

Monitoring whale populations from acoustic data over large temporal and spatial scales

Danielle Harris, Len Thomas & Peter Tyack

University of St Andrews, UK



University of
St Andrews

09 September 2025

Acknowledgments

Support from:

The Richard Lounsbery Foundation

Interns: Viktor Tretiakov, Helen Black,
Maddie Doran

Data from the Comprehensive Nuclear
Test Ban Treaty Organisation



The rest of the CORTADO team:

Kerri D. Seger, re1 LLC

John Boyle

David K. Mellinger, Oregon State University

Jennifer L. Miksis-Olds, University of New Hampshire

Gabrielle Arrieta, University of St Andrews

Kevin D. Heaney, Applied Ocean Sciences, LLC

Rose Hilmo, University of Tampa

Tiago Marques, University of St Andrews

Luis Matias, University of Lisbon

Andreia Pereira, University of Lisbon

William Wilcock, University of Washington



University of
St Andrews

Background

- Wildlife monitoring programs are costly.
 - How many are there?
 - What are their patterns/trends
 - Often required for conservation and management
- Alternative cost-efficient approaches?
- One option: “platforms of opportunity”.
- Example: Comprehensive Nuclear Test Ban Treaty Organization International Monitoring System (CTBTO IMS)



Images courtesy of Maxim Weise at FreeDigitalPhotos.net

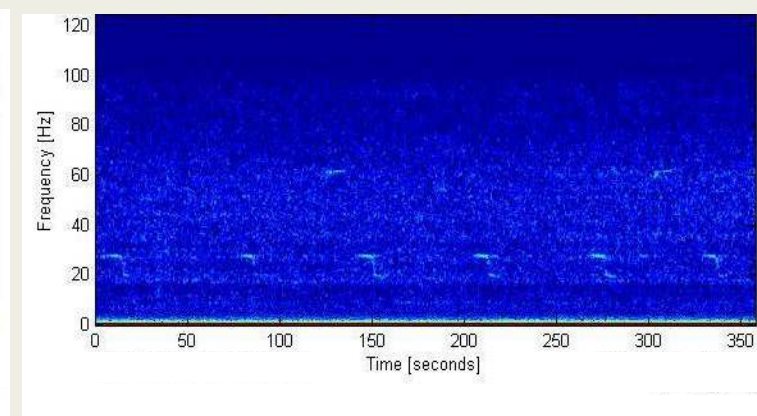
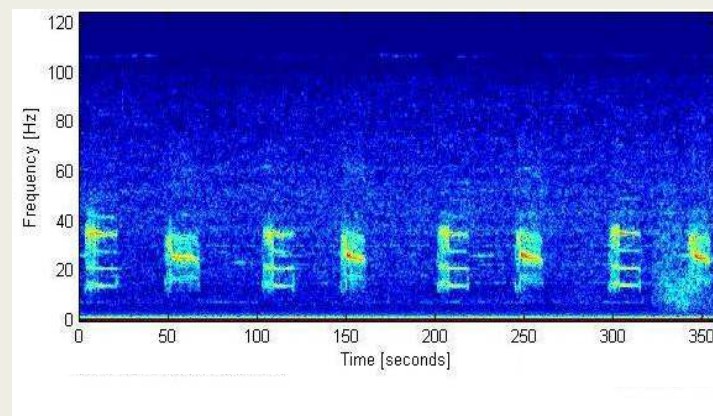
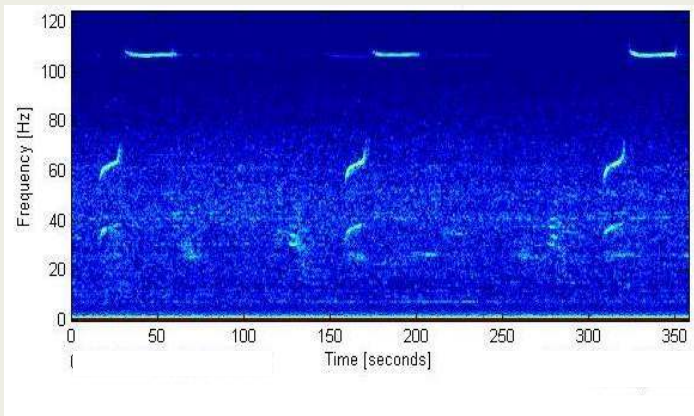


Example: Comprehensive Nuclear Test Ban Treaty Organization International Monitoring System (CTBTO IMS)

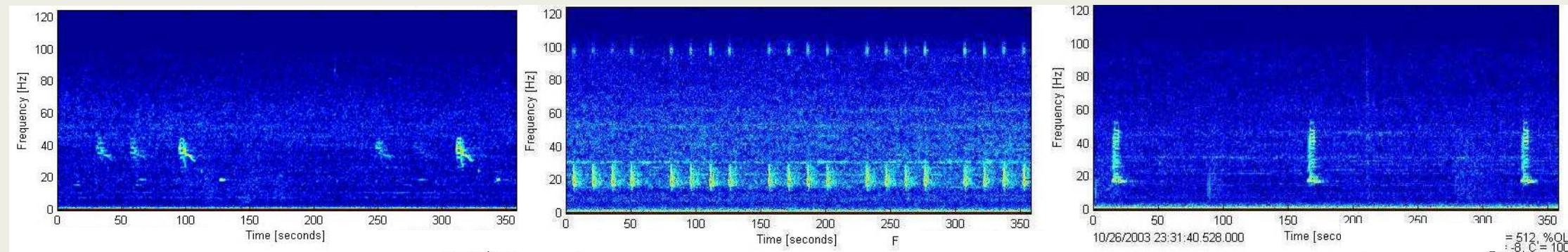


Circles denote hydrophone stations (as opposed to land-based T-phase stations). Adapted from <https://www.ctbto.org/map/>

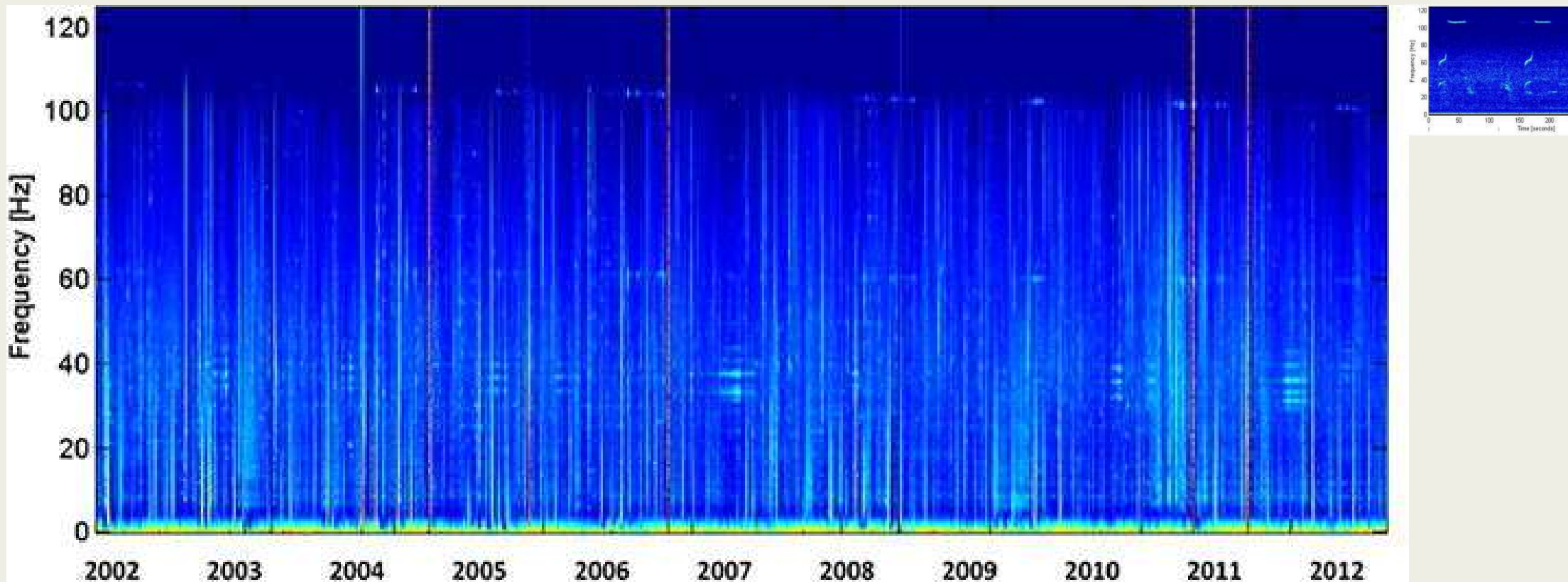
Indian Ocean baleen whale sounds (some examples)



Indian Ocean baleen whale sounds (some examples)



A lot of data available



Absolute density estimation from acoustic data

- Various methods available to estimate animal absolute densities or abundances

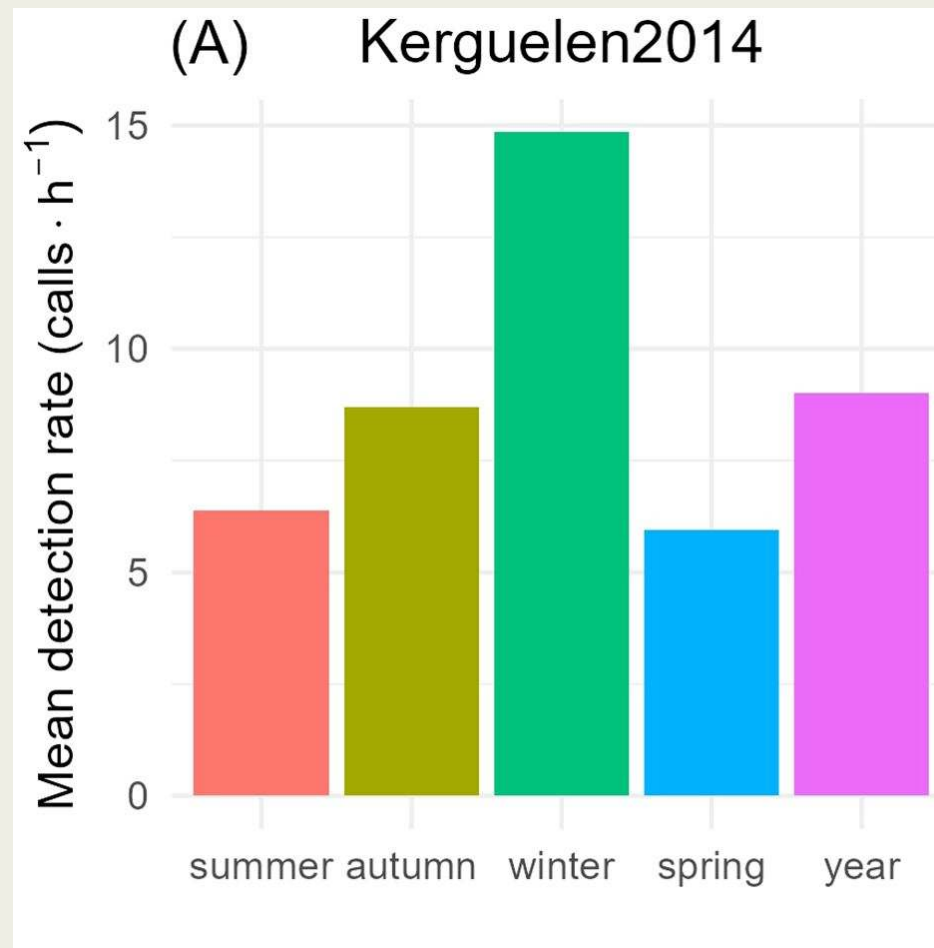
e.g., distance sampling, spatial capture recapture, simulation-based
- These methods estimate the **probability of detection**, a key parameter for absolute density/abundance estimation

Counting calls (“cue counting”)

$$\hat{D} = \frac{n(1 - \hat{c})}{\pi w^2 k \hat{p} T \hat{r}}$$

- \hat{D} = estimated density
- n = number of detections
- \hat{c} = false positive proportion
- w = radius of points
- k = number of points
- \hat{p} = proportion of animals detected
- T = monitoring time per point
- \hat{r} = cue production rate

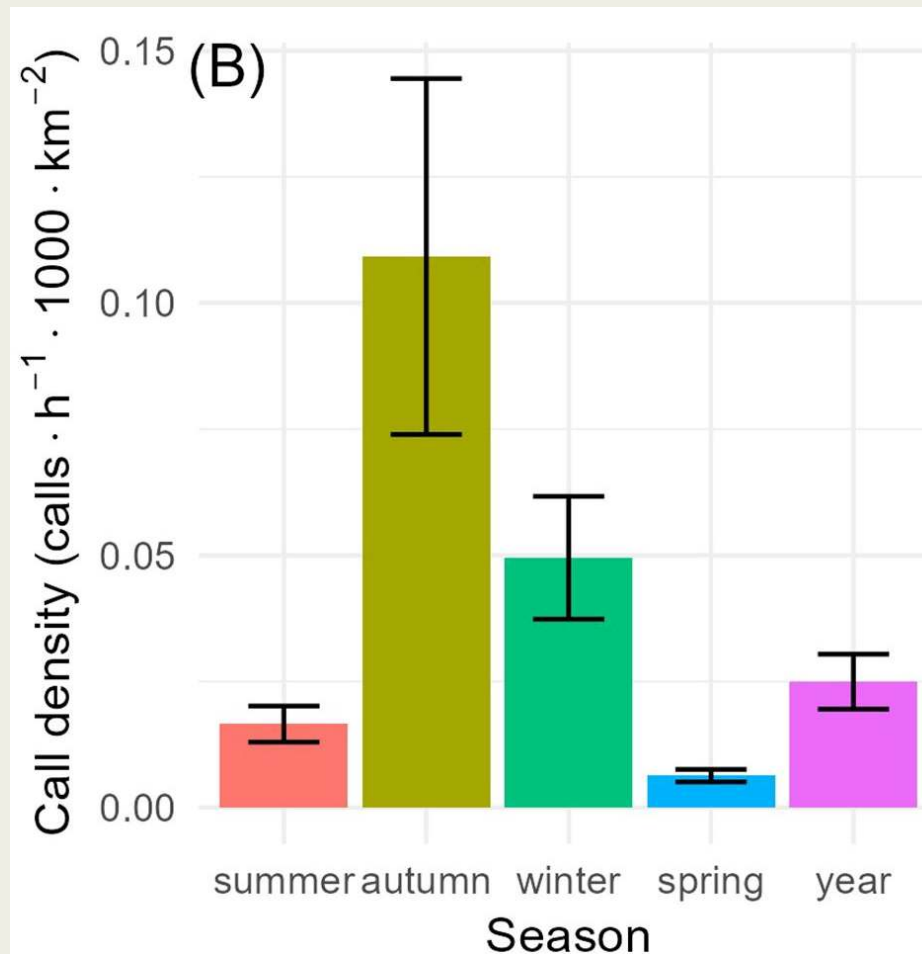
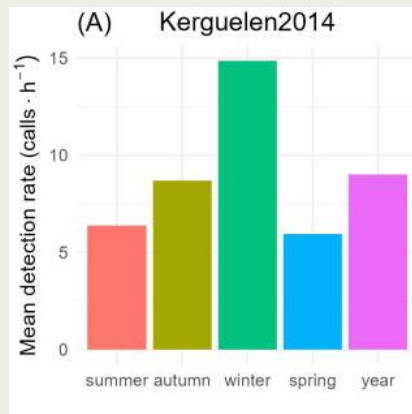
Why is detection probability important?



de Castro FR, Harris DV, Buchan SJ, Balcazar N and Miller BS (2024) Beyond counting calls: estimating detection probability for Antarctic blue whales reveals biological trends in seasonal calling. *Front. Mar. Sci.* 11:1406678. doi: 10.3389/fmars.2024.1406678
© 2024 de Castro, Harris, Buchan, Balcazar and Miller.



Why is detection probability important?



de Castro FR, Harris DV, Buchan SJ, Balcazar N and Miller BS (2024) Beyond counting calls: estimating detection probability for Antarctic blue whales reveals biological trends in seasonal calling. *Front. Mar. Sci.* 11:1406678. doi: 10.3389/fmars.2024.1406678
© 2024 de Castro, Harris, Buchan, Balcazar and Miller.

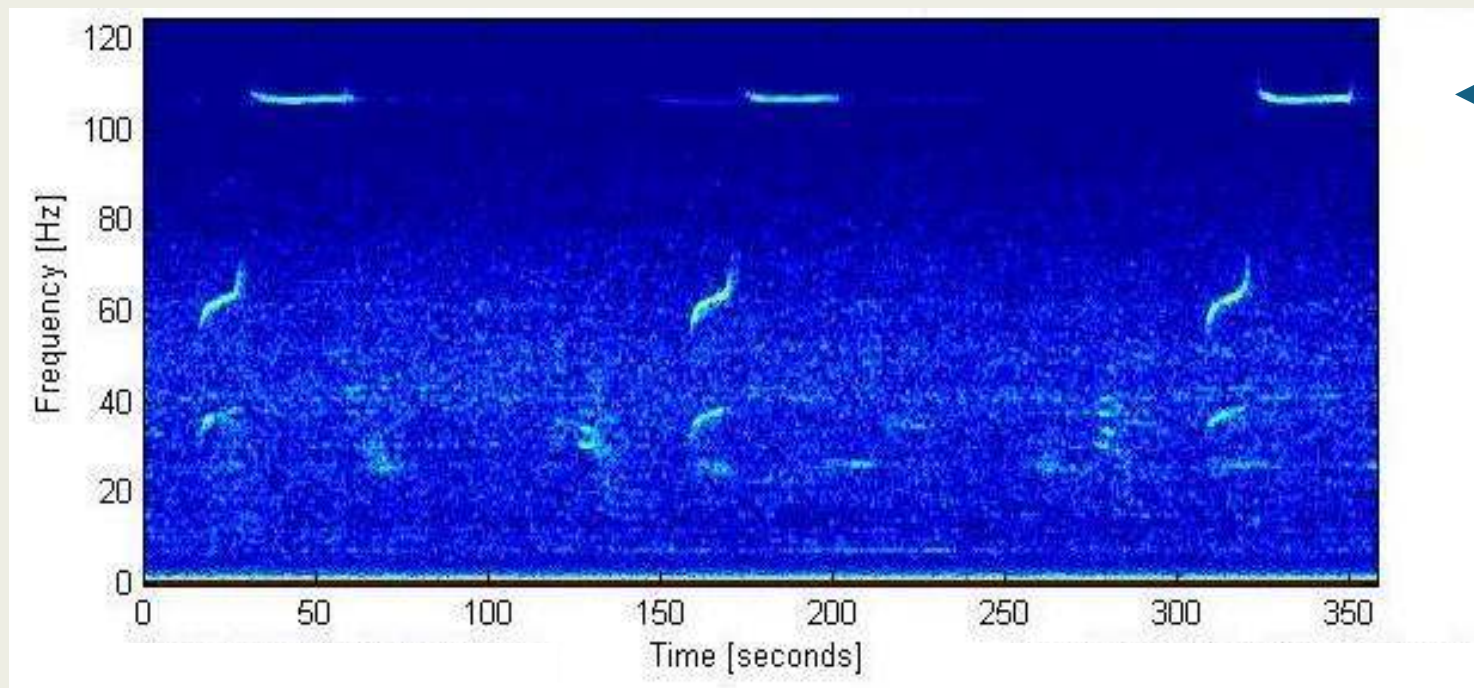
Monte Carlo simulation-based approaches using CTBTO data

- Approach:
 - Based on the **passive sonar equation**
 - \approx how well sound travels through water and is detected by a sensor
 - Simulations use
 - bearings to automatically detected calls,
 - sound propagation models,
 - noise level measurements and
 - assumed source level distribution of the target calls to estimate P .
- Considerations:
 - Numerous parameter inputs
 - Assumptions about animal distribution (V. Tretiakov, student internship)



Monte Carlo simulation-based approaches using CTBTO data

Case study: Indian Ocean Sri Lankan blue whale song units (**2024** data)



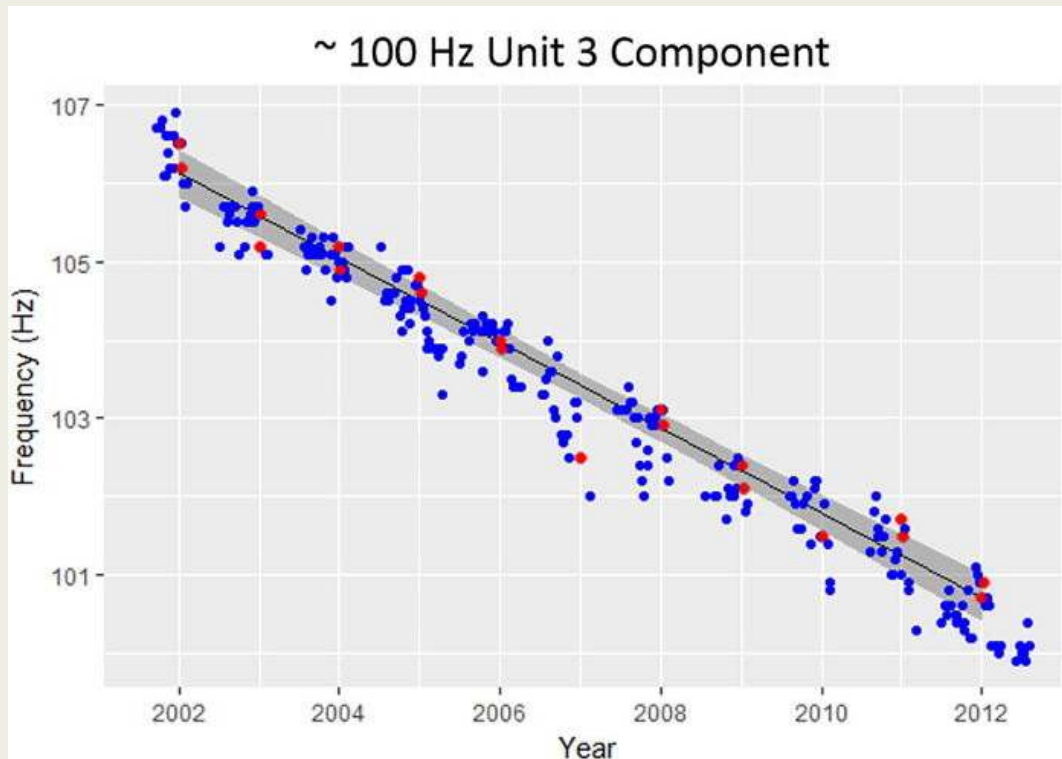
Data: courtesy of the
CTBTO



University of
St Andrews

Monte Carlo simulation-based approaches using CTBTO data

Results: automated detection of calls



Continued decline from 2017 onwards investigated (Black & Harris, in prep).

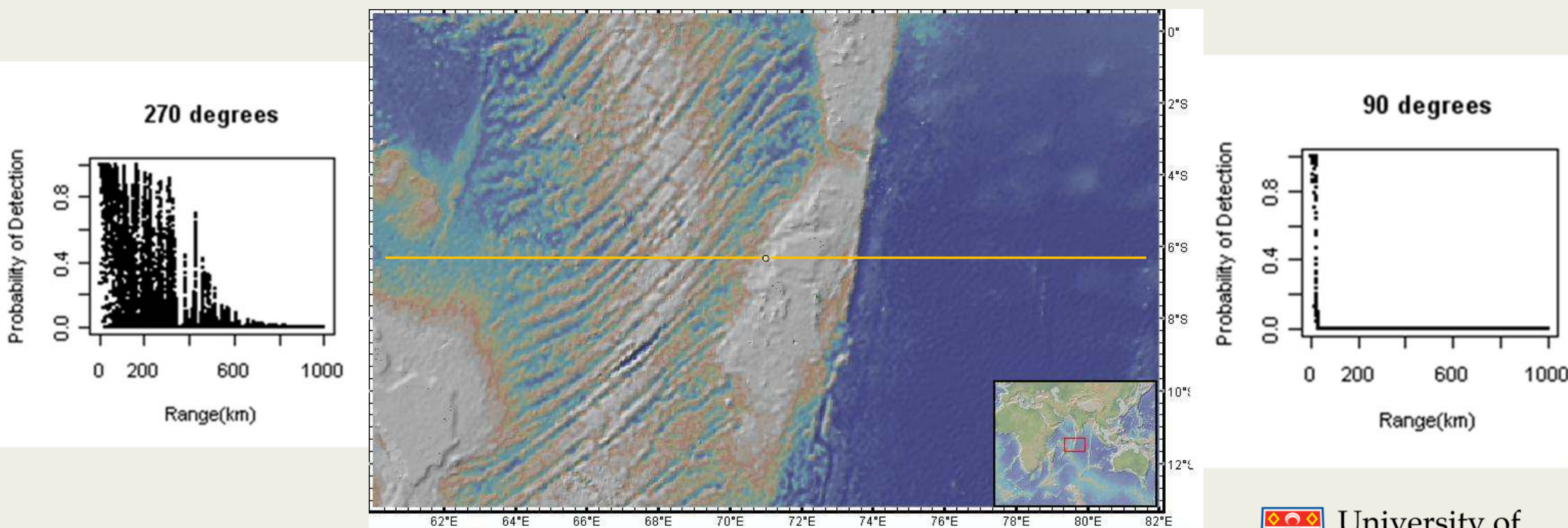
Results informing automatic detector development.

Published in: Jennifer L. Miksis-Olds; Sharon L. Nieuwkirk; Danielle V. Harris;
The Journal of the Acoustical Society of America **144**, 3618-3626 (2018)
DOI: 10.1121/1.5084269. Copyright © 2018 Acoustical Society of America



Monte Carlo simulation-based approaches using CTBTO data

Results: P is spatially variable due to extreme bathymetry (updated results in Harris et al., in press)



Conclusions

- Example of maximising use of available data (over large spatial and temporal scales).
- Density estimation methods can help to standardise acoustic datasets collected across different sites/years.
- There are many studies with sparsely distributed instruments.



Adapted from <https://www.ctbto.org/map/>

Thank you!