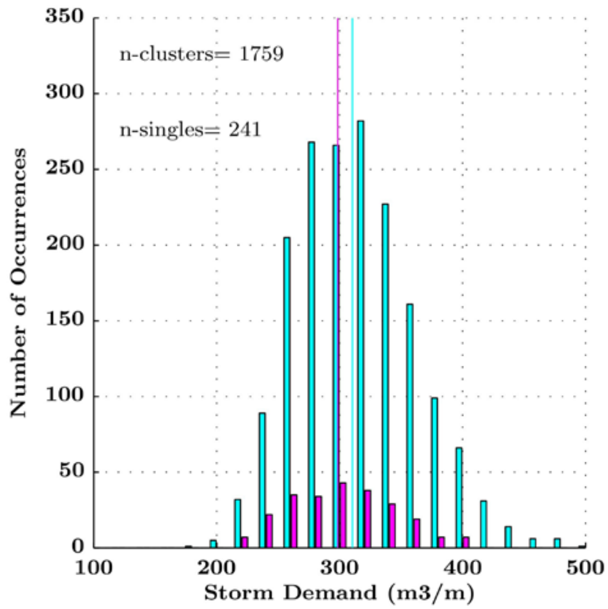

Figure 17. Histogram of rank one *clustered events* (pop. B, cyan) and *non-clustered events* (pop. C, magenta).

Conclusions

A hybrid cross-shore and longshore morphodynamic shoreline evolution model was developed to model the sediment transport inside the Old Bar coastal compartment. A suite of probabilistic synthetic time series of waves and tides were used to force the model and make robust statistical assessments of the modelled dune recession (erosion) and storm demand. Results were in line with previous studies indicating continued recessions of 0.5-1m/yr and a 50 year storm demand that exceeds 200m^3/m. A clustering analysis suggests that the expected recession and storm demand for the combined population of *clustered events* and *non-clustered events* are greater than for the population of *individual events*. However, the median storm demand for *non-clustered events* was of a similar magnitude to that of the *clustered events*. These findings suggest that traditional "design storm" methods based solely on the most severe individual storm event may tend to underestimate recession and storm demand ARI, but that *non-clustered events* may be appropriate for a design storm approach. Results will aid ongoing management and planning supported by NSW Office of Environment and Heritage and Midcoast Council to better understand the nature of the coastal hazards that continue to place some beachfront properties at risk.

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