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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 capability with EO spatial analysis tools from `odc-geo` (odc-geo contributors, 2024). This allows tides to be modelled in parallel 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 EO analysis.

`eo-tides` tools can be applied directly 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 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. These open source tools support the efficient, scalable and robust analysis of coastal EO data for any time period or location globally.

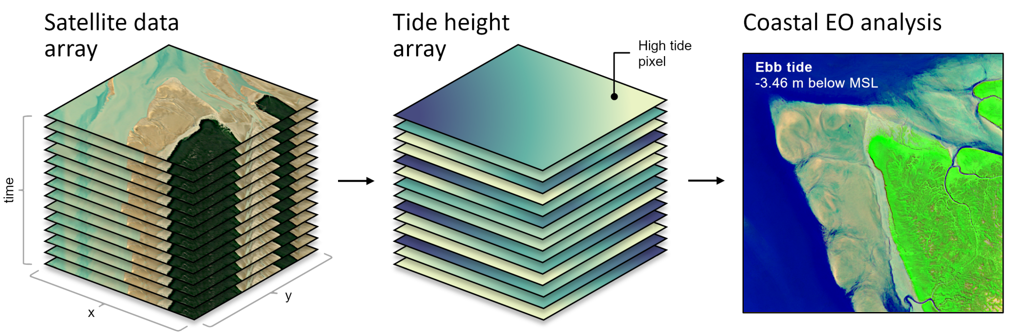

Figure 1: A typical `eo-tides` coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (for example, from ESA's Sentinel-2 or NASA/USGS Landsat), then combined to derive insights into dynamic coastal environments.

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Statement of need

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). 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 over time (Vos et al., 2019). 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 coastal processes observed by satellites.

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

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

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 improve performance by clipping large model files to smaller regions, significantly reducing processing times for high-resolution models like FES2022. Comprehensive documentation is available to assist setting up commonly used 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.

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 aims to simplify the calculation of ocean and earth tides. Tides are frequently decomposed into harmonic constants (or constituents) associated with the relative positions of the sun, moon and Earth. pyTMD.io contains routines for reading and spatially interpolating major constituent values from commonly available ocean tide models. pyTMD.astro contains routines for computing the positions of celestial bodies for a given time. For ocean tides, pyTMD computes the longitudes of the sun (S), moon (H), lunar perigree (P), ascending lunar node (N) and solar perigree (PP). pyTMD.arguments combines astronomical coefficients with the "Doodson number" of each constituent, and adjusts the amplitude and phase of each constituent based on their modulations over the 18.6 year nodal period. Finally, pyTMD.predict uses results from those underlying functions to predict tidal values at a given location and time.

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

Combining tides with satellite data

The eo_tides.eo module integrates modelled tides with xarray-format satellite data. eo-tides offers two tide attribution approaches that differ in complexity and performance: tag_tides assigns a single tide height per timestep for small-scale studies, while pixel_tides models tides spatially and temporally for larger-scale analyses, returning a unique tide height for each pixel in a dataset (Table 2, (Figure 3)). These functions can be applied to satellite data for any coastal location on the planet, for example using free and 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 timestep - Ideal for local or site-scale analysis - Fast, low memory use - Single tide height per image can produce artefacts and discontinuities	- 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

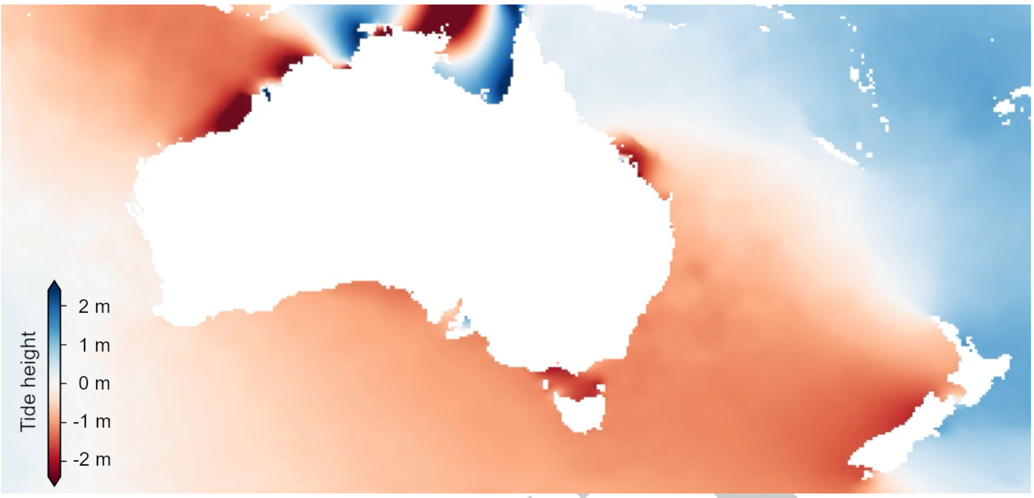

Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

Calculating tide statistics and satellite biases

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

```
🌊 Modelled astronomical tide range: 9.30 metres.
🛰️ Observed tide range: 6.29 metres.

🔴 68% of the modelled astronomical tide range was observed at this location.
🟢 The highest 8% (0.77 metres) of the tide range was never observed.
🔴 The lowest 24% (2.25 metres) of the tide range was never observed.

🌊 Mean modelled astronomical tide height: -0.00 metres.
🛰️ Mean observed tide height: 0.69 metres.
```

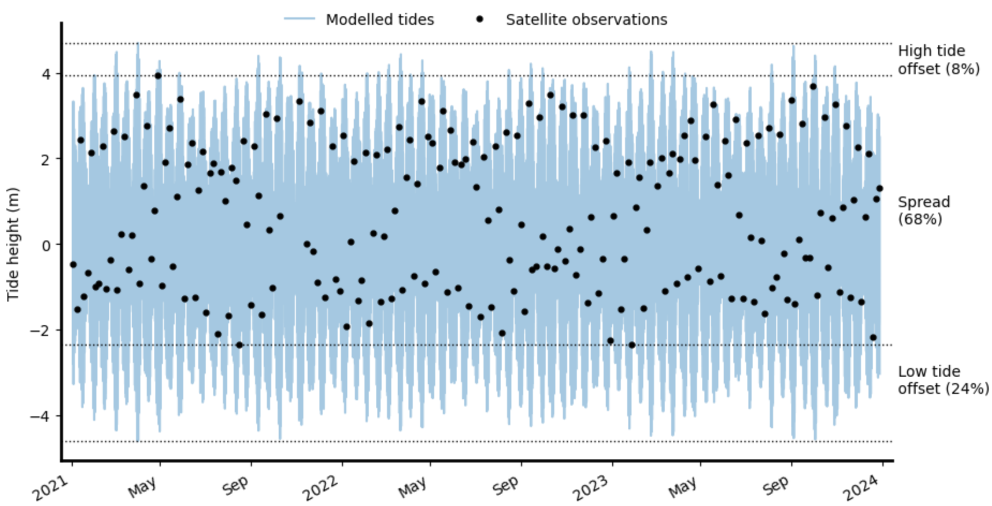

Figure 4: An example of tidally-biased satellite coverage, where only ~68% of the modelled astronomical tide range is observed.

Validating modelled tides

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

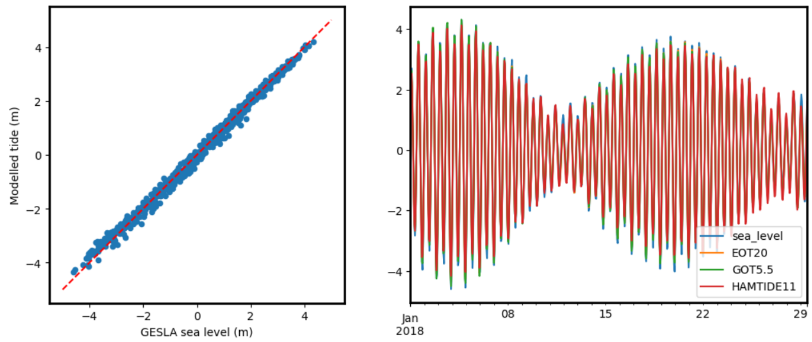

Figure 5: A comparison of multiple tide models (EOT20, GOT5.5, HAMTIDE11) against observed sea level data from the Broome 62650 GESLA tide gauge.

Research projects

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

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