

Three gaps for foundation models to address in satellite remote sensing of inland waters

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This is a non-peer-reviewed preprint submitted to EarthArXiv.

The manuscript has been submitted as a Perspective Paper to the *ISPRS Journal of Photogrammetry and Remote Sensing*. Subsequent versions of this manuscript may have slightly different content. If accepted, the final version will be available via the “Peer-reviewed Publication DOI” link on the EarthArXiv page of this preprint.

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Abstract

Long-term Earth observation of inland waters depends on continuity between satellite missions, adequate combinations of spectral, spatial and temporal resolution, and representative calibration and validation datasets. Discontinuities and trade-offs in these components constrain the records available for studying inland waters and their change. We examine three gaps affecting inland water remote sensing: a mission gap between comparable 300 m ocean colour observations from MERIS and OLCI during 2012–2016, a coverage gap in spectral, spatial and temporal sampling, and a generalisation gap when retrieval algorithm accuracy declines beyond bio-optical properties and atmospheric conditions represented during development. Foundation models (FMs) could help address these gaps by learning reusable representations from satellite archives before adaptation to a particular retrieval task. We hypothesise that relationships learned across overlapping satellite missions can support reconstruction of what a sensor would have measured during the mission gap, that combining complementary sensors can extend usable observation coverage, and that pretraining on satellite archives, which cover more water bodies and a wider range of bio-optical properties and atmospheric conditions than available field datasets, can improve retrieval algorithm generalisation. Testing these hypotheses requires criteria that define progress. We quantify the three gaps, define a progress criterion for each and assess 100 recent machine learning studies against the criteria. For the mission gap, three studies address continuity across sensor eras, and none recovers a record from a withheld mission period. For the coverage gap, 23 studies combine complementary observations, but only three test them on withheld water bodies or periods. For the generalisation gap, only seven studies withhold whole water bodies or later periods from all model development. Across all three gaps, none of the six studies that use pretraining compares it with the same architecture trained without pretraining on independent water bodies. The assumption common to all three hypotheses, that archive pretraining adds information beyond established methods, therefore remains untested. Applying the criteria to existing generic Earth observation FMs, then to FMs pretrained on inland waters, would determine which gaps pretraining can reduce.

Keywords: Inland water remote sensing, Foundation models, Self-supervised learning, Pretraining, Mission gap, Generalisation, Uncertainty quantification, Sentinel, Landsat

1. Learning from satellite archives

Satellite remote sensing provides regular Earth observations (EO) of inland waters from regional to global scales. Retrieval algorithms use reflectance (R), defined here as the sunlight returned from the illuminated layer of optically deep water, to estimate constituents such as chlorophyll-*a* (Chl*a*) or optically active dissolved and particulate matter. Repeated observations resolve the timing, spatial extent and duration of changes in phytoplankton biomass, suspended sediment and coloured dissolved matter, including events and spatial patterns that sparse field sampling can miss. Combined with field monitoring and models, EO supports water resource management (El Serafy et al., 2021), products at continental scale and climate analyses (Carrea et al., 2023; Odermatt et al., 2018).

Inland waters concentrate three problems of satellite EO: continuity between missions, compromises among spectral, spatial and temporal resolution, and sparse reference measurements. The mission gap concerns multispectral 300 m ocean colour observations with a high signal-to-noise ratio (SNR) and extends from the end of the Medium Resolution Imaging Spectrometer (MERIS) on Envisat in April 2012 to the launch of the Ocean and Land Colour Instrument (OLCI) on Sentinel-3A in 2016. The coverage gap arises because no single routine global mission fulfils the requirements for inland waters, namely narrow visible and infrared bands, spatial resolution better than 100 m and daily revisit (Mouw et al., 2015). Instead, ocean colour, land imaging and imaging spectroscopy missions provide different combinations of these capabilities (Drusch et al., 2012; Werdell et al., 2019). The generalisation gap occurs when retrieval accuracy declines beyond the bio-optical properties and atmospheric conditions represented during development (Stock et al., 2023; Werther et al., 2025). Moreover, uneven reference sampling and inconsistent measurement quality and protocols constrain calibration and validation even within the represented conditions. Because missing observations from the past cannot be recovered directly, bridging the gaps requires methods that infer unobserved information from recurring relationships in satellite and *in situ* records.

Current machine learning retrieval approaches map R to defined optical properties or constituent concentrations using field measurements or radiative transfer (RT) simulations.

Established neural network processors illustrate these two different retrieval pathways. The Case 2 Regional CoastColour processor (C2RCC) retrieves inherent optical properties (IOPs) from R , and converts them to constituent concentrations (Müller et al., 2026). The OLCI Neural Network Swarm (ONNS) uses separate neural networks to retrieve constituent concentrations directly from R instead of deriving them from retrieved IOPs (Hieronymi et al., 2017). Both approaches depend on the optical conditions represented during development, while conversion from IOPs to concentrations additionally requires assumptions about absorption

and scattering per unit constituent concentration that vary strongly among inland waters (Ylöstalo et al., 2014). IOPs and concentrations therefore require separate evaluation. These retrieval approaches are developed for predefined target variables, such as constituent concentrations or IOPs. Foundation models (FMs) introduce an earlier pretraining stage in which a model learns a reusable representation from a large, varied dataset before adaptation to a specific retrieval task (Schneider et al., 2024). In EO, this representation is learned from satellite imagery archives (Zhu et al., 2026). An encoder converts the input observations into numerical features representing spectral shape, spatial variation and temporal change (Bengio et al., 2013). During adaptation, reference measurements are used to fit an output model that maps these features to the required variable, while the encoder can remain unchanged or be updated (Marsocci et al., 2026).

Self-supervised learning enables such pretraining without requiring field measurements. Masked autoencoders, for example, reconstruct withheld information from the remaining input (He et al., 2022). SatMAE applies this approach across spectral bands and observation times (Cong et al., 2022). Other EO FMs extend pretraining across sensors and observation types. DOFA uses wavelength information to accommodate different band configurations (Xiong et al., 2024), Copernicus-FM incorporates metadata across Sentinel missions (Wang et al., 2025) and TerraMind learns from several types of EO observations (Jakubik et al., 2025). AlphaEarth Foundations and TESSERA provide global annual embeddings at 10 m resolution, learned from multi-sensor time series (Brown et al., 2025; Feng et al., 2025).

Together, these EO FMs motivate one hypothesis per gap. For the mission gap, relationships learned from sensors that overlapped with MERIS or OLCI could be used to estimate what those instruments would have measured in 2012–2016. For the coverage gap, pretraining across sensors with complementary spectral, spatial and temporal sampling could supply information that no single sensor provides. For the generalisation gap, pretraining could extend accurate retrieval beyond the range represented during adaptation, because satellite archives span more water bodies, bio-optical properties and atmospheric conditions than any reference dataset.

Testing these hypotheses requires evaluation criteria that define progress. Building on general requirements for EO FMs (Zhu et al., 2026), we quantify the observation gaps, assess limitations of field and simulated datasets relevant to generalisation, define one progress criterion for each gap and examine how far 100 studies published between 2020 and 2026 meet them. We then outline how the criteria can be applied in stages, from released models and embeddings to aquatic pretraining, and the scientific payoffs for limnology, water management and climate studies if the hypotheses hold.

2. Three gaps in satellite remote sensing of inland waters

2.1 The mission gap

After MERIS ended in April 2012, the Aqua Moderate Resolution Imaging Spectroradiometer (MODIS), the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (VIIRS) and Landsat continued to observe inland waters. The Sentinel-2 MultiSpectral Instrument (MSI) followed in 2015, and OLCI resumed comparable 300 m ocean colour observations in 2016 (Figure 1). During the intervening period, MODIS and VIIRS provided coarser spatial and spectral sampling, while Landsat and Sentinel-2 resolved more inland waters spatially but with substantially lower spectral and temporal definition, and lower SNR over water. Bridging the mission gap therefore requires estimating R in the MERIS or OLCI bands on a 300 m grid at specified dates between 2012 and 2016, using the sensors that continued observing.

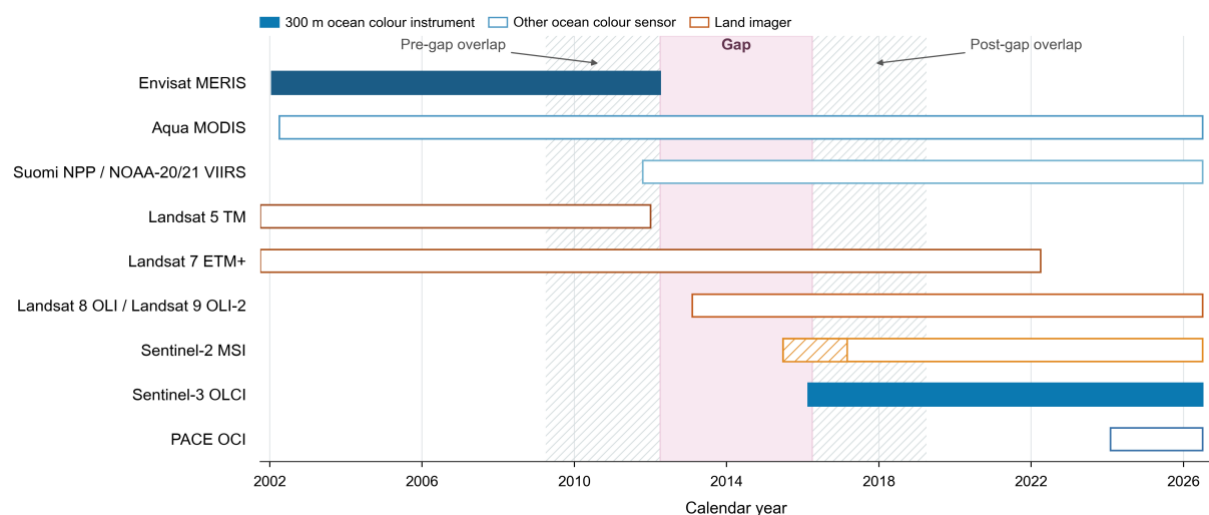


Figure 1. Operating periods of optical satellite instruments used for inland waters, 2002–2026, and the 2012–2016 gap in 300 m ocean colour observations between MERIS and OLCI. Grey hatching marks the reference overlaps before and after the gap. Landsat 7 operated without its scan line corrector from May 2003, and the hatched Sentinel-2 bar marks the period with only Sentinel-2A (Donlon et al., 2012; Drusch et al., 2012).

The European Space Agency Lakes Climate Change Initiative (ESA Lakes_cci) currently fills the gap with MODIS where its time series agrees with MERIS and OLCI during three years of overlap before and after the gap. Of more than 1,000 large and medium lakes investigated, only 73 meet this condition in the Climate Data Research Package v3.0.0 (Asfour et al., 2026). The approach applies selectively because the MODIS ocean colour bands are sampled at about 1 km, leaving few interior pixels sufficiently far from shore in many lakes, and their spectral sampling limits accurate retrieval in optically complex and turbid waters (Feng et al., 2018).

An FM would use the same overlap periods but learn from all sensors that continued observing, including the 30 m land imagers that resolve the water bodies MODIS cannot, and then be adapted to estimate the missing MERIS or OLCI observations. The unresolved question is

whether relationships between observations from the continuing sensors and MERIS or OLCI reflectance, learned during the overlap periods, also hold for atmospheric conditions, bio-optical properties or events that occurred only during the gap. Existing methods demonstrate related forms of harmonisation across sensors. The Harmonized Landsat Sentinel-2 (HLS) product combines Landsat and Sentinel-2 observations after adjustments for differences in spectral response, viewing geometry and spatial sampling (Claverie et al., 2018), and Lomeo et al. (2026) use a mixture density network to make optical water type classification consistent between MSI and OLCI without reconstructing the OLCI spectrum. These methods provide precedents for combining sensors, but neither clarifies whether observations from the sensors operating during 2012–2016 contain sufficient information to reconstruct the missing MERIS or OLCI record.

2.2 The coverage gap

To quantify the spectral component of the coverage gap, we analysed 5,000 hyperspectral R spectra from Pitarch and Brando (2025). For each spectrum, we tested whether any other spectrum with a different shape (spectral angle above 2° over 400–780 nm) would be nearly indistinguishable to a given sensor (band values within 5% in every band). Spectral ambiguity, the percentage of the 5,000 spectra with at least one such match, was 48.7% for MSI and 55.7% for OLI, compared with 8.0% for MERIS, 7.7% for MODIS, 6.9% for OLCI and 0.4% for OCI (Figure 2A). These percentages depend on the library, which spans a wide range of optical complexity but is not specific to inland waters and excludes extremely turbid and waters dominated by cyanobacteria, and on the bands and thresholds used.

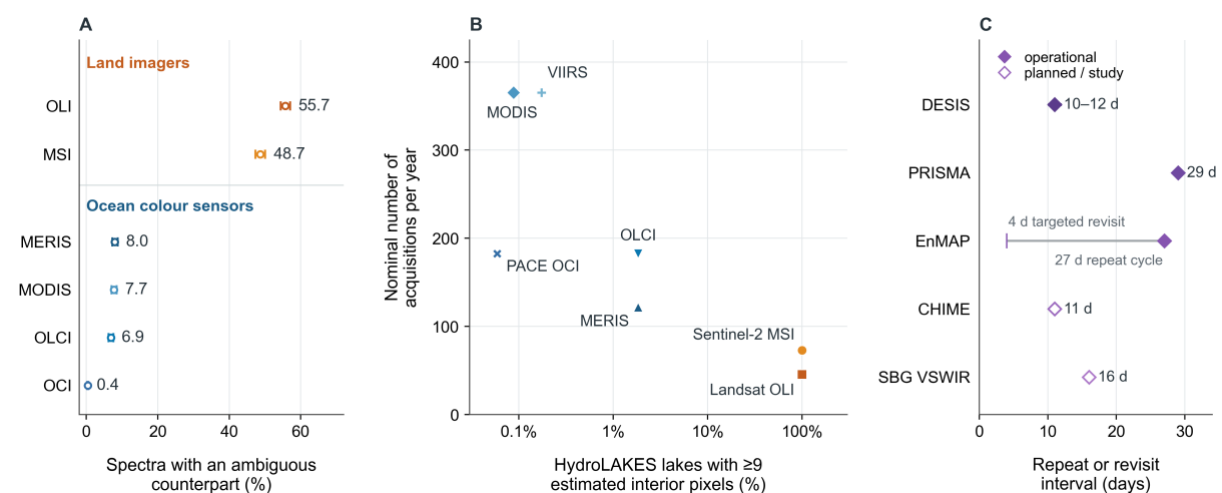


Figure 2. The coverage gap in spectral, spatial and temporal terms. (A) Percentage of 5,000 simulated spectra for which a spectrally different spectrum is nearly indistinguishable in the bands of the sensor, with 95% bootstrap intervals. (B) Percentage of HydroLAKES lakes estimated to contain at least nine interior pixels at the nominal spatial resolution of each sensor, against the nominal number of acquisitions per year. (C) Repeat or revisit intervals of imaging spectroscopy missions. The EnMAP bar spans targeted revisit to repeat cycle. The DESIS range indicates revisit opportunities. Sensor names, datasets and calculations are given in Appendix A1.3.

The higher ambiguity for MSI and OLI indicates that, with fewer and wider bands, distinct hyperspectral R spectra can yield nearly identical band values, consistent with earlier analyses of the inverse problem (Defoin-Platel and Chami, 2007). MERIS and OLCI have similar band configurations (Donlon et al., 2012; Liu et al., 2024) and both sensors yielded low ambiguity. Beyond spectral detail, spatial resolution determines which lakes contain sufficient interior water area, while revisit time determines how often observations are available. Using HydroLAKES, a global database of 1,427,688 lake outlines (Messenger et al., 2016), we estimated the area remaining after excluding a shoreline strip one pixel wide and counted lakes in which this area contained at least nine sensor pixels. Comparison with geometric buffering for 4,000 randomly selected lakes indicated that the approximation was conservative for resolved lakes (Appendix A1.3). MSI and OLI meet the criterion for 99.98% and 99.76% of HydroLAKES outlines, compared with 1.84% for OLCI, 0.088% for MODIS and 0.059% for OCI. The corresponding OLCI, MODIS and OCI lakes contain 71.5%, 50.9% and 49.0% of the cumulative area of HydroLAKES outlines. Imaging spectroscopy missions add spectral detail at about 30 m spatial resolution but revisit only every few weeks or when tasked (Figure 2C). An approach to this gap would pretrain on observations from complementary sensors, retaining their spectral response, spatial sampling and acquisition times. Spectrally, complementary spectral observations could constrain information that is not resolved by the broader bands of an individual sensor. Spectral reconstruction from multispectral imagery provides a precedent for this type of mapping (Du et al., 2023). Spatially, observations at 20 to 30 m resolution could provide information on aquatic processes that are unresolved by 300 m ocean colour sensors, while the latter provide greater spectral discrimination. Temporally, observations from several sensors could be combined using their acquisition times, as in existing methods that fuse irregular and asynchronous image time series from Landsat and Sentinel-2 (Michel and Inglada, 2026).

2.3 The generalisation gap

The algorithm generalisation gap arises when retrieval accuracy declines in water bodies with bio-optical properties or atmospheric conditions that differ from those represented during development (Werther et al., 2025). Changes in constituent concentrations and composition alter optical properties. Atmospheric and illumination conditions, observation geometry and sensor configuration introduce further differences. Sampling particular regions, seasons or events may capture only a small part of this combined variability (Lehmann et al., 2023). Both atmospheric correction (AC) and retrieval of target variables from R can be affected (IOCCG, 2019).

Nominal annual satellite pixel visits exceed the cumulative records in selected field databases by approximately 4.1 to 9.7 orders of magnitude, while target measurements remain unevenly

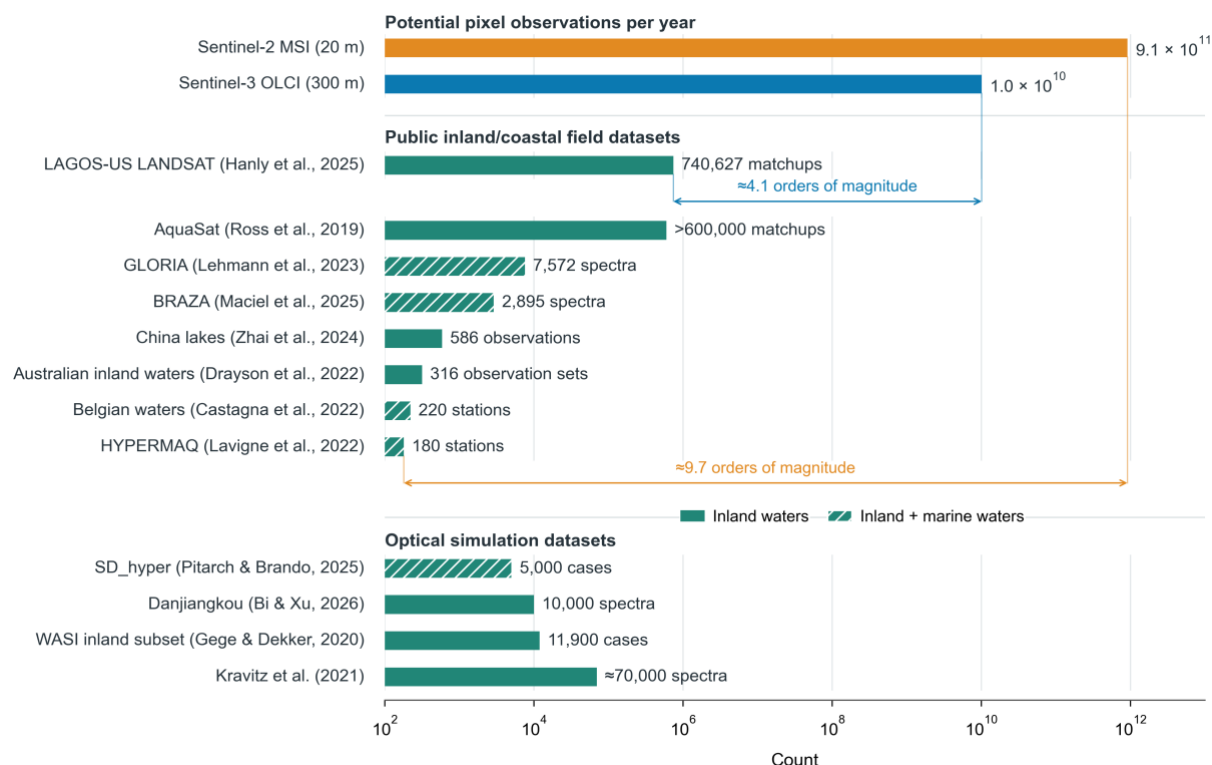


Figure 3. Potential satellite observations per year compared with public field and simulated datasets for inland and coastal waters (Bi and Xu, 2026; Castagna et al., 2022; Drayson et al., 2022; Gege and Dekker, 2020; Hanly et al., 2025; Kravitz et al., 2021; Lavigne et al., 2022; Lehmann et al., 2023; Maciel et al., 2025; Ross et al., 2019; Zhai et al., 2024). Satellite values are geometric upper bounds from GLOWABO lake area (Verpoorter et al., 2014), pixel area and revisit frequency. Field dataset counts are matchups, spectra, observations or stations as labelled. Arrows mark the orders of magnitude between OLCI visits and the largest field dataset and between MSI visits and the smallest.

available (Figure 3). Even the largest field databases are small and uneven relative to the satellite record: of 7,572 records in GLORIA, 5,132 include Chla but only 1,252 include turbidity, an optical proxy for suspended matter (Lehmann et al., 2023). Simulation libraries add optical training datasets informed by field measurements (Figure 3) and can be much larger than field datasets, for example about 5 million cases for C2RCC (Brockmann et al., 2016). Such cases combine the magnitudes of a few absorption and scattering components within one bio-optical model (five in C2RCC), sampled over ranges derived from field datasets, with varied sun and viewing geometries and atmospheric and surface conditions (Müller et al., 2026). Large simulation libraries are therefore many variations of the same model instead of millions of distinct bio-optical situations, and represent only the optical variability included in their bio-optical models and parameter ranges.

Supervised learning requires a target value for every training observation, whereas self-supervised pretraining can use the satellite archive without them. Adaptation still needs reference measurements to link the learned representation to a target variable. Whether pretraining improves that link beyond the properties and conditions those measurements represent is the hypothesis at the centre of this gap. For water quality retrieval, the pretraining archive should contain consistently processed R with sensor identity, AC method, quality flags

and acquisition conditions alongside each observation. Achieving this consistency across imagery archives is itself a substantial processing and validation task.

3. Progress criteria

For each gap we define one progress criterion: reference information that is known but withheld during model development must be estimated with lower error than by established methods and by the same architecture trained without pretraining (Table 1). Each criterion is applied through a test. The mission test removes selected intervals from the MERIS and OLCI eras. The coverage test withholds target observations and examines whether complementary spectral, spatial or temporal information improves their estimation. The generalisation test reserves complete water bodies and, separately, optical conditions, constituent ranges, sensors, campaigns, events, laboratories and analytical protocols. Evaluation beyond the conditions represented by adaptation measurements can still include imagery used during pretraining. Evaluation beyond all development datasets requires excluding the reserved water bodies, periods or conditions from pretraining, adaptation, preprocessing and model selection.

Table 1. Progress criteria for the three gaps.

Gap	Proposed FM contribution	Independent evaluation	Evidence of progress
Mission continuity	Learn relationships among overlapping missions to estimate R in MERIS or OLCI bands during 2012–2016.	Withheld intervals from the MERIS and OLCI eras, excluded from all development steps.	Lower error than climatology, persistence, established harmonisation and the same architecture without archive pretraining. Preserved seasonality, anomalies and breakpoints.
Spectral, spatial and temporal coverage	Learn complementary information across sensors with different band configurations, spatial sampling and acquisition times.	Water bodies near resolving limits of a sensor, withheld observation periods and observations from several sensors evaluated on a matched spatial footprint.	Lower error than the better single sensor chosen in advance, an established method and the same architecture without archive pretraining.
Generalisation	Learn a reusable representation from large archives of satellite observations of R before adaptation with field matchups.	Reserved water bodies, optical conditions, constituent ranges, sensors, campaigns, events, laboratories and protocols, with exposure during pretraining documented.	Lower error than supervised and generic EO alternatives at matched configuration, capacity and field datasets. Comparable retrieval accuracy with fewer field measurements.

To isolate the contribution of archive pretraining, all three tests compare the inland water pretrained model, on the same withheld observations, with predefined references: an established method for the same task and the same neural network architecture trained without

archive pretraining. The generalisation test additionally compares inland water pretraining with generic EO pretraining. Reference approaches include a harmonic climatology per lake, persistence or other established continuity methods (Atton Beckmann et al., 2025; Liu et al., 2024), and the better single sensor chosen on the development datasets. The PANGAEA benchmark, in which supervised models remain competitive with EO FMs, motivates these matched comparisons (Marsocci et al., 2026).

Random splitting assumes that observations are independent and that evaluation datasets follow the same distribution as development datasets. Field measurements and their satellite matchups rarely satisfy this assumption: measurements from the same water body, campaign, season or sensor share characteristics. Random splits can therefore place related observations on both sides of the evaluation, causing knowledge leakage, and overstate generalisability (Stock et al., 2023; Werther et al., 2025). Dawson et al. (2025) evaluated an OLCI FM with random folds and found underestimation above the adaptation range. Reserving entire water bodies and constituent ranges is thus the logical next step. Uncertainty calibration should also be tested: how often stated probability intervals contain the reference observations, and how wide they are, when application conditions differ from those represented during pretraining or adaptation (Werther et al., 2025).

4. Current practice against the criteria

We analysed 100 studies published between 2020 and 2026 (85 on inland waters, 15 spanning inland and coastal waters) to assess the extent to which current practice already meets the progress criteria (Figure 4). These studies cover retrieval, simulation in satellite bands and implemented products, using supervised learning, transfer learning or pretraining. The numbers of studies reported below refer to this corpus only. Appendix 1 describes the selection and classification approach.

Few studies test what the progress criteria require. Only three address the mission gap, and none reconstructs a withheld mission period. The coverage gap is addressed in 23 studies, which combine or reconstruct complementary observations. Where these studies use another satellite product as reference instead of field measurements, agreement demonstrates consistency between products rather than accuracy. Generalisation to unseen water bodies or periods is rarely tested: only seven studies exclude them from every development step. Another 34 reserve separate groups but leave exposure unresolved, for example through preprocessing or model selection on the full dataset or geographically overlapping sources. Random splits of individual observations, used in 37 studies, mainly assess interpolation (Stock et al., 2023; Werther et al., 2025). In the remaining 22, the separation of the evaluation dataset from model development could not be determined (19) or no new inland evaluation was reported (3).

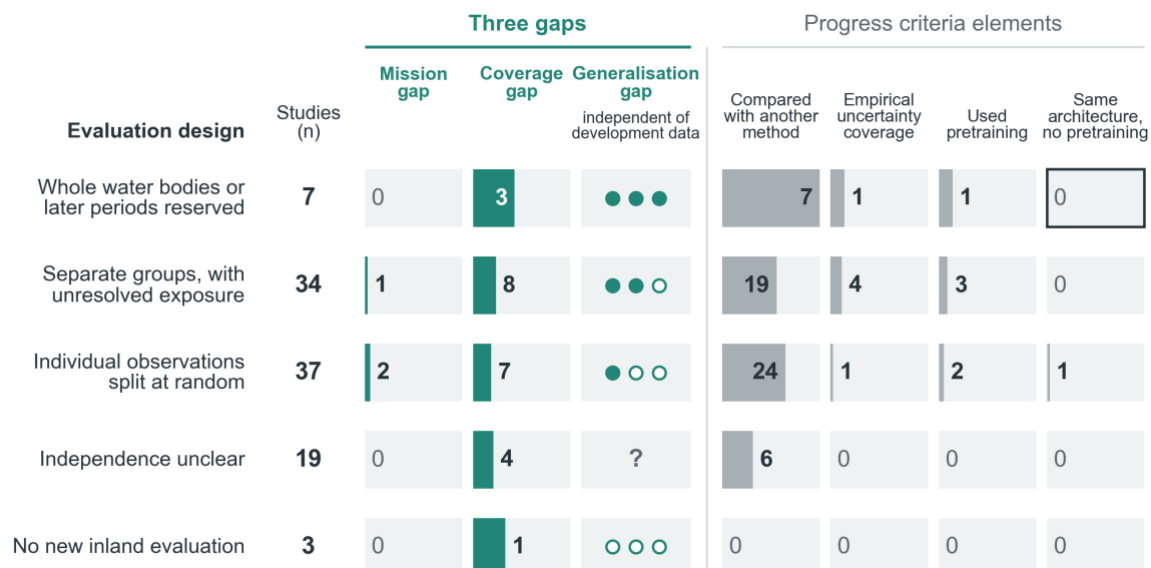


Figure 4. Current practice in 100 inland and mixed inland/coastal studies published 2020–2026. Rows: strongest evaluation design reported by each study. Teal columns: the three gaps. Mission and coverage gap: studies addressing the gap. Generalisation gap: dots rate the independence of the evaluation dataset from model development, from three filled (excluded from every development step) to one (random split). Open circles mark no new inland evaluation and ? marks unclear independence. Grey columns: studies with each element of the progress criteria. Method comparisons used the same evaluation dataset. Numerals count studies, bar length represents their share of the studies in the row (n), and a study can appear in several columns. Outlined cell: no reviewed study compared a pretrained model with the same architecture without pretraining on reserved water bodies or periods.

In 56 studies, the method is compared with another method on the same evaluation dataset, a precondition for demonstrating lower error. Uncertainty intervals are evaluated against reference observations in six studies. Of the six studies that use pretraining, only one compares the pretrained model with the same architecture trained without pretraining, within a single lake and on a random split. No reviewed study makes this comparison on reserved water bodies or periods (Figure 4, outlined cell).

The benefit of pretraining can already be evaluated with released models. Copernicus-FM includes Sentinel-3 OLCI among its pretraining inputs, Dawson et al. (2025) describe an OLCI FM for ocean colour, and AlphaEarth Foundations and TESSERA summarise each year and therefore cannot resolve specific observation times (Brown et al., 2025; Feng et al., 2025). These models can be evaluated on inland water datasets with documented measurement quality against the criteria in Table 1. Where evaluation imagery contributed to pretraining, the result tests generalisability beyond adaptation measurements. Isolating the contribution of pretraining additionally requires comparison with the same architecture without it. Limitations exposed by these tests would identify where specific and novel aquatic pretraining is needed.

5. Scientific payoffs

A successful mission reconstruction would extend records across missions through 2012–2016 with probabilistic estimates that remain distinguishable from direct observations. Of the

26,246 HydroLAKES lakes classified as resolved at 300 m under the approximation in Figure 2B, only 1,257 are resolved by the 1 km MODIS bands used for the current gap fill. The other 24,989 are resolved by Landsat. Their records could be extended wherever valid Landsat observations exist during the gap. Longer records would help separate persistent change from interannual variability (Carrea et al., 2023; Liu et al., 2024). Reducing the coverage gap could extend estimates of narrow band spectral information to the roughly 98% of HydroLAKES lakes that meet the spatial criterion for MSI or OLI but not for OLCI, with uncertainty that accounts for unresolved spectral ambiguity, while combining observations across sensors could increase temporal sampling. Generalisation beyond the water bodies and conditions represented during development would extend accurate retrieval to the millions of lakes without field measurements, with uncertainty that indicates when a retrieval can be trusted, and would reduce the field sampling needed to adapt a model to a new region. Products that pass these tests and provide calibrated uncertainty could also supply observations for data assimilation (Baracchini et al., 2020).

6. Conclusion

The scientific value of FMs for inland water remote sensing depends on whether archive pretraining measurably reduces the mission, coverage and generalisation gaps beyond existing approaches. The proposed criteria evaluate this with reserved mission intervals, complementary sensor observations, and water bodies and conditions excluded from model development. None of the 100 recent studies we assessed combines the required evaluation and comparison. Existing generic EO FMs and embeddings provide a starting point, but their evaluation can only establish progress where appropriate baseline comparisons are available, and the evaluation datasets were not used during pretraining.

A null result would identify where archive pretraining has not improved on established harmonisation, the better single sensor, or supervised and generic EO baselines under the evaluated conditions. It would not, by itself, determine whether the missing information is absent from the available observations or whether the model failed to extract it. Across the three gaps, the criteria would therefore establish where reusable pretraining extends reliable observations across missions, water bodies and environmental conditions, and where further progress depends on additional field measurements, improved observing systems or other algorithmic advances.

Declaration of competing interest

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Swiss National Science Foundation (SNSF) under the Lake3P project, grant no. 204783. It has been prepared with joint financing of the European Union, the Swiss Federal Office of the Environment, the Swiss Federal Office for Spatial Development, and the cantons of Appenzell Innerrhoden, Luzern, Nidwalden, Schwyz, Thurgau, Uri, Valais, Zug and Zurich, through the Interreg Alpine Space programme, project DiMark.

Appendix 1. Literature review and Figure 2 calculations

A1.1 Scope and selection of the reviewed studies

The review covers studies published from 1 January 2020 to 15 September 2026 that apply machine learning to optical satellite observations of inland waters, or of inland and coastal waters together, for retrieval of water quality variables, reconstruction across sensors or missions, or combination of complementary observations. A study was eligible if it evaluated its method on satellite observations or on reflectance resampled to satellite bands. Reviews, proposals without an implementation, studies of marine or land targets only, and methods applied only to field datasets without evaluation or application to satellite imagery were excluded.

Candidate studies were identified through three searches of titles and abstracts in the OpenAlex database. The searches covered retrieval, reconstruction across missions and sensors, and pretraining and transfer learning. The exact search strings are given in Section A1.2. The searches returned 1,977 unique records after deduplication, which were checked by title and abstract. We assessed full texts in two stages. First, 70 studies were read in full, selected for their relevance to the three gaps and availability of the full text. To reduce the influence of this targeted selection, the remaining records with an accessible full text were placed in a random order and assessed in turn until the corpus reached 100 studies. The final corpus comprises 85 studies on inland waters and 15 spanning inland and coastal waters.

Each study was coded for the gaps it addresses and for the elements of the progress criteria it contains. A study addresses mission continuity when it implements reconstruction or continuity across missions or sensor eras. It addresses complementary coverage when it combines or reconstructs observations with complementary spectral, spatial or temporal sampling. Every retrieval study concerns the generalisation gap.

The strongest evaluation design reported by each study was assigned to one of five classes. In the first, whole water bodies or later periods are excluded from every development step, including preprocessing and model selection. In the second, separate groups are reserved but some exposure remains unresolved, for example through preprocessing on the full dataset, geographically overlapping sources or a restricted external reference dataset. In the third, individual observations are split at random between development and evaluation, allowing observations from the same water body or campaign on both sides. In the fourth, an evaluation

is reported but the study does not provide enough information to determine whether the evaluation dataset was kept separate from model development. In the fifth, an existing method is applied to inland waters, for example to produce a new map or product, without evaluation against new inland reference measurements.

Three further elements were recorded. We assessed whether the method was compared with another method on the same evaluation dataset, whether stated probability intervals were evaluated against reference observations, and, for studies using pretraining, whether the same architecture trained without pretraining was included as a comparison. Where a reported improvement relied on different training datasets, input variables or evaluation datasets, this limitation was recorded as a qualification.

A1.2 Search strings

The OpenAlex searches used the publication date range from 1 January 2020 to 15 September 2026. OpenAlex identifiers and DOIs were deduplicated before different versions of the same study were reconciled. The three searches were:

1. Retrieval: (lake OR reservoir OR river OR inland) AND (satellite OR “remote sensing” OR “Sentinel-2” OR “Landsat”) AND (“machine learning” OR “deep learning” OR “neural network” OR “random forest” OR “support vector” OR “gradient boosting” OR “mixture density”) AND (“water quality” OR chlorophyll OR turbidity OR “suspended matter” OR “suspended sediment” OR “water clarity” OR “dissolved organic”)
2. Mission and coverage: (lake OR reservoir OR river OR inland) AND (satellite OR “remote sensing” OR “Sentinel-2” OR “Sentinel-3” OR Landsat OR MERIS OR OLCI) AND (fusion OR reconstruction OR harmonisation OR harmonization OR “gap filling”) AND (“water quality” OR chlorophyll OR turbidity OR “water reflectance” OR “ocean colour” OR “ocean color”)
3. Pretraining and transfer: (water OR aquatic OR lake OR reservoir OR river OR ocean) AND (satellite OR “remote sensing” OR “Sentinel-2” OR “Sentinel-3” OR OLCI) AND (“foundation model” OR “self-supervised” OR pretraining OR “pre-training” OR embeddings OR “transfer learning” OR “contrastive learning”) AND (“water quality” OR chlorophyll OR turbidity OR reflectance OR “ocean colour” OR “ocean color”)

A1.3 Calculations supporting Figure 2

Spectral ambiguity (Figure 2A). We used 5,000 distinct optical property scenarios from the SD_hyper library (Pitarch and Brando, 2025), retaining one reflectance spectrum per scenario at a solar zenith angle of 30°, viewing zenith angle of 0° and relative azimuth of 0°. Spectra were sampled every 1 nm from 400 to 780 nm.

We converted each spectrum to the bands of six satellite sensors using their spectral response functions. For Landsat 8 OLI, we used bands 1 to 4 centred at 443, 482, 561 and 655 nm. For Sentinel 2A MSI, we used bands 1 to 6 centred at 443, 492, 560, 665, 704 and 740 nm. For

Envisat MERIS, we used bands 1 to 11 centred from 413 to 762 nm. For Aqua MODIS, we used ocean colour bands 8 to 15 centred from 412 to 748 nm. For Sentinel 3A OLCI, we used bands Oa02 to Oa15 centred from 412 to 768 nm. For PACE OCI, we used 194 channels centred between 405.13 and 776.83 nm. Band values were calculated as response weighted averages over 400 to 780 nm. Spectral response outside this wavelength range was excluded and the remaining response was normalised within the available range.

For each spectrum, we searched the remaining 4,999 spectra for at least one counterpart that differed by no more than 5% in every sensor band while having a spectral angle greater than 2° over the complete 400 to 780 nm spectrum. Spectral ambiguity is the percentage of the 5,000 spectra for which such a counterpart exists. The 95% intervals in Figure 2A were calculated from 5,000 bootstrap samples of the resulting ambiguity classifications, with replacement, using the 2.5th and 97.5th percentiles. The intervals therefore describe sampling variability within the spectral library under the selected bands and thresholds.

The distinction between the land imagers and ocean colour sensors remained when the thresholds were varied, although the absolute ambiguity percentages changed. At a spectral angle threshold of 2°, reducing the band tolerance from 5% to 3% reduced ambiguity from 55.7% to 28.2% for OLI and from 48.7% to 21.8% for MSI. At a band tolerance of 5%, changing the spectral angle threshold from 1° to 3° changed ambiguity from 62.5% to 46.8% for OLI and from 54.7% to 40.9% for MSI. Across these sensitivity tests, both land imagers retained higher ambiguity than the ocean colour sensors.

Lakes resolved (Figure 2B). We analysed the 1,427,688 lake and reservoir outlines in HydroLAKES version 1.0 (Messenger et al., 2016), which targets water bodies of at least 10 ha. For each lake, we used lake area A and shoreline length L to estimate the interior water area remaining after excluding a shoreline strip one pixel wide. For a pixel width p , the estimated interior area was:

$$A - Lp + \pi p^2. \quad (1)$$

Negative estimates, and cases where the pixel width exceeded the radius implied by the shoreline length, were set to zero. A lake was considered resolved when the estimated interior area contained at least nine pixel areas.

The pixel widths were 20 m for Sentinel-2 MSI, 30 m for Landsat OLI, 300 m for MERIS and Sentinel-3 OLCI, 750 m for VIIRS, 1,000 m for the Aqua MODIS ocean colour bands and 1,200 m for PACE OCI. Under this criterion, 26,246 HydroLAKES lakes were resolved at 300 m, 1,257 at the 1,000 m MODIS resolution and 846 at the 1,200 m OCI resolution. These correspond to 1.84%, 0.088% and 0.059% of the inventory and contain 71.5%, 50.9% and 49.0% of its summed lake area, respectively. The 24,989 additional lakes discussed in Section 5 are the difference between the 300 m and MODIS results.

We assessed the approximation against geometric buffering of the actual outlines for 4,000 lakes selected at random without replacement. At 300 m, the two methods agreed for 3,951 lakes, or 98.8%. Geometric buffering classified 117 lakes as resolved. The area and shoreline approximation identified 68 of these and missed 49, while producing no false positive classifications. It missed 17 of the 22 lakes with between nine and fewer than twelve interior pixel areas, although missed cases were not restricted to lakes close to the threshold. The approximation was therefore conservative for resolved lakes in this sample despite the high overall agreement. Neither calculation places the actual sensor pixel grid over each lake. Pixel orientation, changes in pixel size away from nadir, optically shallow water and adjacency effects beyond the shoreline strip are therefore not represented.

Acquisitions per year and revisit intervals (Figures 2B and 2C). The nominal number of acquisitions per year was calculated as 365 divided by the nominal revisit interval published for each mission or constellation. The DLR Earth Sensing Imaging Spectrometer (DEGIS) has no fixed repeat cycle. Its range in Figure 2C represents revisit opportunities. The PRecursores IperSpettrale della Missione Applicativa (PRISMA) and the Environmental Mapping and Analysis Program (EnMAP) repeat every 29 and 27 days, with shorter revisit possible for targeted acquisitions. The Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) is planned with a systematic revisit of 11 days from two satellites, and the Surface Biology and Geology (SBG) visible to shortwave infrared imaging spectrometer has a design requirement of 16 days or better. These values do not account for cloud, ice, sun glint or other causes of invalid observations.

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