

¹ eo-tides: Tide modelling tools for large-scale satellite Earth observation analysis

³ **Robbi Bishop-Taylor**  ¹¶, **Claire Phillips**  ¹, **Stephen Sagar**  ¹, **Vanessa Newey**¹, and **Tyler Sutterley**  ²

⁵ 1 Geoscience Australia, Australia  ² University of Washington Applied Physics Laboratory, United States of America  ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) ↗
- [Repository](#) ↗
- [Archive](#) ↗

Editor: [Open Journals](#) ↗

Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).

Summary

The eo-tides package provides powerful parallelised tools for integrating satellite Earth observation (EO) data with ocean tide modelling. The package provides a flexible Python toolkit for attributing modelled tide heights to a time-series of satellite images based on the spatial extent and acquisition time of each satellite observation (Figure 1).

eo-tides leverages advanced tide modelling functionality from the pyTMD tide prediction software (Sutterley et al., 2017), combining this capability with EO spatial analysis tools from the [Open Data Cube](#) (ODC)'s odc-geo ([odc-geo contributors](#), 2024). This allows tides to be modelled in parallel using over 50 supported models, and returned in standardised pandas (McKinney, 2010; pandas development team, 2020) and xarray (Hoyer & Joseph, 2017) data formats for EO analysis.

eo-tides tools can be applied to petabytes of freely available satellite data loaded from the cloud using ODC's odc-stac or datacube packages (e.g. using [Digital Earth Australia](#) or [Microsoft Planetary Computer's](#) STAC SpatioTemporal Asset Catalogues). Additional functionality allows users to assess potential satellite-tide biases and validate modelled tides with external tide gauge data — critical considerations for ensuring the reliability and accuracy of coastal EO workflows. These open-source tools support the efficient, scalable and robust analysis of coastal EO data for any time period or location globally.

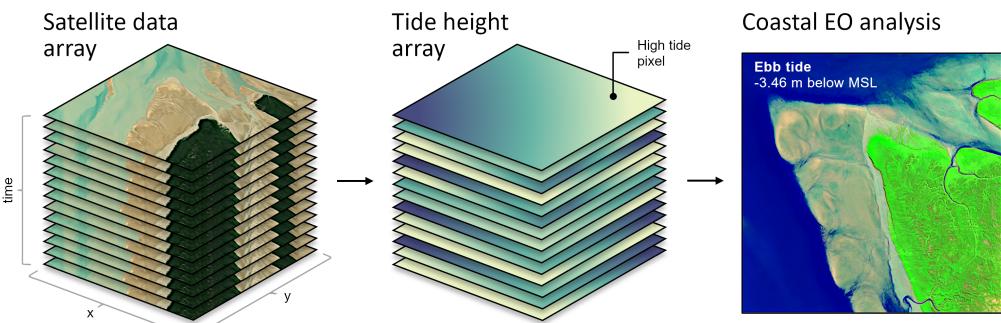


Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (e.g. Sentinel-2 or Landsat), then combined to derive insights into dynamic coastal environments.

25 Statement of need

26 Satellite remote sensing offers an unparalleled resource for examining dynamic coastal environments through time or across large regions (Turner et al., 2021; Vitousek et al., 2023).
 27 However, the highly variable influence of ocean tides can complicate analyses, making it difficult
 28 to separate the influence of changing tides from patterns of true coastal change (Vos et al.,
 29 2019). This is a particularly challenging for large-scale coastal EO analyses, where failing to
 30 account for tide dynamics can lead to inaccurate or misleading insights into satellite-observed
 31 coastal processes.

33 Conversely, information about ocean tides can provide unique environmental insights that can
 34 significantly enhance the value of EO data. Traditionally, satellite data dimensions include
 35 the geographic “where” and temporal “when” of acquisition. Introducing tide height as an
 36 additional analysis dimension allows data to be filtered, sorted, and analysed based on tidal
 37 dynamics, offering a transformative re-imagining of traditional multi-temporal EO analysis
 38 (Sagar et al., 2017). For instance, satellite data can be analysed to focus on ecologically
 39 significant tidal stages (e.g., high tide, low tide, spring or neap tides) or specific tidal processes
 40 (e.g., ebb or flow tides; Sent et al. (2025)).

41 This concept has been used to map coastal change at continental-scale (Bishop-Taylor et al.,
 42 2021), map intertidal zone extent and elevation (Bishop-Taylor et al., 2019; Murray et al.,
 43 2012; Sagar et al., 2017), and creating tidally-constrained coastal image composites (Sagar
 44 et al., 2018). However, these methods have traditionally relied on bespoke, closed-source, or
 45 difficult-to-install tide modelling tools, limiting their reproducibility and portability. To support
 46 the next generation of coastal EO workflows, there is a pressing need for efficient open-source
 47 tools for combining satellite data with tide modelling. eo-tides addresses this need through
 48 functionality offered in five main analysis modules (utils, model, eo, stats, validation).

49 Features

50 Setting up tide models

51 The `eo_tides.utils` module simplifies the setup of ocean tide models, addressing a common
 52 barrier to coastal EO workflows. Tools like `list_models` provide feedback on available and
 53 supported models (Figure 2), while `clip_models` can significantly improve performance by
 54 clipping large high-resolution model files (e.g. FES2022) to smaller study area extents.

	Model	Expected path
✓	EOT20	tide_models/EOT20/ocean_tides
✗	FES2014	tide_models/fes2014/ocean_tide
✓	HAMTIDE11	tide_models/hamtide
...

Summary:
 Available models: 2/50

Figure 2: A `list_tides` output providing a useful summary of available and supported tide models.

55 Modelling tides

56 The `eo_tides.model` module is powered by tide modelling functionality from the pyTMD Python
 57 package (Sutterley et al., 2017). pyTMD is an open-source tidal prediction software that
 58 simplifies the calculation of ocean and earth tides.

59 The `model_tides` function from `eo_tides.model` wraps pyTMD functionality to return tide
 60 predictions in a standardised pandas.DataFrame format, enabling integration with EO data
 61 and parallelisation for improved performance (Table 1). The `model_phases` function can
 62 additionally classify tides into high/low/flow/ebb phases, critical for correctly interpreting
 63 satellite-observed coastal processes like turbidity (Sent et al., 2025).

Table 1: A benchmark comparison of tide modelling parallelisation, for a typical large-scale analysis involving a month of hourly tides modelled at 10,000 points using three models (FES2022, TPXO10, GOT5.6).

Cores	Parallelisation	No parallelisation	Speedup
8	2min 46s ± 663 ms	9min 28s ± 536 ms	3.4x
32	55.9 s ± 560 ms	9min 24s ± 749 ms	10.1x

64 Combining tides with satellite data

65 The `eo_tides.eo` module integrates modelled tides with xarray-format satellite data (Hoyer &
 66 Joseph, 2017). The `tag_tides` and `pixel_tides` functions (Table 2, Figure 3) can be applied
 67 to attribute tides to satellite data for any coastal location on the planet, for example using
 68 open data loaded from the cloud using ODC and STAC (STAC contributors, 2024).

Table 2: Comparison of the `tag_tides` and `pixel_tides` functions.

tag_tides	pixel_tides
<ul style="list-style-type: none"> - Assigns a single tide height to each satellite image time-step - Single tide height per image can produce artefacts and discontinuities - Fast, low memory use - Ideal for local, site-scale analysis 	<ul style="list-style-type: none"> - Assigns a tide height to every individual pixel through time - Produce spatially seamless results across large regions - Slower, higher memory use - Ideal for large-scale analysis

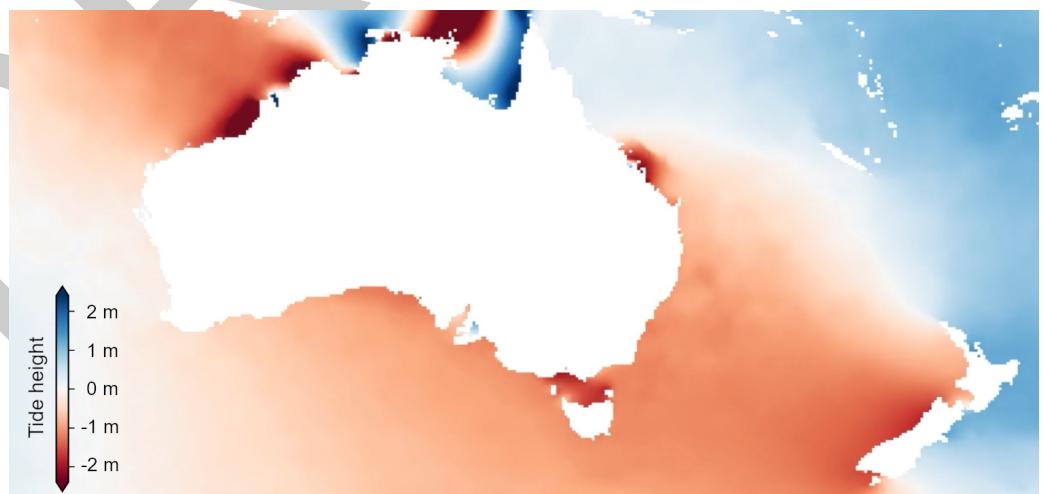


Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

69 Calculating tide statistics and satellite biases

70 The `eo_tides.stats` module identifies biases caused by complex tide aliasing interactions that
 71 can prevent satellites from observing the entire tide cycle (Bishop-Taylor et al., 2019; Eleveld

⁷² et al., 2014; Sent et al., 2025). The tide_stats and pixel_stats functions produce useful
⁷³ statistics that summarise how well satellite data captures real-world tides (Figure 4).

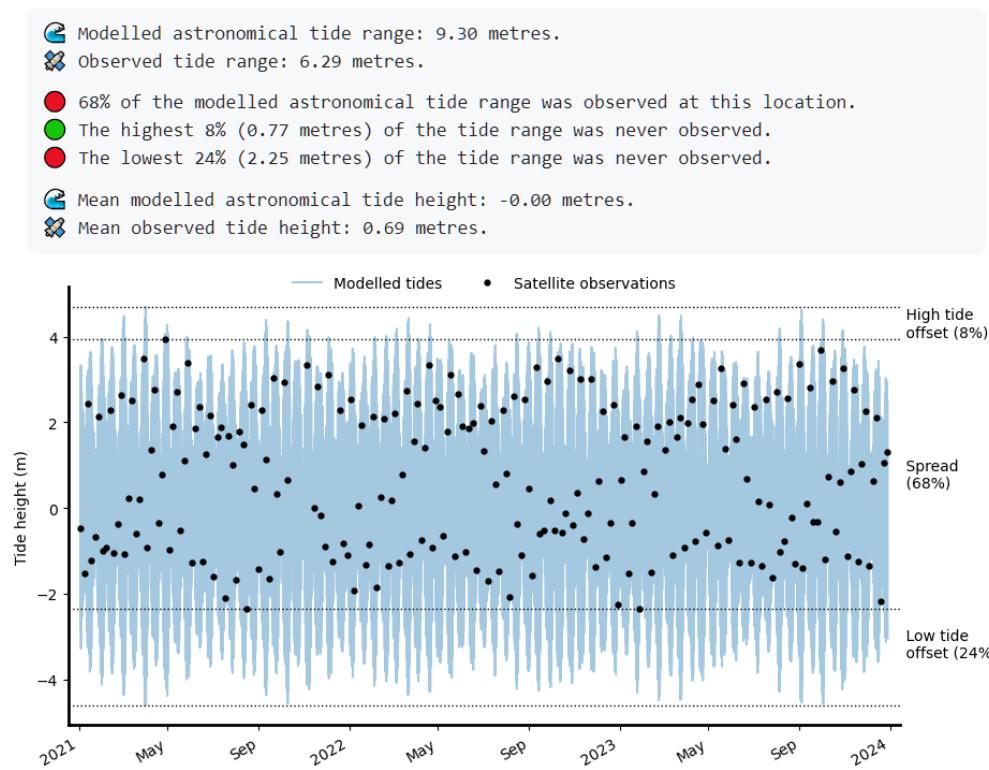


Figure 4: An example of tidally-biased satellite coverage, where only ~68% of the astronomical tide range is observed.

⁷⁴ **Validating modelled tides**

⁷⁵ The `eo_tides.validation` module validates modelled tides against observed sea-level measurements,
⁷⁶ assisting users to evaluate and select optimal models for their application (Figure 5).

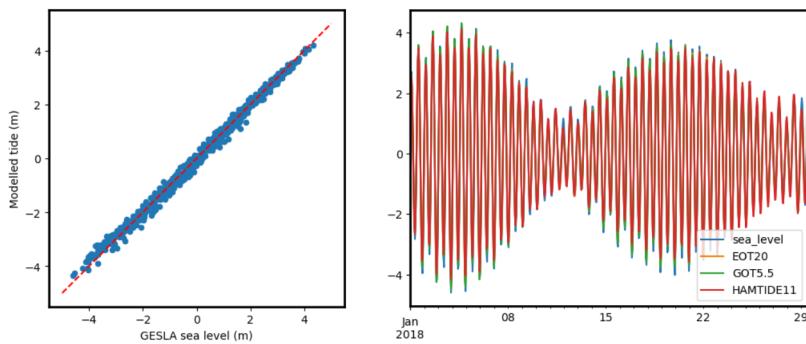


Figure 5: A comparison of multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge (Haigh et al., 2023).

77 Research projects

78 Early versions of eo-tides functions have been used for continental-scale intertidal mapping
79 ([Bishop-Taylor et al., 2024](#)), multi-decadal shoreline mapping across Australia ([Bishop-Taylor](#)
80 [et al., 2021](#)) and [Africa](#), and for correcting satellite-derived shoreline in the CoastSeg Python
81 package ([Fitzpatrick et al., 2024](#)).

82 Acknowledgements

83 Functions from eo-tides were originally developed in the Digital Earth Australia Notebooks
84 repository ([Krause et al., 2021](#)). This paper is published with the permission of the Chief
85 Executive Officer, Geoscience Australia.

86 References

- 87 Bishop-Taylor, R., Nanson, R., Sagar, S., & Lymburner, L. (2021). Mapping Australia's
88 Dynamic Coastline at Mean Sea Level using Three Decades of Landsat Imagery. *Remote*
89 *Sensing of Environment*, 267, 112734. <https://doi.org/10.1016/j.rse.2021.112734>
- 90 Bishop-Taylor, R., Phillips, C., Newey, V., & Sagar, S. (2024). *Digital Earth Australia Intertidal*.
91 Commonwealth of Australia (Geoscience Australia). <https://doi.org/10.26186/149403>
- 92 Bishop-Taylor, R., Sagar, S., Lymburner, L., & Beaman, R. J. (2019). Between the tides:
93 Modelling the elevation of australia's exposed intertidal zone at continental scale. *Estuarine,*
94 *Coastal and Shelf Science*, 223, 115–128. <https://doi.org/10.1016/j.ecss.2019.03.006>
- 95 Eleveld, M. A., Van der Wal, D., & Van Kessel, T. (2014). Estuarine suspended par-
96 ticular matter concentrations from sun-synchronous satellite remote sensing: Tidal
97 and meteorological effects and biases. *Remote Sensing of Environment*, 143, 204–215.
98 <https://doi.org/10.1016/j.rse.2013.12.019>
- 99 Fitzpatrick, S., Buscombe, D., Warrick, J. A., Lundine, M. A., & Vos, K. (2024). CoastSeg: An
100 accessible and extendable hub for satellite-derived-shoreline (SDS) detection and mapping.
101 *Journal of Open Source Software*, 9(99), 6683. <https://doi.org/10.21105/joss.06683>
- 102 Haigh, I. D., Marcos, M., Talke, S. A., Woodworth, P. L., Hunter, J. R., Hague, B. S.,
103 Arns, A., Bradshaw, E., & Thompson, P. (2023). GESLA version 3: A major update to
104 the global higher-frequency sea-level dataset. *Geoscience Data Journal*, 10(3), 293–314.
105 <https://doi.org/10.1002/gdj3.174>
- 106 Hoyer, S., & Joseph, H. (2017). xarray: N-d labeled arrays and datasets in python. *Journal of*
107 *Open Research Software*, 5(1). <https://doi.org/10.5334/jors.148>
- 108 Krause, C., Dunn, B., Bishop-Taylor, R., Adams, C., Burton, C., Alger, M., Chua, S., Phillips, C.,
109 Newey, V., Kouzoubov, K., Leith, A., Ayers, D., & Hicks, A. (2021). *Digital Earth Australia*
110 *notebooks and tools repository*. <https://github.com/GeoscienceAustralia/dea-notebooks/>;
111 Commonwealth of Australia (Geoscience Australia). <https://doi.org/10.26186/145234>
- 112 McKinney, Wes. (2010). Data Structures for Statistical Computing in Python. In Stéfan van
113 der Walt & Jarrod Millman (Eds.), *Proceedings of the 9th Python in Science Conference*
114 (pp. 56–61). <https://doi.org/10.25080/Majora-92bf1922-00a>
- 115 Murray, N. J., Phinn, S. R., Clemens, R. S., Roelfsema, C. M., & Fuller, R. A. (2012).
116 Continental scale mapping of tidal flats across east asia using the landsat archive. *Remote*
117 *Sensing*, 4(11), 3417–3426. <https://doi.org/10.3390/rs4113417>
- 118 odc-geo contributors. (2024). Opendatacube/odc-geo. In *Github repository*. GitHub.
119 <https://github.com/opendatacube/odc-geo>

- 120 pandas development team. (2020). *Pandas-dev/pandas: pandas* (latest). Zenodo. <https://doi.org/10.5281/zenodo.3509134>
- 121
122 Sagar, S., Phillips, C., Bala, B., Roberts, D., Lymburner, L., & Beaman, R. J. (2018).
123 Generating continental scale pixel-based surface reflectance composites in coastal regions
124 with the use of a multi-resolution tidal model. *Remote Sensing*, 10(3), 480. <https://doi.org/10.3390/rs10030480>
- 125
126 Sagar, S., Roberts, D., Bala, B., & Lymburner, L. (2017). Extracting the intertidal extent and
127 topography of the australian coastline from a 28 year time series of landsat observations.
128 *Remote Sensing of Environment*, 195, 153–169. <https://doi.org/10.1016/j.rse.2017.04.009>
- 129 Sent, G., Antunes, C., Spyrikos, E., Jackson, T., Atwood, E. C., & Brito, A. C. (2025). What
130 time is the tide? The importance of tides for ocean colour applications to estuaries. *Remote*
131 *Sensing Applications: Society and Environment*, 37, 101425. <https://doi.org/10.2139/ssrn.4858713>
- 132
133 STAC contributors. (2024). *SpatioTemporal Asset Catalog (STAC) specification*. <https://stacspec.org>
- 134
135 Sutterley, T. C., Alley, K., Brunt, K., Howard, S., Padman, L., & Siegried, M. (2017). *pyTMD: Python-based tidal prediction software*. Zenodo. <https://doi.org/10.5281/zenodo.5555395>
- 136
137 Turner, I. L., Harley, M. D., Almar, R., & Bergsma, E. W. J. (2021). Satellite optical imagery
138 in Coastal Engineering. *Coastal Engineering*, 167, 103919. <https://doi.org/10.1016/j.coastaleng.2021.103919>
- 139
140 Vitousek, S., Buscombe, D., Vos, K., Barnard, P. L., Ritchie, A. C., & Warrick, J. A. (2023).
141 The future of coastal monitoring through satellite remote sensing. *Cambridge Prisms: Coastal Futures*, 1, e10. <https://doi.org/10.1017/cft.2022.4>
- 142
143 Vos, K., Splinter, K. D., Harley, M. D., Simmons, J. A., & Turner, I. L. (2019). CoastSat: A
144 Google Earth Engine-enabled Python toolkit to extract shorelines from publicly available
145 satellite imagery. *Environmental Modelling & Software*, 122, 104528. <https://doi.org/10.1016/j.envsoft.2019.104528>
- 146