

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Published: unpublished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](#)).

⁷ Summary

⁸ The eo-tides package provides powerful parallelized tools for integrating satellite Earth ⁹ observation (EO) data with ocean tide modelling. The package provides a flexible Python-based ¹⁰ toolkit for modelling and attributing tide heights to a time-series of satellite images ¹¹ based on the spatial extent and acquisition time of each satellite observation (Figure 1).

¹² eo-tides leverages advanced tide modelling functionality from the pyTMD tide prediction ¹³ software (Sutterley et al., 2017), combining this capability with EO spatial analysis tools from ¹⁴ odc-geo (odc-geo contributors, 2024). This allows tides to be modelled in parallel using over ¹⁵ 50 supported tide models, and returned in standardised pandas (McKinney, 2010; pandas ¹⁶ development team, 2020) and xarray (Hoyer & Joseph, 2017) data formats for further EO ¹⁷ analysis.

¹⁸ eo-tides tools can be applied directly to petabytes of freely available satellite data loaded from ¹⁹ the cloud using Open Data Cube (ODC)'s odc-stac or datacube packages (e.g. using Digital ²⁰ Earth Australia or Microsoft Planetary Computer's STAC SpatioTemporal Asset Catalogues). ²¹ Additional functionality enables evaluating potential satellite-tide biases, and validating modelled ²² tides using external tide gauge data — both important considerations for assessing the reliability ²³ and accuracy of coastal EO workflows. These open source tools support the efficient, scalable ²⁴ and robust analysis of coastal EO data for any time period or location globally.

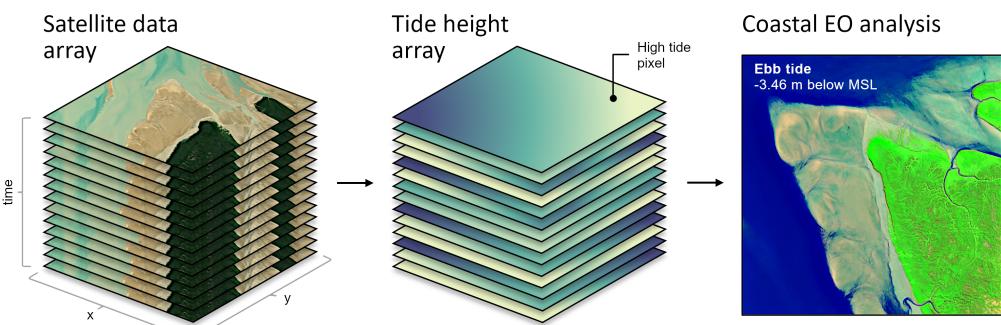


Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (for example, from ESA's Sentinel-2 or NASA/USGS Landsat), then combined to derive insights into dynamic coastal environments.

25 Statement of need

26 Satellite remote sensing offers an unparalleled resource for examining dynamic coastal environments over large temporal and spatial scales (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 over time
 29 (Vos et al., 2019). This is a particularly challenging for large-scale coastal EO analyses, where
 30 failing to account for tide dynamics can lead to inaccurate or misleading insights into coastal
 31 processes observed by satellites.

33 Conversely, information about ocean tides can also provide unique environmental insights
 34 that can greatly enhance the utility of EO data. Conventionally, satellite data dimensions
 35 consider the geographic “where” and the temporal “when” of data acquisition. The addition
 36 of tide height as a new analysis dimension allows data to be filtered, sorted and analysed with
 37 respect to tidal processes, delivering a powerful re-imagining of traditional multi-temporal EO
 38 analysis (Sagar et al., 2017). For example, satellite data can be analysed to focus on specific
 39 ecologically-significant tidal stages (e.g. high, low tide, spring or neap tides), or particular tidal
 40 processes (e.g. ebb or flow tides; Sent et al. (2025)).

41 This concept has been used to map coastal change from Landsat satellite data at continental
 42 scale (Bishop-Taylor et al., 2021), map the extent and elevation of the intertidal zone (Bishop-
 43 Taylor et al., 2019; Murray et al., 2012; Sagar et al., 2017), and create tidally-constrained
 44 imagery composites of the coastline (Sagar et al., 2018). However, these approaches have been
 45 historically based on bespoke, closed-source or difficult to install tide modelling tools, limiting
 46 the reproducibility and portability of these techniques. To support the next generation of
 47 coastal EO workflows, there is a pressing need for performant open-source tools for combining
 48 satellite data with tide modelling. `eo-tides` aims to address this need through functionality
 49 provided in five main analysis modules (`utils`, `model`, `eo`, `stats`, `validation`) described briefly
 50 below.

51 Features

52 Setting up tide models

53 The `eo_tides.utils` module simplifies the setup of ocean tide models, addressing a common
 54 barrier to coastal EO workflows. Tools like `list_models` provide feedback on available and
 55 supported models (Figure 2), while `clip_models` can improve performance by clipping large
 56 model files to smaller regions, significantly reducing processing times for high-resolution models
 57 like FES2022. Comprehensive documentation is available to assist setting up commonly used
 58 tide models, including downloading and organizing model files.

	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: An example output from `list_tides`, providing a useful summary table which clearly identifies available and supported tide models.

59 Modelling tides

60 The `eo_tides.model` module is powered by tide modelling functionality from the pyTMD Python
 61 package ([Sutterley et al., 2017](#)).

62 pyTMD is an open-source tidal prediction software that aims to simplify the calculation of ocean
 63 and earth tides. Tides are frequently decomposed into harmonic constants (or constituents)
 64 associated with the relative positions of the sun, moon and Earth. pyTMD.io contains routines
 65 for reading and spatially interpolating major constituent values from commonly available ocean
 66 tide models. pyTMD.astro contains routines for computing the positions of celestial bodies for
 67 a given time. For ocean tides, pyTMD computes the longitudes of the sun (S), moon (H), lunar
 68 perigee (P), ascending lunar node (N) and solar perigee (PP). pyTMD.arguments combines
 69 astronomical coefficients with the “Doodson number” of each constituent, and adjusts the
 70 amplitude and phase of each constituent based on their modulations over the 18.6 year nodal
 71 period. Finally, pyTMD.predict uses results from those underlying functions to predict tidal
 72 values at a given location and time.

73 The `model_tides` function from `eo_tides.model` wraps pyTMD functionality to return tide
 74 predictions in a standardised pandas.DataFrame format, enabling integration with satellite
 75 EO data and parallelized processing for improved performance. Parallelisation in eo-tides is
 76 automatically optimised based on available workers and requested tide models and tide modelling
 77 locations. This parallelisation can significantly improve performance, especially for large-scale
 78 analyses run on a multi-core machine ([Table 1](#)). Additional functions like `model_phases` classify
 79 tides into high/low/flow/ebb phases, critical for interpreting satellite-observed coastal processes
 80 like changing turbidity and ocean colour ([Sent et al., 2025](#)).

Table 1: A [benchmark comparison](#) of tide modelling performance with parallelisation on vs. off, for a typical large-scale analysis involving a month of hourly tides modelled at 10,000 modelling locations using three tide 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

81 Combining tides with satellite data

82 The `eo_tides.eo` module integrates modelled tides with xarray-format satellite data. eo-tides
 83 offers two tide attribution approaches that differ in complexity and performance: `tag_tides`
 84 assigns a single tide height per timestep for small-scale studies, while `pixel_tides` models
 85 tides spatially and temporally for larger-scale analyses, returning a unique tide height for each
 86 pixel in a dataset ([Table 2, Figure 3](#)). These functions can be applied to satellite data for any
 87 coastal location on the planet, for example using free and open data loaded from the cloud
 88 using [ODC](#) and STAC ([STAC contributors, 2024](#)).

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

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

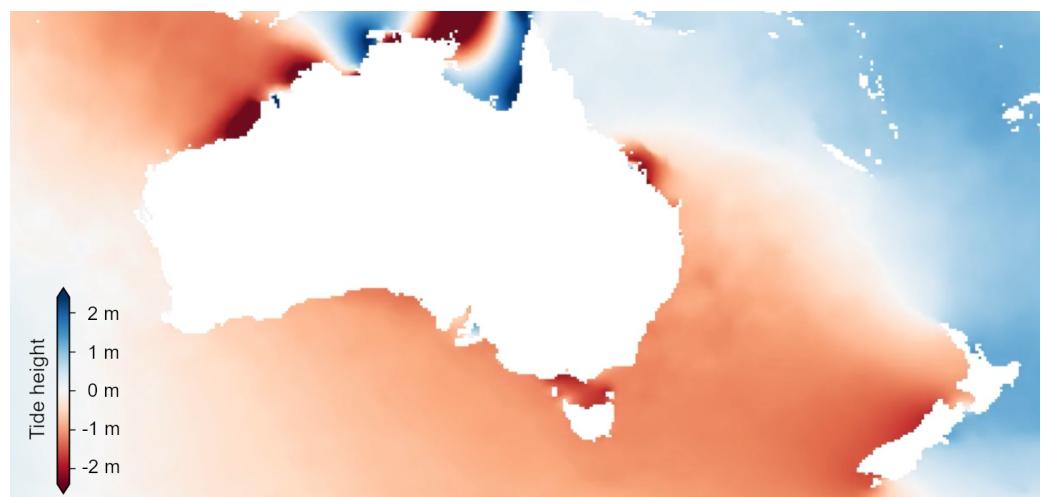


Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

89 Calculating tide statistics and satellite biases

90 The `eo_tides.stats` module identifies biases caused by complex tide aliasing interactions
 91 between tidal dynamics and satellite observations. These interactions can prevent satellites
 92 from observing the entire tide cycle (Eleve et al., 2014; Sent et al., 2025), leading coastal
 93 EO studies to produce biased or misleading results (Bishop-Taylor et al., 2019). The module
 94 produces a range of useful automated reports, plots and statistics that summarise how well a
 95 satellite time series captures real-world tidal conditions (Figure 4).

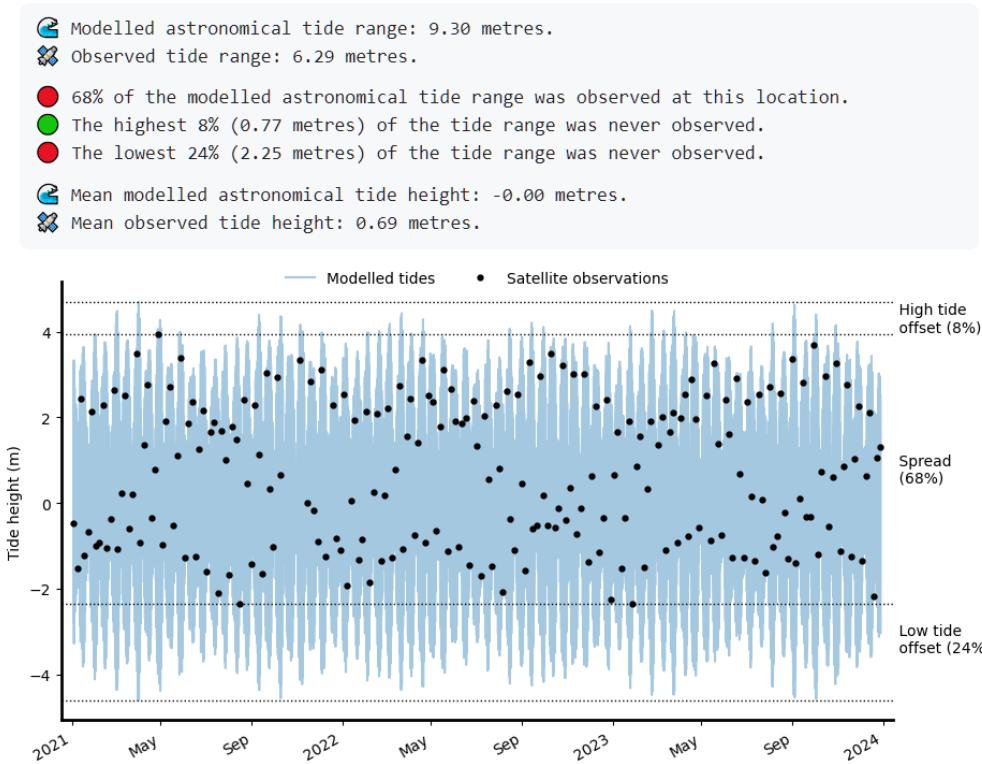


Figure 4: An example of tidally-biased satellite coverage, where only ~68% of the modelled astronomical tide range is observed.

96 Validating modelled tides

97 The `eo_tides.validation` module validates modelled tide heights using sea-level measure-
 98 ments from the GESLA Global Extreme Sea Level Analysis (Haigh et al., 2023) archive
 99 (Figure 5). It enables comparison of multiple tide models against observed data, allowing users
 100 to choose optimal tide models for their specific study area or application (Figure 5).

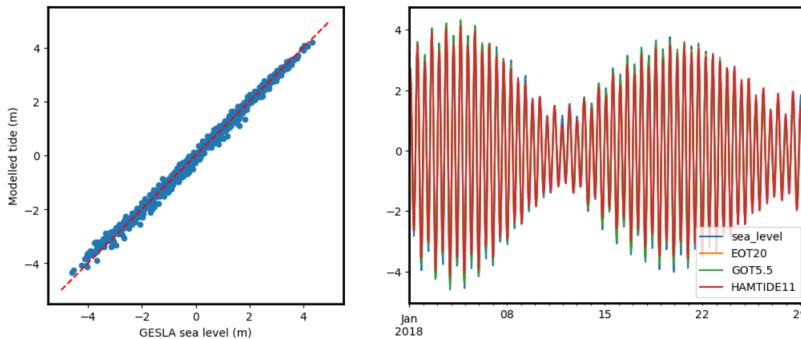


Figure 5: A comparison of multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge.

101 Research projects

102 Early versions of `eo-tides` functions have been used for continental-scale intertidal zone
 103 mapping (Bishop-Taylor et al., 2024), multi-decadal shoreline mapping across Australia (Bishop-
 104 Taylor et al., 2021) and Africa, and for tide correction of satellite-derived shorelines in the
 105 CoastSeg Python package (Fitzpatrick et al., 2024).

106 Acknowledgements

107 Functions from `eo-tides` were originally developed in the Digital Earth Australia Notebooks
 108 and Tools repository (Krause et al., 2021). We thank all DEA Notebooks contributors for
 109 their invaluable assistance with code review, feature suggestions and code edits. This paper is
 110 published with the permission of the Chief Executive Officer, Geoscience Australia. Copyright
 111 Geoscience Australia (2025).

112 References

- 113 Bishop-Taylor, R., Nanson, R., Sagar, S., & Lymburner, L. (2021). Mapping Australia's
 114 Dynamic Coastline at Mean Sea Level using Three Decades of Landsat Imagery. *Remote
 115 Sensing of Environment*, 267, 112734. <https://doi.org/10.1016/j.rse.2021.112734>
- 116 Bishop-Taylor, R., Phillips, C., Newey, V., & Sagar, S. (2024). *Digital Earth Australia Intertidal*.
 117 Commonwealth of Australia (Geoscience Australia). <https://doi.org/10.26186/149403>
- 118 Bishop-Taylor, R., Sagar, S., Lymburner, L., & Beaman, R. J. (2019). Between the tides:
 119 Modelling the elevation of australia's exposed intertidal zone at continental scale. *Estuarine,
 120 Coastal and Shelf Science*, 223, 115–128. <https://doi.org/10.1016/j.ecss.2019.03.006>
- 121 Elefeld, M. A., Van der Wal, D., & Van Kessel, T. (2014). Estuarine suspended par-
 122 ticulate matter concentrations from sun-synchronous satellite remote sensing: Tidal
 123 and meteorological effects and biases. *Remote Sensing of Environment*, 143, 204–215.
 124 <https://doi.org/10.1016/j.rse.2013.12.019>

- 125 Fitzpatrick, S., Buscombe, D., Warrick, J. A., Lundine, M. A., & Vos, K. (2024). CoastSeg: An
126 accessible and extendable hub for satellite-derived-shoreline (SDS) detection and mapping.
127 *Journal of Open Source Software*, 9(99), 6683. <https://doi.org/10.21105/joss.06683>
- 128 Haigh, I. D., Marcos, M., Talke, S. A., Woodworth, P. L., Hunter, J. R., Hague, B. S.,
129 Arns, A., Bradshaw, E., & Thompson, P. (2023). GESLA version 3: A major update to
130 the global higher-frequency sea-level dataset. *Geoscience Data Journal*, 10(3), 293–314.
131 <https://doi.org/10.1002/gdj3.174>
- 132 Hoyer, S., & Joseph, H. (2017). xarray: N-d labeled arrays and datasets in python. *Journal of*
133 *Open Research Software*, 5(1). <https://doi.org/10.5334/jors.148>
- 134 Krause, C., Dunn, B., Bishop-Taylor, R., Adams, C., Burton, C., Alger, M., Chua, S., Phillips, C.,
135 Newey, V., Kouzoubov, K., Leith, A., Ayers, D., & Hicks, A. (2021). *Digital Earth Australia*
136 *notebooks and tools repository*. <https://github.com/GeoscienceAustralia/dea-notebooks/>;
137 Commonwealth of Australia (Geoscience Australia). <https://doi.org/10.26186/145234>
- 138 McKinney, Wes. (2010). Data Structures for Statistical Computing in Python. In Stéfan van
139 der Walt & Jarrod Millman (Eds.), *Proceedings of the 9th Python in Science Conference*
140 (pp. 56–61). <https://doi.org/10.25080/Majora-92bf1922-00a>
- 141 Murray, N. J., Phinn, S. R., Clemens, R. S., Roelfsema, C. M., & Fuller, R. A. (2012).
142 Continental scale mapping of tidal flats across east asia using the landsat archive. *Remote*
143 *Sensing*, 4(11), 3417–3426. <https://doi.org/10.3390/rs4113417>
- 144 odc-geo contributors. (2024). Opendatacube/odc-geo. In *Github repository*. GitHub.
145 <https://github.com/opendatacube/odc-geo>
- 146 pandas development team. (2020). Pandas-dev/pandas: pandas (latest). Zenodo. <https://doi.org/10.5281/zenodo.3509134>
- 148 Sagar, S., Phillips, C., Bala, B., Roberts, D., Lymburner, L., & Beaman, R. J. (2018).
149 Generating continental scale pixel-based surface reflectance composites in coastal regions
150 with the use of a multi-resolution tidal model. *Remote Sensing*, 10(3), 480. <https://doi.org/10.3390/rs10030480>
- 152 Sagar, S., Roberts, D., Bala, B., & Lymburner, L. (2017). Extracting the intertidal extent and
153 topography of the australian coastline from a 28 year time series of landsat observations.
154 *Remote Sensing of Environment*, 195, 153–169. <https://doi.org/10.1016/j.rse.2017.04.009>
- 155 Sent, G., Antunes, C., Spyrikos, E., Jackson, T., Atwood, E. C., & Brito, A. C. (2025). What
156 time is the tide? The importance of tides for ocean colour applications to estuaries. *Remote*
157 *Sensing Applications: Society and Environment*, 37, 101425. <https://doi.org/10.2139/ssrn.4858713>
- 159 STAC contributors. (2024). SpatioTemporal Asset Catalog (STAC) specification. <https://stacspec.org>
- 161 Sutterley, T. C., Alley, K., Brunt, K., Howard, S., Padman, L., & Siegried, M. (2017). pyTMD:
162 Python-based tidal prediction software. Zenodo. <https://doi.org/10.5281/zenodo.5555395>
- 163 Turner, I. L., Harley, M. D., Almar, R., & Bergsma, E. W. J. (2021). Satellite optical imagery
164 in Coastal Engineering. *Coastal Engineering*, 167, 103919. <https://doi.org/10.1016/j.coastaleng.2021.103919>
- 166 Vitousek, S., Buscombe, D., Vos, K., Barnard, P. L., Ritchie, A. C., & Warrick, J. A. (2023).
167 The future of coastal monitoring through satellite remote sensing. *Cambridge Prisms:*
168 *Coastal Futures*, 1, e10. <https://doi.org/10.1017/cft.2022.4>
- 169 Vos, K., Splinter, K. D., Harley, M. D., Simmons, J. A., & Turner, I. L. (2019). CoastSat: A
170 Google Earth Engine-enabled Python toolkit to extract shorelines from publicly available
171 satellite imagery. *Environmental Modelling & Software*, 122, 104528. <https://doi.org/10.1016/j.envsoft.2019.104528>

DRAFT