Marine control over negative power law scaling of mass wasting events in chalk sea cliffs with implications for future recession under the UKCP09 medium emission scenario

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Abstract

Coastal cliff erosion represents a significant geohazard for people and infrastructure. Forecasting future erosion rates is therefore of critical importance to ensuring the resiliency of coastal communities. We use high precision monitoring of chalk cliffs at Telscombe, UK to generate monthly mass movement inventories between August 2016 and July 2017. Frequency-magnitude analysis of our inventories demonstrate negative power law scaling over 7 orders of magnitude and, for the first time, we report statistically significant correlations between significant wave height ($H_s$) and power law scaling coefficients ($r^2$ values of 0.497 and 0.590 for $\beta$ and $s$ respectively). Applying these relationships allows for a quantitative method to predict erosion at the site based on $H_s$ probabilities and sea level forecasts derived from the UKCP09 medium emission climate model (A1B). Monte-Carlo simulations indicate a range of possible erosion scenarios over 70 years (2020-2090) and we assess the impact these may have on the A259 coastal road which runs proximal to the cliffs. Results indicate a small acceleration in erosion compared to those based on current conditions with the most likely scenario at the site being 21.7 m of cliff recession by 2090. However, low-probability events can result in recession an order of magnitude higher in some scenarios. In the absence of negative feedbacks, we estimate an ~11% chance that the A259 will be breached by coastal erosion by 2090.
Keywords: Cliff recession, power law scaling, numerical modelling

**Introduction**

The evolution of sea cliffs has received greater attention in the research literature since the turn of the century (e.g. Lee et al., 2001; Trenhaile, 2002; Dong & Guzzetti, 2005; Teixeira, 2006; Marques, 2008; Lim et al., 2010; Hurst et al., 2016). However, decadal scale quantitative prediction of coastal erosion in response to changing environmental controls over decadal time scales remains a major research objective (Wong et al., 2014). Sea cliff environments are more dynamic than terrestrial slopes due to exogenic forcing from both sub-aerial and marine processes. These, in conjunction with material properties, control the evolution of sea cliffs (Emery & Kuhn, 1982; Lim et al., 2010). Although the mechanical properties of rock slopes are well understood (e.g. Selby, 1993; Wyllie & Mah, 2004; Stead & Coggan, 2012), deterministic approaches become impractical over large spatial and temporal scales due to the difficulties involved in parameterising the sub-surface and in predicting the variability of environmental controls (e.g. Stead & Coggan, 2012). Therefore, an alternate approach is required involving empirically-based stochastic models which extrapolate limited observations over spatial and temporal scales more applicable to landscape evolution (Barlow et al., 2012). Most estimates of future sea cliff erosion are based on change detection between historical maps and aerial photographs (e.g. Moore et al., 2003a; 2003b; Dornbusch et al., 2008). However, this approach is problematic in that measured recession rates are often similar to the precision of the data and extrapolating rates forward in time assumes erosion will not be influenced by projected changes in exogenic boundary conditions (Rosser et al., 2005; Lim et al., 2010). The ability to conduct high-precision monitoring through terrestrial or airborne laser scanning (TLS or ALS) and more recently through UAV photogrammetry has
greatly improved the precision of coastal erosion data (Slatton et al., 2007; Remondino et al., 2011; Haala & Rothermel, 2012; Hugenholtz et al., 2013; Gonçalves & Henriques, 2015). However, linking cliff erosion to environmental conditions remains difficult as mass wasting events often occur through progressive failure such that triggering events and failure do not necessarily correlate through time (Lim et al., 2010; de Vilder et al., 2017).

Magnitude-frequency analysis is a statistical method for characterising geomorphic events in space and time (Wolman & Miller, 1960; Stark & Guzzetti, 2009). A substantial amount of research has been undertaken on the methods and characteristics of landslide magnitude-frequency distributions (e.g. Hovius et al., 1997, 1998, 2000; Pelletier et al., 1997; Stark & Hovius, 2001; Guzzetti et al., 2002; Martin et al., 2002; Hergarten, 2003; Malamud, 2004; Van Den Eeckhaut et al., 2007; Brunetti et al., 2009; Rossi et al., 2010). Mathematically, these studies have demonstrated that a negative power law best describes landslide magnitude-frequency distributions, generally expressed as (Brunetti et al., 2009):

$$f(V_R) = sV_R^{-\beta}$$

where $f(V_R)$ is the frequency density, $V_R$ is the magnitude of a given event and $s$ and $\beta$ are empirically derived scaling parameters. Many authors have noted the variability of negative power law scaling parameters due to regional characteristics such as structural geology, morphology, hydrology and climate (Stark & Hovius, 2001; Dussauge et al., 2003; Brardinoni & Church, 2004; Guthrie & Evans, 2004; Malamud et al., 2004; Dong & Guzzetti, 2005; Van Den Eeckhaut et al., 2007; White et al., 2008; Marques, 2008; Brunetti et al., 2009; Rossi et al., 2010; Barlow et al., 2012). However, establishing a numerical link between the scaling parameters and environmental
conditions represents a significant challenge in applying power law statistics to predictive models of landscape evolution (Barlow et al., 2012).

The frequency of failure events along coastal cliffs is generally much higher than that of terrestrial cliffs making them ideal for magnitude-frequency analysis. This research assesses the erosion of chalk cliffs at Telscombe, UK using an inventory of mass movements derived from 12 months of high-precision monitoring. The cliffs are predominantly composed of Newhaven Chalk, which is mechanically weak. High-magnitude instability within the chalk is controlled by sliding across two key joint sets such that a wedge-type failure mechanism is common (Mortimore et al., 2004a; Barlow et al., 2017). Wave attack at the base of cliff influences stability both through direct erosion and through microseismic accelerations. Brain et al. (2014) demonstrated that microseismic shaking induced by storm waves can exceed the strength properties of weaker rocks in areas of high stress concentration. More recently, Earlie et al. (2015) observed that high-magnitude waves can cause ground accelerations an order of magnitude greater than have previously been observed and rates of erosion two orders of magnitude larger than the time-averaged mean for cliffs formed of mudstones, siltstones, and sandstones. The shear strength of joints is significantly influenced by the presence of co-planar rock bridges (Bonilla-Sierra et al., 2015). These results suggest that crack nucleation and progressive failure of rock bridges is likely accelerated due to microseismic shaking associated with high-magnitude storm waves. We hypothesise that the weakness of the chalk combined with the structural control and microseismic accelerations associated with high-magnitude storm waves act to minimise the time of progressive failure. Observations over long sections of cliff that include multiple potential failure blocks should therefore provide a quantitative link between mass movements and wave action at the base of cliff. Indeed, this research
aims to provide a constraint for the power law parameters so that future erosion at Telscombe can be determined using probabilistic erosion models. These models are based on the current and future marine projections provided by the UKCP09 medium emission forecast between 2020 and 2090 and account for sea level rise through a time of exposure approach. Our method is applicable to any coastal cliffs composed of weak rock that respond quickly to basal erosion. Results provide a probabilistic recession model that should be of great use to coastal managers.

**Study site**

Telscombe cliffs are located along the southeast coast of the UK as shown in Figure 1 and represent one of the few sections of sea cliff between Brighton and Newhaven.

Figure 1: Study area at Telscombe, UK with natural and artificial cliff toe protection identified and cliff model produced through photogrammetry (2013 aerial imagery downloaded from the Channel Coastal Observatory CCO).
that remains undefended. The main coastal road (A259) runs within 42.1m of the cliff edge with an average monthly traffic flow of 21,450 vehicles between 2013 and 2016 (Brighton & Hove City Council, 2017). Formed of Cretaceous Chalk of the Newhaven and Culver formations, the cliffs are approximately 750 m in length with dry valleys at either end of the site (Mortimore, 1997). The maximum elevation is approximately 49 m and the cliffs are orientated towards the dominant wave direction from the south-west (May, 2003). To the west the cliffs have been decoupled from wave action through construction of a sea wall and promenade and have been artificially regraded. Rock armour protects the toe of the cliff for the western 50 m of the site to prevent outflanking of the sea wall (Figure 1). At the eastern extremity a concrete groyne which protects the sewage outfall pipe acts as a barrier to the transport of sediment. As a result, a substantial shingle beach protects the toe of the cliff which tapers over approximately 300 m (Figure 1). The site is macro-tidal with an average spring tidal range of 6.1 m (CCO, 2015) which submerges the shore platform at high tide and enables wave interaction with the base of cliff on a daily basis along the exposed section. Where the cliff is protected by the shingle beach wave interaction occurs during storm events for approximately the western 50-100m when the shingle has been removed from the foreshore. For the remaining section of cliff line the shingle beach remains and therefore wave interaction for this section is minimal. Annual rainfall averages at 720 mm and significant wave heights for this section of coast average at 0.64 m and 1.04 m for the summer and winter months respectively (CCO, 2015). Kinematic analysis of the chalk at the site indicates two steeply inclined joint sets as illustrated in Figure 2 (Barlow et al., 2017). The orientation of these relative to the strike of the cliff face indicates wedge failure as the most likely mode of slope instability. These structural controls produce the characteristic pyramidal morphology
of Newhaven formation cliffs (Mortimore et al., 2004a). When saturated, Newhaven Chalk has a cohesion of 600 KN/m$^2$ and an angle of internal friction of 24° which increase to 2400 KN/m$^2$ and 43.5° respectively when dry (Mortimore et al., 2004b).

This weakness suggests that the chalk will respond quickly to changes in the stress environment brought on by wave erosion.

**Methods**

This study utilises UAV photogrammetry to populate monthly mass movement inventories based on change detection between sequential 3D cliff models. The resultant magnitude-frequency data were used to develop negative power law models whose parameters $\alpha$ and $\beta$ were correlated with $H_s$. The probability of the maximum failure volume in any given month was used to complete the methodology. Each method and parameter is explained in the following sections.

**UAV photogrammetry for obtaining a rockfall inventory**
High precision monitoring of the site was conducted using a DJI S1000 octocopter, fitted with a Nikon D810 FX DSLR 36 mega-pixel camera with an AF Nikkor 24mm f/2.8D lens. The camera settings were optimised for the aircraft speed; aperture f/8 and shutter speed of 0.002 (1/5000) sec and natural lighting conditions ISO ranged from 800-1600, over the twelve surveys. An automated flight path was used for each survey which maintained a distance of 50 m between cliff face and the camera with a flying altitude of 21 m (approx. mid-cliff height). During the flights, the camera was maintained orthogonal to the cliff face via live streaming onboard video. A traditional strip plan was selected as the best method of capture for long stretches of cliff line captured from a relatively close distance with short focal length (Birch, 2006). Flight speed was set at 3 ms^-1 with an image capture interval of 5 s such that an image was captured every 15 m. Initial surveys utilised a ground control network of 23 points located using differential global positioning system and total station surveys. Following the initial surveys, a network of flints was selected and their coordinates extracted from the models to form a relative control network which reduced the field surveying time. Survey accuracy produced a 3D standard error of 0.05 m. Bundle adjustments, generation of epipolar images and point cloud generation was undertaken in the ADAM 3DM software environment. Point clouds which had an average density of 351 points/m² were then rasterised to a cell size of 0.1m before a 2.5D change detection (Rosser et al., 2005) was undertaken between successive datasets. The 2.5D change detection was undertaken using the average plane of the cliff which was recorded at 204°. Sub-sections of the study area were investigated and showed ±4°, the impact on the results would considered to be negligible, therefore only one plane was used in all subsequent 2.5D change detection analysis. Error assessment found the greatest component residual error from any monthly dataset was 0.10m, as a result volumetric
estimations were calculated with a minimum reliable detectable rockfall size of $1 \times 10^{-3}$ m$^3$. A total of 10,085 failures were recorded over the 12 months.

**Negative power law parameter estimation**

Magnitude-frequency histograms were plotted on logarithmic axes (Figure 3A) using logarithmic binning methods (Guzetti et al., 2002; White et al., 2008; Barlow et al., 2012). Frequency densities were calculated for each bin by using the formula (Malamud et al., 2004):

$$f(V_R) = \frac{\delta N_R}{\delta V_R}$$

where $f(V_R)$ is the frequency density of events with magnitude $V_R$, $\delta N_R$ is the number of rockfalls within the specified volume range of $\delta V_R$, and $\delta V_R$ corresponds to the width of the bin. The power law parameters were found using least squares regression (LSR) on the logarithmically transformed data (Hovius et al., 1997; Korup, 2005; Barlow et al., 2012). Modelled frequencies were compared to those observed following Barlow et al. (2012) using the integral of Equation 1:

![Figure 3: Power law estimation parameters for August to September 2016 (A) frequency density and magnitude of failures for the entire study area, (B) the predicted vs. observed frequency of failures for all binned data, (C) frequency density and magnitude of failures for the undefended section and (D) frequency density and magnitude of failures for the natural defended section (shingle beach) [black lines depict best fit models].](image)
\[ \delta N_R = \int_{sV_R^{max}}^{sV_R^{min}} sV_R^{-\beta} \, dV_R \]  
(3)

\[ \delta N_R = \frac{sV_R^{max}^{-\beta} - sV_R^{min}^{-\beta}}{1-\beta} \]  
(4)

By using Equation 4 and setting the \( V_R^{max} \) and \( V_R^{min} \) to the bin widths it is possible to assess the accuracy of the estimated power law parameters against the actual observations (Barlow et al., 2012), an example taken from the month August to September 2016 is provided in Figure 3B. The \( r^2 \) value of 0.9981 shows definitive agreement between the observations and the power law model providing confidence that modelled frequencies are reliable. As the period between surveys varied, the frequency densities were normalised by time and area (\( \text{km}^2 \text{ month}^{-1} \)), with a month represented by 30.4375 days (365.25 days per year / 12 months). The study area was subdivided into 'undefended' and 'naturally defended' to account for the impact of the shingle beach on the power law estimations (E.g. Aug- Sep undefended – Figure 3C & naturally defended – Figure 3D) and subsequent analyses. The \( r^2 \) values for the power law estimation parameters (E.g. Figure 3A) varied from 0.9697 to 0.9947 for the entire study area, 0.9693 to 0.9942 for the undefended section and 0.9042 to 0.9979 for the naturally defended section (Table 1).

<table>
<thead>
<tr>
<th>Month</th>
<th>Entire study area</th>
<th>Undefended (no beach)</th>
<th>Naturally defended (beach)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta )</td>
<td>( s )</td>
<td>( r^2 )</td>
</tr>
<tr>
<td>Aug – Sep 2016</td>
<td>1.592</td>
<td>544.82</td>
<td>0.9947</td>
</tr>
<tr>
<td>Sep – Oct 2016</td>
<td>1.636</td>
<td>175.20</td>
<td>0.9916</td>
</tr>
<tr>
<td>Oct – Nov 2016</td>
<td>1.573</td>
<td>393.35</td>
<td>0.9984</td>
</tr>
<tr>
<td>Nov – Dec 2016</td>
<td>1.471</td>
<td>487.50</td>
<td>0.9870</td>
</tr>
<tr>
<td>Dec – Jan 2017</td>
<td>1.606</td>
<td>265.07</td>
<td>0.9930</td>
</tr>
<tr>
<td>Jan – Feb 2017</td>
<td>1.645</td>
<td>460.92</td>
<td>0.9875</td>
</tr>
<tr>
<td>Feb – Mar 2017</td>
<td>1.421</td>
<td>904.14</td>
<td>0.9881</td>
</tr>
<tr>
<td>Mar – Apr 2017</td>
<td>1.697</td>
<td>188.83</td>
<td>0.9701</td>
</tr>
<tr>
<td>Apr – May 2017</td>
<td>1.680</td>
<td>209.69</td>
<td>0.9697</td>
</tr>
<tr>
<td>May – Jun 2017</td>
<td>1.955</td>
<td>67.76</td>
<td>0.9811</td>
</tr>
<tr>
<td>Jun – Jul 2017</td>
<td>1.914</td>
<td>33.79</td>
<td>0.9806</td>
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Table 1: Power law estimation parameters for Telscombe cliffs (Bold identifies those used for the probabilistic modelling).
Modeling cliff erosion with Hs and sea level rise (SLR)

Erosional flux can be calculated for a given magnitude of event by multiplying the frequency density of the event by the magnitude, the result of applying this to the power law equation is (Barlow et al., 2012):

\[ V_{RC} = sV_R^\beta V_R \]  
\[ V_{RC} = sV_R^{\beta+1} \]  

where \( V_{RC} \) is the volume in m\(^3\) km\(^{-2}\) month\(^{-1}\) for an event of magnitude \( V_R \). Thus, the total volumetric erosional flux \( (V_T) \) of rock between a minimum and maximum magnitude can be calculated by (Barlow et al., 2012):

\[ V_T = \int_{V_{R,min}}^{V_{R,max}} sV_R^{\beta+1} dV_R \]  
\[ V_T = \frac{sV_{R,max}^{\beta+2}}{2\beta} - \frac{sV_{R,min}^{\beta+2}}{2\beta} \]  

The maximum volume \( (V_{R,max}) \) for Equation 8 can be easily extracted from the rockfall inventory, the minimum value can be more difficult to determine. The minimum detectable rockfall volume using our method was \( 1 \times 10^{-3} \) m\(^3\). To avoid data censoring of smaller volumes (e.g. Stark & Hovius, 2001), a value of \( 1 \times 10^{-6} \) m\(^3\) was used as the minimum threshold in Equation 8.

The distribution of the monthly power law scaling parameters was tested for correlation with Hs, temperature, precipitation, and wind speed data. The atmospheric data was downloaded from the Brighton Marina meteorological station (CCO, 2017a) and the wave data from the distal wave buoy at Seaford, approx. 8.5km from Telscombe at a depth of 11 m CD provided by the Channel Coastal Observatory (CCO, 2017b). To determine the waves which interact with the base of cliff the minimum elevation of the cliff toe was extracted from the photogrammetry models. Tidal data downloaded from the British Oceanographic Centre (BODC, 2017) for Newhaven enabled a binary classification of tidal interaction with the base of cliff. This
classification was then applied to the dataset so only waves which interacted with the cliff were considered in the analysis.

The projections of future wave climate are presented by the UKCP09 (Lowe et al., 2009) and were generated using the medium emission scenario (IPCC scenario A1B, Leake et al., 2009). This scenario was chosen as it represents the model which global climate change is most closely following (DEFRA, 2009). The wave model was run for the UK continental shelf and meteorological parameters of wind and pressure obtained from the Hadley Centre Met Office were used to force the wave and surge models (Brown et al., 2012). The regional model was divided into approximate 12km grid cells, with the nearest to the study site selected for data extraction. This grid cell was considered an appropriate level of detail for the modelling as it represents a comparable distance between the study site and the distal wave buoy (8.5km). The wave climate is therefore assumed to be representative of the area. A detailed explanation of the wave model and data generation is provided by Brown et al. (2012).

The 6-h time series dataset was grouped by month and averaged over 20 years to obtain each decade (e.g. 2010-2029 generates the decade 2020-2029) as is the case with all UKCP09 sub-aerial and marine projections. Probability plots were obtained for each month in each decade between January 2020 and December 2089 (e.g. Figure 4) and a relationship between probability and $H_s$ was found for each month. Random number generation between 0 and 1 could then be used to obtain a $H_s$ value which would calculate $\beta$ and $s$ using relationships discussed below later. To account for SLR the percentage of the tidal cycle that interacts with the base of cliff was recorded, under present conditions 28.58% of the tidal cycle is at or above the minimum cliff height. Using the relative sea level (RSL) rise data presented by the UKCP09 (Lowe et al., 2009), under the medium emission scenario, the 50th percentile
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was extracted for each year. This increase in sea level was added to the observed data and reflected as a percentage of the tidal cycle which interacted with the cliff. From the current observations to 2090 there is a predicted increase from 28.58% to 33.85%.

To reflect this in the model the total volume ($V_T$) calculated from Equation 8 under current conditions whereby 28.58% of the tidal cycle interacts with the cliff was given a scaling factor of 1. The yearly increase in sea level was then given a scaling factor relative to this base level. Therefore, by 2090 when there is a predicted increase of 5.27% in the percentage of the tidal cycle interacting with the cliff, the scaling factor applied to $V_T$ for that year was 1.0527.

For the $V_{R_{\text{max}}}$ values, a cumulative probability plot was generated (Figure 5) from the inventory so that a random number between 0 and 1 could generate a maximum failure volume to be used in Equation 8. As no single model accurately expressed the relationship between cumulative probability and maximum failure, two logarithmic relationships were selected (intersect when cumulative probability = 0.822).
Using the numerical relationships presented a Monte Carlo simulation model was run based on Equation 8. To determine the most likely erosion scenario, 10,000 iterations of the model were run from 2020-2090 (70 years). Comparisons between the model outputs and historical recession rates were undertaken to assess model reliability. The $V_T$ for 2020-2090 under current conditions, maintained for the entire temporal period, and future conditions as discussed were then used to calculate cliff top recession which enabled an assessment of the risk to the A259 coastal road for this time period.

**Model validation**

We validated our initial model results by plotting the observed $V_T$ against the modelled $V_T$. The $r^2$ value for the undefended section was very strong at 0.9918 and the model predicted 97% of the observed $V_T$ for this section. The model performs well with respect to the months with the largest failures and the model overestimates $V_T$ when the total volumetric flux for a given month is less than approximately 10 m$^3$ as also reported by Barlow et al. (2012). The undefended section produced the stronger model with respect to $H_s$ as the neighbouring section of cliff with the natural beach
offered substantial protection from wave action affecting the toe, and therefore the monthly erosion ($V_T$) of the naturally defended cliff section was significantly reduced (Table 2).

Orthorectification of aerial images from 1957, 1973, 1991 and 2013 of the study area was undertaken using photogrammetric methods. Historical recession rates were calculated using the ArcGIS extension - Digital Shoreline Analysis System (DSAS) developed by the United States Geological Society (Thieler et al., 2009). The model predicts average annual recession under current conditions of $0.29 \text{ m yr}^{-1}$, the historical recession rate obtained from the orthorectified imagery between 1957 and 2013 for the same area was $0.31 \text{ m yr}^{-1} \pm 0.16 \text{ m (2σ)}$ which is similar to other published retreat rates for the site in the scientific literature (Dornbusch et al., 2008). The similarity of the results using different methods of calculating cliff recession provides greater confidence in the model output. The subsequent analysis therefore focuses on the undefended section of cliff line.

Results and discussion

2.5D surface change detection

Our high-precision monitoring has provided evidence of erosional cycles at the site focused around the conjugate joint sets. Figure 6 illustrates the 2.5D surface change detection results which identify toe erosion between August 2016 (Figure 6A) and February 2017 (Figure 6F) totalling $104.90 \text{ m}^3$, concentrated in the lower section of the cliff. As a result of this erosion, the mean slope angle of the cliff face increased from $\sim 76^\circ$ to $\sim 80.5^\circ$. This steepening resulted in a large wedge failure observed in March 2017 (Figure 6G). Over time wave action will remove the debris at the base of cliff and restart the cycle.
Erosion modelling

We sampled mass movements across 7 orders of magnitude. Given that the largest event in our inventory involved the entire rock face at the highest point in the cliffs, we are confident that we have data covering the entire range of failure magnitudes that are possible at the site. The inventory is comprised of 10,085 mass movements with a total volumetric flux of 3,889.35 m³. The surface area of the cliff face for the entire study area is 23,597.45 m², this was subdivided into the undefended section and the naturally defended beach section with surface areas of 13,890.46 m² and 9,706.99 m² respectively. Although accounting for approximately 59% of the study area, the undefended section had a total volumetric flux of 3,872.62 m³, representing 99.57% of the entire study area total. The monthly inventories are listed in Table 2 and comparisons made between the total volumes (V_t) for the undefended (no beach) and naturally defended (beach) sub-sections. The largest failure was observed between February and March 2017 with an estimated volume of 2,546.81 m³. Other notable failures occurred between November and December 2016 and in the late summer of 2016 (August – September 2016) with estimated volumes of 512.23 m³ and 152.66 m³ respectively. Correlations can be drawn between these larger failures and the distal wave environment of the period between surveys. The average \( H_s \) for Aug-Sep, Nov-Dec and Feb-Mar were 1.26 m, 2.12 m and 2.31 m respectively. Furthermore, the percentage of waves which interacted with the cliff that were classified as distal storm waves, \( H_s > 3.85 \) m (Bovington et al., 2015), were 6% (Aug-Sep), 9% (Nov-Dec) and 14% (Feb-Mar), the highest percentage in the remainder of the dataset was 3% between May and June. These results indicate a minimal lag time between delivery of high energy waves and large magnitude events, either through
toe erosion or a significant increase in the stress environment propagating along conjugate joints (Sunamura, 2015).

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<tbody>
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<td>Undefended (no beach)</td>
<td>119.16</td>
<td>622.01</td>
<td>64.41</td>
<td>31.42</td>
<td>2702.04</td>
<td>20.07</td>
<td>32.03</td>
<td>4.59</td>
<td>2.24</td>
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<tr>
<td>Naturally defended (beach)</td>
<td>0.81</td>
<td>1.02</td>
<td>0.47</td>
<td>1.83</td>
<td>1.59</td>
<td>0.67</td>
<td>3.79</td>
<td>1.8</td>
<td>0.69</td>
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</table>

Table 2: Monthly observed total volumetric erosion ($V_t$) for the undefended and naturally defended cliff line at Telscombe.

**Scaling parameters**

Significant linear regression correlations, at the 95.5% (2σ) confidence level, were found between $H_s$ and the $\beta$ and $s$ values with $r^2$ values of 0.4971 and 0.5902 respectively for the undefended section of cliff (Figure 7A & 7B). A dataset with a greater spatial extent would likely increase the strength of these relationships as the site has a limited number of conjugate joint sets where wedge failures occur, each at a different stage of the failure cycle. Reoccuring failures are therefore temporarily limited by the erosional cycle. With a greater sample of conjugate joint sets the likelihood that delivery of high energy waves would lead to failure is increased, thus strengthening the relationships between $H_s$ and the power law scaling parameters. The linear regression relationship between $s$ and $H_s$ intersects the x axis at 0.602 m for the undefended section (Figure 7B). When comparing the erosion activity to the $H_s$ values from the observation dataset it was considered appropriate to determine that if the value of $H_s$ in the model was below this threshold the erosion activity would be set to zero. Furthermore a control site at Brighton marina, where the cliffs are...
protected disconnected from wave energy by a sea wall recorded no detectable erosion during the same period. Although sub aerial and marine erosion below the threshold do occur, the influence of these on the total overall mass flux appears to be negligible. No significant correlation was found between the scaling parameters and wave direction (r² values of 0.0884 for β and 0.0293 for s), or sub-aerial conditions of precipitation (r² values of 0.0002 for β and 0.0006 for s) and air temperature (r² values of 0.2628 for β and 0.2178 for s) for the undefended section. Likewise there were no significant correlations found for the naturally defended beach section for any marine or sub-aerial variables considered.

The s value provides an indication on the level of activity within a given dataset whereas β describes the relative contribution of high-magnitude events to the total volume (Barlow et al., 2012). For example, as β increases, smaller magnitude events contribute a greater amount to the total volume than the larger magnitude failures. The normalised scaling parameters for the undefended section of cliff vary between 1.409 to 1.829 for β and from 59.36 to 1459.50 for s. The range in β values is consistent with those presented in other scientific research (Van Den Eeckhaut et al., 2007; Brunetti et al., 2009; Barlow et al., 2012). The smaller β and larger s values are generally found in the winter months (winter ave. β=1.537, ave. s=895.51, summer...
ave. $\beta=1.744$, ave. $s=348.38$) when an increase in erosion would be expected due to
the frequency of storms. With regards to the maximum failure volume ($V_{max}$), this is
primarily controlled by the slope morphology (Martin et al., 2002). By finding
statistically significant relationships between the scaling parameters ($\beta$ & $s$) with $H_s$
the power law model can be constrained to provide a useful predictive capability for
future coastal management which is presented in the following section.

Erosion scenarios

Results from our Monte Carlo simulations enabled a comparison between
predicted erosion under current conditions and that predicted under UKCP09
conditions. Scaling parameters were controlled through the derived relationships with
$H_s$ (Figures 6A & 6B) and the maximum failure volume calculated using the cumulative
probability relationships found from the inventory (Figure 5).

The results of the Monte Carlo simulation are provided in Figure 8 and Table 3.
The mean total recession increases by 1.31 m (approx.+6%) over the 70 year period

![Figure 8: Monte Carlo simulation histogram of Log10 transformation of total recession between 2020 and 2090.](image)
between the future and current conditions (Table 3), highlighting the impact of future
sea level rise and an increase in significant wave height. The results from the Monte
Carlo simulation were normally distributed with a strong positive skew due to the
influence of extreme events. In order to apply parametric statistics, the skew was
eliminated using a log_{10} transformation as shown in Figure 8. The maximum recession
distances produced by the model were 121.97 m and 143.56 m under current and future conditions (under the UKCP09 medium emission scenario) respectively. The reason for these extremes values are twofold, firstly due to the high magnitude failure (2546.81 m$^3$) observed in the February to March 2017, this magnitude of failure can be generated in any month of the simulation due to the cumulative probability relationship (Figure 5). This, in combination with projected increases in $H_s$, enables the model to predict a monthly $V_T$ several orders of magnitude greater than observed in the inventory during the 70 year simulation. However, it should be noted that for these extreme cases the frequency of occurrence was reported as 1/10,000. As the model was run over a 70 year period, the chance of this extreme event occurring is one in 700,000 years. This corresponds to over three standard deviations from the mean under both current and future conditions, reaffirming the unlikelihood of occurrence. The influence of the extreme events impacts the standard deviation resulting in annual recession uncertainty that is approximately three times greater than the calculated historical recession rates ($2\sigma$). However, assessing the range of recession values closer ($<2\sigma$) to the mean (Figure 8) reveals a significant chance that recession totals between 30 - 60 m over the 70 year period.

<table>
<thead>
<tr>
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<th>Current conditions</th>
<th>UKCP09 medium emission forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recession (m)</td>
<td>Log$_{10}$(m)</td>
</tr>
<tr>
<td>Average</td>
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<td>20.45</td>
</tr>
<tr>
<td>Max</td>
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<td>121.97</td>
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<tr>
<td>Min</td>
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<td>5.18</td>
</tr>
<tr>
<td>95.5%CI</td>
<td>1.750</td>
<td>56.26</td>
</tr>
</tbody>
</table>

Table 3: Results of Monte Carlo simulation.
The distance between the cliff edge and the A259 ranges between 42.07 m to 52.75 m with an average of 46.62 m. Under the most likely erosion scenario (mean in Table 3) approximately 56.6% and 59.7% of the area between the cliff line and minimum distance to the road could be lost by 2090 for current and future conditions respectively (Figure 9). Under both modelled scenarios the 95.5% certainty limit breaches the A259 coastal road (Figure 9) and therefore highlights the potential risk to infrastructure if recession exceeds the modelled average. Assessing the minimum distance from the cliff top to the road approximately 8% of model runs would lead to a breach under current conditions, this increases to about 11% accounting for future conditions as illustrated in Figure 10. The results from this analysis indicate that coastal management policies may need to be reviewed with regards to the current position and future risk to the coastal road. As evidenced with neighbouring sections of cliff line when defences have been installed the annual recession rate has decreased by an order of magnitude. Beach growth is a negative feedback to cliff erosion, where recession results in delivery of flint from the cliff to the beach.

Figure 9: Decadal total cliff recession from Monte Carlo Simulation after 10,000 model runs (Mean recession depicted by data points).
Alternatively accelerated recession within the undefended section could create an embayment and lead to the formation of a pocket beach. The effectiveness of a beach at the cliff toe is evident from the naturally defended section with a significant reduction in erosion (Table 2). The model predictions assume the current state of the site, undefended versus naturally defended (beach), persists into the future.

![Figure 10: Probability of cliff erosion breaching the A259 at Telscombe cliffs assuming current $H_s$ conditions (grey line) and the UKCP09 forecast for $H_s$ (black line)](image)

**Conclusions**

This study demonstrates the first statistical link between power law scaling parameters and significant wave height ($H_s$). This relationship suggests that there is minimal lag between delivery of high energy waves to the base of cliff and failure events. Such relationships offer the potential to quantify the evolution of landscapes under varying environmental boundary conditions. Our results demonstrate the importance of $H_s$ in driving cliff recession at the site, and offer the potential to quantify the evolution of landscapes under varying marine conditions. This relationship suggests that there is minimal lag between delivery of high energy waves to the base of cliff and failure events. The simulations involving increased $H_s$ predicted by the UKCP09 model result...
in a slight acceleration in cliff recession at the site with the most likely outcome being 21.7 m by 2090. However, the possibility of extreme events within the model is such that the probability of breaching the A259 increases from ~0% in 2020 to ~11% by 2090. The model presented explains ~50% and ~59% of the variation of $\beta$ and $s$ respectively. Much of the remaining variability is probably controlled by endogenic processes and represents an interesting topic for future research. Although our approach is data hungry, once the inventory data is in place it does not require specialist software to run the simulations such that predictions can be readily updated should improved climate forecasts become available. These methods are transferrable to other sites where the lag between triggering events and mass movement are considered to be minimal. Therefore, our method provides coastal managers with a probabilistic tool to evaluate potential risk to infrastructure through time to facilitate effective planning and mitigation.

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