

Extreme Water Levels for Australian Beaches using Empirical Equations for Shoreline Wave Setup

J. G. O'Grady¹, K. L. McInnes¹, M. A. Hemer², R. K. Hoeke¹, A. Stephenson³ and F. Colberg⁴.

¹CSIRO Ocean and Atmosphere, Melbourne, Australia. ²CSIRO Ocean and Atmosphere, Hobart, Australia. ³CSIRO DATA61, Melbourne, Australia. ⁴BOM, Melbourne, Australia.

Corresponding author: Julian O'Grady (julian.ograde@csiro.au)

Key Points:

- Quantile comparison of shoreline wave setup equations vs measurements demonstrates their ability to predict the highest measured levels
- New ~30yr hindcasts of shoreline wave setup are used with a storm-tide hindcast to predict the extreme mean total water level climate
- Beach slope is shown to be important to the contribution of waves to mean total water levels

Keywords

Shoreline wave setup; mean total water level; extreme water level; empirical regression analysis; hindcast

Abstract

Empirical equations for wave breaking and wave setup are compared with archived shoreline wave setup measurements to investigate the contribution of wind-waves to extreme Mean Total Water Levels (MTWL, the mean height of the shoreline), for natural beaches exposed to open ocean wind-waves. A broad range of formulations are compared through linear regression and quantile regression analysis of the highest measured values. Shoreline wave setup equations are selected based on the availability of local beach slope data and the ability of the quantile regression to show a good representation of the highest measured levels. Wave parameters from an existing spectral wave hindcast are used as input to the selected equations and are combined with a storm-tide time series to quantify the relative contribution of shoreline wave setup to the extreme MTWL climate along Australian beaches. A multi-pass analysis is provided to understand the ability to capture the shoreline wave setup estimates with and without considering beach slope. The national scale analysis which does not include beach slope indicates there are multiple contributing factors to MTWL. Examples are provided at two locations of differing local beach slope to show the importance of including local beach slope in determining the contribution of waves to MTWL. A tool is in development for further investigation of wave setup for Australian beaches.

38 Plain Language Summary

39 Understanding how high ocean water levels can reach up the coast is important for designing
40 coastal protection from coastal inundation and erosion. This is particularly important as
41 climate change affects wind and weather conditions and sea-level rise with the subsequent
42 modification to the occurrence of the largest storm-driven water levels. While the height of
43 storm-driven water levels are well understood for protected harbors and estuaries, new
44 research is providing estimates of how high water levels can reach for coastlines exposed to
45 dangerous wave/surf conditions. This study uses mathematical model simulations spanning
46 ~30 years of historical water levels and ocean waves. Statistical analysis is performed to
47 determine how high the largest storm events will likely reach on natural sandy beaches
48 directly exposed to large wave/surf conditions. The study demonstrates that estimates are
49 very sensitive to local beach characteristics. The paper presents the science behind a tool
50 (which is in development) to allow further investigation of the contribution of waves/surf to
51 the highest water levels for individual beaches.

52

53 1. Introduction

54 Understanding the climate of extreme water levels is important for coastal protection,
55 particularly as climate change affects wind and weather conditions and sea-level rise,
56 subsequently modifying extreme water levels (McInnes et al., 2016; Vitousek et al., 2017;
57 Vousdoukas et al., 2018; Wong et al., 2014). The contributing processes to water level
58 extremes include ocean-basin scale steric and barotropic sea levels, astronomical tide,
59 atmospheric forced coastal storm surge, wind-wave driven wave setup and wave runup, each
60 of which can occur in isolation or coincidentally. Wave setup is defined as the increase in the
61 mean water level across the surf zone due to the presence of waves and can be a major
62 contributor to inundation for coastlines exposed to large waves (O'Grady & McInnes, 2010).
63 Wave setup provides the mean contribution of waves to the shoreline water level. Wave
64 runup provides the further contribution of waves to shoreline water levels by including higher
65 water levels which are only reached by the highest swash motions up the beach face. In this
66 manuscript the term Mean Total Water Level (MTWL) is used to indicate the mean height of
67 shoreline water level with the inclusion of wave setup, juxtaposed to the Total Water Level
68 (TWL) which has been used to indicate the shoreline height which is exceeded at higher
69 percentiles (e.g. 2% exceedance percentile or maximum height) of the water level with
70 inclusion of wave runup (e.g. Serafin et al., 2017).

71 There is increased interest in the contribution of waves to extreme water levels given recent
72 storm events, for example the Sydney June 2016 event (Mortlock et al., 2017) and reports on
73 the compounding effect of sea level rise on wave-driven extreme events (Melet et al., 2018;
74 Rueda et al., 2017; Vitousek et al., 2017). There is also increasing availability of regional and
75 global hindcast and reanalysis datasets of the various contributing factors to extreme water
76 level, and a requirement to provide these data through climate services (Le Cozannet et al.,
77 2017). Accurate predictions of the contribution of waves to MTWL (or TWL) are dependent
78 on the local beach slope (Nielsen, 1988). The lack of systematic beach-profile measurements
79 makes it difficult to accurately predict the contribution of waves to MTWL at the global or
80 national scale (Turner et al., 2016). There are also few observations of the contribution of
81 waves to MTWL, particularly in Australia, to validate the model prediction of extreme wave
82 conditions (Hanslow & Nielsen, 1993; Nielsen, 1988).

83 Australia has a wide diversity of coastal beaches, including fringing reef coastlines and rocky
84 platforms, each of which produce a different shoreline wave effect (Buckley et al., 2018;
85 Merrifield et al., 2014; Power et al., 2018). As first step to identifying the contribution of
86 waves to extreme water levels, this paper will focus on estimates for natural sandy beaches
87 directly exposed to open ocean wind-waves only. Estimates will be provided for the entire
88 coast for continuity in the first pass analysis, which will include cliffed coastlines and
89 coastlines behind fringing reefs. Therefore, local scale interpretation of the national maps
90 should consider the nearshore bathymetry and coastal geomorphology. This initial effort to
91 include waves will also limit the focus on the shoreline wave setup, which is the maximum
92 value of the wave setup water surface across the surf zone and is measured as the time-
93 averaged height of the shoreline. The analysis of wave runup, measured as higher percentile
94 shoreline heights, is not presented in detail here to narrow the focus of the study to wave
95 setup. Wave runup has related processes and empirical equations to shoreline wave setup and
96 is as important as wave setup to extreme sea level hazards. The remainder of this paper is
97 organised with a review of previous studies on extreme water levels (Section 2), shoreline
98 wave setup equations (Section 3) and description of the data and models used in this study
99 (section 4). Results are presented (Section 5) reanalysing historic field measurements, then
100 providing national maps of shoreline wave setup and MTWL as a broad scale analysis
101 followed by examples for Australian beaches. Discussion and conclusions are provided
102 (Section 6) with the aim of developing a tool to access the return level curves for MTWL for
103 each Australian Beach.

104 **2. Extreme water level climate**

105 The contributors to extreme water level, (e.g. MTWL or TWL), depend on where the water
106 level is measured (Figure 1) and the statistical measure of the water level, (e.g. mean or 98th
107 percentile value). The different terms for the contributors are summarised in Table 1. This
108 definition of MTWL as used in this paper is along the lines of the TWL but without wave
109 runup heights at the beach as described in Serafin et al., (2017).

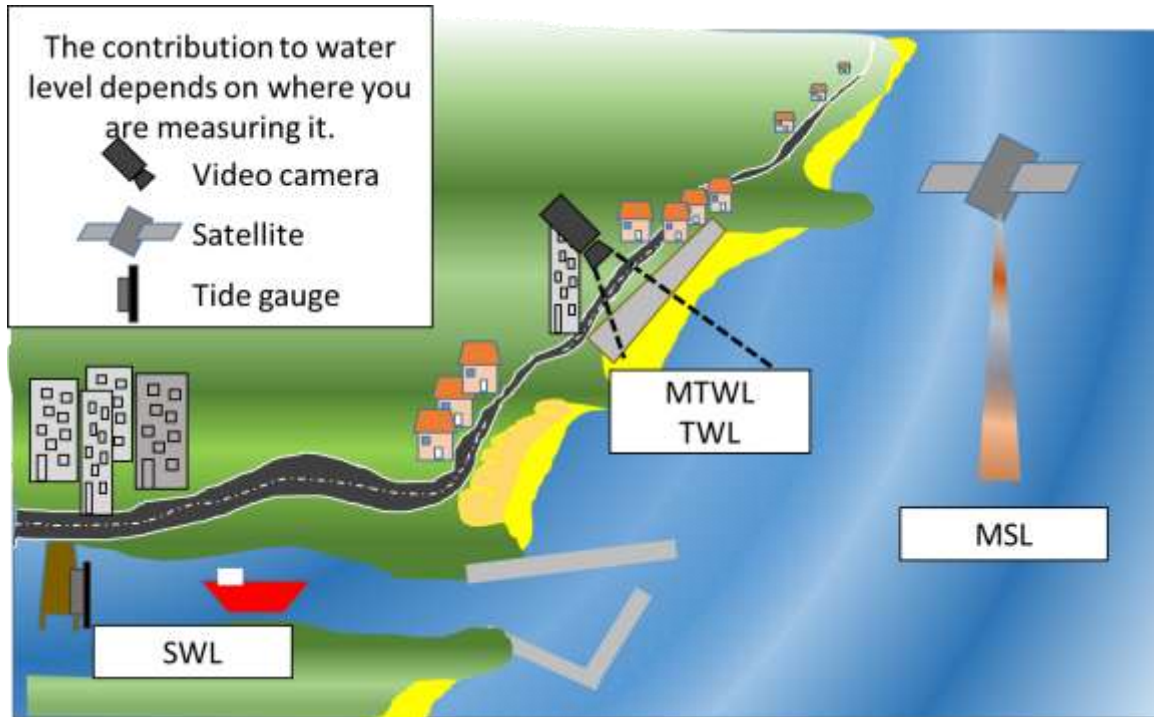


Figure 1 Diagram showing the location of different measurements of extreme water level. Vertical level abbreviations are described in Table 1.

110

111 Figure 2 shows the cross-shore beach profile of the contributors to MTWL and TWL. Above
 112 a physical datum, the still water level (SWL) is defined as the time-averaged water level (on
 113 the order of 6 minutes to one hour) due to astronomical tide, atmospheric driven water level
 114 (surge) and steric and barotropic effects. For an open ocean beach, the SWL is assumed to be
 115 horizontal across the surf zone (Figure 2). Wave setup is defined as the increase in the time-
 116 averaged (on the order of 15 minutes to one hour) water level due to the presence of waves.
 117 The horizontal wave setup water surface increases shoreward across the surf zone (Figure 2).
 118 The maximum value of wave setup, which occurs at the beach face is defined as the shoreline
 119 wave setup and it corresponds to the MTWL (Table 1). Shoreline wave setup is measured as
 120 the time-averaged swash line height relative to the SWL. It is assigned the term shoreline
 121 wave setup $\bar{\eta}_s$, where η is the free water surface relative to the SWL, the over-bar denotes the
 122 time-average and the subscript s indicates that it is at the location of the shoreline.

123

124 *Table 1 Description of water level terms. In each column, a bold 'X' indicates the important*
 125 *measured component(s) which differentiates the water level term from the water level terms*
 126 *in the other columns. See Figure 2 for graphical representation.*

Description	Mean sea level	Still water level	Mean total water level	Total water level
Abbreviation	MSL	SWL	MTWL	TWL
Commonly Measured by a location	Satellite altimeter Open ocean	Tide gauge Sheltered harbor	Video camera Beach shoreline	Video camera Beach shoreline
Includes:				
-Wave runup				X
-Wave setup			X	x
-Atmospheric surge		X	x	x
-Astronomical tide	x	X	x	x
-Barotropic	X	x	x	x
-Steric	X	x	x	x
Typical sampling statistic	Interannual mean	6-60 min mean	15-60 min mean	15-60 min 98 th percentile
How is the important component (X) resolved?	Low-pass filter	Harmonic tidal analysis and high-pass filtered storm surge	SWL at the tide gauge subtracted from MTWL	SWL at the tide gauge subtracted from TWL

127

128 Studies have investigated the contribution of waves to TWL at a global and national scale
 129 (Melet et al., 2018; Serafin et al., 2017). In Australia, studies have investigated the extreme
 130 water level climate considering tide and storm surge contributions, using tide gauge
 131 measurements and hindcast simulations that represent the SWL at the coast (Colberg et al.,
 132 2019; Haigh, MacPherson, et al., 2014; Haigh, Wijeratne, et al., 2014). In this study a
 133 historical dataset of wave setup is generated from a numerical spectral wave hindcast
 134 (Durrant et al., 2013). Empirical shoreline wave setup equations are then used to estimate the
 135 contribution of wave setup to the extreme MTWL climate along the ocean coast of Australia.

136

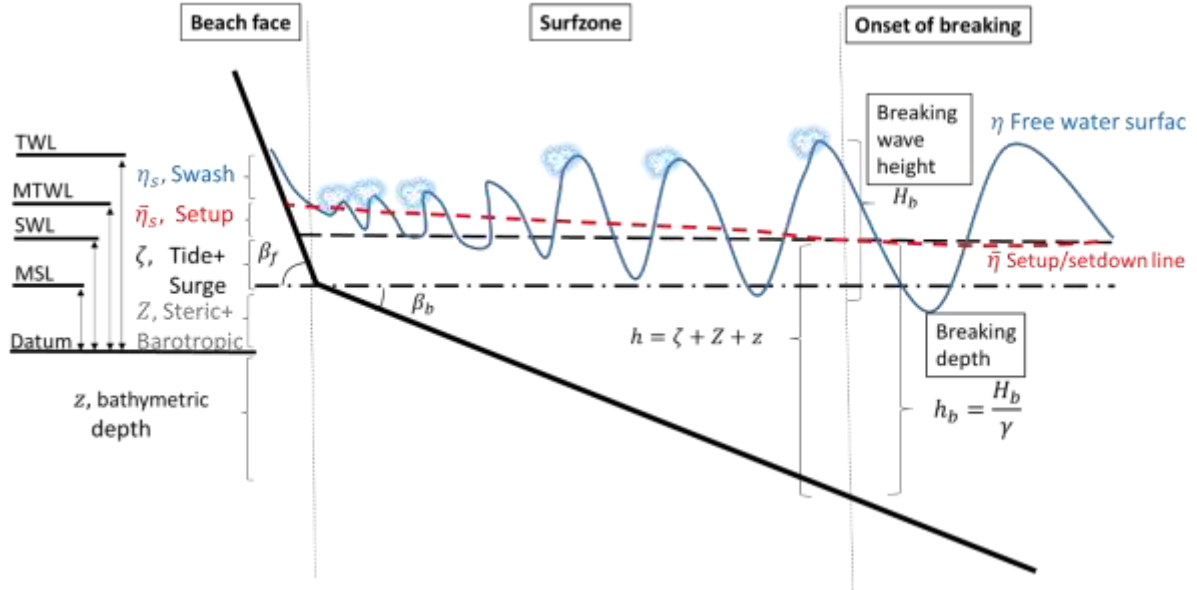


Figure 2 Diagram of wave setup in extreme water levels. Blue curved line is the instantaneous free water surface wave η , red dashed curve is the time-averaged wave setup and set down water surface $\bar{\eta}_s$, black dashed line is the still water level (SWL), black dot-dashed line is the mean sea level (MSL) and black solid line is the beach bathymetric profile z . Vertical water level abbreviations (MSL, SWL, MTWL and TWL) are described in Table 1. H_b is the height of the waves at the onset of breaking.

137 **3. Shoreline wave setup equations for natural sandy beaches**

138 The mathematical theory of wave setup, represented by partial differential equations (PDEs)
 139 for the wave stress gradient (Longuet-Higgins & Stewart, 1964) has been used to predict
 140 wave setup across the surf zone, e.g. by solving the numerical approximations of the PDEs,
 141 as done in the SWAN model (Battjes and Janssen, 1978; Holthuijsen, 2007). The PDE in the
 142 cross-shore direction can be simplified with the generalised assumption that across the surf
 143 zone the ratio of wave height to depth (γ , breaking parameter) remains constant and waves
 144 are non-dispersive in the shallow water (wave group speed equals the phase speed). This
 145 simplification results in the horizontal gradient in wave setup being roughly proportional to
 146 the bathymetric gradient (Longuet-Higgins & Stewart, 1964). The PDE of wave setup can
 147 then be simply integrated horizontally across the surf zone to work out the value of wave
 148 setup at the shoreline (Dalrymple & Dean, 1991; Holthuijsen, 2007),

$$\bar{\eta}_s = \alpha \gamma H_b, \quad 1$$

149 where H_b is the height of the waves at the onset of breaking and α is the constant value of
 150 0.31 in Holthuijsen, (2007) and varies with γ in Dalrymple and Dean, (1991). The challenge
 151 with this equation is that H_b is difficult to measure in the field, and there is no analytical
 152 equation relating H_b to deep water wave theory characteristics. Furthermore the assumption
 153 on a constant breaking parameter across the surf zone is questionable (e.g. Apotsos et al.,
 154 2008).

155 Shoreline wave setup $\bar{\eta}_s$ has been measured (as the mean elevation at the shoreline relative to
 156 the SWL) by pressure sensors, resistance wires, photogrammetry (video cameras) and remote
 157 SONAR or LIDAR ping-return range finder sensors (Brodie *et al.*, 2015; Gourlay, 1992;

158 Stockdon *et al.*, 2006 and references therein). Accompanying this, regression analysis has
 159 shown relationships between empirical parametrisations and measurements of shoreline wave
 160 setup, wave and beach characteristics. The simplest regression parametrisation relates $\bar{\eta}_s$ as
 161 proportional to deep water wave height, which is commonly referred to as the ‘rule of thumb’
 162 (Guza & Thornton, 1981). More involved empirical relationships have presented a
 163 dependence on the surf similarity or Iribarren number (Bowen *et al.*, 1968; Nielsen, 1988),
 164 which compares the bathymetric (β_b in Figure 2) or beach slope (β_f in Figure 2) to the wave
 165 steepness ratio and has been used to predict breaking type, surging, plunging or spilling
 166 breakers (Iribarren & Nogales, 1949),

$$\xi = \beta \left(\frac{H}{L}\right)^{-n}, \quad 2$$

167 where β represents the bathymetric or beach slope, H is the wave height and L is the wave
 168 length. The exponent n is most commonly assigned the value of 0.5, but 0.3 has been used
 169 (Gourlay, 1992). Using Equation 2, regression analysis has shown,

$$\bar{\eta}_s \propto \alpha H \xi, \quad 3$$

170 where α is the slope parameter of the zero crossing regression analysis. Differences in the
 171 empirical formulation of γ , ξ and $\bar{\eta}_s$ throughout the literature arise because the wave
 172 parameters can represent bulk parameters, such as significant wave height (H_0), peak period
 173 (T_p) measured in the field, or represent individual waves in flume studies to better align with
 174 linear wave theory. The wave parameters can also represent deep water waves or the waves at
 175 the onset of breaking.

176 We note that the main difference between the mathematical solution to $\bar{\eta}_s$ in Equation 1 and
 177 the empirical regression parametrisation in Equation 3 is that the former is formulated on the
 178 basis of the bathymetric slope (β_b) across the surf zone, i.e. radiation stress from wave
 179 shoaling (setdown) and depth-induced breaking, and the latter is dependent on beach slope
 180 (β_f), i.e. wave swash which is influenced by the asymmetric swash/runup effect on the beach
 181 slope (Gourlay, 1992; Holman & Sallenger, 1985). This is important when considering that
 182 the measured mean shoreline level (shoreline wave setup) is a function of both wave breaking
 183 induced setup across the surf zone, and a component of time-averaged asymmetric swash
 184 effect. Having noted this, numerical coupled wave-hydrodynamic models have been tuned to
 185 match both the empirical models (Equation 3) and measurements and account for the
 186 combined bathymetric depth-induced breaking induced setup and beach swash slope effect (Ji
 187 *et al.*, 2018; Stockdon *et al.*, 2014).

188 An approach which could be considered to have separated the contribution of bathymetric
 189 depth-induced breaking and beach swash processes, though not explicitly indicated, is the
 190 spectral partitioning analysis of the swash height (Buckley *et al.*, 2018; Stockdon *et al.*, 2006,
 191 2014). The bathymetric depth-induced breaking effect could be largely (but not exactly)
 192 attributed to spectral significant height of frequencies lower than the chosen threshold, e.g.
 193 0.05Hz (infragravity waves) and the beach face swash effect to significant height of
 194 frequencies higher than that threshold (incident waves) considering the studies such as Guza
 195 & Thornton, (1982); Symonds & Bowen, (1984). Here, the data presented in Stockdon *et al.*,
 196 (2006) indicates that the measured significant swash height contributions from the
 197 infragravity partition (bathymetric depth-induced breaking) and incident partition (beach face
 198 swash) are of similar magnitude for the chosen partition frequency (0.05Hz).

199 Other studies have added an extra wave setup term to the parameterisation of wave runup to
 200 improve their regression analysis of wave runup, but do not directly attribute this extra
 201 parameter to either the depth-induced breaking or a mean component of the asymmetric
 202 beach face swash effect (Atkinson et al., 2017; Holman, 1986). Nevertheless, from multiple
 203 lines of evidence, regression analysis against measurements and numerical model simulations
 204 has shown the parametrisation of the combined $\bar{\eta}_s$ from bathymetric depth-induced breaking
 205 induced setup and beach swash effect to be proportional to the wave height (at breaking or in
 206 deep water) multiplied by the surf similarity parameter (Equation 3).

207 Few field measurements of shoreline wave setup exist at coastal locations in Australia
 208 (Nielsen, 1988; Nielsen & Hanslow, 1991). In the subsequent sections of this study we test
 209 empirical equations for wave breaking and wave setup (Gourlay, 1992) with setup
 210 measurements using video cameras from beaches in the Northern Hemisphere (Stockdon et
 211 al., 2006) to understand the ability of the different empirical formulations to predict shoreline
 212 wave setup. These equations are then compared to measurements in Australia of swash
 213 transgressions past an array of stakes utilising the assumption that the shoreline follows a
 214 Rayleigh distribution (Nielsen & Hanslow, 1991). Spectral wave hindcast fields (Durrant et
 215 al., 2013) are provided as input to the selected empirical equations and combined with a time
 216 series of regional ocean model system (ROMS) modelled SWL (Colberg et al., 2019) to
 217 resolve the contribution of shoreline wave setup to the extreme MTWL climate at Australian
 218 beaches.

219 4. Measurements, model data and methods

220 4.1. Observations

221 Observations of waves, beach slopes and shoreline wave setup were sourced from the video
 222 camera experiments presented by Stockdon et al., (2006). Deep water wave length is
 223 estimated with the equation,

$$L_0 = gT_0^2 / (2\pi), \quad 4$$

224 where L_0 is the deep water wave length and T_0 is the deep water peak period.

225 Additional Australian field data of waves and setup were sourced from Nielsen & Hanslow,
 226 (1991). Here, shoreline wave setup was measured by counting the swash transgression past a
 227 number of stakes. Assuming swash waves follow a Rayleigh distribution, $\bar{\eta}_s = 0.89L_{zwm}$,
 228 where $L_{zwm} = C_1(H_{0,rms}L_0)^{0.5}$, C_1 is the best-fit parameter and $H_{0,rms}$ is the root-mean-
 229 squared wave height. By convention, wave heights are assumed to obey the Rayleigh
 230 distribution in deep water, indicating that, $H_0/H_{0,rms} = \sqrt{2}$ (Ji et al., 2018). Here the L_0 was
 231 calculated with Equation 4 with T_0 equal to the deep water significant wave period T_s . The
 232 non-directional Sydney wave-rider buoy measurement for the study period (1988-1990)
 233 indicate $H_0/H_{0,rms} \approx \sqrt{2}$ and $T_p/T_s \approx 1.2$.

234 Observed tide gauge SWL return levels were sourced from Haigh *et al.*, (2014a). These
 235 values were used for validation of the extreme value distributions fitted to the ROMS
 236 hindcast data.

237 Beach slope observations were selected from the long term beach profile monitoring on the
 238 New South Wales (NSW) coastline (Turner et al., 2016, <http://narrabeen.wrl.unsw.edu.au/>).
 239 The mean intertidal beach slope for the five transects was calculated as slope between the

240 linear interpolated zero and 2m water elevations which correspond to the range of the
241 intertidal zone and is relative to the Australian Height Datum (AHD)(Turner et al., 2016).

242 **4.2. Numerical hindcast data**

243 Time series of SWL from computed storm surge and tide (storm-tide) were sourced for a
244 string of points around the coastline at 10km intervals from a ROMS model simulations
245 (Colberg et al., 2019). The ROMS model was run from the start of 1981 to the end of 2013 on
246 a ~5km resolution regular grid and was forced with hourly ~38km grid resolution Climate
247 Forecast System Reanalyses (CFSR) atmospheric data. The ROMS hindcast is used in this
248 study because it uses the same atmospheric reanalysis as the wave model and because of the
249 availability of end of 21st century climate simulations for future research into the changes in
250 extreme water level climate. Extreme SWL distributions fitted to a modelled hindcast using
251 Danish Hydraulic Institute's (DHI) Mike-21 flexible mesh model were sourced from Haigh *et*
252 *al.*, (2014a) at the same string of points around Australia as the ROMS simulations. The
253 Mike-21 model was run from 1949 to 2009 on a unstructured grid, with a maximum
254 resolution of ~10km at the coast and forced by 6 hourly ~250km grid resolution National
255 Center for Environmental Prediction (NCEP) atmospheric data. The Mike-21 distributions
256 were used to reference the 1-year ROMS SWL to the Australian height datum (AHD), using
257 the method described in Haigh, Wijeratne, et al., (2014). For each corresponding ROMS
258 coastal point, the nearest grid point in a depth of at least 20 m was identified in a Wave
259 Watch three (WWIII) spectral wave hindcast (Durrant et al., 2013) which was run on a ~7km
260 grid. At these locations, the significant wave height and peak wave period is extracted for the
261 years 1981 to 2013 inclusive. Empirical wave setup was calculated at all coastal WWIII
262 points for every output time step. A time series of MTWL is computed by adding the hourly
263 time series of empirical wave setup $\bar{\eta}_s$ to the hourly time series ROMS SWL.

264 **4.3. Extreme value analysis**

265 The annual maximum method (AMM) is used to evaluate extreme MTWL, shoreline wave
266 setup, and SWL, where the highest value each year is selected to create time series of yearly
267 annual maximum values. For longer return periods, the annual recurrence interval (*RI*) can be
268 written in terms of the probability of exceedance (*EP*) (Pugh, 1996),

$$RI(EP) = -1/\log(EP) \quad 5$$

269 This approximation, which is used for plotting in R statistical software package *ismev* (Coles,
270 2001), can be used with the Gumbel distribution quantile function (cumulative distribution
271 function) to predict the water level return interval extreme value distribution (EVD),

$$z(RI) = \mu - \lambda \log\left(\frac{1}{RI}\right), \quad 6$$

272 where *z* is the water level return level corresponding to either the shoreline wave setup ($\bar{\eta}_s$),
273 SWL or MTWL, μ is the location parameter, and λ is the scale parameter fitted to the
274 hindcast AMM values. The Gumbel EVD was preferred over EVDs that include an additional
275 shape parameter, to avoid including the assumption that the ~30 year dataset is long enough
276 to also correctly represent this additional parametric term of asymptotic curvature at higher
277 RI (Arns et al., 2013). R's *ismev* package is used to fit Equation 6 to the AMM hindcast data
278 to identify the maximum likelihood estimates of the μ and λ parameters and their covariance
279 matrix (*COV*). The 5 and 95th percentile uncertainty curves are calculated as,

$$z_u(RI) = \mu - \lambda \log\left(\frac{1}{RI}\right) \pm 1.96se(RI), \quad 7$$

280 where $se(RI)$ is the standard error calculated as,

$$V(RI) = [1, \exp(-1/RI)] \times COV \times [1, \exp(-1/RI)]^T, \\ se(RI) = \sqrt{V}, \quad 8$$

281 and V is the matrix multiplication of the exceedance probabilities with the covariate matrix
 282 (COV) from the model fit. The Gumbel parameters in Equation 6 were first calculated from
 283 the AMM of the hourly time series for each coastal point in the ROMS SWL simulations,
 284 then from the hourly time series for the corresponding WWIII point for two shoreline wave
 285 setup ($\bar{\eta}_s$) equations, and finally from the hourly time series of the ROMS SWL added to
 286 each of the hourly shoreline wave setup equations to create the MTWL time series. The one
 287 year and 100-year RI return levels were then calculated with Equation 6 for the SWL,
 288 shoreline wave setup and MTWL using the corresponding Gumbel parameters.

289 5. Results

290 5.1. Validation of empirical equations for shoreline wave setup

291 In this section an empirical relationship is sought to describe shoreline wave setup from the
 292 list the equations in Table 2 that have been used in regression analyses with empirical
 293 measurements of shoreline wave setup (Stockdon et al., 2006). Some of the equations are
 294 more related to wave breaking than shoreline wave setup (e.g. Van Dorn, 1978). The order of
 295 the equations in the table starts with a single dependence of deep water significant wave
 296 height H_0 then includes beach slope β_f and the wave steepness $(H/L)^{-n}$ parameters from
 297 Equation 2. Beach slope in the empirical dataset changes on the time scale of a single tidal
 298 cycle and with seasonal storm climate. Only a mean value of beach slope is available for
 299 some Australian beaches, so the mean beach slope at each location $\bar{\beta}_f$ (in the empirical
 300 dataset) is included in the regression analysis. A zero crossing regression is used to fit the
 301 data, with the consideration that a wave with zero height will result in zero wave setup.

302 The Pearson correlation coefficient, r , is squared to represent the coefficient of determination
 303 and is used to indicate the proportion, or percentage, of variance in the dependant variable
 304 (measured $\bar{\eta}_s$) that is predictable from the independent variable(s) (H_0 , β_f and L_0). On its
 305 own, the deep water significant wave height rule of thumb equation captures 30% of the
 306 variance of shoreline wave setup (Table 2). Including the wave steepness parameter with H_0
 307 and $n = -1/2$ explains a further 8% of the variance, while the equation with an optimised
 308 regression value of $n \approx -1/3$, similar to Van Dorn (1978), explains a further 12%. Including
 309 the mean location beach slope $\bar{\beta}_f$ with H_0 explains a further 12%, and $\bar{\beta}_f$ with H_0 and the
 310 wave steepness parameter explains a further 8%. Including the time varying value of beach
 311 slope typically explains 4% more than mean location beach slope. The root mean square error
 312 (RMSE) improves from a value of 0.25 to 0.20m through including more parameters in the
 313 equations.

314 At best, the analysis shows that the empirical equations can capture 54% of the variance. So
 315 to summarise, it appears that the significant wave height explains the largest portion of the
 316 variance, followed by beach slope and then the wave steepness term. The remaining variance
 317 could be accounted for by camera and tide gauge SWL datum measurement error, unresolved
 318 parameterisation of the effect of local sea vs remote swell, wave direction, embayment
 319 characteristics, beach porosity and water table effects (Gourlay, 1992).

320

321 *Table 2 Empirical model zero crossing regression parameters α and n and goodness of fit*
322 *parameters. The r^2 values indicates the percentage of the total variation in the measurements*
323 *can be explained by the linear relationship between empirical model and the Stockdon et al.,*
324 *(2006) measurements. The row values in bold are from (Stockdon et al., 2006). Coloured text*
325 *corresponds to Figure 3, Figure 6 and Figure 7.*

regression		regression parameters		Pearson	
Form $\bar{\eta}_s$	Appears in	α	n	r^2	RMSE (m)
αH_0	Guza & Thornton 1981	0.31	-	0.299	0.253
$\alpha \bar{\beta}_f H_0$	-	3.71	-	0.434	0.231
$\alpha \beta_f H_0$	-	3.61	-	0.466	0.229
αH_0^n	-	0.40	0.61	0.317	0.235
$\alpha \bar{\beta}_f H_0^n$	-	4.65	0.66	0.430	0.217
$\alpha \beta_f H_0^n$	-	4.56	0.63	0.456	0.214
$\alpha H_0 \left(\frac{H_0}{L_0}\right)^{-\frac{1}{2}}$	-	0.03	-	0.38	0.224
$\alpha \bar{\beta}_f H_0 \left(\frac{H_0}{L_0}\right)^{-\frac{1}{2}}$	Nielson 1988	0.35	-	0.42	0.223
$\alpha \beta_f H_0 \left(\frac{H_0}{L_0}\right)^{-\frac{1}{2}}$	Stockdon et al 2006	0.35	-	0.485	0.213
$\alpha H_0 \left(\frac{H_0}{L_0}\right)^n$	-	0.06	-0.36	0.416	0.218
$\alpha \bar{\beta}_f H_0 \left(\frac{H_0}{L_0}\right)^n$	Gourlay 1992	1.06	-0.28	0.499	0.206
$\alpha \beta_f H_0 \left(\frac{H_0}{L_0}\right)^n$	-	0.92	-0.30	0.543	0.200
$\alpha H_0 \left(\frac{H_0}{L_0}\right)^{-\frac{1}{3}}$	Van Dorn 1978	0.07	-	0.415	0.218
$\alpha \bar{\beta}_f H_0 \left(\frac{H_0}{L_0}\right)^{-\frac{1}{3}}$	-	0.81	-	0.492	0.207
$\alpha \beta_f H_0 \left(\frac{H_0}{L_0}\right)^{-\frac{1}{3}}$	-	0.79	-	0.540	0.200

326

327 Quantile regression analysis (Q-Q) plots for a selection of equations in Table 2 are compared
328 to the empirical measurements to examine how well the fitted linear regression parameters
329 (Table 2) represent the highest measured levels of the distribution (Figure 3). For the

330 equations not considering local beach slope (Figure 3a), the basic rule of thumb relationship
 331 of $\bar{\eta}_s = 0.31H_0$ best captures the highest measured levels and should be considered when
 332 using empirical equations for extreme value analysis where the beach slope is unknown. With
 333 the inclusion of beach slope, the relationships including wave height and wave steepness are
 334 better at resolving the highest measured levels (Figure 3b). The challenges with building a
 335 national shoreline wave setup hindcast, is that there is limited beach slope data (Turner et al.,
 336 2016), which limits how well we can represent the population of extremes ($\bar{\eta}_s$ and MTWL)
 337 and how the event timing of the wave extremes with surge and tide will play out. Therefore
 338 an initial first-pass national analysis is presented in the next section, which uses the simple
 339 rule of thumb to capture the extremes where the beach slope is unknown.

340 The analysis in the next section is also presented for a higher-order second-pass beach scale
 341 analysis for three beach slope categories; gentle, moderate and steep based on the distribution
 342 of the empirical dataset (Stockdon et al., 2006). The moderate beach slope of 0.087 is based
 343 on the mean beach slope in the empirical dataset. We note that the slope of the regression
 344 equations (α) (Table 2) without a beach slope are equivalent to the corresponding equation
 345 with a beach slope $\bar{\beta}_f \approx 0.083$ to 0.086. To represent a wide range of beach slope categories
 346 within the measured profiles, a gentle beach slope was assigned the 5th percentile 0.023 and
 347 the steep beach slope was assigned the maximum value 0.16 from the empirical dataset
 348 (Stockdon et al., 2006). The maximum value was chosen because beach slopes in Australia
 349 have been measured larger than 0.16 (Turner et al., 2016).

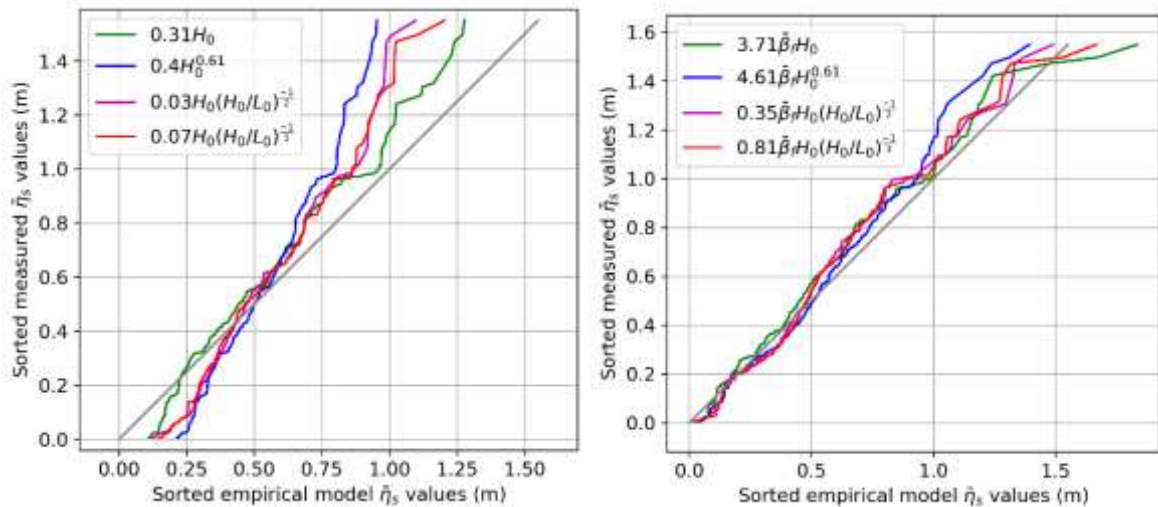


Figure 3 Empirical quantile-quantile plots. The 491 sorted measured values (Stockdon et al., 2006) are plotted against the sorted empirical model estimates to show the comparison of climate population highest measured levels. See Table 2 for time series model comparison.

350

351 Repeating this regression analysis with the 38 measurements for the Australian beaches
 352 (Nielsen & Hanslow, 1991) yielded a similar scale parametrisation (α) but with a reduced
 353 goodness of fit for both the rule of thumb $\bar{\eta}_s = \alpha H_0$ ($\alpha = 0.29, r^2 = 0.25, RMSE = 0.334$)
 354 and the equation including wave steepness $\bar{\eta}_s = \alpha H_0 (H_0/L_0)^{-1/3}$ ($\alpha = 0.07, r^2 =$
 355 $0.25, RMSE = 0.3$). Including beach slope showed a reduced scale parameterisation (α) and
 356 reduced goodness of fit for both the rule of thumb $\bar{\eta}_s = \alpha \bar{\beta}_f H_0$ ($\alpha = 2.8, r^2 =$

357 0.45, $RMSE = 0.39$) and the equation including wave steepness $\bar{\eta}_s = \alpha \bar{\beta}_f H_0 (H_0/L_0)^{-1/3}$
358 ($\alpha = 0.71, r^2 = 0.47, RMSE = 0.36$) for the Australian beaches. Therefore there is
359 reasonable agreement between the northern hemisphere video camera-based measurements
360 (Stockdon et al., 2006) and the Australian transgressions past an array of stakes
361 measurements which have reduced measurement sample and assumptions on the Rayleigh
362 distribution (Nielsen & Hanslow, 1991).

363 5.2. Extreme value analysis results

364 5.2.1. ROMS SWL validation

365 Computed annual return levels (Equation 6) from ROMS SWL (Colberg et al., 2019)
366 hindcast simulations and extreme value analysis are compared to detrended measurements at
367 30 validation sites in Haigh *et al.*, (2014) using their method for adjusting for the AHD. We
368 note that this method to adjust for AHD removes any validation of storm-tide at the 1-year
369 return level and improves the comparison at higher return intervals (10- 50- and 100-year) by
370 removing any issues in the modelled tidal range or storm surge magnitude captured in 1-year
371 return level from the higher return levels. The limitations with the ROMS and Mike-21
372 modelled tidal range and storm surge magnitudes are provided in the cited source literature
373 (Colberg et al., 2019; Haigh, Wijeratne, et al., 2014). The Haigh *et al.*, (2014) study presented
374 results for a generalised extreme value (GEV) fit but indicates the preferred distribution was
375 the Gumbel (GUM) which provided similar results to GEV r-largest method. Table 3
376 compares the GEV fitted using AMM 10-, 50- and 100-year measured return levels to the
377 ROMS modelled GUM values. The model comparison performs poorly at the Wyndham tide
378 gauge where there are complex storm-tide conditions, so is removed from the comparison.
379 The average differences across the 29 sites (excluding Wyndham) are 0.03 m larger than the
380 Haigh study, which is understandable given they used GEV fits with a limiting shape
381 parameter for the comparison. The difference between the models is small considering Mike-
382 21 is run for a period around double that of the ROMS simulations, while the ROMS
383 simulation have twice the grid resolution of the Mike-21 model at the coast and a much
384 higher temporal and spatial atmospheric forcing data. This perhaps suggest higher temporal
385 and spatial resolution storm-tide modelling can offset the shortcoming of shorter duration
386 modelling to estimate extreme values.

387

388 *Table 3 Comparison of the SWL 10-,50- and 100- year tide-gauge measured GEV using a*
 389 *AMM and ROMS model predicted GUM using a AMM return levels for 2010 (relative to m*
 390 *AHD).*

Site Name	10-year			50-year			100-year		
	Meas.	Pred.	Abs.	Meas.	Pred.	Abs.	Meas.	Pred.	Abs.
Point Lonsdale	1.18	1.16	0.02	1.27	1.28	0.01	1.32	1.33	0.01
Geelong	1.02	0.99	0.03	1.08	1.10	0.02	1.11	1.15	0.04
Williamstown	1.03	1.05	0.02	1.10	1.19	0.09	1.13	1.24	0.11
Fort Denison	1.35	1.30	0.05	1.46	1.36	0.10	1.55	1.38	0.17
Newcastle	1.25	1.21	0.04	1.34	1.27	0.07	1.42	1.30	0.12
Brisbane	1.65	1.64	0.01	1.69	1.69	0.00	1.70	1.71	0.01
Bundaberg	2.02	1.96	0.06	2.11	2.04	0.07	2.17	2.08	0.09
Mackay	3.75	3.61	0.14	3.96	3.68	0.28	4.12	3.71	0.41
Townsville	2.40	2.34	0.06	2.62	2.43	0.19	2.80	2.48	0.32
Cairns	1.96	1.89	0.07	2.08	1.97	0.11	2.14	2.00	0.14
Darwin	1.66	1.53	0.13	1.92	1.70	0.22	2.13	1.77	0.36
Milner Bay	3.97	3.98	0.01	4.08	4.05	0.03	4.15	4.09	0.06
*Wyndham	4.12	3.77	0.35	4.33	3.77	0.56	4.58	3.78	0.80
Broome	5.25	5.27	0.02	5.35	5.41	0.06	5.38	5.47	0.09
Port Hedland	3.76	3.65	0.11	4.04	3.76	0.28	4.30	3.81	0.49
Carnarvon	1.29	1.14	0.15	1.43	1.18	0.25	1.53	1.20	0.33
Geraldton	1.06	0.91	0.15	1.19	1.02	0.17	1.27	1.06	0.21
Fremantle	1.11	0.98	0.13	1.27	1.07	0.20	1.39	1.11	0.28
Bunbury	1.18	1.04	0.14	1.37	1.15	0.22	1.52	1.20	0.32
Albany	1.01	1.00	0.01	1.06	1.06	0.00	1.08	1.09	0.01
Esperance	1.18	1.18	0.00	1.24	1.28	0.04	1.26	1.33	0.07
Thevenard	1.91	1.82	0.09	2.05	1.97	0.08	2.13	2.03	0.10
Port Lincoln	1.67	1.46	0.21	1.86	1.57	0.29	1.99	1.62	0.37
Port Pirie	2.61	2.41	0.20	2.86	2.63	0.23	3.03	2.73	0.30
Port Adelaide outer	2.39	2.17	0.22	2.62	2.31	0.31	2.78	2.37	0.41
Port Adelaide	2.26	2.05	0.21	2.44	2.18	0.26	2.56	2.24	0.32
Victor Harbour	1.51	1.43	0.08	1.61	1.54	0.07	1.67	1.59	0.08
Hobart	1.18	1.13	0.05	1.36	1.25	0.11	1.52	1.30	0.22
George Town	1.84	1.79	0.05	1.93	1.90	0.03	1.98	1.95	0.03
Burnie	1.92	1.87	0.05	2.02	1.99	0.03	2.08	2.04	0.04
*Mean excluding			0.09			0.13			0.19

391 **5.2.2. First-pass national analysis**

392 The first-pass analysis of the contribution of coastline wave setup to MTWL is calculated
 393 with the rule of thumb equation, because it is shown to be best suited to capture the highest
 394 measured levels (Figure 3a) in the absence of a reliable dataset of beach slope for the entire
 395 Australian coastline. Figure 4 shows the maps of the SWL, shoreline wave setup and the
 396 MTWL for a 1-year and 100-year event. The 1-year SWL (Figure 4a) is largest in northwest
 397 of Western Australia (NWWA) and can be principally attributed to the magnitude of the
 398 highest astronomical tide (McInnes et al., 2016). For the 100-year SWL levels (Figure 4b),
 399 the influence of storm surge is increased for the southern margin in the South Australian
 400 Bight and Bass Strait, notionally driven by eastward travelling extratropical cyclones and

401 fronts most frequent in winter months (McInnes et al., 2016). The 1-year shoreline wave
402 setup is largest for the southern coastline, facing the southwest, exposed to the large waves
403 generated in the Southern Ocean (Hemer et al., 2017). The 100-year shoreline wave setup
404 plot (Figure 4d) shows the largest shoreline wave setup values along the west coast of
405 Tasmania. The same map also shows the increased levels along the NWWA coastline and in
406 the Gulf of Carpentaria, both locations subject to the impacts of tropical cyclones. We note
407 the ~30 year hindcast includes a limited number of the infrequent occurring tropical cyclone
408 events, and the resolution of the atmospheric forcing reanalysis does not capture their full
409 intensity to properly resolve the return levels at longer return periods. The resulting combined
410 MTWL for the 1-year return levels (Figure 4e) is largest along the NWWA coastline where
411 the contribution is dominated by SWL. The 100-year MTWL map (Figure 4f) shows a greater
412 contribution from waves/storms than the SWL at longer return periods for the southern
413 coastlines, which are exposed to large waves.

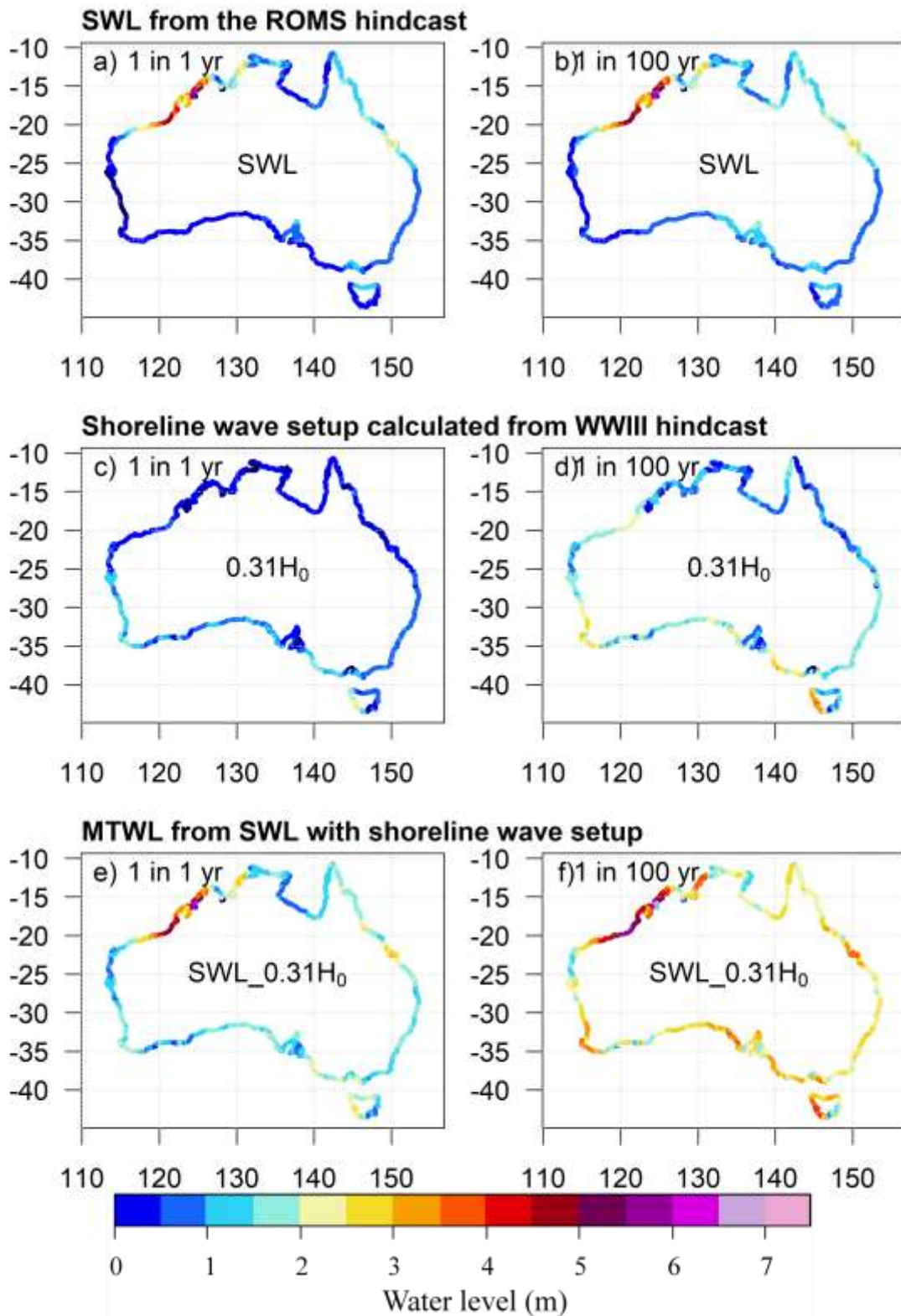


Figure 4 Maps of the return level for ROMs SWL (top row), empirical shoreline wave setup (middle row) and combined MTWL (bottom row). Text and equations at the centre of the maps describe the mapped colour values in metres. The left column is the 1-year and right column is the 100-year RL.

414 Figure 5a) and b) presents the ratio of the rule of thumb results with the results including
415 wave steepness for a 1-year and 100-year event. Where the ratio is one, both sets of results
416 are the same and the equations (numerator/denominator) in Figure 5 are equal. The 1-year
417 shoreline wave setup calculated with the wave steepness parameter predicts in general a 10-
418 20% lower water level than that calculated with rule of thumb equation (Figure 5a). The
419 corresponding 100-year values shows a similar pattern, predicting in general a 20-30% lower
420 water level, where the lower estimates occur along the south west of Western Australia
421 (SWWA) (Figure 5b). These results are in line with regression analysis showing the under
422 prediction of the equation with wave steepness (and without beach slope) at the highest
423 measured levels (Figure 3a).

424 Figure 5c) and d) compare the 1-year and 100-year Gumbel EVD estimates from the
425 difference between the MTWL and SWL *vs* the shoreline wave setup on its own. Figure 5 d)
426 can be considered to compare the likely nonlinear contribution of shoreline wave setup in the
427 100-year MTWL estimates *vs* the 100-year shoreline wave setup value calculated
428 independently of the SWL. Values larger than one indicates the contribution of shoreline
429 wave setup to the 100-year MTWL is larger than the 100-year shoreline wave setup value
430 calculated independently and hence could be considered to represent a longer ARI shoreline
431 wave setup occurred with the 100-year MTWL ARI. Conversely, values smaller than one
432 indicates the contribution of shoreline wave setup to the 100-year MTWL is smaller than the
433 100-year shoreline wave setup value calculated independently and hence could be considered
434 to represent a shorter ARI shoreline wave setup occurred with the 100-year MTWL ARI.
435 Here, the exact contributions of waves to MTWL for the 100-year event which occurs due to
436 the dynamic nature of the atmospheric forcing and stage of the tide cannot be inferred from
437 this analysis. Nowhere in the analysis is this value one or greater. Large values in Figure 5c)
438 and d) for the southern Australian coast indicate that the shoreline wave setup contributing to
439 MTWL compared to the independent shoreline wave setup correspond with relatively longer
440 ARIs than the lower values in NWWA.

441 The contribution of shoreline wave setup to MTWL is presented in Figure 5e and f. The 1-
442 year plot (Figure 5e) shows that for parts of the NWWA coastline the contribution of wave
443 setup to MTWL is less than 10% and that for sections of the southern coastline the
444 contribution of wave setup to MTWL exceeds 60%. The corresponding figure for the 100-
445 year level (Figure 5f) shows greater contribution of wave setup to MTWL at most locations.

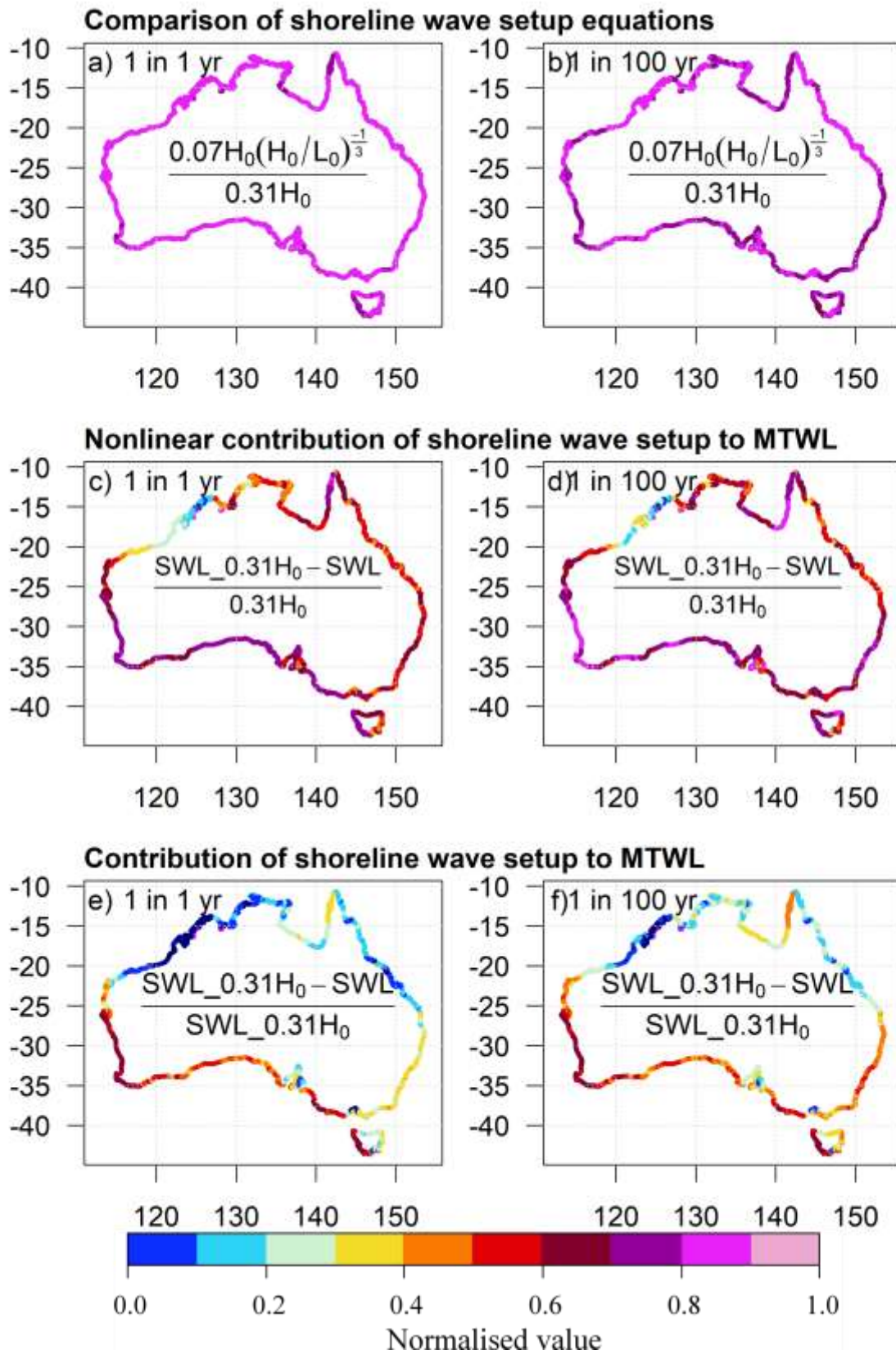


Figure 5 Maps comparing shoreline wave setup equations and the contribution of shoreline wave setup and ROMS SWL to MTWL. Equations describe the ratio of the colour

map. The first row compares the rule of thumb to the optimised shoreline wave setup equation. The middle row compares the non-linear addition of shoreline wave setup. The bottom column compares the contribution of wave setup to MTWL. The left column is the 1-year and right column is the 100-year RL.

446 **5.2.3. Second-pass beach scale analysis**

447 The second-pass analysis is provided here for two example locations which will be provided
448 via a tool at the beach scale for 11,000 beaches around Australia (Short, 2007). The first
449 example is provided for the Collaroy-Narrabeen shoreline in Eastern Australia (Figure 6) -
450 chosen because of the availability of long term beach profile monitoring at that location
451 (Turner et al., 2016, <http://narrabeen.wrl.unsw.edu.au/>). The mean intertidal beach slope for
452 the five transects, calculated as slope between the linear interpolated zero and 2m water
453 elevations, ranges from 0.097 to 0.12 but individual surveyed slopes are recorded above 0.2.
454 Figure 6 shows the return levels with the steep beach slope (0.16) and without slope for
455 evaluation along the Narrabeen Collaroy coastline. The rule of thumb equation estimates
456 higher return levels than the equation including wave steepness, as was seen previously in
457 Figure 3a) and Figure 5a and b). The second-pass analysis assuming a steep profile suggests
458 that shoreline wave setup could be around 100% larger than the estimate from the first-pass
459 with no beach slope. At this scale, the ROMS SWL model matches the Mike-21 SWL, and
460 the Fort Denison tide gauge located 15km away (Table 3).

461 The second example is provided for Seven Mile beach, NSW, which was chosen because
462 there are wave setup measurements available for a gentle beach profile (Nielsen & Hanslow,
463 1991). Figure 7 shows that shoreline wave setup with a gentle beach slope (0.023) could be a
464 third of the estimates without considering beach slope and could be a less significant
465 contributor to MTWL than SWL from storm-tide.

466 The example locations indicate the contribution of shoreline wave setup and SWL to the
467 combined MTWL would look different for a national analysis if a reliable dataset of beach
468 slope were available nationally. The rule of thumb scales significant wave height by 31%, the
469 inclusion of a steep slope scales significant wave height by 59% and including a gentle slope
470 scales by 8.5%, highlighting the importance of including local beach slope in the empirical
471 approximation of shoreline wave setup.

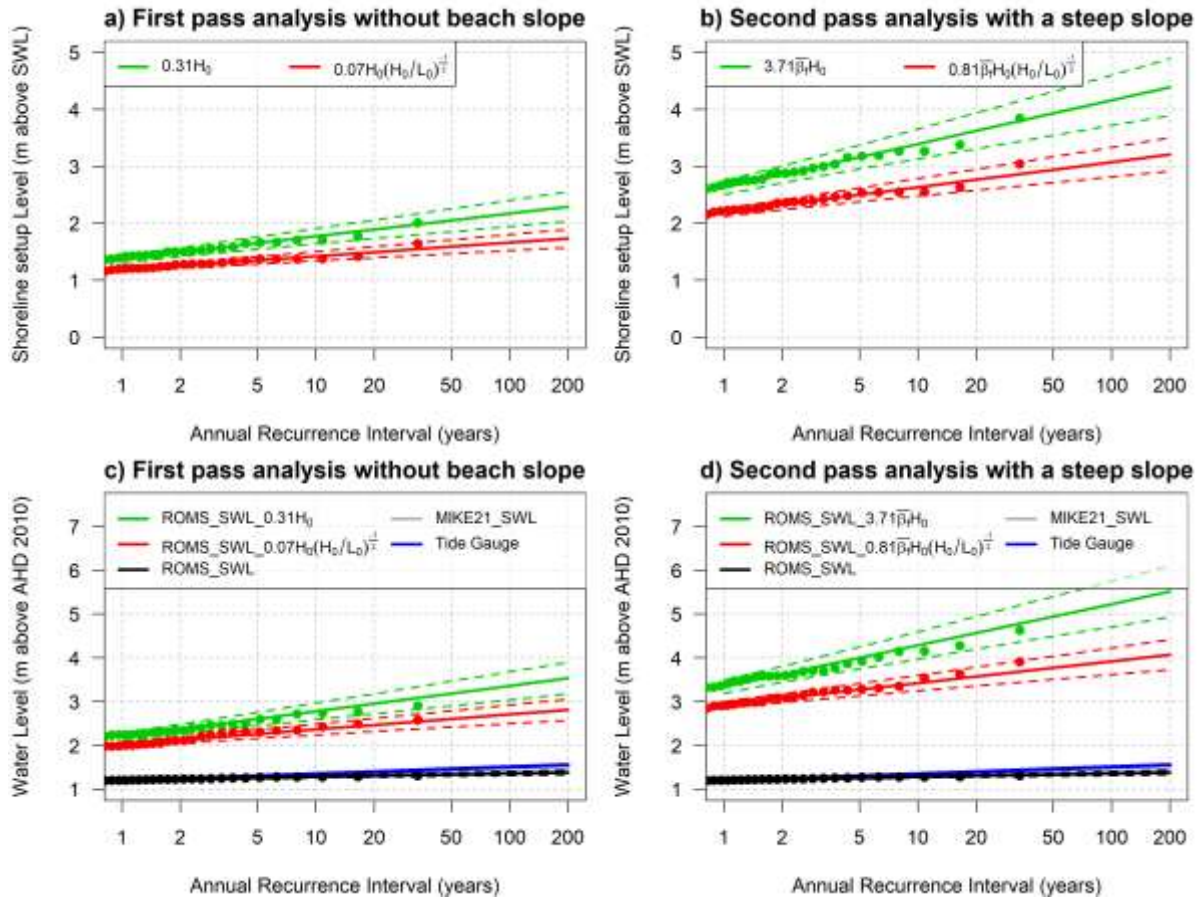


Figure 6 Return level plot second-pass analysis for Narrabeen Collaroy Beach. Lines correspond to equations and text in legend. For a steep slope $\bar{\beta}_f=0.16$. 15km from the Fort Denison tide gauge.

472

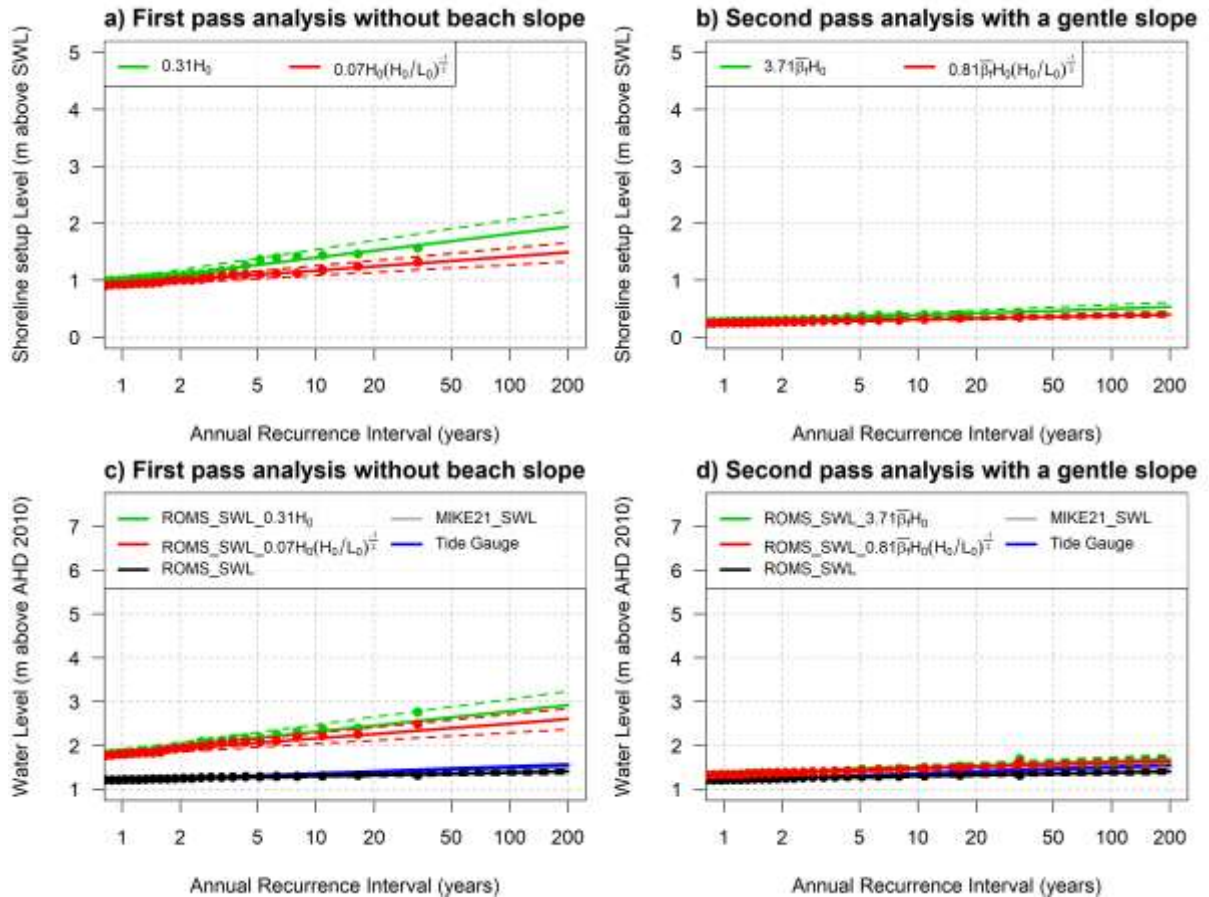


Figure 7 Return level plot second-pass analysis for Seven Mile Beach. Lines correspond to equations and text in legend. For a gentle slope $\beta_f=0.023$. 115km from the Fort Denison tide gauge.

473

474 6. Discussion and conclusion

475 We have presented the first estimates of the contribution of shoreline wave setup to the
 476 MTWL climate for Australia. These results require careful consideration given the limited
 477 measurements and significant reliance on model prediction, which we will discuss here in this
 478 final section.

479 Regression analysis and the r^2 value indicate that at best, the available empirical equations
 480 can capture up to 54% of the measured variance. It appears that the deep water significant
 481 wave height explains most of the variance, followed by beach slope and then the wave
 482 steepness term. The remaining variance could be accounted for by camera and SWL datum
 483 measurement error, unresolved parameterisation of the effect of local sea vs remote swell,
 484 wave direction, embayment characteristics and beach porosity and water table effects
 485 (Gourlay, 1992). The analysis shows reasonable agreement with studies conducted for the
 486 Australian coastline (Nielsen & Hanslow, 1991). The selection of shoreline setup equations
 487 for the different levels of analysis were based on 1) the availability of data, in particular the
 488 beach slope, and 2) the Q-Q plots, which indicated the performance of the equations at the
 489 highest levels of the measured distributions. Here the deep water wave steepness to the power
 490 of $n = 1/3$ (Equation 3) was chosen over the commonly used $n = 1/2$ because of optimal

491 regression analysis and Q-Q investigation. More observational studies are required to
492 understand how the wave steepness transforms from the deep water into the shallow water
493 surf zone.

494 Storm-tide return levels provided by the different numerical model configurations of the
495 ROMS and Mike-21 simulations show similar validation to the tide gauge measurements. We
496 note that the method to adjust for AHD removes any validation of storm-tide at the 1-year
497 return level and improves the comparison at higher return intervals (10- 50- and 100-year) by
498 removing any issues in the modelled tidal range or storm surge magnitude captured in the 1-
499 year return level from the higher return levels. The ~30 year hindcast includes a limited
500 number of the infrequent occurring tropical cyclone events, and the resolution of the
501 atmospheric forcing reanalysis does not capture their full intensity to properly resolve the
502 return levels at longer return periods. The extreme value analysis presented here could be
503 repeated in future studies using datasets of synthetically modelled tropical cyclone waves and
504 storm surge (e.g. Haigh, MacPherson, et al., 2014). The Gumbel EVD is shown to match the
505 highest AMM values in the ~30 year simulations for the example locations (Figure 6 and
506 Figure 7). Longer datasets (e.g. 100 years of data) would provide better estimates of the
507 extremes at longer RIs (e.g. the 100-year level), including any asymptotic curvature
508 representing a physical limit to the height of the extreme water levels. A further limitation of
509 the modelling of the extremes presented is the extrapolation of the shoreline wave setup
510 empirical equations beyond the highest values in the measured dataset. This is particularly
511 evident for the south and west coast 100-year ARI where modelled significant wave heights
512 are more than three times larger than the highest values in the measured dataset. Addressing
513 this limitation would require long term monitoring of shoreline wave setup at more locations.

514 This article provides a first-pass national analysis of wave setup for Australia and examples
515 of second-pass analysis for Australia's beaches. It is planned that the second-pass analysis
516 will be made available to coastal engineers, scientists and practitioners through an online
517 tool. Third, or higher, order analysis would involve site specific field measurements of the
518 waves and beach profile. The first pass analysis shows a large contribution of shoreline wave
519 setup to MTWL estimates, however the example second-pass locations provided demonstrate
520 the inclusion of local beach slope could change the estimates to be twice as large or only a
521 third as large as values presented from the national first-pass analysis. This reinforces the
522 challenges and shortcomings with providing estimates of wave setup on national and global
523 scales where the magnitude of the shoreline wave setup estimates are very sensitive to local
524 beach characteristics (Melet et al., 2018; Serafin et al., 2017). While the first-pass estimates
525 provide a national view of the important contributors to extreme MTWL, for the above
526 reasons we strongly discourage using this simplification for local-beach scale analysis.

527 The method for estimating the nonlinear contribution of extreme shoreline wave setup to
528 MTWL (e.g. Figure 5c, d, e & f) can only provide the likely contribution of waves to the
529 MTWL for a 1-year or 100-year event. I.e., the exact contributions of waves to MTWL for
530 the 100-year event which occurs due to the dynamic nature of the atmospheric forcing and
531 stage of the tide cannot be inferred from this analysis. It should also be noted that the
532 contribution of wave runup leads to significant additional transient contributions to extreme
533 water levels. TWL including wave runup, is important for beach erosion hazard. However,
534 while wave runup and overtopping are more likely to cause any inundation, the damage is
535 moderate compared to the amount of water behind a storm-tide SWL that stretches across the
536 shelf and can contribute to catastrophic inundation. The inundation potential of elevated
537 water across the surf zone from wave setup sits between the runup and storm-tide inundation

538 potential. The MTWL estimates provided in this study should be used with caution for
539 bathtub type inundation studies as waves will have a more dynamic interaction with the
540 inundated coastline (dunes and seawalls) than the rising storm-tide. Inundation studies should
541 also consider terrestrial sources during coincided storm events (Wu et al., 2018).

542 The evolution of different formulations in Equations 1 and 3 of shoreline wave setup being
543 either based on surf zone bathymetry or beach slope respectively requires further
544 investigation to better determine the contribution of depth-induced breaking and the beach
545 swash effect. More recent LIDAR survey technology provides the opportunity to survey the
546 wave setup line across the surf zone (Brodie et al., 2015), which may lead to improved
547 formulations of empirical shoreline wave setup that include both beach slope and the effect of
548 the bathymetry and the generation of infragravity waves (Symonds et al., 1982).

549 **7. Acknowledgements**

550 This study was supported by the Earth Science and Climate Change Hub of the Australian
551 Government's National Environmental Science Programme (NESP). We would like to thank
552 the two anonymous journal reviewers for their valuable comments that have improved this
553 manuscript. The field measurements used in this study are available from
554 <https://pubs.usgs.gov/ds/602/>. The ROM SWL hindcast data can be found here
555 <https://doi.org/10.4225/08/5a7280a3a0d2a> and the WWII hindcast can be found here
556 <http://dx.doi.org/10.4225/08/523168703DCC5>.

557 **8. References**

- 558 Apotsos, A., Raubenheimer, B., Elgar, S., & Guza, R. T. (2008). Testing and calibrating
559 parametric wave transformation models on natural beaches, *55*, 224–235.
560 <https://doi.org/10.1016/j.coastaleng.2007.10.002>
- 561 Arns, A., Wahl, T., Haigh, I. D., Jensen, J., & Pattiaratchi, C. (2013). Estimating extreme
562 water level probabilities: A comparison of the direct methods and recommendations for
563 best practise. *Coastal Engineering*, *81*, 51–66.
564 <https://doi.org/10.1016/j.coastaleng.2013.07.003>
- 565 Atkinson, A. L., Power, H. E., Moura, T., Hammond, T., Callaghan, D. P., & Baldock, T. E.
566 (2017). Assessment of runup predictions by empirical models on non-truncated beaches
567 on the south-east Australian coast. *Coastal Engineering*, *119*(March 2016), 15–31.
568 <https://doi.org/10.1016/j.coastaleng.2016.10.001>
- 569 Battjes, J. A., & Janssen, J. P. F. M. (1978). Energy Loss and Set-Up Due To Breaking of
570 Random Waves. *Coastal Engineering Proceedings*, (1), 569–587.
571 <https://doi.org/10.1061/9780872621909.034>
- 572 Bowen, A. J., Inman, D. L., & Simmons, V. P. (1968). Wave 'set-down' and set-Up. *Journal*
573 *of Geophysical Research*, *73*(8), 2569–2577. <https://doi.org/10.1029/JB073i008p02569>
- 574 Brodie, K. L., Raubenheimer, B., Elgar, S., Slocum, R. K., & McNinch, J. E. (2015). Lidar
575 and pressure measurements of inner-surfzone waves and setup. *Journal of Atmospheric*
576 *and Oceanic Technology*, *32*(10), 1945–1959. [https://doi.org/10.1175/JTECH-D-14-](https://doi.org/10.1175/JTECH-D-14-00222.1)
577 [00222.1](https://doi.org/10.1175/JTECH-D-14-00222.1)
- 578 Buckley, M. L., Lowe, R. J., Hansen, J. E., van Dongeren, A. R., & Storlazzi, C. D. (2018).
579 Mechanisms of Wave-Driven Water Level Variability on Reef-Fringed Coastlines.
580 *Journal of Geophysical Research: Oceans*, *123*(5), 3811–3831.

- 581 <https://doi.org/10.1029/2018JC013933>
- 582 Colberg, F., McInnes, K. L., O’Grady, J., & Hoeke, R. K. (2019). Atmospheric Circulation
583 Changes and their Impact on Extreme Sea Levels around Australia. *Natural Hazards*
584 *and Earth System Sciences*, 19, 1067–1086. <https://doi.org/10.5194/nhess-2018-64>
- 585 Coles, S. (2001). *An Introduction to Statistical Modeling of Extreme Values* (Vol. 208).
586 London: Springer London. <https://doi.org/10.1007/978-1-4471-3675-0>
- 587 Le Cozannet, G., Nicholls, R., Hinkel, J., Sweet, W., McInnes, K. L., Van de Wal, R., et al.
588 (2017). Sea Level Change and Coastal Climate Services: The Way Forward. *Journal of*
589 *Marine Science and Engineering*, 5(4), 49. <https://doi.org/10.3390/jmse5040049>
- 590 Dalrymple, R. A., & Dean, R. G. (1991). *Water wave mechanics for engineers and scientists*
591 (Vol. 2). Prentice-Hall. https://doi.org/10.1142/9789812385512_0006
- 592 Van Dorn, W. G. (1978). Breaking invariants in shoaling waves. *Journal of Geophysical*
593 *Research*, 83(C6), 2981. <https://doi.org/10.1029/JC083iC06p02981>
- 594 Durrant, T. H., Greenslade, D. J. M., Hemer, M. A., & Trenham, C. (2013). A Global Wave
595 Hindcast focussed on the South Pacific. In *Proceedings of the 13th International*
596 *Workshop on wave hindcasting and forecasting & 4th Coastal Hazard Symposium,*
597 *Banff, Canada, October*. Proceedings of the 13th International Workshop on wave
598 hindcasting and forecasting & 4th Coastal Hazard Symposium; Banff, Canada.
- 599 Gourlay, M. R. (1992). Wave set-up, wave run-up and beach water table: Interaction between
600 surf zone hydraulics and groundwater hydraulics. *Coastal Engineering*, 17(1–2), 93–
601 144. [https://doi.org/10.1016/0378-3839\(92\)90015-M](https://doi.org/10.1016/0378-3839(92)90015-M)
- 602 Guza, R. T., & Thornton, E. B. (1981). Wave set-up on a natural beach. *Journal of*
603 *Geophysical Research*, 86(C5), 4133–4137. <https://doi.org/10.1029/JC086iC05p04133>
- 604 Guza, R. T., & Thornton, E. B. (1982). Swash oscillations on a natural beach. *Journal of*
605 *Geophysical Research*, 87(C1), 483–491. <https://doi.org/10.1029/JC087iC01p00483>
- 606 Haigh, I. D., Wijeratne, E. M. S., MacPherson, L. R., Pattiaratchi, C. B., Mason, M. S.,
607 Crompton, R. P., et al. (2014). Estimating present day extreme water level exceedance
608 probabilities around the coastline of Australia: Tides, extra-tropical storm surges and
609 mean sea level. *Climate Dynamics*, 42(1–2), 121–138. <https://doi.org/10.1007/s00382-012-1652-1>
610
- 611 Haigh, I. D., MacPherson, L. R., Mason, M. S., Wijeratne, E. M. S., Pattiaratchi, C. B.,
612 Crompton, R. P., & George, S. (2014). Estimating present day extreme water level
613 exceedance probabilities around the coastline of Australia: tropical cyclone-induced
614 storm surges. *Climate Dynamics*. <https://doi.org/10.1007/s00382-012-1653-0>
- 615 Hanslow, D., & Nielsen, P. (1993). Shoreline set-up on natural beaches. *Journal of Coastal*
616 *Research, Special Issue*, (15), 1–10.
- 617 Hemer, M. A., Zieger, S., Durrant, T., O’Grady, J. G., Hoeke, R. K., McInnes, K. L., &
618 Rosebrock, U. (2017). A revised assessment of Australia’s national wave energy
619 resource. *Renewable Energy*, 114(Part A), 85–107.
620 <https://doi.org/10.1016/j.renene.2016.08.039>

- 621 Holman, R. A. (1986). Extreme value statistics for wave run-up on a natural beach. *Coastal*
 622 *Engineering*, 9(6), 527–544. [https://doi.org/10.1016/0378-3839\(86\)90002-5](https://doi.org/10.1016/0378-3839(86)90002-5)
- 623 Holman, R. A., & Sallenger, A. H. (1985). Setup and swash on a natural beach. *Journal of*
 624 *Geophysical Research*, 90(C1), 945. <https://doi.org/10.1029/JC090iC01p00945>
- 625 Holthuijsen, L. H. (2007). *Waves in Oceanic and Coastal Waters*. Cambridge University
 626 Press. Cambridge University Press. <https://doi.org/10.5670/oceanog.2007.42>
- 627 Iribarren, C. R., & Nogales, C. M. (1949). Protection des ports. In *PIANC congress 1949 SII-*
 628 *C4* (pp. 180–193). <https://doi.org/uuid:7ab718ff-a74d-4141-8c3f-413044c751c4>
- 629 Ji, C., Zhang, Q., & Wu, Y. (2018). An empirical formula for maximum wave setup based on
 630 a coupled wave-current model. *Ocean Engineering*, 147(September 2017), 215–226.
 631 <https://doi.org/10.1016/j.oceaneng.2017.10.021>
- 632 Longuet-Higgins, M. S., & Stewart, R. W. (1964). Radiation stresses in water waves; a
 633 physical discussion, with applications. *Deep Sea Res.*, 11(4), 529–562. Retrieved from
 634 <http://www.sciencedirect.com/science/article/pii/0011747164900014>
- 635 McInnes, K. L., White, C. J., Haigh, I. D., Hemer, M. A., Hoeke, R. K., Holbrook, N. J., et al.
 636 (2016). Natural hazards in Australia: sea level and coastal extremes. *Climatic Change*,
 637 139(1), 69–83. <https://doi.org/10.1007/s10584-016-1647-8>
- 638 Melet, A., Meyssignac, B., Almar, R., & Le Cozannet, G. (2018). Under-estimated wave
 639 contribution to coastal sea-level rise. *Nature Climate Change*, 8(3), 234–239.
 640 <https://doi.org/10.1038/s41558-018-0088-y>
- 641 Merrifield, M. A., Becker, J. M., Ford, M., & Yao, Y. (2014). Observations and estimates of
 642 wave-driven water level extremes at the Marshall Islands. *Geophysical Research Letters*,
 643 41(20), 7245–7253. <https://doi.org/10.1002/2014GL061005>
- 644 Mortlock, T. R., Goodwin, I. D., McAneney, J. K., & Roche, K. (2017). The June 2016
 645 Australian East Coast Low: Importance of wave direction for coastal erosion
 646 assessment. *Water*, 9(2), 1–22. <https://doi.org/10.3390/w9020121>
- 647 Nielsen, P. (1988). Wave setup: A field study. *Journal of Geophysical Research: Oceans*,
 648 93(C12), 15643–15652. <https://doi.org/10.1029/JC093iC12p15643>
- 649 Nielsen, P., & Hanslow, D. J. (1991). Wave Runup Distributions on Natural Beaches.
 650 *Journal of Coastal Research*, 7(4), 1139–1152. Retrieved from
 651 <http://www.jstor.org/stable/4297933>
- 652 O’Grady, J. G., & McInnes, K. L. (2010). Wind waves and their relationship to storm surges
 653 in northeastern Bass Strait. *Australian Meteorological and Oceanographic Journal*,
 654 60(04), 265–275. <https://doi.org/10.22499/2.6004.004>
- 655 Power, H. E., Kinsela, M. A., Stringari, C. E., Kendall, M. J., Morris, B. D., & Hanslow, D. J.
 656 (2018). Automated sensing of wave inundation across a rocky shore platform using a
 657 low-cost camera system. *Remote Sensing*, 10(1). <https://doi.org/10.3390/rs10010011>
- 658 Pugh, D. (1996). *Tides, Surges and mean sea-level*. John Wiley & Sons Ltd.
- 659 Rueda, A., Vitousek, S., Camus, P., Tomás, A., Espejo, A., Losada, I. J., et al. (2017). A
 660 global classification of coastal flood hazard climates associated with large-scale

- 661 oceanographic forcing /704/106/829/2737 /704/4111 /141 /129 article. *Scientific*
662 *Reports*, 7(1), 1–8. <https://doi.org/10.1038/s41598-017-05090-w>
- 663 Serafin, K. A., Ruggiero, P., & Stockdon, H. F. (2017). The relative contribution of waves,
664 tides, and nontidal residuals to extreme total water levels on U.S. West Coast sandy
665 beaches. *Geophysical Research Letters*, 44(4), 1839–1847.
666 <https://doi.org/10.1002/2016GL071020>
- 667 Short, A. D. (2007). ABSAMP. Retrieved from
668 [http://catalogue.aodn.org.au/geonetwork/srv/eng/metadata.show?uuid=a5bf4b30-1969-](http://catalogue.aodn.org.au/geonetwork/srv/eng/metadata.show?uuid=a5bf4b30-1969-11dc-819b-00188b4c0af8)
669 [11dc-819b-00188b4c0af8](http://catalogue.aodn.org.au/geonetwork/srv/eng/metadata.show?uuid=a5bf4b30-1969-11dc-819b-00188b4c0af8)
- 670 Stockdon, H. F., Holman, R. A., Howd, P. A., & Sallenger, A. H. (2006). Empirical
671 parameterization of setup, swash, and runup. *Coastal Engineering*, 53(7), 573–588.
672 <https://doi.org/10.1016/j.coastaleng.2005.12.005>
- 673 Stockdon, H. F., Thompson, D. M., Plant, N. G., & Long, J. W. (2014). Evaluation of wave
674 runup predictions from numerical and parametric models. *Coastal Engineering*, 92, 1–
675 11. <https://doi.org/10.1016/j.coastaleng.2014.06.004>
- 676 Symonds, G., & BOWEN, A. J. (1984). Interactions of nearshore bars with incoming wave
677 groups (long wave modelling). *Journal of Geophysical Research*, 89(C2), 1953–1959.
678 <https://doi.org/10.1029/JC089iC02p01953>
- 679 Symonds, G., Huntley, D. A., & Bowen, A. J. (1982). Two-dimensional surf beat: Long wave
680 generation by a time-varying breakpoint. *Journal of Geophysical Research*, 87(1), 492–
681 498. <https://doi.org/10.1029/JC087iC01p00492>
- 682 Turner, I. L., Harley, M. D., Short, A. D., Simmons, J. A., Bracs, M. A., Phillips, M. S., &
683 Splinter, K. D. (2016). A multi-decade dataset of monthly beach profile surveys and
684 inshore wave forcing at Narrabeen, Australia. *Scientific Data*, 3, 1–13.
685 <https://doi.org/10.1038/sdata.2016.24>
- 686 Vitousek, S., Barnard, P. L., Fletcher, C. H., Frazer, N., Erikson, L., & Storlazzi, C. D.
687 (2017). Doubling of coastal flooding frequency within decades due to sea-level rise.
688 *Scientific Reports*, 7(1), 1–9. <https://doi.org/10.1038/s41598-017-01362-7>
- 689 Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Verlaan, M., Jevrejeva, S., Jackson, L.
690 P., & Feyen, L. (2018). Global probabilistic projections of extreme sea levels show
691 intensification of coastal flood hazard. *Nature Communications*, 9(1), 1–12.
692 <https://doi.org/10.1038/s41467-018-04692-w>
- 693 Wong, P., Lonsada, I., Gattuso, J., Hinkel, J., Burkett, V., & Codignotto, J. (2014). Coastal
694 Systems and Low-Lying Areas. In *Climate Change 2014 Impacts, Adaptation, and*
695 *Vulnerability* (pp. 361–410). <https://doi.org/10.1017/CBO9781107415379.010>
- 696 Wu, W., McInnes, K. L., O’Grady, J. G., Hoeke, R., Leonard, M., & Westra, S. (2018).
697 Mapping Dependence Between Extreme Rainfall and Storm Surge. *Journal of*
698 *Geophysical Research: Oceans*, 123(4), 1–14. <https://doi.org/10.1002/2017JC013472>
- 699