

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

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eo-tides tools can be applied to petabytes of freely available satellite data loaded from the cloud using Open Data Cube (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.

⁷ Summary

⁸ The eo-tides package provides powerful parallelised tools for integrating satellite Earth
⁹ observation (EO) data with ocean tide modelling. The package provides a flexible Python-
¹⁰ based toolkit for attributing modelled tide heights to a time-series of satellite images based on
¹¹ 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 EO analysis.

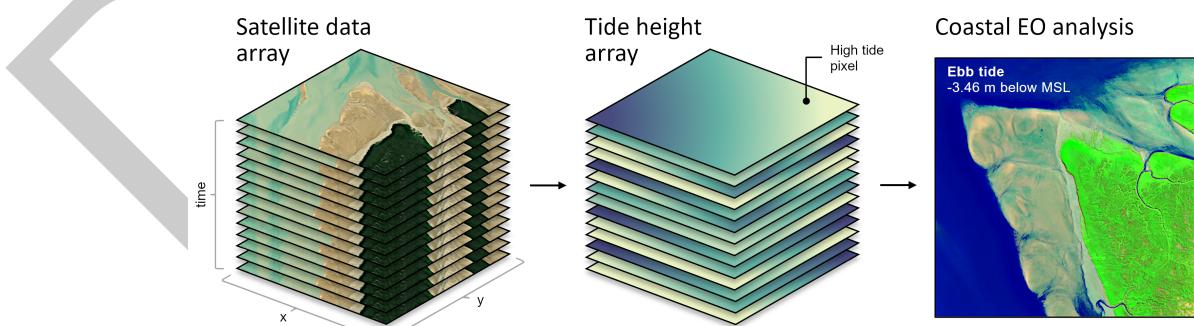


Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (for example, from ESA’s Sentinel-2 or NASA/USGS Landsat), then combined to derive insights into dynamic coastal environments.

²⁴ Statement of need

²⁵ 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).
²⁶ However, the highly variable influence of ocean tides can complicate analyses, making it difficult
²⁷ to separate the influence of changing tides from patterns of true coastal change (Vos et al.,
²⁸ 2019). This is a particularly challenging for large-scale coastal EO analyses, where failing to
²⁹ account for tide dynamics can lead to inaccurate or misleading insights into satellite-observed
³⁰ coastal processes.
³¹

³² Conversely, information about ocean tides can provide unique environmental insights that can
³³ significantly enhance the value of EO data. Traditionally, satellite data dimensions include
³⁴ the geographic “where” and temporal “when” of acquisition. Introducing tide height as an
³⁵ additional analysis dimension allows data to be filtered, sorted, and analysed based on tidal
³⁶ dynamics, offering a transformative re-imagining of traditional multi-temporal EO analysis
³⁷ (Sagar et al., 2017). For instance, satellite data can be analysed to focus on ecologically
³⁸ significant tidal stages (e.g., high tide, low tide, spring or neap tides) or specific tidal processes
³⁹ (e.g., ebb or flow tides; Sent et al. (2025)).

⁴⁰ This concept has been used to map coastal change at continental-scale (Bishop-Taylor et al.,
⁴¹ 2021), map intertidal zone extent and elevation (Bishop-Taylor et al., 2019; Murray et al.,
⁴² 2012; Sagar et al., 2017), and creating tidally-constrained coastal image composites (Sagar
⁴³ et al., 2018). However, these methods have traditionally relied on bespoke, closed-source, or
⁴⁴ difficult-to-install tide modeling tools, limiting their reproducibility and portability. To support
⁴⁵ the next generation of coastal EO workflows, there is a pressing need for efficient open-source
⁴⁶ tools for combining satellite data with tide modeling. eo-tides addresses this need through
⁴⁷ functionality offered in five main analysis modules (utils, model, eo, stats, validation)
⁴⁸ described below.

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 improve performance by clipping large
⁵⁴ model files to smaller regions, significantly reducing processing times for high-resolution models
⁵⁵ like FES2022. Comprehensive documentation is available to assist setting up commonly used
⁵⁶ tide models, including downloading and organising 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 that clearly identifies available and supported tide models.

57 Modelling tides

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

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

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

79 Combining tides with satellite data

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

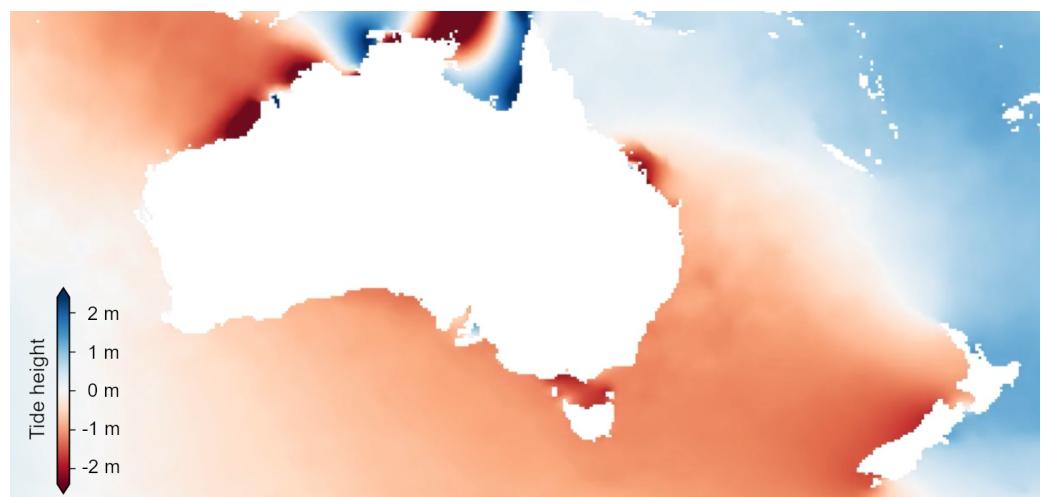


Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

87 Calculating tide statistics and satellite biases

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

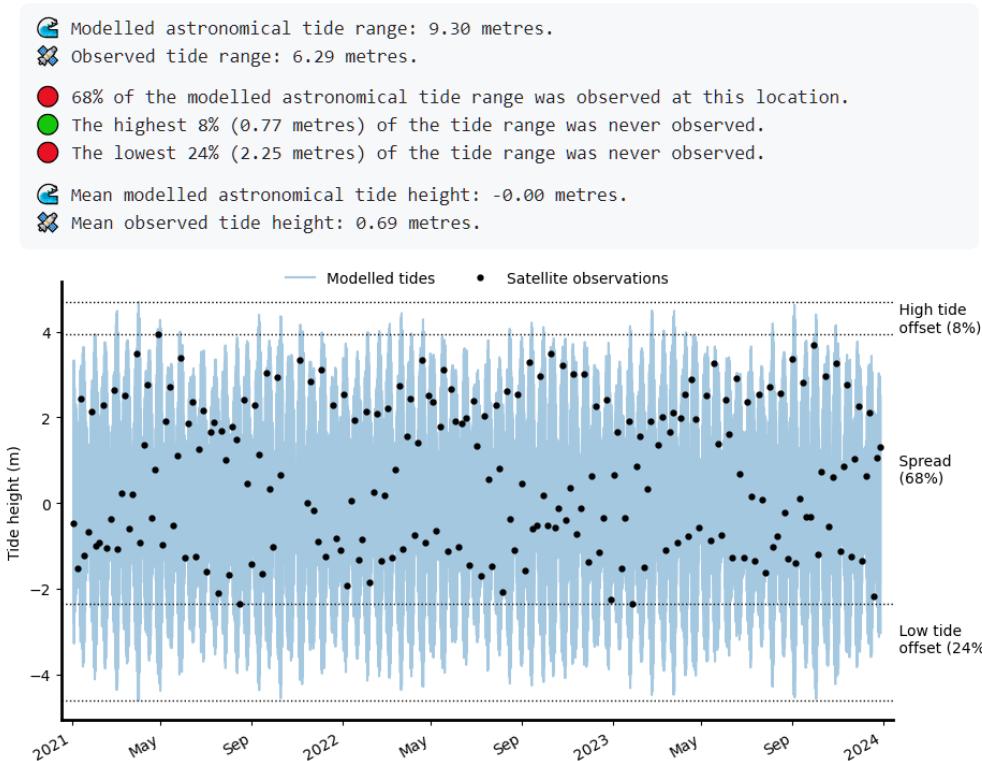


Figure 4: An example of tidally-biased satellite coverage, where only ~68% of the modelled astronomical tide range is observed.

94 Validating modelled tides

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

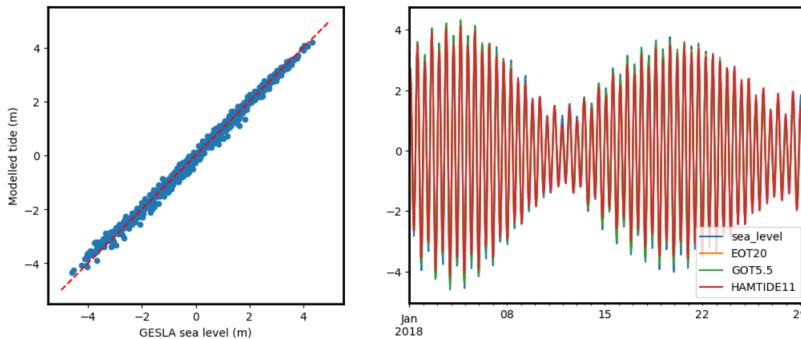


Figure 5: A comparison of multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge.

99 Research projects

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

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 109 2025).

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