

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.

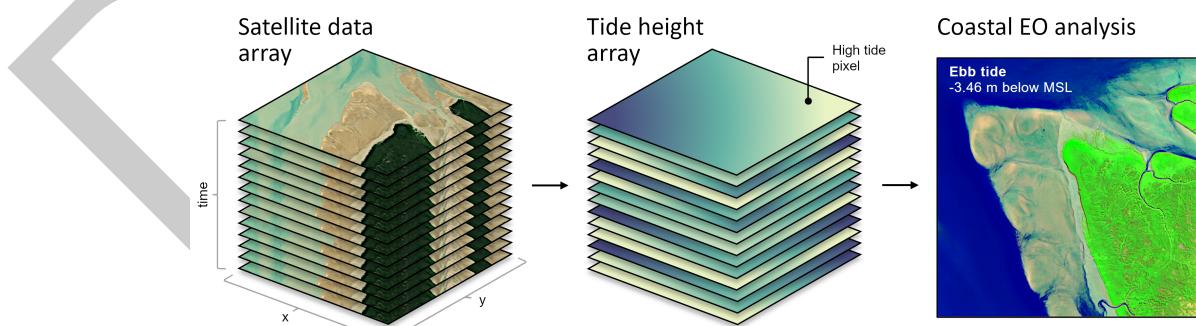


Figure 1: A typical eo-tides coastal EO workflow, with tide heights modelled into every pixel in a spatio-temporal stack of satellite data (for example, from Sentinel-2 or Landsat), then combined to derive insights into dynamic coastal environments.

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 Features

⁴⁹ Setting up tide models

⁵⁰ The `eo_tides.utils` module simplifies the setup of ocean tide models, addressing a common
⁵¹ barrier to coastal EO workflows. Tools like `list_models` provide feedback on available and
⁵² supported models (Figure 2), while `clip_models` can significantly improve performance by
⁵³ clipping large high-resolution model files (e.g. FES2022) to smaller study area extents.

	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.

⁵⁴ Modelling tides

⁵⁵ The `eo_tides.model` module is powered by tide modelling functionality from the pyTMD Python
⁵⁶ package (Sutterley et al., 2017). pyTMD is an open-source tidal prediction software that

57 simplifies the calculation of ocean and earth tides. Tides are frequently decomposed into
 58 harmonic constants (or constituents) associated with the relative positions of the sun, moon
 59 and Earth. pyTMD.io contains routines for reading and spatially interpolating major constituent
 60 values from commonly available ocean tide models.

61 The `model_tides` function from `eo_tides.model` wraps pyTMD functionality to return tide
 62 predictions in a standardised pandas.DataFrame format, enabling integration with satellite EO
 63 data and parallelised processing for improved performance ([Table 1](#)). Additional functions like
 64 `model_phases` classify tides into high/low/flow/ebb phases, critical for interpreting satellite-
 65 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

66 Combining tides with satellite data

67 The `eo_tides.eo` module integrates modelled tides with xarray-format satellite data. These
 68 functions ([Table 2](#), [Figure 3](#)) can be applied to attribute tides to satellite data for any coastal
 69 location on the planet, for example using open data loaded from the cloud using [ODC](#) and
 70 [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 time-step - Single tide height per image can produce artefacts and discontinuities - Fast, low memory use - Ideal for local, site-scale analysis 	<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 coastal product generation

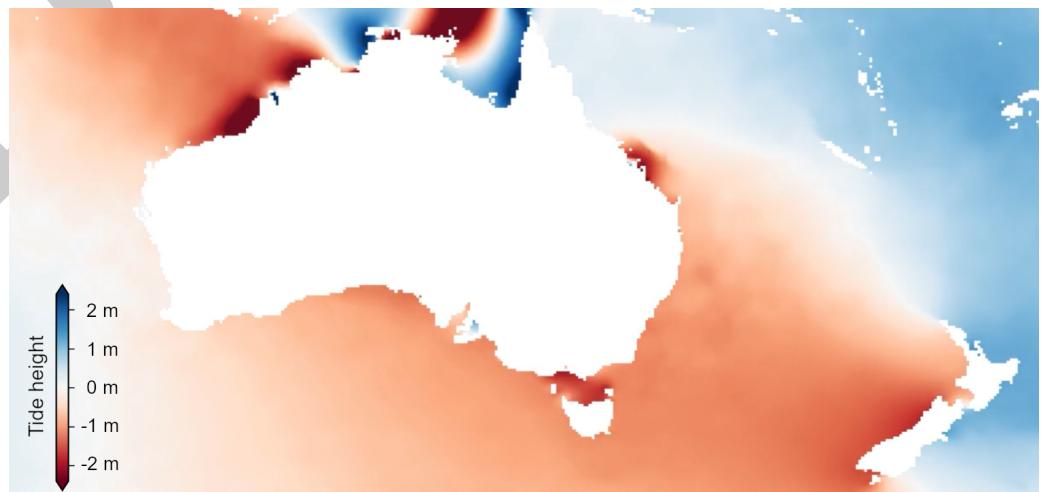
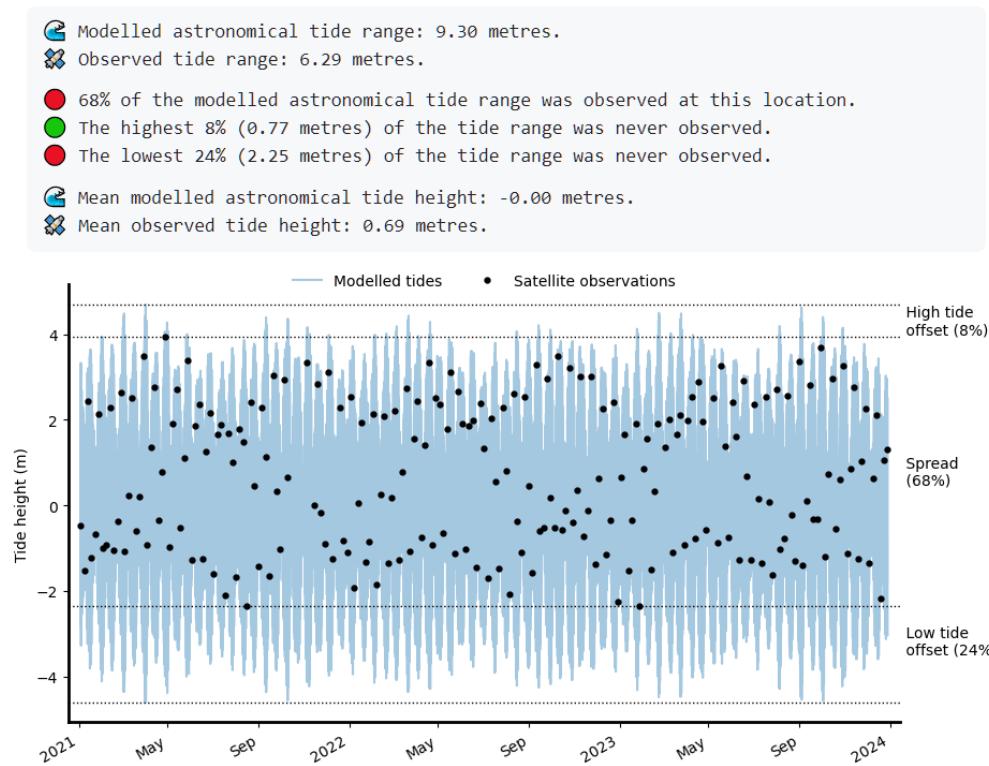


Figure 3: An example spatial tide height output produced by the `pixel_tides` function.

71 Calculating tide statistics and satellite biases

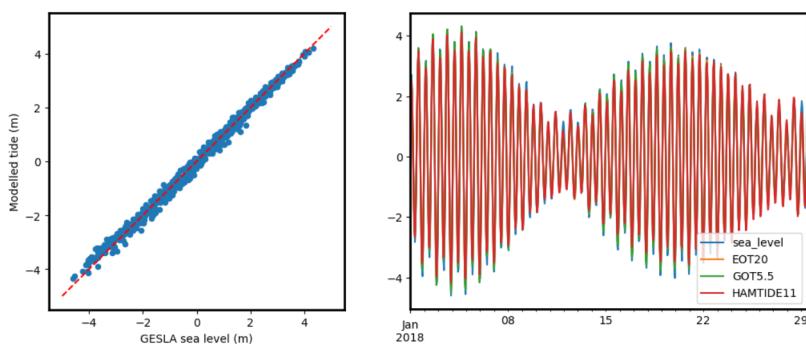
72 The `eo_tides.stats` module identifies biases caused by complex tide aliasing interactions that
 73 can prevent satellites from observing the entire tide cycle (Bishop-Taylor et al., 2019; Eleveld
 74 et al., 2014; Sent et al., 2025). The `tide_stats` and `pixel_stats` functions produce useful
 75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



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

76 Validating modelled tides

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



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

79 Research projects

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

84 Acknowledgements

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86 repository ([Krause et al., 2021](#)). This paper is published with the permission of the Chief
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