Table S1. Summary of the optically active water quality indicators measured through inland water remote sensing studies. Specific studies, sensor information, and modelling approaches focusing on the listed parameters and included in the review can be accessed through the inland water quality remote sensing index linked to in Appendix A. For a more detailed, technical discussion of specific algorithms and spectral responses for each parameter see Matthews (2011)[4], Gholizadeh et al. (2016)[3], and Giardino et al. (2019)[18]

Parameter	Parameter Description	Measurement Purpose	Dominant Spectral Response	Number of Studies Reviewed
Chlorophyll-a	Photosynthetically active compounds found in plants, algae, and cyanobacteria that convert light into energy for photosynthesis	Lake productivity/trophic state, harmful algal bloom detection	Fluorescents - 680 nm; Absorption - 450-475 nm and 670 nm; Backscattering: ~550 nm and ~700 nm	132
Total Suspended Solids	Inorganic and organic particles held in suspension throughout a water column	Inorganic sediment flux, biogeochemical cycling, light conditions	Reflectance peak between ~500 and ~800 depending on concentration	94
Colored Dissolved Organic Matter	Colored portion of total dissolved organic carbon	Carbon production and cycling, light conditions	Highly absorptive, especially below 500 nm	30
Water Clarity	Measure of total light penetration into a waterbody, typically measured as Secchi Disk Depth or turbidity	Lake productivity/trophic state, light conditions, sediment concentrations, harmful algal bloom detection	Highly dependent on the composition of the previous parameters with generally higher reflectance across the spectrum at lower values	89

Table S2. Summary of the common approaches to algorithm development for remote sensing of inland waters studies. Specific studies using the described approaches and included in the review can be accessed through the inland water quality remote sensing index linked to in Appendix A.

Modelling Approach	Description	Benefits	Limitations	Number of Studies Reviewed
Empirical	Algorithms involving empirical relationships between spectral bands and band ratios and the water quality parameter of interest, typically through linear regression.	Transparent, easily interpretable, no a priori assumptions required	Non-generalizable beyond the range and setting of the training data, unable to handle complex non-linear interactions	279
Semi-Empirical	Spectral band-ratio algorithms based on the physical properties of the water quality constituent of interest	Easily interpretable, more generalizable than empirical approaches	Unable to handle non-linear interactions, requires site-specific calibration and validation	15
Semi-Analytical	Analytical inversion-based models calibrated using field observations	Theoretically generalizable, mechanistic, potential for cross-sensor transferability	Requires representative field data for calibration and validation, computationally more expensive	61
Machine Learning	A subset of empirical methods which leverage large amounts of data and iterative learning to extract relationships between spectral properties and water quality parameters	Capable of handling non-linear relationships, no a priori assumptions required, generalizable depending on training data	Prone to overfitting, opaque, computationally expensive	29

Table S3. Summary of collected information for the detailed literature review index.

Index Parameter	Parameter Description
Identifying information	Composed of an index number, author(s), journal, title, year of publication, DOI, and total citation count pulled from SCOPUS.
Locational Information	Country of focus and central latitude and longitude of the study area.
Study Scale	The order of magnitude of the study area in km2. The surface area of the waterbody for single waterbody studies, total area of all waterbodies for spatially discontinuous studies, or the total area of the entire region if the study area was contiguous. Represented as 10^1 km2, 10^2 km2, 10^3 km2, etc.
Study Period	The duration of the study. If no temporal analysis was conducted than the period was marked na. Total study length was determined as the date of the first image to the date of the final image.
Sensor Information	Satellite and/or airborne sensors utilized and the spectral resolution of each sensor (hyperspectral or multispectral)
Atmospheric Correction	A binary yes/no regarding the application of an atmospheric correction for the final model.
Parameters	The water quality parameters included in the study.
Waterbody Type	The waterbody of focus (Rivers, Lakes/Reservoirs, Estuaries, or Deltas)
Modeling Approach Information	The model inputs, chosen modelling methodology, and total number of models used. Also included is information on if different modelling approaches were compared (i.e. empirical vs semi-analytical approaches).
Number of Methodology Figures	The total count of figures focused on background information. These include study area maps, flow charts, tables with input data, and other figures depicting the theory or method behind the modelling approach.
Number of Validation Figures	The total count of figures focused on model validation. These include tables of error metrics and actual vs. predicted plots.
Number of Trend, Impact, and Driver Figures	The total count of figures and tables depicting some spatial or temporal trend. These include maps, timelines, figures depicting correlations between water quality parameters and climatic or anthropogenic drivers, and figures or tables examining the impacts of changing water quality parameters on ecological or anthropogenic systems.
Paper Category	The final classification of the paper based on total figure counts and proposed hypothesis/science questions.
Model Fit Error	Reported error metrics for model fit.
Model Validation Error	Reported error metrics for model validation based on data not used in model development.

Table S4. Summary of studies using remote sensing to analyze impacts and drivers of water quality and classified as water quality science papers within the analysis.

	Author	Scale (km²)	Duration	Water body	Approach	Constituent	Analysis Summary
Anthropogenic Drivers	Ren et al., 2018 [231}	10^3	1-5 Years	Lakes	Empirical	SDD	Examines spatiotemporal variations in water clarity and sediment discharge connected to the Three Gorges Dam. Finds that certain areas have inversely corelated clarity driven by surface flow dynamics.
	Hou et al., 2017 [232]	10^5	>10 Years	Lakes	Empirical	TSS	Examines the spatiotemporal response of TSS in the Yangtze River Basin to the construction of the Three Gorges Dam. Found that the reservoir construction drove varying regional effects, and that recent improvements in TSS are likely correlated with increased NDVI in the area.
	Cui et al., 2013 [229]	10^3	5-10 Years	Lakes	Empirical	TSS	Examines the spatiotemporal trends of TSS in a Chinese lake and how it correlates with dredging activities and climactic drivers.
	McCullough et al., 2013 [238]	10^4	>10 Years	Lakes	Empirical	SDD	Utilizes Landsat data to examine water clarity in Maine over 15 years. Finds that decreased clarity is somewhat correlated to the presence of timber harvesting in a watershed.
	Cui, Wu, and Liu, 2009 [230]	10^3	1-5 Years	Lakes	Empirical	SDD	Examines the interactions between elevated TSS levels driven by river backflow into Poyang Lake (China) and lake dredging. Finds that the combined impact is greater than either event by itself.
	Wu et al., 2007 [254]	10^3	5-10 Years	Lakes	Empirical	SDD	Utilizes Landsat and MODIS data to measure the effect of dredging on water clarity.
Climatic Drivers	Lymburner et al., 2016 [175]	10^5	>10 Years	Lakes	Semi Analytical	TSS	Examines interactions between decadal climate variations (ENSO) and TSS concentrations in optically heterogenous lakes across western Australia.
	Robert et al., 2017 [255]	10^2	>10 Years	Lakes	Empirical	TSS	Examines climactic drivers of TSS extremes and seasonal cycles in Mali lakes.
	Huang et al., 2015 [256]	10^3	< 1 Month	Lakes	Empirical	TSS, Chl-a, TP	Examines how the provision of phosphorous from sediment resuspension controls TSS and chl-a dynamics in a shallow lake.

	Author	Scale (km^2)	Duration	Water body	Approach	Constituent	Analysis Summary
	Zhu et al., 2014 [227]	10^3	1-5 Years	Lakes	Semi Empirical	Algal Blooms	Examines how typhoon induced sediment resuspension and nutrient mixing impact the development dynamics of algal blooms.
	Curtarelli et al., 2015 [96]	10^2	< 1 Year	Lakes	Empirical	Chl-a	Combines remote sensing with hydrodynamic modelling to examine the role of thermal stratification and mixing on chl-a dynamics.
	Huang et al., 2014 [164]	10^3	>10 Years	Lakes	Semi Empirical	Chl-a	Examines the role of wind, precipitation, decadal climate signals, and resuspension driven nutrient availability on the presence/dynamics of algal blooms.
	Nellis, Harrington, & Wu, 1998 [256]	10^2	< 1 Year	Lakes	Semi Analytical	TSS	Examines the impacts of a flood event on sediment concentration, pool size, and water quality dynamics in a Kansas reservoir.
	Wang et al., 2012 [226]	10^3	5-10 Years	Multiple	Empirical	Turbidity	Examines the role of hurricanes in controlling turbidity levels in Florida's Lake Okeechobee and two connected estuaries.
	Ng et al., 2011 [225]	10^2	< 1 Year	Lakes	Semi Empirical	Chl-a	Incorporates remote sensing data into a 3D hydrological model to analyze dinoflagellate dispersion within a lake ecosystem. Finds that bloom growth is controlled by stratification while dispersion is driven by wave forces.
	Sass et al., 2008 [228]	10^3	>10 Years	Lakes	Empirical	Chl-a	Examines variations in trophic state within boreal lakes driven by climactic variables. Finds that growing season length and May temperatures are key drivers.
	Bayley et al., 2007 [150]	10^2	>10 Years	Lakes	Empirical	Chl-a	Tests the 'stable states' hypothesis regarding trophic status for boreal lakes and finds that most lakes in the study area have one dominate state rather than two.
	Feng et al., 2015 [258]	10^4	5-10 Years	Lakes	Semi Empirical	Chl-a	Identifies high risk eutrophication areas and their relationship to connectivity and precipitation.
	Duan et al., 2017 [190]	10^2	>10 Years	Lakes	Machine Learning	Chl-a	Analyzes spatiotemporal distributions of phycocyanin and chl-a and develops a hazard assessment map to identify safe areas for drinking water outlets.

	Author	Scale (km^2)	Duration	Water body	Approach	Constituent	Analysis Summary
Landscape Level Drivers	Dvornikov et al., 2018 [50]	10^2	Snapshot	Lakes	Empirical	CDOM	Analyzes landscape level drivers of CDOM in arctic lakes and finds significant relationships between thermocirque presence and elevated CDOM levels.
	Sass et al., 2008 [259]	10^3	>10 Years	Lakes	Empirical	Chl-a	Examines connectivity, wetland area, and concentrations of Ca and Mg that control the trophic state of boreal lakes.
	Rose et al., 2017 [147]	10^5	>10 Years	Lakes	Empirical	SDD	Examines how watershed and riparian zone characteristics drive water clarity and finds that during wet years, watershed scale drivers dominate while for dry years riparian characteristics are more important.
Forecasting	Qin et al., 2015 [27]	10^3	1-5 Years	Lakes	Empirical	Chl-a	Develops a dynamic forecasting model incorporating wind, precipitation, and remotely sensed chl-a concentration to predict algal bloom development in Lake Taihu, China. The applied model helped remove over 1,000,000 tons of algal scum from the lake.
	Imen et al., 2015 [182]	10^3	1-5 Years	Lakes	Machine Learning	TSS	Utilizes remotely sensed TSS data to construct a real-time forecasting model for predicting degraded water quality near drinking water outlets in Lake Mead.
	Zhang et al., 2013 [98]	10^3	< 1 Month	Lakes	Mixed	Chl-a	Develops forecasting model capable of predicting algal blooms 3-5 days in advance in shallow Lake Taihu in China.
Water Quality Impacts	Sandström et al., 2016 [235]	10^3	5-10 Years	Lakes	Product	Chl-a	Utilizes remotely sensed water quality parameters to identify and explain variations in fish habitat and species composition. Found that habitat was highly correlated with CDOM and chl-a levels.
	Torbick et al., 2014 [237]	10^5	1-5 Years	Lakes	Empirical	Chl-a	Examines distribution of algal blooms in relation to reported cases of amyotrophic lateral sclerosis (ALS) to identify high risk areas for the disease.
	Potes, Costa, & Salgado, 2012 [260]	10^2	1-5 Years	Lakes	Empirical	Turbidity	Incorporates remotely sensed turbidity into a two-layer bulk model to predict surface water temperature.

	Author	Scale (km^2)	Duration	Water body	Approach	Constituent	Analysis Summary
	Finger et al., 2014 [237]	10^3	5-10 Years	Lakes	Product	Chl-a	Incorporates remotely sensed chl-a data into a model examining the dynamics and drivers of cholera outbreaks in the Democratic Republic of Congo.
	Pavelsky and Smith, 2009 [233]	10^3	< 1 Year	Lakes/ River	Empirical	TSS	Utilizes remotely sensed TSS concentration to examine river velocity, flow reversal, and hyrodologic recharge of floodplain lakes in the Peace-Athabasca Delta.
	Telmer et al., 2006 [118]	10^5	>10 Years	Rivers	Empirical	TSS	By using the correlation between TSS and mercury, the authors present a remote estimation of mercury concentrations, which they use to examine likely drivers of increased mercury concentrations from gold-mining.
	Overeem et al., 2017 [110]	10^4	>10 Years	Rivers	Empirical	TSS	Examined flux of suspended sediment from Greenland ice sheet, highlighting disproportionately high global contribution of sediment.
Water Quality Dynamics	Griffin et al., 2011 [137]	10^4	5-10 Years	Rivers	Empirical	CDOM	Used remote sensing of CDOM and DOC to highlight the interannual variability of both, while also highlighting that the spatial and temporal variability likely causes underestimates of DOC flux from Kolyma River.
	Walker, 1996 [115]	10^5	1-5 Years	Estuaries	Semi Analytical	TSS	With remote sensing estimates of suspended sediments, Walker explores causes of plume variability in the Mississippi River.
	Falcini et al., 2012 [28]	10^4	< 1 Year	Rivers	Product	TSS	Used remote estimates of TSS to examine sedimentation in wetlands and link them to hydrodynamics with implications for wetland restoration

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