

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

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Summary

The eo-tides package provides powerful parallelized tools for integrating satellite Earth observation (EO) data with ocean tide modelling. The package provides a flexible Python-based toolkit for modelling and attributing 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 fundamental tide modelling capability with EO spatial analysis tools from odc-geo ([odc-geo contributors, 2024](#)). This allows tides to be modelled in parallel automatically using over 50 supported tide models, and returned in standardised pandas ([McKinney, 2010](#); [pandas development team, 2020](#)) and xarray ([Hoyer & Joseph, 2017](#)) data formats for further analysis.

Tools from eo-tides are designed to be applied directly to petabytes of freely available satellite data loaded from the cloud using Open Data Cube's odc-stac or datacube packages (e.g. using [Digital Earth Australia](#) or [Microsoft Planetary Computer's SpatioTemporal Asset Catalogues](#)). Additional functionality enables evaluating potential satellite-tide biases, and validating modelled tides using external tide gauge data — both important considerations for assessing the reliability and accuracy of coastal EO workflows. In combination, these open source tools support the efficient, scalable and robust analysis of coastal EO data for any time period or location globally.

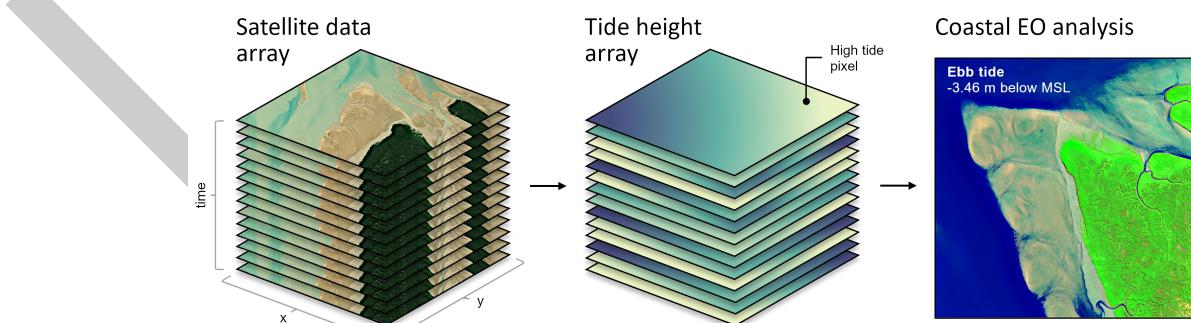


Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (for example, from ESA's Sentinel-2 or NASA/USGS Landsat), then combined to derive insights into dynamic coastal environments.

²⁶ Statement of need

²⁷ Satellite remote sensing offers an unparalleled method to examine dynamic coastal environments
²⁸ over large temporal and spatial scales (Turner et al., 2021; Vitousek et al., 2023). However,
²⁹ the variable and sometimes extreme influence of ocean tides in these regions can complicate
³⁰ analyses, making it difficult to separate the influence of changing tides from patterns of true
³¹ coastal change over time (Vos et al., 2019). This is a particularly challenging for continental-
³² to global-scale coastal EO analyses, where failing to account for tide dynamics can lead to
³³ inaccurate or misleading insights into coastal processes observed by satellites.

³⁴ Conversely, information about ocean tides can also provide unique environmental insights that
³⁵ can greatly enhance the utility of coastal EO data. Conventionally, satellite data dimensions
³⁶ consider the geographical “where” and the temporal “when” of data acquisition. The addition
³⁷ of tide height as a new analysis dimension allows data to be filtered, sorted and analysed with
³⁸ respect to tidal processes, delivering a powerful re-imagining of traditional multi-temporal EO
³⁹ data analysis (Sagar et al., 2017). For example, satellite data can be analysed to focus on
⁴⁰ specific ecologically-significant tidal stages (e.g. high, low tide, spring or neap tides) or on
⁴¹ particular tidal processes (e.g. ebb or flow tides; Sent et al. (2025)).

⁴² This concept has been used to map tidally-corrected annual coastlines from Landsat satellite
⁴³ data at continental scale (Bishop-Taylor et al., 2021), generate maps of the extent and elevation
⁴⁴ of the intertidal zone (Bishop-Taylor et al., 2019; Murray et al., 2012; Sagar et al., 2017), and
⁴⁵ create tidally-constrained imagery composites of the coastline (Sagar et al., 2018). However,
⁴⁶ these approaches have been historically based on bespoke, closed-source or difficult to install
⁴⁷ tide modelling tools, limiting the reproducibility and portability of these techniques to new
⁴⁸ coastal EO applications. To support the next generation of coastal EO workflows, there is
⁴⁹ a pressing need for new open-source tools for combining satellite data with tide modelling.
⁵⁰ eo-tides aims to address this need through functionality provided in five main analysis modules
⁵¹ (utils, model, eo, stats, validation) which are described briefly below.

⁵² Features

⁵³ Setting up tide models

⁵⁴ The `eo_tides.utils` module simplifies the setup of ocean tide models, addressing a common
⁵⁵ barrier to coastal EO workflows. Tools like `list_models` provide feedback on available and
⁵⁶ supported models (Figure 2), while `clip_models` can improve performance by clipping large
⁵⁷ model files to smaller regions, significantly reducing processing times for high-resolution models
⁵⁸ like FES2022. Comprehensive documentation is available to assist setting up commonly used
⁵⁹ tide models, including downloading, uncompressing, 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.

60 Modelling tides

61 The `eo_tides.model` module is powered by tide modelling functionality from the pyTMD Python
 62 package ([Sutterley et al., 2017](#)). pyTMD is an open-source tidal prediction software that
 63 aims to simplify the calculation of ocean and earth tides. Tides are frequently decomposed
 64 into harmonic constants (or constituents) associated with the relative positions of the sun,
 65 moon and Earth. pyTMD.io contains routines for reading and spatially interpolating major
 66 constituent values from commonly available ocean tide models. pyTMD.astro contains routines
 67 for computing the positions of celestial bodies for a given time. For ocean tides, pyTMD computes
 68 the longitudes of the sun (S), moon (H), lunar perigee (P), ascending lunar node (N) and
 69 solar perigee (PP). pyTMD.arguments combines astronomical coefficients with the “Doodson
 70 number” of each constituent, and adjusts the amplitude and phase of each constituent based
 71 on their modulations over the 18.6 year nodal period. Finally, `pyTMD.predict` uses results
 72 from those underlying functions to predict tidal 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`
 76 is automatically optimised based on available workers and requested tide models and tide
 77 modelling locations. This parallelisation can significantly improve tide modelling performance,
 78 especially for large-scale analyses run on a multi-core machine ([Table 1](#)). Additional functions
 79 like `model_phases` classify high, low or flow/ebb tides, critical for interpreting satellite-observed
 80 coastal processes 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. For
 83 tide attribution, `eo-tides` offers two approaches that differ in complexity and performance:
 84 `tag_tides` assigns a single tide height per timestep for small-scale studies, while `pixel_tides`
 85 models tides spatially and temporally for larger-scale analyses, returning a unique tide height
 86 for each pixel in a dataset ([Table 2](#)). These functions can be applied to satellite data for any
 87 coastal or ocean location on the planet, for example using free and open data loaded from the
 88 cloud using [Open Data Cube](#) and SpatioTemporal Asset Catalogue ([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 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 |

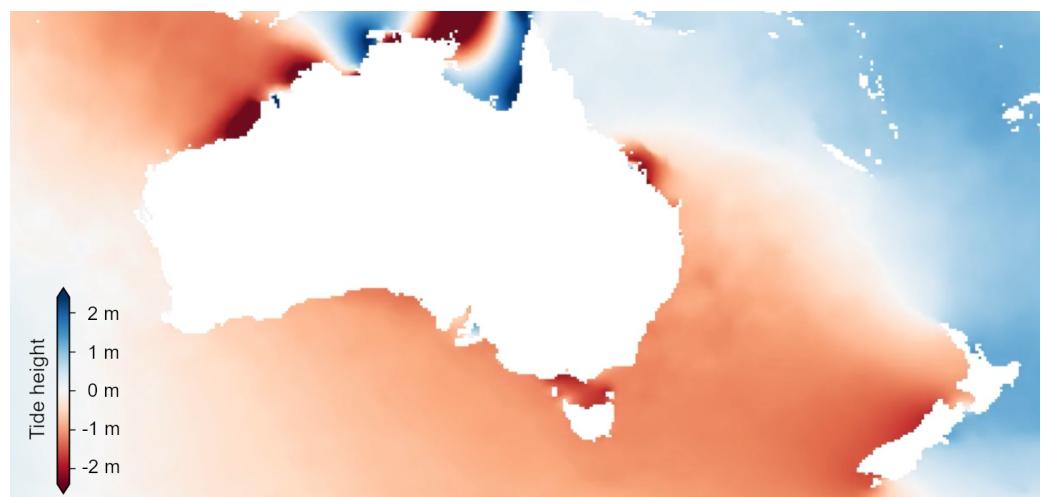


Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

89 Calculating tide statistics and satellite biases

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

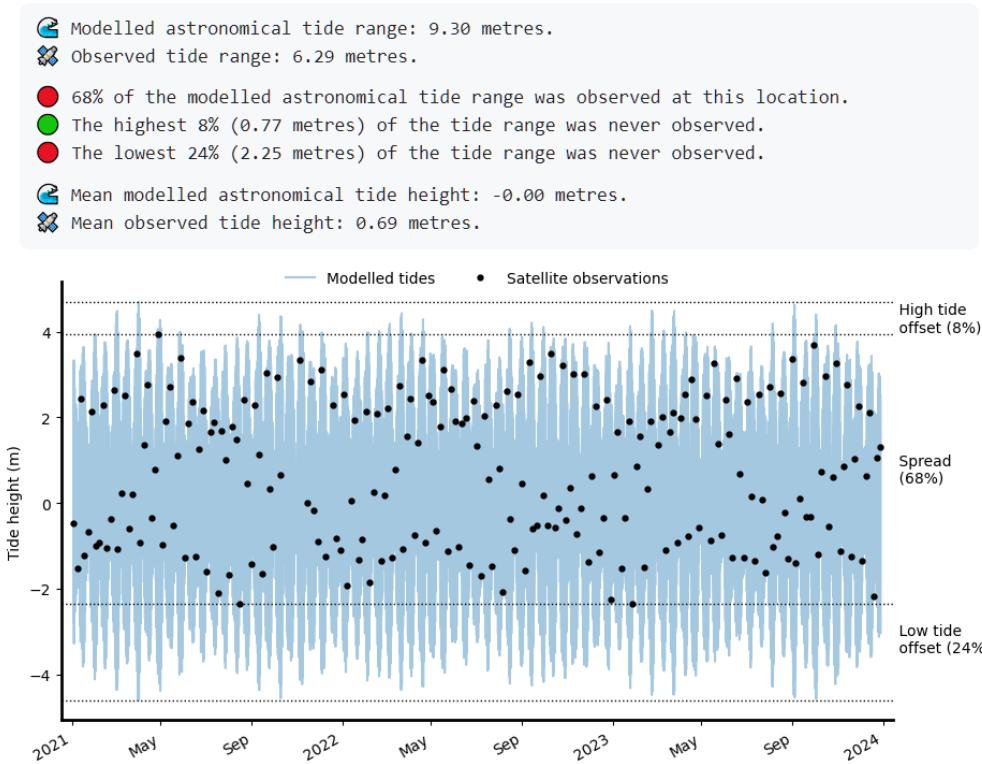


Figure 4: An example of tidally-biased satellite coverage, where the sensor only observes ~68% of the modelled astronomical tide range and never observes the lowest 24% of tides.

96 Validating modelled tides

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

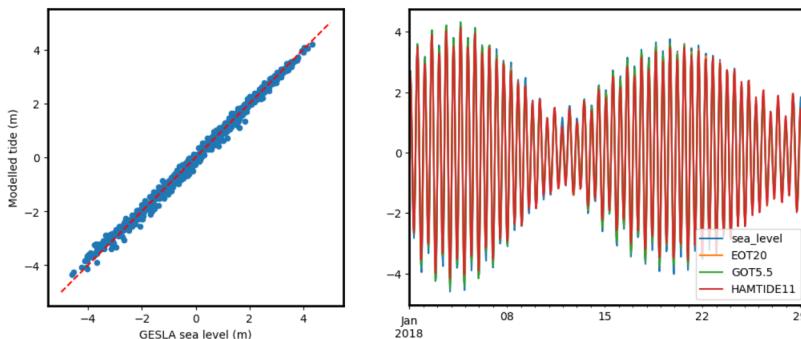


Figure 5: A comparison of modelled tides from multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge.

102 Research projects

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

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 111 published with the permission of the Chief Executive Officer, Geoscience Australia. Copyright
 112 Geoscience Australia (2025).

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