RBR

Welcome, the RBR Webinar will begin shortly…

RBR
rbr-global.com

Product Overview: RBR*solo*³ D

Stef Stimson

Business Development Manager (Asia-Pacific)

Loggers

OEM

Sensors

Systems

RBR


RBRcoda
RBRconcerto³
RBRmaestro³
RBRconcerto³
RBRbrevio³
RBRsolo³

RBR

RBRcervello
RBRduet3
RBRsolo3
RBRsolo3
RBRsolo3
RBRduet3
RBRsolo3
RBRsolo3
RBRsolo3
RBRsolo3
RBRduet3
RBRvirtuoso3
RBRvirtuoso3
RBRfermata
RBRfermette3
RBRssm
RBRcoda T.ODO
Depth rating:
Serial number:
RBRcoda3
RBRcoda3
RBRcoda3
RBRcoda3
RBRmaestro3
RBRconcerto3
RBRconcerto3
RBRquartz3
RBRquartz3
RBRquartz3
WIREWALKER
RBR

RBR*solo*^{3} D

Compact depth logger (self contained memory + battery)

Range: 0 to 20, 50, 100, 200, 500, 750 dbar (1000, 2000, 4000, 6000, 10 000 dbar in titanium)

±0.05% FS accuracy

<0.001% resolution

1Hz sampling = ~400 days / ~34 million readings on a single AA battery

2Hz sampling = >2 month / ~11 million readings on a single AA battery

5s sampling = 4.9 years / ~32 million readings on a single AA battery

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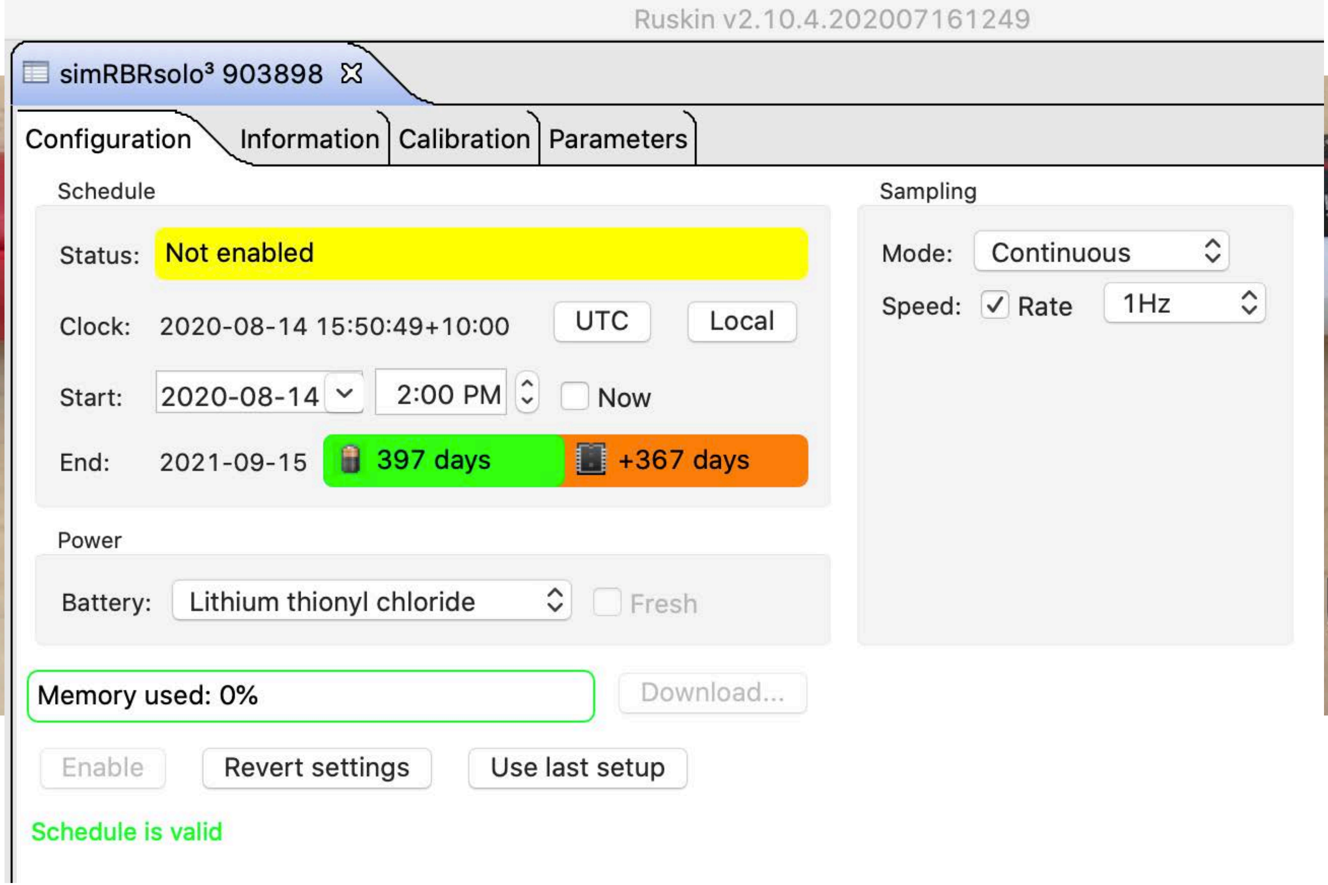
Compact depth logger versions

- RBR*solo*³ D – shallow (1,000m) with ≦2Hz sampling

- RBR*solo* ³ D|fast8 (16Hz or 32Hz) – shallow with fast sampling
- RBR*solo* ³ D|tide16 or |wave16 – with tide and/or wave averaging
- RBR*solo* ³ D|deep – deep (10 000m) with above options

- RBR*duet* ³ T.D – as above with addition of thermistor (standard / fast)

Inside the RBR*solo*³ D



RBR

Big Sister

- **RBRvirtuoso³ D**
- **RBRduo³ D**
  - 8x AA batteries
  - ~240 million readings
  - Twist Activation
  - WiFi ready
  - External communications options

RBR

Upcoming Webinars

Future Webinars

Measuring the pore pressure response in sandy beaches using RBR*solo*³ Ds

Nina Stark (Virginia Tech)

August 26, 2020 at 12PM EDT (GMT-4)

Surf zone monitoring at the Palm Beach artificial reef using nine RBR*duet* T.Ds

Evan Watterson (Bluecoast Consulting Engineers)

August 27, 2020 at 11AM AEST (GMT+10)

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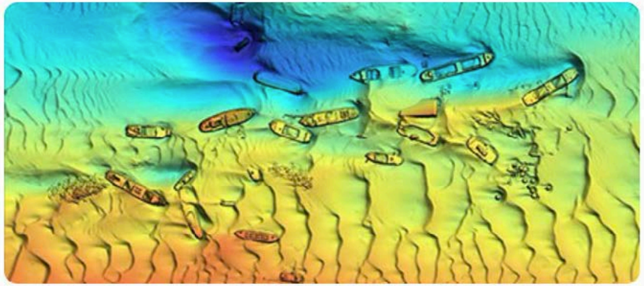
Future Webinars

Observing beach breaching in Carmel, CA

Mara Orescanin (Naval Postgraduate School)

September 2, 2020 at 12PM EDT (GMT-4)



Tidal measurements to support hydrographic operations in Queensland

Giles Stimson (Port of Brisbane Ltd)

September 3, 2020 at 11AM AEST (GMT+10)

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Thank You

Contact Us

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RBR

Measuring waves to better quantify coastal hazards

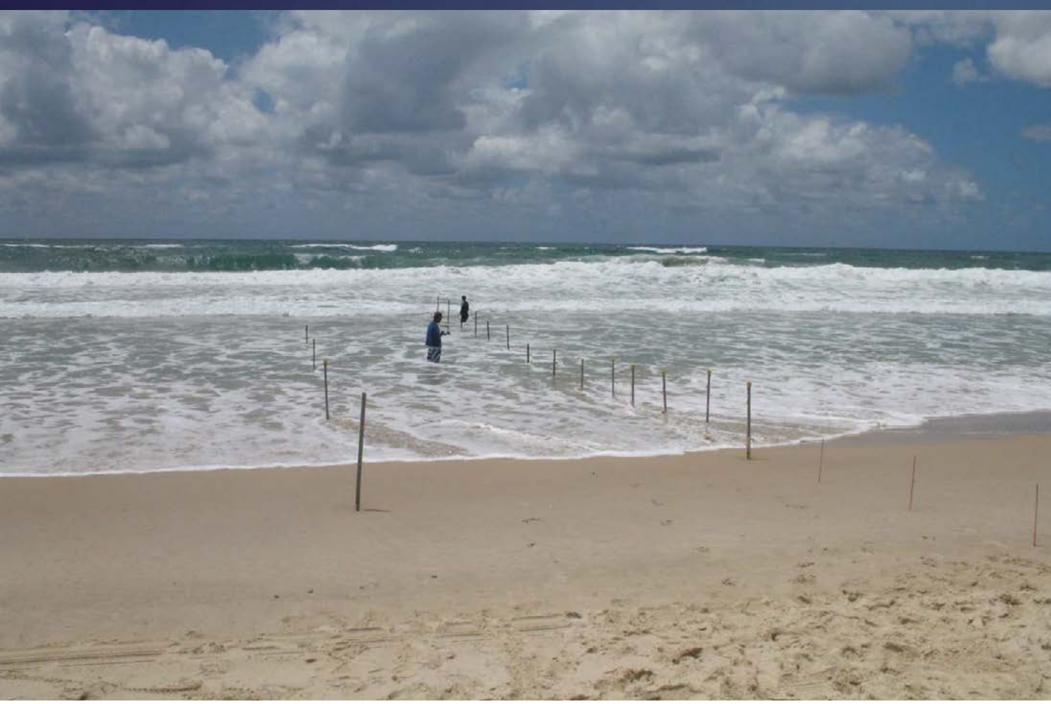
Photo: Michael Kinsela

DR HANNAH POWER

SCHOOL OF ENVIRONMENTAL AND LIFE SCIENCES, UNIVERSITY OF NEWCASTLE, NSW, AUSTRALIA

Coastal wave hazards

- Sandy beaches:
  - Wave runup



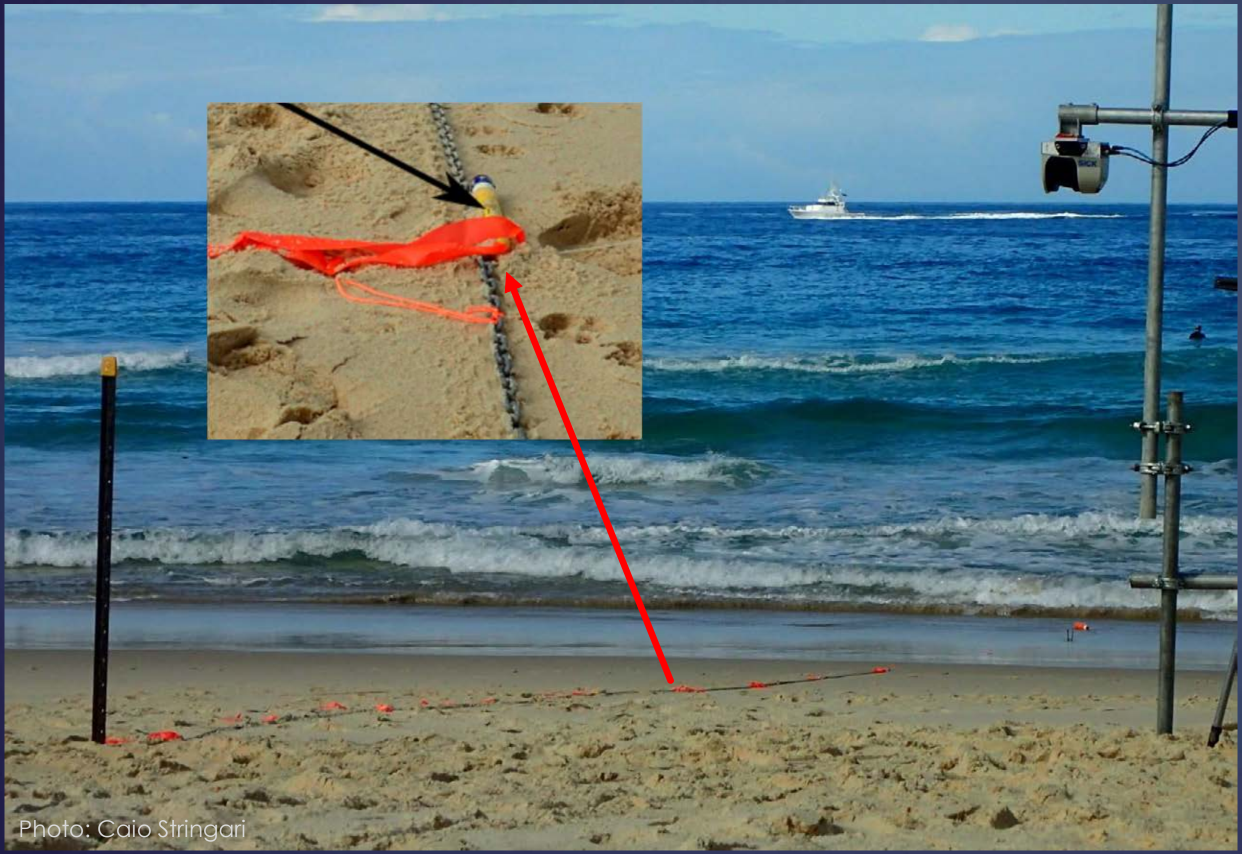
- Rock platforms:
  - Wave overwash/overtopping

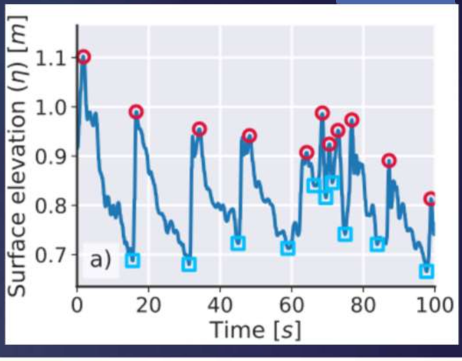
Wave runup

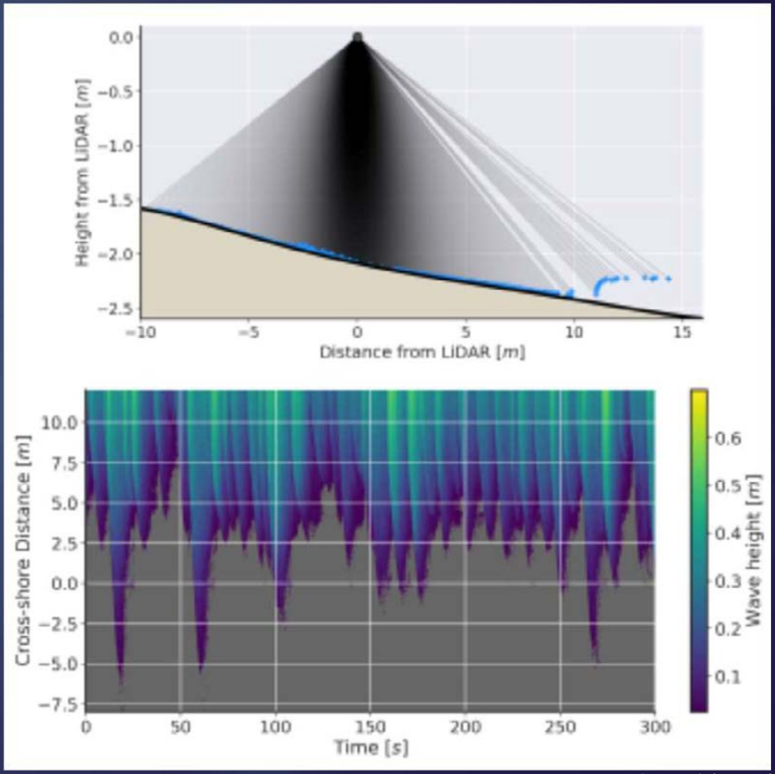
Key research questions:

- What processes drive extreme wave runup?
- Can we better predict wave runup?

Measuring wave runup

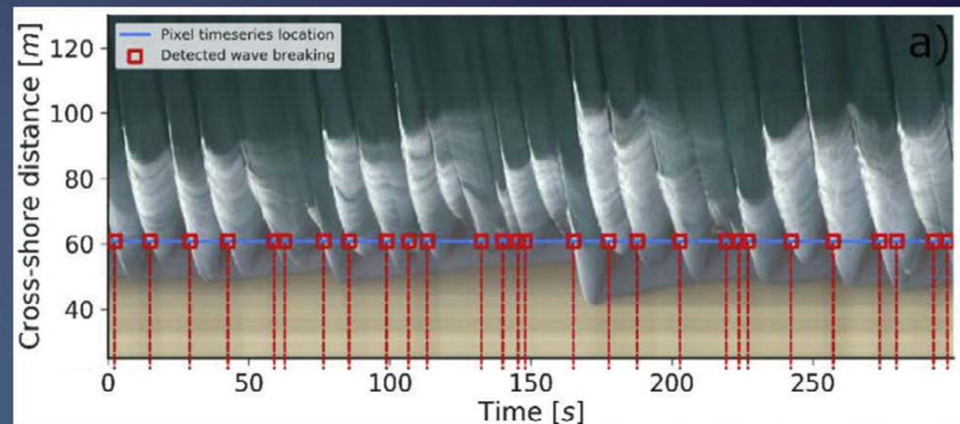


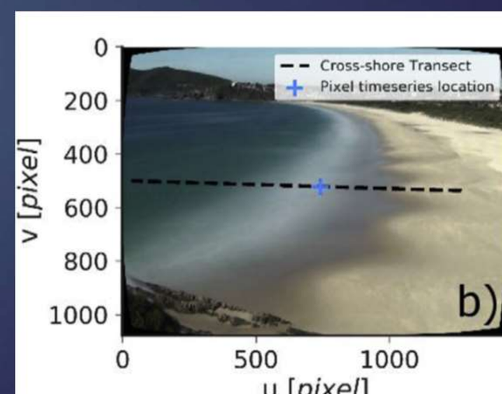




Source: Stringari (2020)

Measuring wave runup

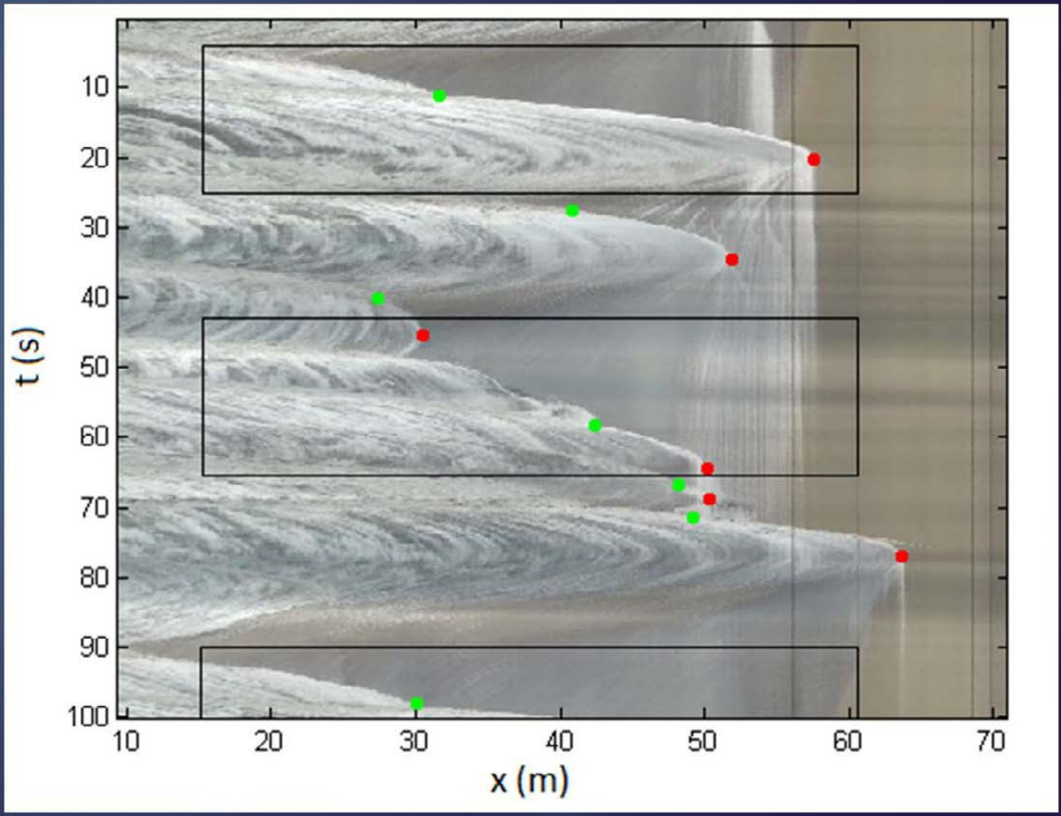




Source: Stringari et al. (2019)

Measuring wave runup

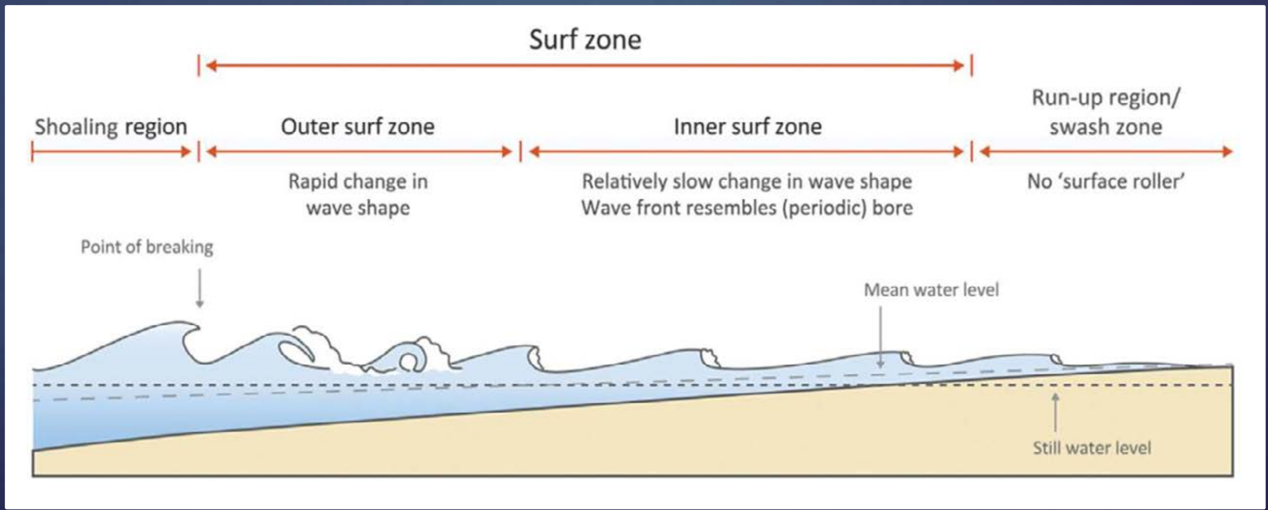
- Capture runup maxima via video or lidar
- Obtain elevations
- Calculate statistical descriptors
  - $R_{2\%}$
  - R_{max}



Source: Power et al. (2013)

What processes drive extreme wave runup?

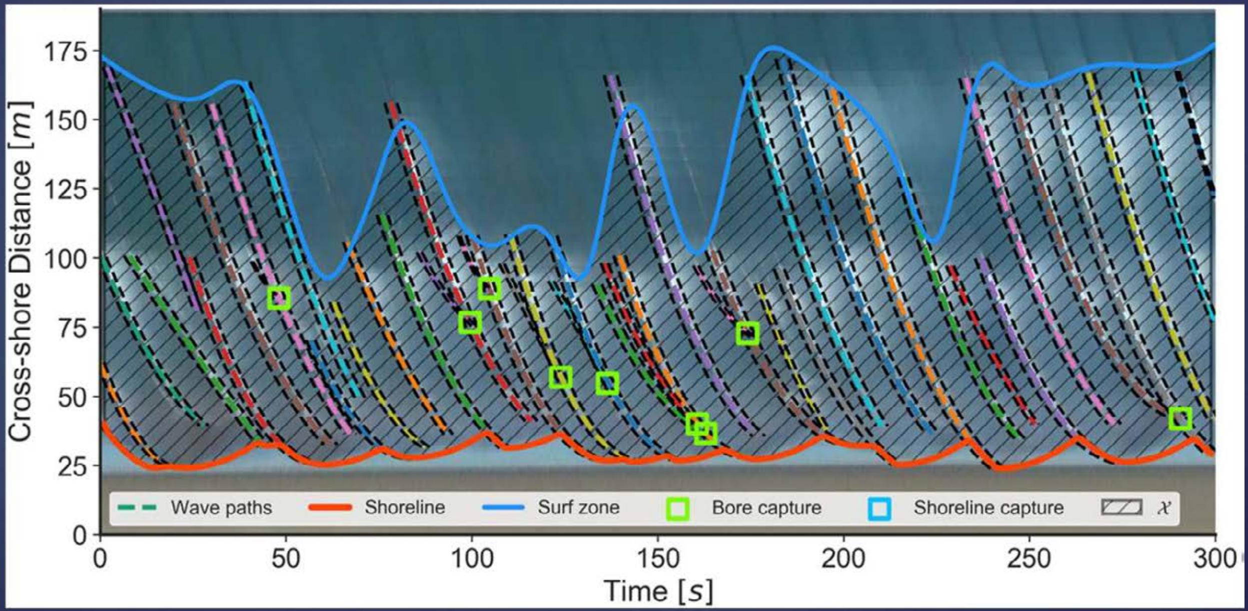
- Offshore wave conditions, local conditions
  - Wave height, wavelength, wave direction
  - Beach slope and morphology
- Need to consider what happens to a wave prior to a runup event



Source: Power (2020)

How do surf zone processes affect wave runup?

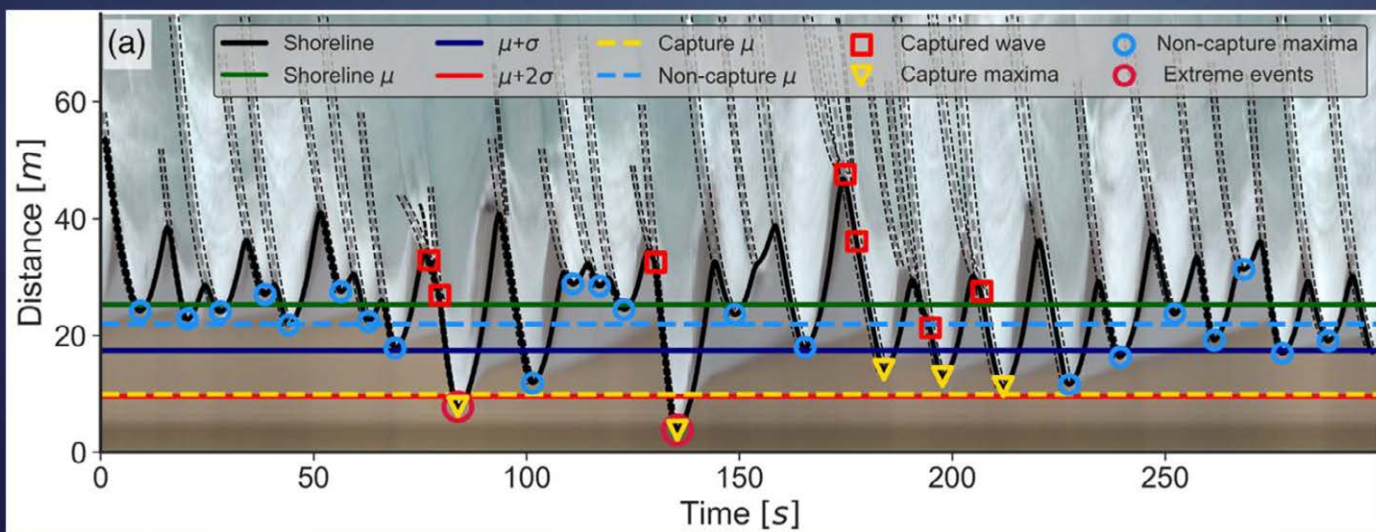
- Wave merging, bore-bore capture, wave overrunning occurs in the surf zone

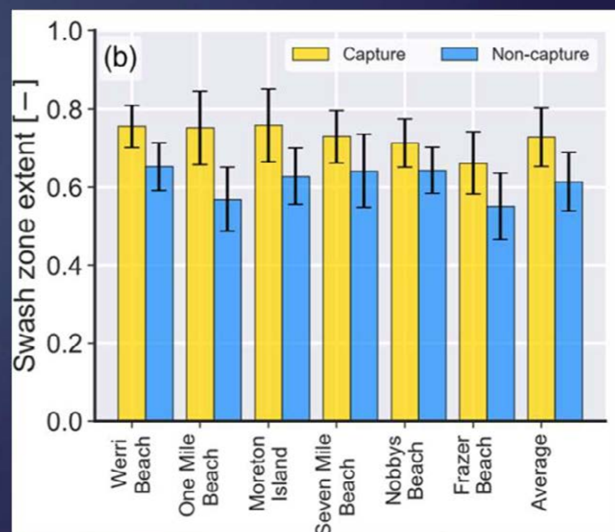


Source: Stringari & Power (2020)

How do surf zone processes affect wave runup?

- Capture process drives extreme wave runup events:
  - >97% of extreme shoreline maxima driven by waves that had undergone bore-bore capture
  - Shoreline maxima driven by capture events extend further up the beach





Source: Stringari & Power (2020)

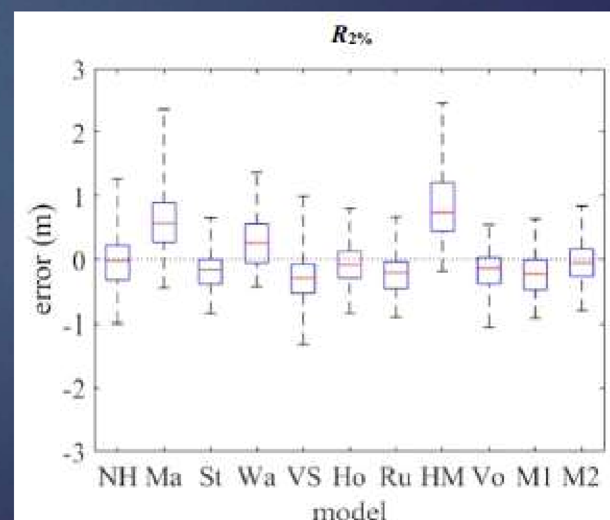
Can we better predict runup?

- Multitude of predictors for wave runup:

$$R_{2\%} = \begin{cases} 0.83 \tan\beta\sqrt{H_s L_p} + 0.2H_s \\ 1.98L_R + Z_{100\%}{}^{**} \quad \left. \begin{array}{l} L_R = 0.85\tan\beta\sqrt{H_s L_s} \\ L_R = 0.085\sqrt{H_s L_s} \end{array} \right\} \\ 0.043\sqrt{H_s L_p} \\ 1.1\left(\frac{\sqrt{H_s L_p(0.563\beta^2 + 0.004)}}{2} + 0.35\beta\sqrt{H_s L_p}\right) \\ 0.53\beta\sqrt{H_s L_p} + 0.58\tan\beta H_s + 0.45 \\ 0.33\tan\beta^{0.5} T_p H_s \\ 0.21 D_{50}^{-0.15}\tan\beta^{0.5} T_{m-1m0} H_s \ {}^{**} \\ 0.92\tan\beta\sqrt{H_s L_p} + 0.16H_s \end{cases}$$

Source: Power et al. (2019)

- Most are subject to large and variable errors if uncalibrated
- Best performing models have significant errors (NMSE 0.23) on unseen data



Source: Atkinson et al. (2017)

Can we better predict runup?

- Existing predictors can be optimised and calibrated
  - Requires local measured data
  - Results in equal or improved performance
    - On average: increase r^2 values by 0.06 and decrease RMSE and NMSE by 0.40m and 0.16
  - Uncertainty around value in this
- Machine learning techniques can result in more accurate predictors
  - Still may require data to test or calibrate

```
R2%/Hs = (x2+(((x3.*3)/exp(-5)).*((3.*x3).*x3))) + ((((x1+x3)-2)-
(x3-x2))+((x2-x1)-x3)) + (((x3.^x1)-(x3.^(1/3)))-(exp(x2).^(x1.*3)))
 + sqrt((((x3+x1)-x2)-(x2+log10(x3)))) + ((((x2.^2)./(x1.^(1/3))).^
(x1.^(1/3)))-sqrt(x3)) + ((x2+((x3./x1).^(1/3)))+(log(2)-(1./(1 + exp
(-(x2+x3)))))) + ((sqrt(x3)-(((3.^2)+3).*(x2.^2))).^2) + ((((x3.*-
5).^2).^2)+(((x3+x3).*x1)./(x2.^2))) + log((sqrt(((x2.^2)+(x3.^(1/
3))))+((x2+3).^(1/3)))) + ((((x1./x3).*(-5.^2)).*(x3.^2))-log10((1./
(1 + exp(-(x2+x3)))))) + (x1.^x3) + exp(-((((x3./x1).^exp(4))+(exp
(x3).^3)).^2)) + exp((log((x2-x3))-log(exp(-((-1+x1).^2))))) + ((sqrt
(4).*(((x3./x2)-x2)-(0-x1))).^2) + (2.*((((-5.*x3)+x1).*(2-x3))-
2)) + ((sqrt(4).*(((x3./x2)-x2)-(0-x1))).^2) + ((((-5+x1)-x2).*(x2-
x3)).*((x1-x2)-(-4.^-5))) + (exp(-((x2+(-5-x1)).^2))+((x2+5).*(x3.^2)))
 + sqrt(1./(1 + exp(-((exp(x1)-exp(-((x3+x3).^2)))+((x1.^x3)-
(x3.*4)))))) + ((exp(-((((exp(-(((sqrt(x3).*4) + (1./(1 + exp
(-(x2+2))))).^2))).^2)+x1).^2))).^3)                                (9)
```

where: x1=H_s/L_p, x2=tanβ, and x3=r/H_s

Source: Power et al. (2019)

Future work and considerations

- Majority of wave runup observations are from moderate storms/modal conditions
  - Can these be extrapolated to extreme storm events?
- Most work focusses on cross-shore processes
  - Need to consider alongshore factors
- Model predictive skill varies significantly
  - Between and within sites
  - Almost always improves with optimisation
  - Machine learning can provide some gains
  - Need to further understand processes to improve runup predictions

Wave overwash

Key research questions:

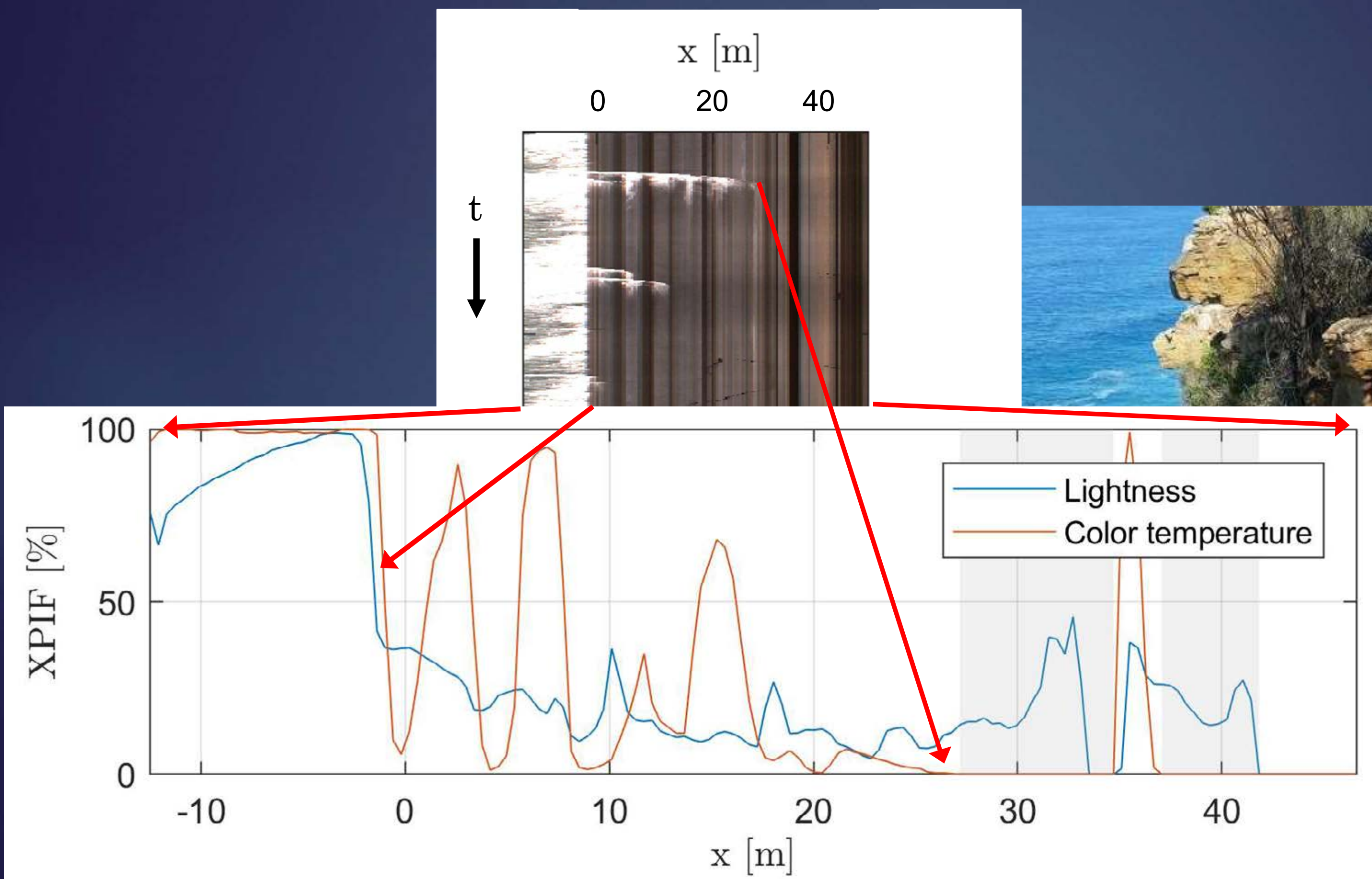
- What conditions drive overwash on rock platforms?
- Can we predict hazardous conditions?

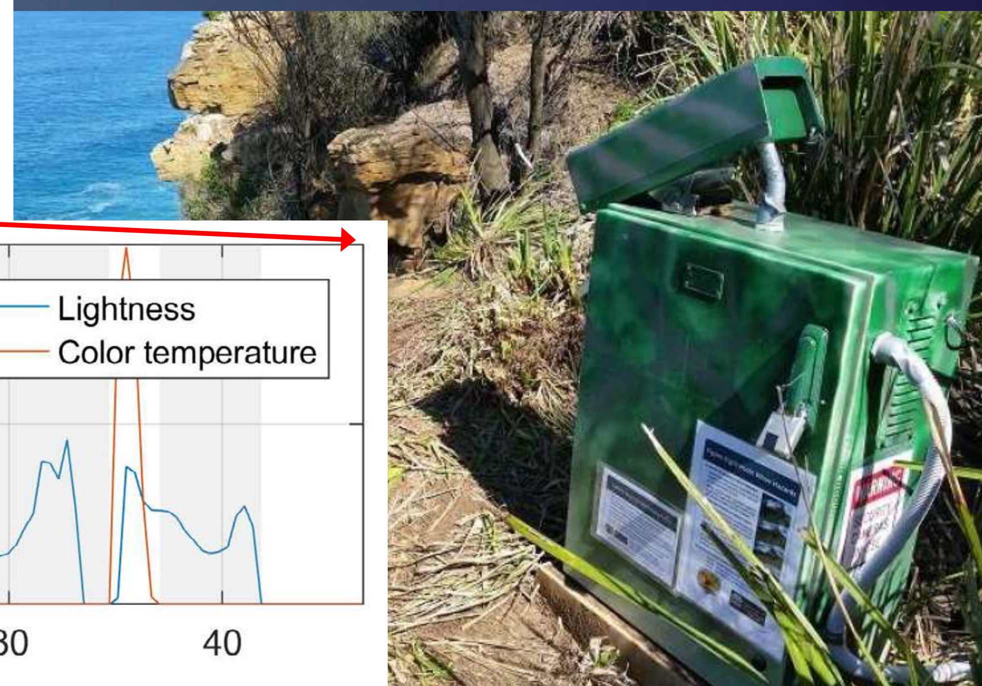
Figure 8 Pools

Figure 8 Pools

Photos: Michael Kinsela

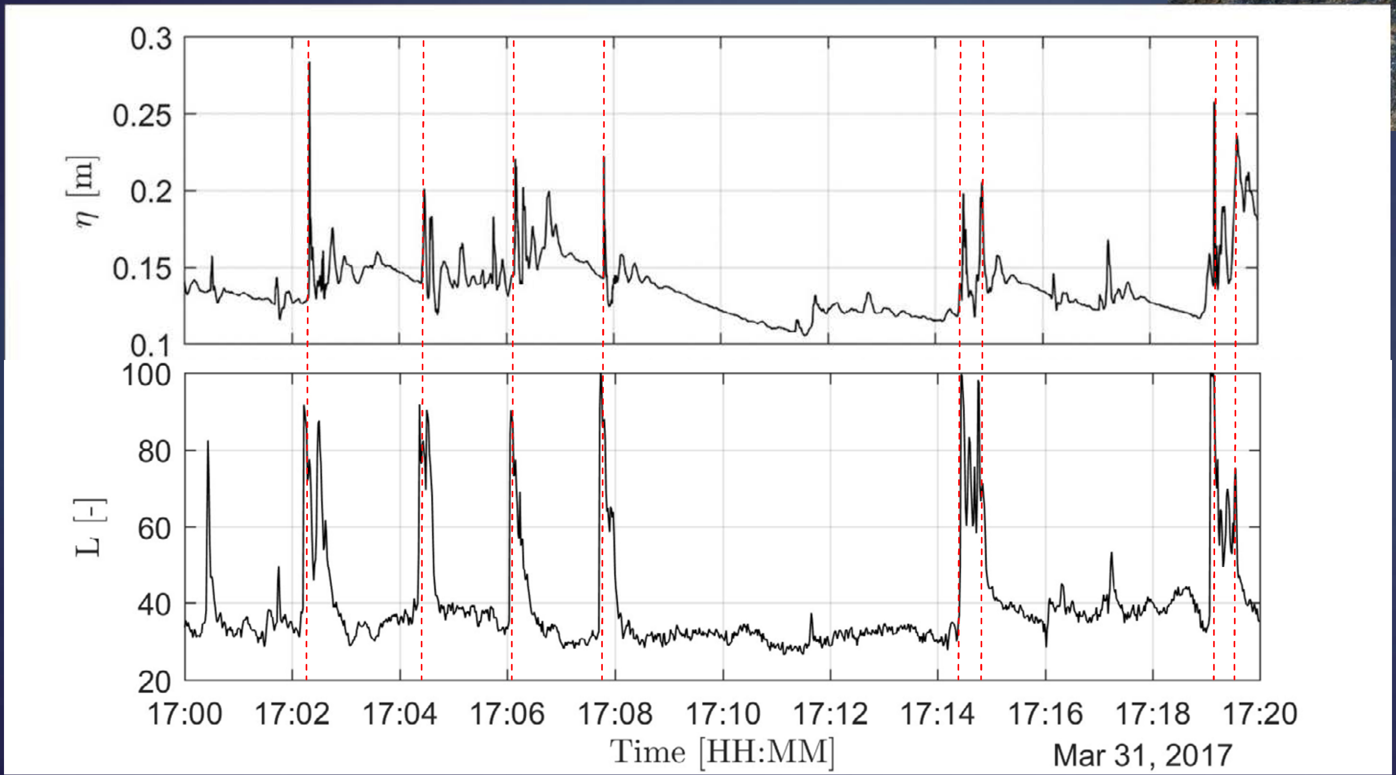
Measuring wave overwash



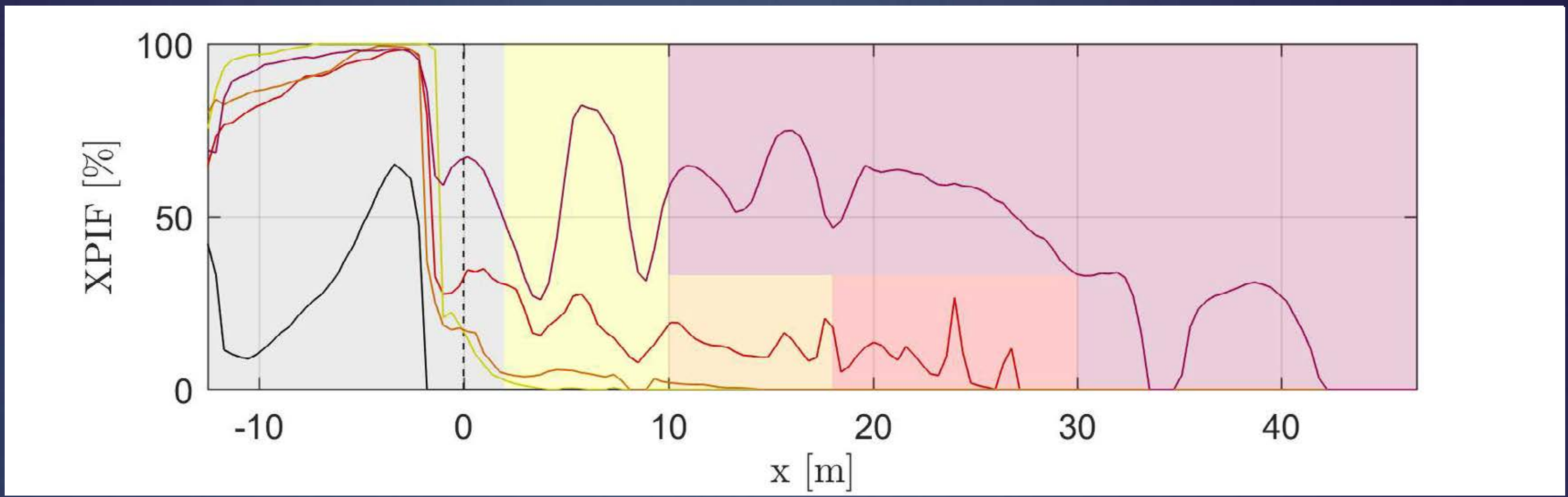


Photos: Michael Kinsela

Measuring wave overwash

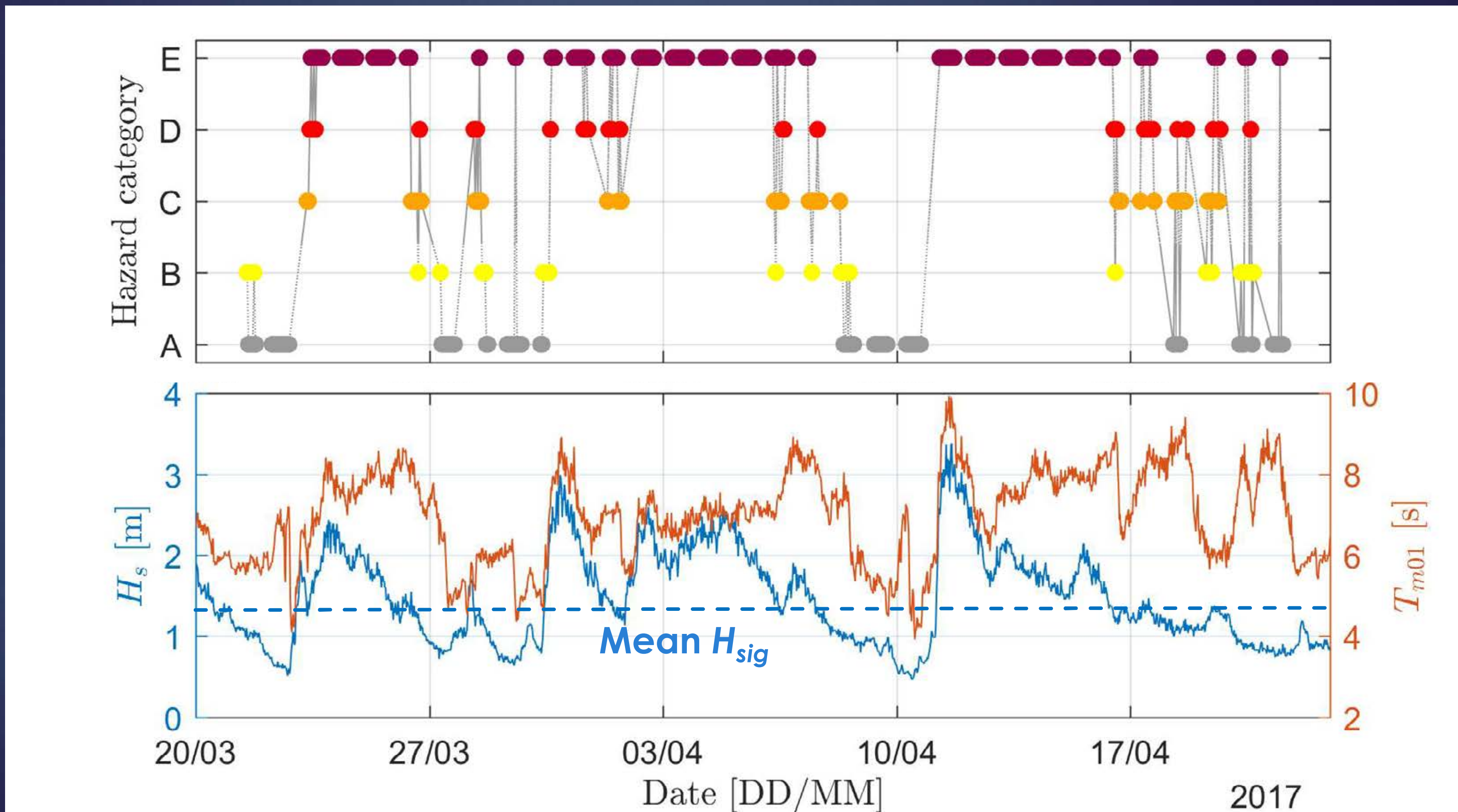


Measuring wave overwash



Category:	A	B	C	D	E
Hazard name:	Low	Minimal overwash	Moderate overwash	Major overwash	Extreme overwash

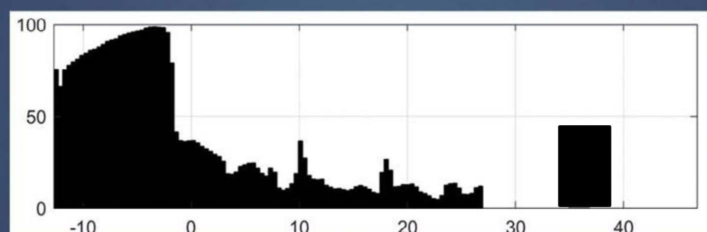
What drives overwash on rock platforms?

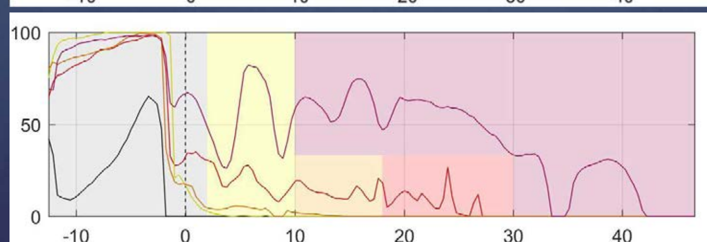


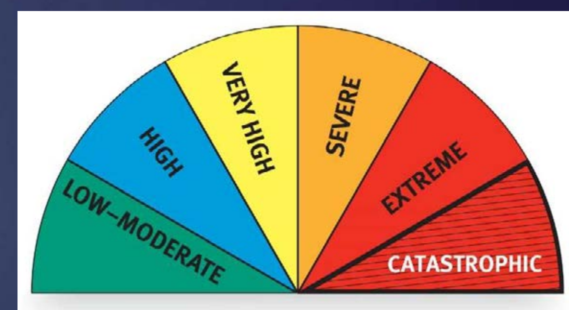
Predicting hazardous conditions

Forecast wave and tide conditions

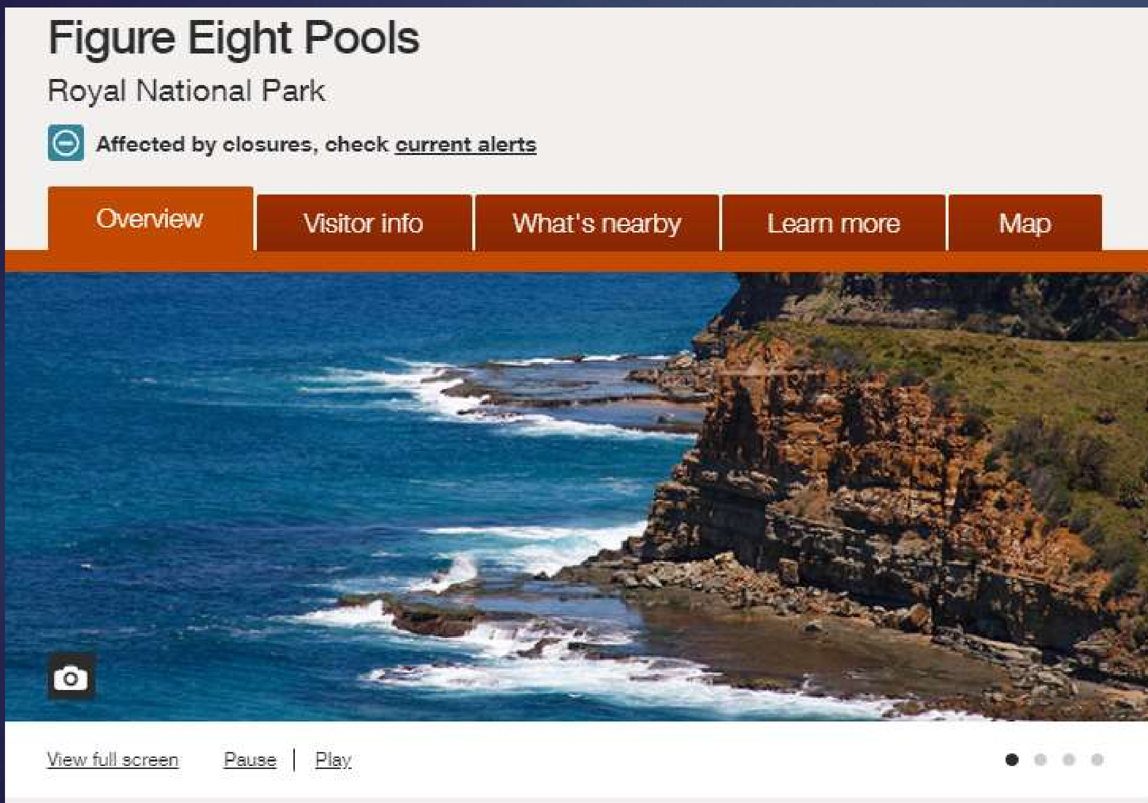
Hazard thresholds from observations

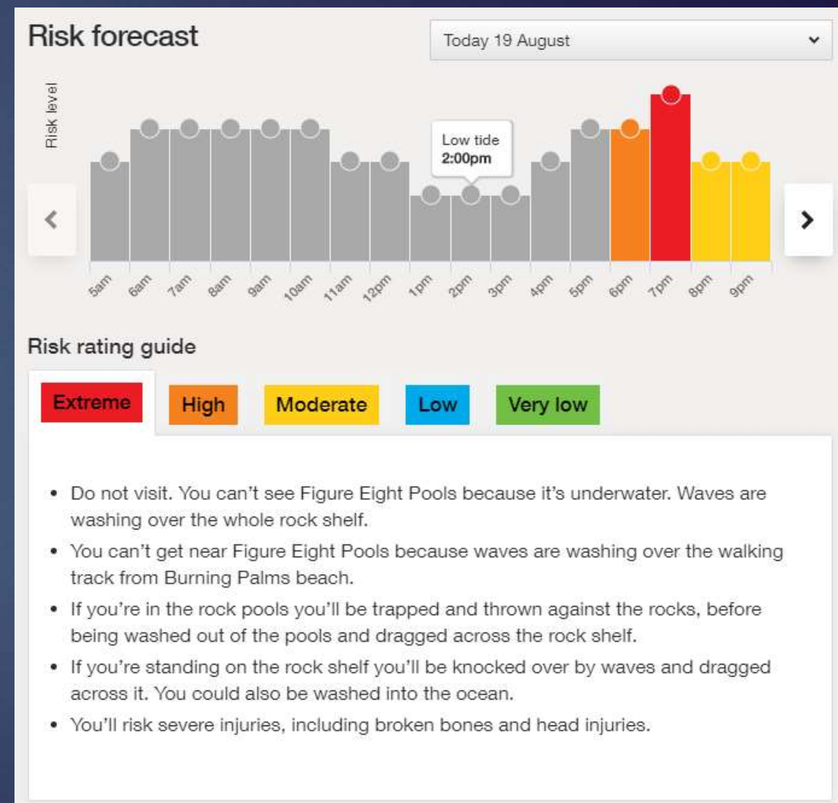






Live wave risk forecast tool





https://www.nationalparks.nsw.gov.au/things-to-do/lookouts/figure-eight-pools

Future work and considerations

- Remote sensing offers excellent opportunities to obtain data in challenging environments
  - Always necessary to ground truth
  - Rock platforms far more challenging than sandy beaches for remote sensing
- It is possible to forecast wave risks on rock platforms
  - Site specific data is critical
  - Challenges lie in understanding these issues more generally

Acknowledgements

- All the many colleagues and students who have contributed to this work and whose figures and photos are shown in this presentation, but particularly:
  - Alex Atkinson, Tom Baldock, Bahram Gharabaghi, David Hanslow, Murray Kendall, Michael Kinsela, Bryson Robertson, and Caio Stringari
- All the colleagues, students, and volunteers who helped out on field experiments that contributed data to these projects and those who provided data directly

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- Stringari, C. E., et al., 2019, A novel machine learning algorithm for tracking remotely sensed waves in the surf zone: C. Eng., 147, 149-158.
- Stringari, C. E., & Power, H. E. 2020, Quantifying bore-bore capture on natural beaches. JGR: Oceans, 125, e2019JC015689.
- Among others!

Measuring waves to better quantify coastal hazards

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