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

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DOI: 10.21105/joss.07786

Software

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Submitted: 17 January 2025
Published: 29 May 2025

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.

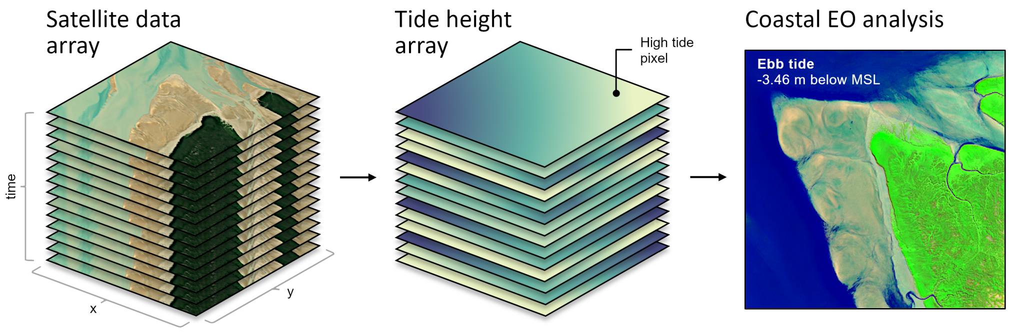

Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (e.g. Sentinel-2 or Landsat), then combined to derive insights into dynamic coastal environments.

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Statement of need

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). However, the highly variable influence of ocean tides can complicate analyses, making it difficult to separate the influence of changing tides from patterns of true coastal change (Vos et al., 2023). This is a particularly challenging for large-scale coastal EO analyses, where failing to account for tide dynamics can lead to inaccurate or misleading insights into satellite-observed coastal processes.

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

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

Features

Setting up tide models

The `eo_tides.utils` module simplifies the setup of ocean tide models, addressing a common barrier to coastal EO workflows. Tools like `list_models` provide feedback on available and supported models (Figure 2), while `clip_models` can significantly improve performance by clipping large high-resolution model files (e.g. FES2022 (Carrere et al., 2022)) to smaller study 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.

Modelling tides

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

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

Combining tides with satellite data

The eo_tides.eo module integrates modelled tides with xarray-format satellite data (Hoyer & Joseph, 2017). The tag_tides and pixel_tides functions (Table 2, Figure 3) can be applied to attribute tides to satellite data for any coastal location on the planet, for example using 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
- 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	- 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

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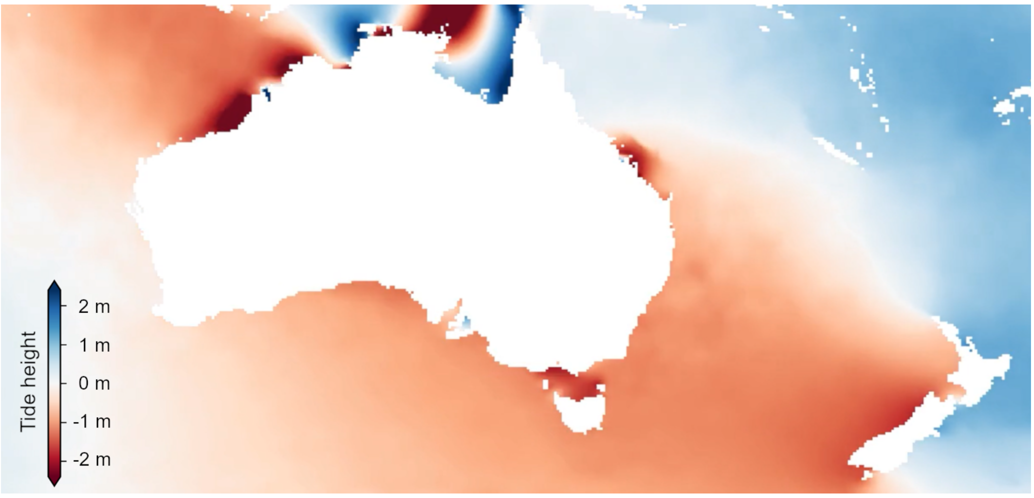

Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

Calculating tide statistics and satellite biases

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

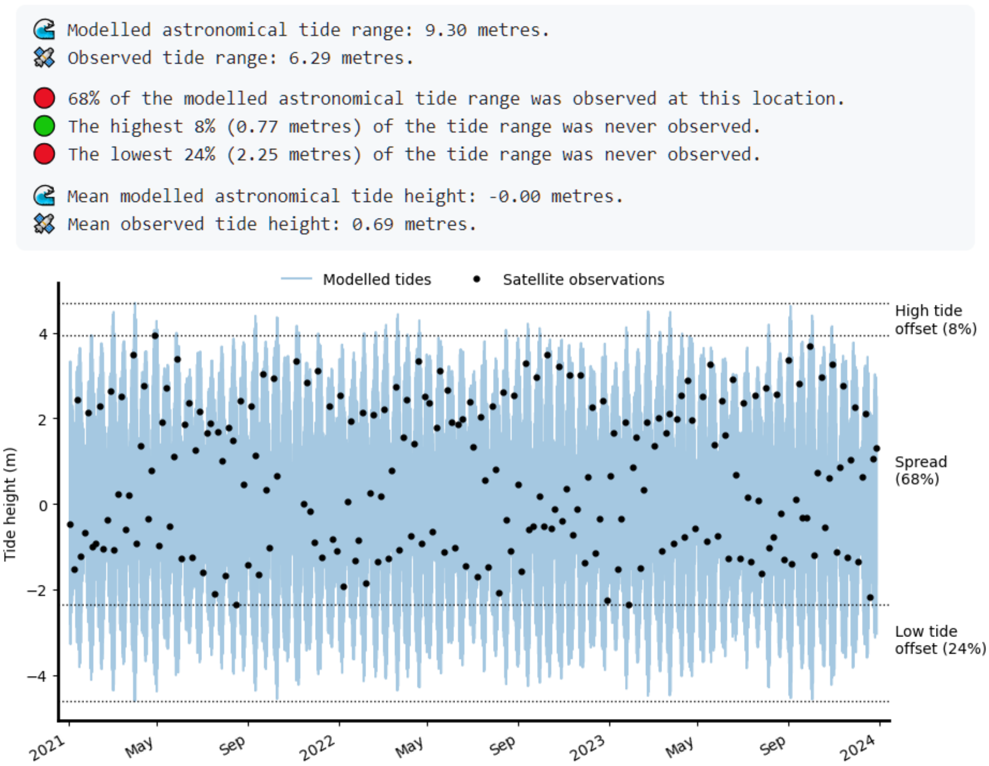

Figure 4: An example of tidally-biased satellite coverage, where only ~68% of the astronomical tide range is observed.

Validating modelled tides

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

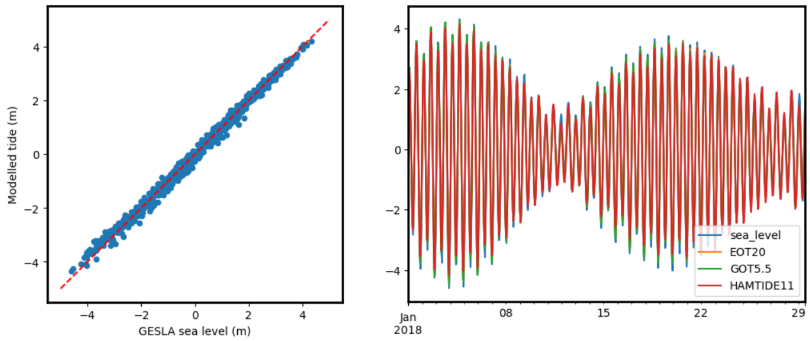

Figure 5: A comparison of multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge (Haigh et al., 2023).

Research projects

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

Acknowledgements

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

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