

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

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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 where ocean tide model data exists.

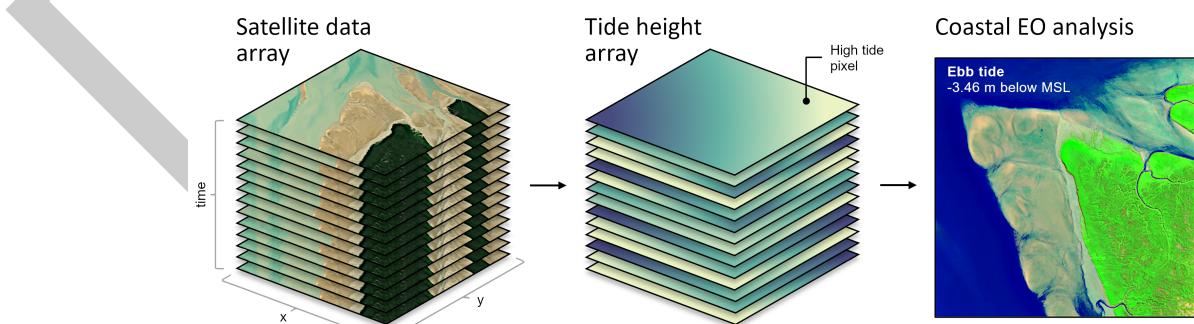


Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (e.g. Sentinel-2 or Landsat), then combined to derive insights into dynamic coastal environments.

²⁶ Statement of need

²⁷ 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).
²⁸ However, the highly variable influence of ocean tides can complicate analyses, making it difficult
²⁹ to separate the influence of changing tides from patterns of true coastal change (Vos et al.,
³⁰ 2023). This is a particularly challenging for large-scale coastal EO analyses, where failing to
³¹ account for tide dynamics can lead to inaccurate or misleading insights into satellite-observed
³² 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
⁴² al., 2021), map intertidal zone extent and elevation (Bishop-Taylor et al., 2019; Fitton et
⁴³ al., 2021; Murray et al., 2012; Sagar et al., 2017), and creating tidally-constrained coastal
⁴⁴ image composites (Sagar et al., 2018). However, these methods have traditionally relied on
⁴⁵ bespoke, closed-source, or difficult-to-install tide modelling tools, limiting their reproducibility
⁴⁶ and portability. To support the next generation of coastal EO workflows, there is a pressing
⁴⁷ need for efficient open-source tools for combining satellite data with tide modelling. eo-tides
⁴⁸ addresses this need through functionality offered in five main analysis modules (utils, model,
⁴⁹ eo, stats, validation).

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 significantly improve performance by
⁵⁶ clipping large high-resolution model files (e.g. FES2022 (Carrere et al., 2022)) to smaller study
⁵⁷ area extents.

	Model	Expected path
✓	EOT20	tide_models/EOT20/ocean_tides
✗	FES2022	tide_models/fes2022b/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.

58 Modelling tides

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

62 The `model_tides` function from `eo_tides.model` wraps pyTMD functionality to return tide
 63 predictions in a standardised `pandas.DataFrame` format, enabling integration with EO data
 64 and parallelisation for improved performance (Table 1). The `model_phases` function can
 65 additionally classify tides into high/low/flow/ebb phases, critical for correctly interpreting
 66 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

67 Combining tides with satellite data

68 The `eo_tides.eo` module integrates modelled tides with xarray-format satellite data (Hoyer &
 69 Joseph, 2017). The `tag_tides` and `pixel_tides` functions (Table 2, Figure 3) can be applied
 70 to attribute tides to satellite data for any coastal location on the planet, for example using
 71 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 small-scale analysis in non-complex tidal environments 	<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 and coastal product generation

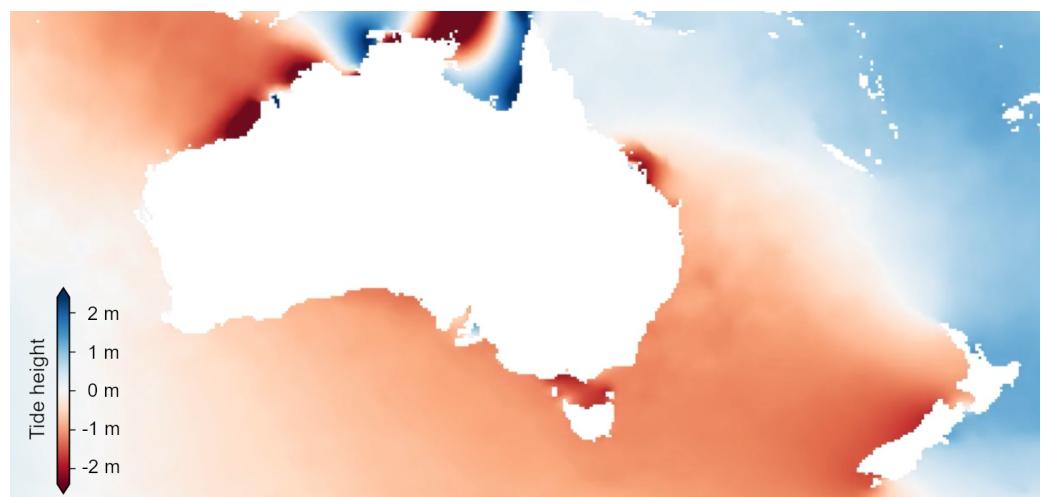


Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

72 Calculating tide statistics and satellite biases

73 The `eo_tides.stats` module identifies biases caused by complex tide aliasing interactions that
 74 can prevent satellites from observing the entire tide cycle (Bishop-Taylor et al., 2019; Elefeldt
 75 et al., 2014; Sent et al., 2025). The `tide_stats` and `pixel_stats` functions produce useful
 76 statistics that summarise how well satellite data captures real-world tides (Figure 4).

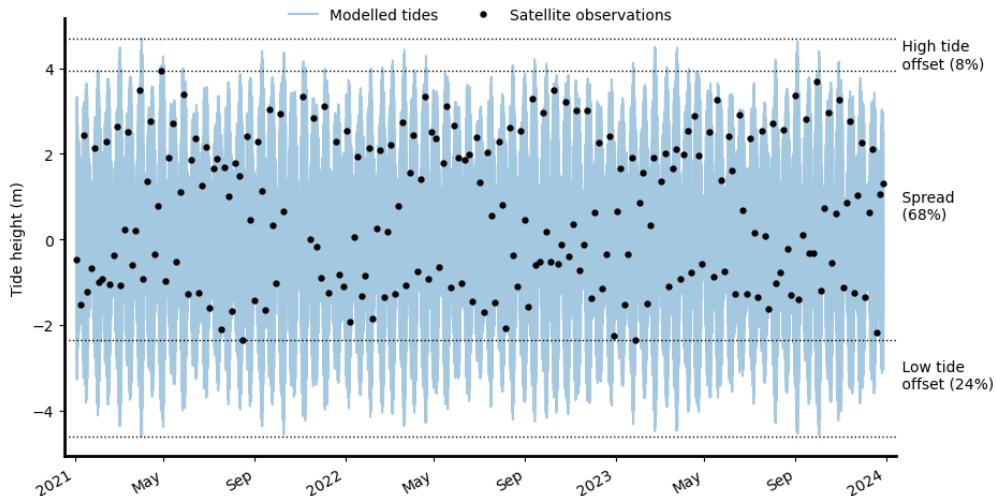
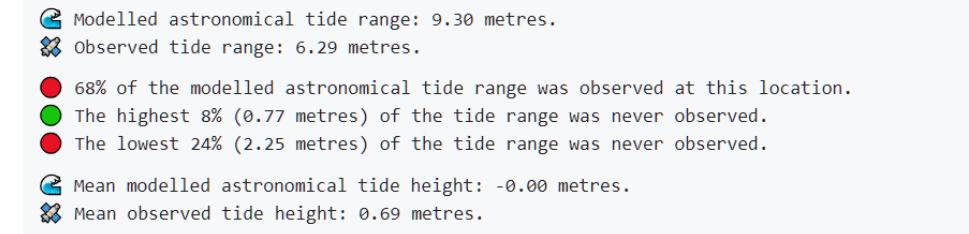


Figure 4: An example of tidally-biased satellite coverage, where only ~68% of the astronomical tide range is observed.

77 Validating modelled tides

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

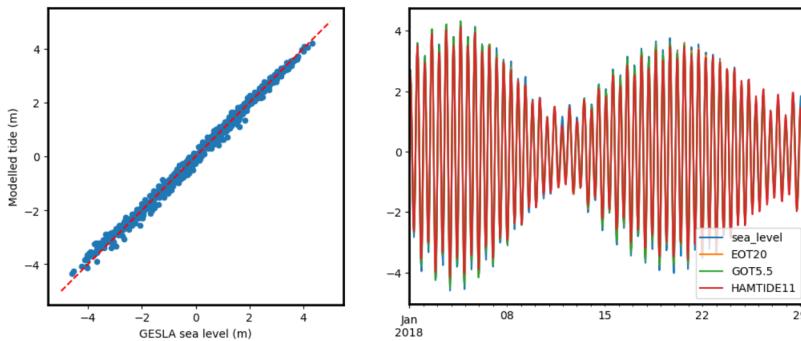


Figure 5: A comparison of multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge (Haigh et al., 2023).

80 Research projects

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

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