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Research article

Satellite imagery as a management tool for monitoring water clarity across freshwater ponds on Cape Cod, Massachusetts

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ABSTRACT

Water clarity serves as both an indicator and a regulator of biological function in aquatic systems. Large-scale, consistent water clarity monitoring is needed for informed decision-making. Inland freshwater ponds and lakes across Cape Cod, a 100-km peninsula in Massachusetts, are of particular interest for water clarity monitoring. Secchi disk depth (SDD), a common measure of water clarity, has been measured intermittently for over 200 Cape Cod ponds since 2001. Field-measured SDD data were used to estimate SDD from satellite data, leveraging the NASA/USGS Landsat Program and Copernicus Sentinel-2 mission, spanning 1984 to 2022. Random forest machine learning models were generated to estimate SDD from satellite reflectance data and maximum pond depth. Spearman rank correlations (r_s) were “strong” for Landsat 5 and 7 ($r_s = 0.78$ and 0.79), and “very strong” for Landsat 8, 9, and Sentinel-2 ($r_s = 0.83$, 0.86, and 0.80). Mean absolute error also indicated strong predictive capacity, ranging from 0.65 to 1.05 m, while average bias ranged from −0.20 to 0.06 m. Long- and recent short-term changes in satellite-estimated SDD were assessed for 193 ponds, selected based on surface area and the availability of maximum pond depth data. Long-term changes between 1984 and 2022 established a retrospective baseline using the Mann-Kendall test for trend and Theil-Sen slope. Generally, long-term water clarity improved across the Cape; 149 ponds indicated increasing water clarity, and 8 indicated deteriorating water clarity. Recent short-term changes between 2021 and 2022 identified ponds that may benefit from targeted management efforts using the Mann-Whitney *U* test. Between 2021 and 2022, 96 ponds indicated deteriorations in water clarity, and no ponds improved in water clarity. While the 193 ponds analyzed here constitute only one quarter of Cape Cod ponds, they represent 85% of its freshwater surface area, providing the most spatially and temporally comprehensive assessment of Cape Cod ponds to date. Efforts are focused on Cape Cod, but can be applied to other areas given the availability of local field data. This study defines a framework for monitoring and assessing change in satellite-estimated SDD, which is important for both local and regional management and resource prioritization.

1. Introduction

Water clarity serves as both an indicator and a regulator of biological and ecological function in aquatic systems. As an indicator, water clarity is highly related to trophic state, nutrient concentration, and algal biomass (Carlson, 1977; Wagner et al., 2017). As a regulator, water clarity impacts the health of aquatic vegetation (Orth et al., 2010) and fish populations (Lester et al., 2004). Water clarity also has important economic implications, as poor water clarity can reduce property values (Clapper and Caudill, 2014) and affect tourism (Keeler et al., 2012). Secchi disk depth (SDD) is a widely used measure of water clarity (Boyce et al., 2012). A Secchi disk is a black and white disk 30 cm in diameter that is lowered into the water column; the depth at which the disk is no longer visible to the observer is recorded as the SDD (Cialdi, 1866).

Changes in water clarity are of particular interest across Cape Cod, a 100-km peninsula located off the coast of Massachusetts in the northeast

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United States. Cape Cod depends on reliable water quality to support its seasonal, tourism-based economy (Perry et al., 2020), and is highly susceptible to water quality stressors (CCC, 2021). There are 883 lakes and ponds across Cape Cod—defined as fresh, static, and permanent inland waterbodies larger than 10,000 ft^2 (or approximately 929 m^2)—hereafter collectively referred to as ponds (CCC, 2021). Ponds across the Cape provide habitat, contribute to estuarine and marine systems, offer recreational opportunities, and support 230,000 year-round residents and nearly 500,000 seasonal visitors each year (CCC, 2019, 2021; U.S. Census Bureau, 2019). Cape Cod's ponds are also used to infer the condition of the region's aquifer (CCC, 2021; Oldale, 1976); the Cape's drinking water is entirely dependent on groundwater from the Cape Cod Aquifer, but groundwater sampling across Cape Cod is limited as no programs exist to regularly monitor the quality of groundwater on a regional basis. Since most ponds across the Cape are directly connected to the groundwater, water quality measured across ponds and across time is used to provide insight regarding the general condition of the Aquifer.

Across Cape Cod, multiple policies are in place to manage inland water quality, including several sections of the Clean Water Act. Sections 205(j) and 303(e) require states to establish methods for compiling and analyzing water quality data. Section 303(d) requires states to evaluate all available water quality-related data to develop an Integrated Waters List, which identifies waters that do not meet established water quality standards. In 2015, the United States Environmental Protection Agency approved the Cape Cod Commission's updated Section 208 Plan, the Area Wide Water Quality Management Plan, which is a watershed-based approach to restore embayment water quality on Cape Cod. The plan recommends strategies, regulatory reforms, and includes a focus on freshwater ponds and lakes.

Yet, current and proposed field monitoring across Cape Cod only represents a small percentage of ponds, which may not be representative or transferrable (CCC, 2021). Only about 10% of ponds had sufficient data to assess water quality in 2021, where at least three years of data from 2016 onward were required for assessment, noting that the lack of sufficient data reflects a serious deficiency in public sector monitoring of freshwater ponds (APCC, 2021). Only 80 ponds across Cape Cod were included in the 2022 Massachusetts' Integrated Waters List, with 29 of these 80 ponds falling under the category of "uses not assessed" due to a lack of data (MassDEP, 2023). Field assessments across the Cape are typically concentrated in developed, easily accessible areas, with many systems rarely or never monitored (McCullough et al., 2012). Moreover, field monitoring can be inconsistent. There are 30 known pond monitoring programs across the Cape (CCC, 2021). This leads to inconsistencies in parameters measured and methods used; therefore, standardized, large-scale methods are needed.

Satellite remote sensing has been established as an effective tool for monitoring water clarity (Lang et al., 2023; Page et al., 2019; Ren et al., 2018; Song et al., 2022), including for waters off the coast of Cape Cod (Hu et al., 2013; Luis et al., 2019). Satellite sensors offer frequent data collection and provide a standardized, repeatable product across locations and time. The 2021 Cape Cod Pond and Lake Atlas listed remote sensing as a potential tool for improving spatial and temporal coverage of water clarity estimates and for reducing costs associated with regional monitoring (CCC, 2021). Another unique advantage of satellite observations is the ability to perform retrospective analyses. Image archives for several Earth-observing satellites date back decades and are available to monitor past changes in water clarity across the Cape. In this study, satellite data is suggested as a complementary tool for managing water quality across Cape Cod ponds, providing data useable for assessing large-scale change, prioritizing resources, and understanding drivers of water clarity.

Here, a multi-sensor satellite approach was used to assess water clarity for 193 ponds. The ponds analyzed in this study were selected based on a minimum surface area threshold of 1 ha and the availability of maximum pond depth data. While these ponds constitute only about one quarter of the 883 ponds across the Cape, they represent over 85% of its freshwater surface area, providing the most spatially comprehensive assessment of Cape Cod ponds to date. This study advances satellite monitoring of water clarity across Cape Cod to Application Readiness Level (ARL) 6 as defined by the National Aeronautics and Space Administration (NASA) Applied Sciences Program, and demonstrates a framework to advance efforts to ARL 7. ARL 6 is reached upon demonstration in a relevant environment, and ARL 7 is reached upon use of an application prototype in a partner's decision making (NASA, 2015). Additionally, this study regularly engaged partners across Cape Cod who intend to use methods presented here as a complementary tool for monitoring and managing inland water quality. Collaborating with local partners is particularly important in regional management contexts (Kearney et al., 2007; Perry et al., 2020). The following research objectives are addressed.

1. Use satellite imagery to estimate SDD by analyzing its relationship with field-measured SDD collected across 154 Cape Cod ponds.
2. Quantify long-term changes in SDD spanning 1984 to 2022 for 193 Cape Cod ponds to establish a retrospective baseline of water clarity across the Cape.
3. Assess recent short-term changes in SDD between 2021 and 2022 for 193 Cape Cod ponds as a tool for identifying ponds that may benefit from additional field monitoring.

2. Materials and methods

2.1. Study area

Cape Cod is a peninsula off the southeast coast of Massachusetts. A narrow canal, the Cape Cod Canal, separates it from the mainland. It is bordered to the south by Nantucket Sound, to the east by the Atlantic Ocean, and to the north by Cape Cod Bay (Fig. 1). Cape Cod can be

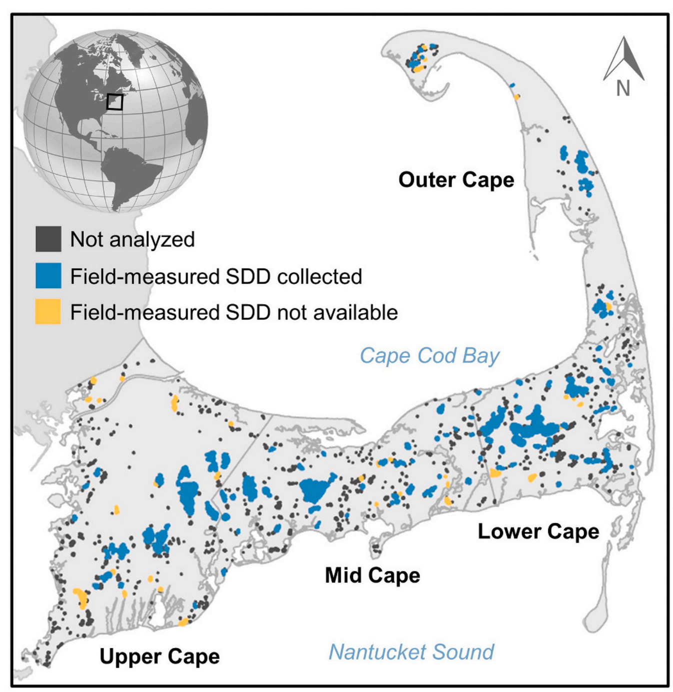

Fig. 1. Cape Cod ponds, including those that were not analyzed in the current study (black), those analyzed that corresponded to field-measured Secchi disk depth (SDD; blue), and those analyzed without field-measured SDD (yellow). Ponds not analyzed were excluded either because they were less than 1 ha in surface area or because maximum pond depth data was not available. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

separated into four regions: the Upper Cape, Mid Cape, Lower Cape, and Outer Cape. Most development on the Cape extends from the Upper to Lower Cape, while over half of the Outer Cape is federally designated land as part of Cape Cod National Seashore (CCC, 2019). Cape Cod's ponds are largely the result of glacial movement that left depressions in the land mass which filled with groundwater following the retreat of the last continental ice sheet approximately 25,000 years ago (Fisher, 1987). Due to their glacial formation, many of Cape Cod's 883 ponds are hydrologically isolated from other surface water, with most lacking outflows and inflows and instead rely on rainfall and groundwater for recharge. Cape Cod ponds also discharge to groundwater on the down-gradient side, and, therefore, their water level fluctuates along with groundwater levels. Cape Cod ponds range in size from less than an acre to 735 acres, covering nearly 4% of the Cape's surface area.

2.2. Field data

Field-measured SDD were compiled by the Cape Cod Commission for the years 2001 through 2022, representing observations collected intermittently across 217 ponds (Fig. S1). This dataset represents an amalgamation of data collection efforts primarily coordinated through volunteer programs, including many town- and pond-specific programs, the Pond and Lake Stewardship (PALS) program, the Association to Preserve Cape Cod (APCC), and unpublished data from Cape Cod National Seashore (S.E. Fox unpublished data, National Park Service). Collection times were not readily available for all measurements, but most regional monitoring programs suggest observations be collected between 7 a.m. and 3 p.m. local time. A single SDD measurement is obtained by repeating the following steps three times and averaging the results: (1) A Secchi disk is lowered into the water and the depth at which the disk is no longer visible to the observer is recorded. (2) The Secchi disk is then raised and the depth at which the disk becomes visible again to the observer is recorded. (3) The depth at which the Secchi disk disappears and the depth at which it reappears are averaged.

Pond depth has been found to improve satellite-estimated SDD (McCullough et al., 2012), and as described in Section 3.1, the addition of maximum pond depth as a predictor variable significantly improved satellite-estimated SDD across Cape Cod. Maximum pond depth was available for only a subset of ponds across the Cape (CCC, 2003), typically collected either using a sonar depth finder or by lowering a Secchi disk to the bottom of the pond. The Cape Cod Commission provided a dataset with maximum pond depth data for 181 of the 883 ponds across the Cape. Maximum pond depth was obtained for 12 additional ponds from Portnoy et al. (2001), the Cape Cod Bay nautical chart, the 2003 Cape Cod Pond and Lake Atlas (CCC, 2003), and unpublished data from the Cape Cod Commission and the Orleans Pond Coalition.

A subset of the Cape's 883 ponds was used for model development and for assessing long- and recent short-term change (Fig. 2). First, ponds at least 1 ha (equivalent to 10,000 m^2) in surface area were retained. This spatial requirement was dictated by the spatial resolution of the satellite sensors used in this study (see Section 2.3), and follows similar methods presented in Song et al. (2022). Applying a surface area threshold of 1 ha resulted in 364 ponds for analysis. Next, only ponds that contained a measurement for the ponds' maximum depth were considered, resulting in 193 ponds assessed for both long- and recent short-term trends (Section 2.5); these 193 ponds correspond to the blue and yellow polygons in Fig. 1. While the 193 ponds analyzed here constitute only 22% of the 883 ponds across the Cape, they represent over 85% of its freshwater surface area. Of these 193 ponds, 154 contained coincident field-measured SDD and were used for random forest machine learning model development (Section 2.4); these 154 ponds correspond to the blue polygons in Fig. 1.

2.3. Satellite data

Satellite imagery was acquired from both the joint NASA and United

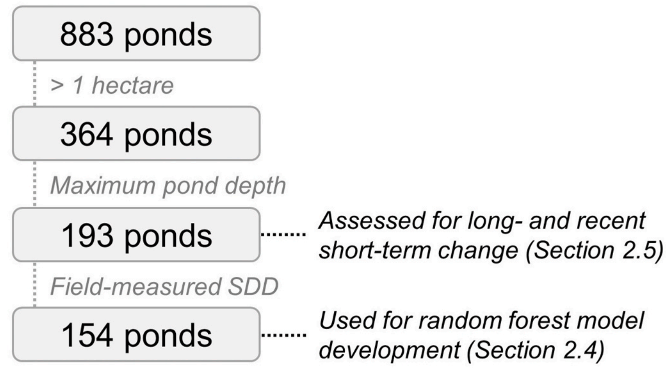

Fig. 2. A flowchart indicating the number of ponds included in each step of pond selection. The 193 ponds at least 1 ha in size and containing data for maximum pond depth were assessed for long- and recent short-term change. Among them, the 154 ponds additionally containing field-measured Secchi disk depth (SDD) were used for random forest machine learning model development.

States Geological Survey (USGS) Landsat Program and the European Space Agency Copernicus Sentinel-2 mission. Leveraging multiple satellites reduces satellite revisit times for a particular location and increases data product accuracy (Masek et al., 2018). The Landsat Program is a series of Earth-observing satellites, which includes the Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI), and Landsat 9 Operational Land Imager 2 (OLI-2). Sentinel-2 data were obtained from the Sentinel-2A and -2B MultiSpectral Instruments (MSI), two functionally similar sensors that are hereafter collectively referred to as Sentinel-2. Each of these satellites covers a different time period spanning 1984 to present, and Landsat 8, Landsat 9, and Sentinel-2 are still operational (Fig. 3). This study is not intended to intercompare satellite performance; instead, the inclusion of these five satellite platforms is intended to build the most temporally comprehensive assessment possible, with overlapping satellite lifespans over the past 39 years offering a longer time period for change assessments and more frequent image acquisition (Fig. S1).

Sentinel-2 offers higher spatial, temporal, and spectral resolutions compared to the Landsat satellites (Table S1). Sentinel-2 collects data in 13 spectral bands in the visible through shortwave infrared portions of the electromagnetic spectrum at spatial resolutions ranging from 10 to 60 m, offering a revisit frequency of 10 days at the Equator prior to the launch of Sentinel-2B and 5 days thereafter. Landsat 5 and Landsat 7 collected data in 6 visible through shortwave infrared spectral bands while Landsat 8 and Landsat 9 collect data in 7 spectral bands, all at a spatial resolution of 30 m and with a revisit frequency of 16 days at the Equator. Given the relatively high latitude of Cape Cod and its location within multiple, overlapping satellite footprints, multiple observations per month were generally available (Fig. S2).

Level 1, top-of-atmosphere reflectance measurements were retrieved for Landsat (Loveland and Dwyer, 2012) and Sentinel-2 (Aschbacher and Milagro-Pérez, 2012) using Google Earth Engine (GEE), a cloud-based geospatial processing platform that provides high-performance computing resources to directly process large geospatial datasets without the need to download data (Gorelick et al., 2017). Satellite images in GEE are pre-processed to facilitate fast and efficient access, including direct interpolation of the satellite imagery to the desired projection and resolution. Top-of-atmosphere reflectances were extracted through GEE and processed separately for each of the five satellite platforms (Table S1). Satellite pixels whose centers fell within a 10 m buffer of the shoreline were removed to reduce the possibility of erroneous values due to land adjacency effects. Satellite pixels impacted by cloud interference were identified using the C Function of Mask algorithm (Zhu et al., 2015); for Landsat data, pixels flagged as

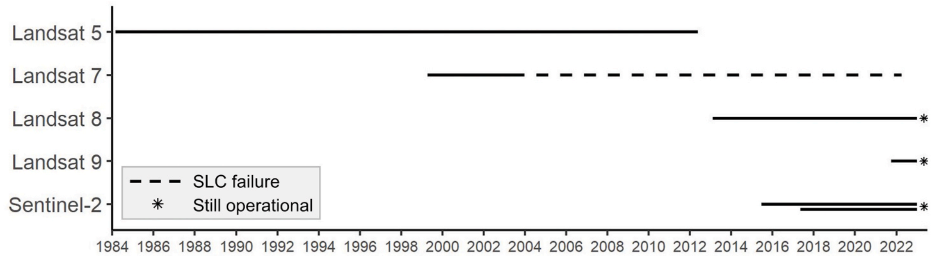

Fig. 3. Time period covered by each of the satellite platforms considered in the present study: Landsat 5 (March 1, 1984 to May 8, 2012), Landsat 7 (April 15, 1999 to April 6, 2022), Landsat 8 (February 11, 2013 to present), Landsat 9 (September 27, 2021 to present), and Sentinel-2, including Sentinel-2A (June 23, 2015 to present) and Sentinel-2B (March 7, 2017 to present). Failure of the Landsat 7 scanline corrector (SLC) reduced its data coverage by approximately 22% after May 31, 2003 (Storey et al., 2005).

"cloud," "dilated cloud," "cirrus cloud," and "cloud shadow" were removed. For Sentinel-2, pixels flagged as "opaque cloud" and "cirrus cloud" were removed.

Only satellite observations collected during the monitoring season were considered, where the monitoring season was defined as 1 April through 31 October of each year, as this is the time period during which most field-measured SDD were collected. To analyze the relationship between satellite-estimated and field-measured SDD, satellite data were extracted within a 10-m buffer of location information provided with each field measurement at 154 ponds where field-measured SDD was available. If for a given location a 10-m buffer corresponded to multiple satellite pixels, reflectance values were averaged across satellite pixels for each spectral band. To assess long- and recent short-term changes in satellite-estimated SDD, satellite data were extracted within a 10-m buffer of the central point within the pond, defined as the point with the maximum distance from shore, at 193 ponds. Again, if this 10-m buffer corresponded to multiple satellite pixels, reflectance values were averaged. To limit the inclusion of floating vegetation in satellite-predicted SDD estimates, the normalized difference vegetation index (NDVI), a commonly used measure of vegetation health, was computed (Rouse et al., 1974). SDD estimates corresponding to an NDVI greater than 0.3 were discarded following Kleinschroth et al. (2021).

2.4. *Predicting SDD using satellite data*

To generate satellite-predicted SDD, a random forest machine learning model was used. While several studies have defined algorithms for predicting SDD from both Landsat and Sentinel-2 data (Lang et al., 2023; Page et al., 2019; Ren et al., 2018; Song et al., 2022), performance for Cape Cod ponds was poor. A random forest is an ensemble machine learning method that consists of a collection of regression trees that use a random subset of data to estimate the response variable given several predictor variables (Breiman, 2001). Random forest machine learning methods have frequently been applied to remote sensing data as they provide a good balance between processing time and model performance, and are relatively insensitive to predictor collinearity (Belgiu and Drăguţ, 2016).

Two different random forest machine learning models were generated for each satellite sensor to assess the effect of maximum pond depth on satellite predictions of SDD. One random forest considered maximum pond depth and spectral information while the other random forest considered exclusively spectral information. For Sentinel-2, only the spectral bands with relatively high (10 and 20 m) spatial resolution were used, while spectral bands with spatial resolutions of 60 m were excluded (see Table S1). Each random forest was generated by creating 500 regression trees and used a random subset of 70% of the data for model training while the remaining 30% of the data was used for model testing; the number of coincident observations used for model training and testing can be found in Table S2. Satellite-predicted SDDs that were greater than field-measured maximum pond depth were set to the maximum pond depth in an effort to reduce inaccurate measurements due to bottom reflectance. Random forest machine learning development was performed in R Version 4.3.0 (R Core Team, 2023), using the *randomForest* package (Liaw and Wiener, 2002).

To statistically assess agreement between field-measured and satellite-predicted SDD, the non-parametric Spearman rank correlation, mean absolute error (MAE), and average bias were used. The Spearman rank correlation (r_s) measures the strength and direction of the monotonic association between two ranked variables (Spearman, 1987), and was interpreted following Prion and Haerling (2014), where $|r_s| < 0.2$ indicates a negligible association between datasets, $0.2 \leq |r_s| < 0.4$ a weak association, $0.4 \leq |r_s| < 0.6$ a moderate association, $0.6 \leq |r_s| < 0.8$ a strong association, and $|r_s| \geq 0.8$ a very strong association. Temporal offsets between satellite image acquisition and field data collection of 1 to 5 days were tested. Across all five satellite platforms, the day offset whose r_s had the highest weighted average, which considers both the strength of the correlation and the sample size, was selected.

MAE and bias were computed to summarize algorithm performance following recommendations in Seegers et al. (2018) for aquatic remote sensing. MAE is the average of the absolute value of the differences between field-measured and satellite-predicted SDDs, in m, where a value of zero indicates perfect agreement between datasets. Bias is the average of the difference between field-measured and satellite-predicted SDDs, and indicates the average depth, in m, that satellite estimates tended to under- or over-predict SDD compared to field measurements. MAE and bias were computed using the *Metrics* package (Hamner and Frasco, 2018) in R Version 4.3.0 (R Core Team, 2023).

2.5. *Assessing long- and recent short-term changes*

2.5.1. *Assessing long-term changes*

Long-term, interannual changes were assessed for 193 ponds to determine if water clarity increased or decreased over the observational period of satellite imagery. First, predicted SDD from each satellite sensor was cross-compared for overlapping time periods (Fig. 2) to determine which sensors, if any, could be analyzed collectively as a single timeseries. Combining satellite observations allows for a longer timeseries to be considered in trend assessments; Coffer et al. (2021) found that a minimum of 10 years of observations are needed for long-term trends in water quality data to exceed variability in the data. Satellite-predicted SDDs from each sensor were averaged for each month during the monitoring season, and corresponding average monthly SDDs were compared. Agreement between satellite-predicted SDD across sensors was again assessed using r_s, MAE, and bias.

Results indicated that all satellite sensors could be analyzed as a single timeseries, spanning 1984 to 2022 (see Section 3.3). Thus, satellite-predicted SDDs were combined for all sensors, averaged for each monitoring season, and a trend assessment was performed. The nonparametric Mann-Kendall test for trend was used to indicate whether a monotonic trend was present in the data (Kendall, 1955; Mann, 1945), and the Theil-Sen slope was used to determine the magnitude of the trend (Sen, 1968; Theil, 1992). This robust trend assessment allows missing data in the timeseries, makes no assumptions regarding data distribution, and is insensitive to outliers. Long-term trends were assessed according to the resulting p-value at a significance level of $\alpha = 0.10$, following the recommendation by Wang et al. (2020) for Mann-Kendall tests of water quality data. The Mann-Kendall test for trend was performed in R Version 4.3.0 (R Core Team, 2023), using the *rkt* package (Marchetto, 2021).

To put observed long-term changes in satellite-predicted SDD into the context of coincident climate conditions, long-term weather observations were obtained. Average annual air temperature and cumulative annual precipitation were retrieved from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) produced by the PRISM Climate Group at Oregon State University (Daly et al., 2008, 2015) and stored as GEE product "OREGONSTATE/PRISM/AN81m." Average annual air temperature was computed by averaging corresponding monthly average air temperatures, and cumulative annual precipitation was computed by summing monthly total precipitation, including rain and melted snow. Weather data were extracted from GEE at the central point of each pond spanning 1984 to 2022, and were aggregated across all 193 ponds to generate a single air temperature and precipitation value per year. The Mann-Kendall test for trend and associated Theil-Sen Slope were used to assess long-term changes in these timeseries at a significance level of $\alpha = 0.10$.

2.5.2. Assessing recent short-term changes

Recent short-term changes were assessed for 193 ponds to determine if water clarity for the current year was statistically different from water clarity for the previous year. This framework can be used by stakeholders to assess recent changes in water clarity, which can be useful for resource prioritization. The most recent monitoring season, 2022, was assessed against the previous 2021 monitoring season by combining observations from two satellites, Landsat 8 and Sentinel-2, as their data archives included full-year timeseries for 2021 and 2022. The nonparametric Mann-Whitney U test was used to assess if satellite-predicted SDDs during the 2021 and 2022 monitoring seasons were generated from the same population (Mann and Whitney, 1947; Wilcoxon, 1992). Only ponds with at least 5 observations per monitoring season were considered, following minimum sample size recommendations from Mundry and Fischer (1998). Additionally, ponds whose satellite-estimated SDDs contained duplicate values for at least half of all estimates were not considered, as their low variance may bias statistical comparisons in rank-based analyses (Divine et al., 2018). Differences were assessed according to the resulting p-value at a significance level of $\alpha = 0.05$.

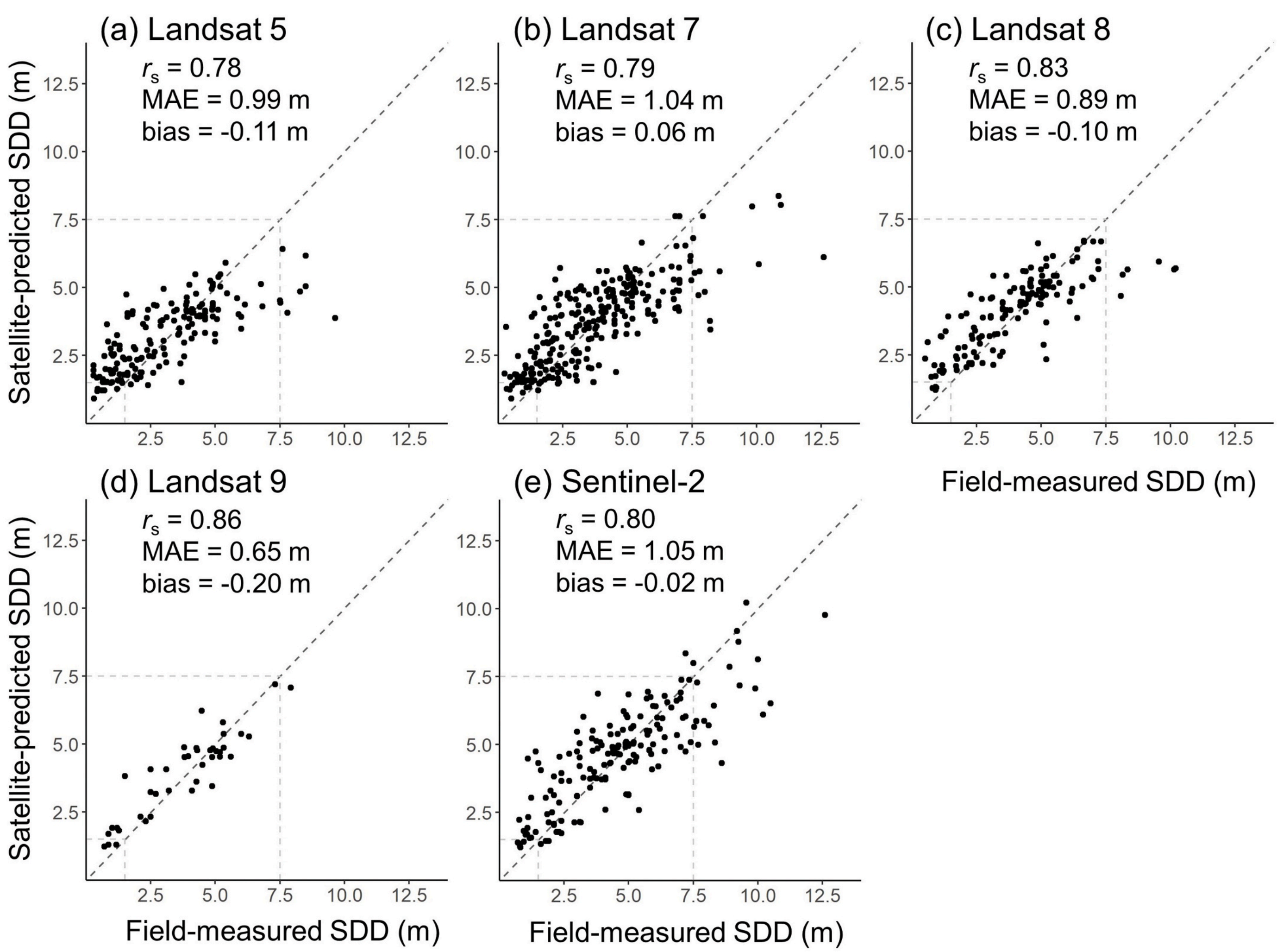

Fig. 4. Comparison of field-measured Secchi disk depth (SDD) versus satellite-predicted SDD for an offset between satellite image acquisition and field data collection of up to 4 days from (a) Landsat 5, (b) Landsat 7, (c) Landsat 8, (d) Landsat 9, and (e) Sentinel-2. The Spearman rank correlation (r_s), mean absolute error (MAE), and bias associated with each comparison are shown for each platform. The dark gray dashed lines represent perfect relationships between datasets (1:1), and the light gray dashed lines represent SDDs of 1.5 and 7.5 m which are discussed in the text.

3. Results

3.1. Association between satellite-predicted and field-measured SDD

Satellite imagery was well-suited for predicting SDD across Cape Cod ponds, with r_s ranging from 0.78 to 0.86 for a temporal offset of up to 4 days between field data collection and satellite imagery acquisition, indicating "strong" and "very strong" associations between datasets (Fig. 4, Table 1). Corresponding r_s was strongest for Landsat 9 ($r_s = 0.86$, $n = 42$) and weakest for Landsat 5 ($r_s = 0.78$, $n = 165$), and the weighted average r_s for all satellites was 0.80 (n = 778). MAE and bias also indicated strong agreement between field-measured and satellite-estimated SDD, with the lowest MAE of 0.65 m corresponding to SDD estimated from Landsat 9 and the highest MAE of 1.05 m corresponding to SDD estimated from Sentinel-2. These MAE values indicate that differences between field-measured and satellite-estimated SDD were typically within 1 m. Bias suggested that nearly all satellite platforms slightly underestimated SDD compared to field measurements as indicated by negative bias values for all satellites except Landsat 7, ranging from −0.2 to 0.06 m. For Landsat 5, 7, and 8, satellite-predicted SDD was more closely related to field measurements for SDDs between approximately 1.5 and 7.5 m; at SDDs shallower than 1.5 m, satellite estimates generally overestimated SDD compared to field measurements, while at SDDs deeper than 7.5 m, satellite estimates generally underestimated SDD. Underestimation at depths greater than 7.5 m was less pronounced in Landsat 9 and Sentinel-2, which both indicated relatively consistent agreement at all field-measured SDDs deeper than 1.5 m.

Generally, the offset between field data collection and satellite overpass had minimal effect on random forest machine learning model performance. The weighted average r_s for offsets up to between 1 to 3 and 5 days ranged between 0.77 and 0.78, indicative of a "strong" association between datasets, while weighted average MAE ranged from 1.02 to 1.14 m and weighted average bias ranged from 0.04 to 0.14 m (Table S3). A temporal offset of up to 4 yielded the strongest weighted average r_s and thus was used for model training and testing; however, similarly strong agreement for temporal offsets of up to between 1 to 3 and 5 days suggest that the offset between satellite image acquisition and field data collection is of minimal importance for obtaining representative satellite-based estimates. Across offsets of up to between 1 to 3 and 5 days, Landsat 9 continued to demonstrate the strongest agreement, with r_s ranging from 0.83 (n = 37) for an offset of up to 3 days to 0.91 for offsets of up to 2 and 5 days (n = 25 and 45, respectively). Similarly, MAE ranged from 0.54 m with a bias of −0.15 m (n = 45) for an offset of up to 5 days to 0.66 m with a bias of −0.12 m (n = 25) for an offset of up to 2 days.

While temporal offset was not particularly important for random forest machine learning model performance, the inclusion of maximum pond depth as a predictor variable strongly impacted model performance (Table S4), consistent with findings from McCullough et al. (2012). When maximum pond depth was not included, the weighted average r_s for offsets of up to between 1 to 5 days ranged from 0.63 for offsets of up to 2 and 5 days (n = 464 and 860, respectively) to 0.68 (n = 216) for an offset of 1 day. Similarly, both MAE and bias increased when maximum pond depth was not included as a predictor variable, with weighted average MAE ranging from 1.22 m with a bias of 0.09 m (n = 778) for an offset of up to 4 days to 1.37 m with a bias of 0.23 m (n = 216) for an offset of up to 1 day. While these r_s values are still considered "strong" associations according to Prion and Haerling (2014), they are considerably lower than equivalent r_s when maximum pond depth was included as a predictor variable, and both MAE and bias also showed notable increases when only spectral information was considered.

Table 1
Agreement statistics between satellite-predicted Secchi disk depth (SDD) and field-measured SDD for each satellite and for an offset between satellite image acquisition and field data collection of up to 4 days; offsets spanning up to between 1 to 3 and 5 days are shown in Table S3. Agreement statistics include Spearman rank correlation (r_s), mean absolute error (MAE) in m, and mean bias in m. Satellite-predicted SDD was generated using random forest machine learning models that considered both spectral information and maximum pond depth as predictor variables; n indicates the sample size of coincident satellite and field measurements used for model testing.

Offset	Satellite	n	r_s	Association[a]	MAE	Bias
4 days	Landsat 5	165	0.78	Strong	0.99	−0.11
	Landsat 7	263	0.79	Strong	1.04	0.06
	Landsat 8	139	0.83	Very strong	0.89	−0.10
	Landsat 9	42	0.86	Very strong	0.65	−0.20
	Sentinel-2	169	0.80	Very strong	1.05	−0.02
	Weighted average	778	0.80	Very strong	0.98	−0.04

[a] Spearman rank correlation was interpreted following Prion and Haerling (2014).

3.2. SDD across Cape Cod ponds

Satellite-estimated SDD was summarized across Cape Cod regions for each of the 193 ponds analyzed and for the 2022 monitoring season, varying from a median of 0.61 m at Israel Pond in the town of Barnstable located in the Mid Cape to 6.0 m at Round Pond (East) in the town of Truro located in the Outer Cape (Fig. 5, Table S5). Distributions of satellite-predicted SDD across Cape Cod's four regions were relatively similar, although the median satellite-predicted SDD in the Upper Cape region was about 1 m deeper than the Mid, Lower, and Outer Cape regions (Fig. 5a). Median satellite-predicted SDDs for the Mid, Lower, and Outer Cape regions were all categorized as "suitable," following Smith and Davies-Colley (1992) who defined categories of perceived aquatic suitability-for-use for recreational activities (Table S6). Median satellite-predicted SDD for the Upper Cape region was categorized as "eminently suitable." Across Cape Cod towns, median satellite-predicted SDDs for the 2022 monitoring season were more variable (Fig. 5b). The town of Truro, located in the Outer Cape, had a median satellite-predicted SDD of nearly 6 m with most of the distribution falling within the "eminently suitable" category. Conversely, the town of Provincetown, which lies just to the north of Truro also in the Outer Cape, had the lowest median satellite-predicted SDD for the 2022 monitoring season and fell within the "unsuitable" category. All other towns had a median within either the "suitable" or "eminently suitable" categories.

3.3. Long-term changes in SDD

For each of the five satellites considered in this study, cross comparisons for average monthly SDD during overlapping satellite time periods demonstrated "very strong" associations, indicating that all satellites could be analyzed collectively as a single timeseries (Table 2, Fig. S3). Overlapping average monthly observations collected from Landsat 7 and Landsat 8 and from Landsat 8 and Sentinel-2 had the highest r_s (0.91; n = 5685 and 4766, respectively). Overlapping average monthly observations collected from Landsat 5 and Landsat 7 had the lowest MAE (0.44 m; n = 6913), while those collected from Landsat 8 and Sentinel-2 had the strongest bias (−0.04 m, n = 4766). The cross comparison between Landsat 9 and Sentinel-2 had the lowest r_s (0.85; n = 784) and highest MAE (0.56 m), with Landsat 9 predicting lower SDDs than Sentinel-2 (bias = −0.13 m). For all satellite cross comparisons, disagreement was higher at deeper satellite-predicted SDDs. Given "very strong" associations for all cross comparisons, satellite-predicted SDD from all five platforms was combined to form a single 39-year timeseries, spanning 1984 to 2022, which was used to assess long-term changes in SDD.

Statistically significant changes in satellite-estimated SDD from 1984 to 2022 were observed in 81% of ponds (157 of 193; Fig. 6, Table S7). 149 of these ponds increased in satellite-estimated SDD, indicating improving water clarity conditions, while 8 ponds decreased in satellite-

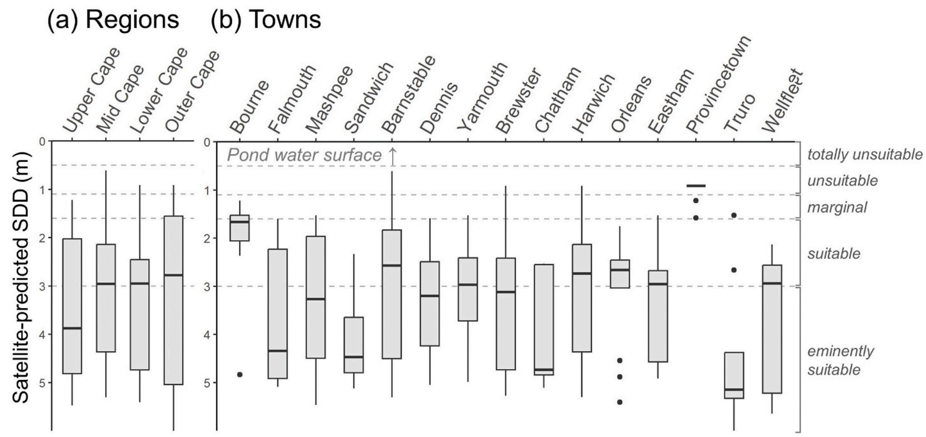

Fig. 5. Boxplots of median satellite-predicted Secchi disk depth (SDD) for each of the 193 ponds assessed and for the 2022 monitoring season for Cape Cod (a) regions and (b) towns. Suitability categories to the right were defined in Smith and Davies-Colley (1992) and represent perceived suitability-for-use for recreational activities (see Table S6). Note, the y-axes are reversed such that the pond water surface is at the top of the figure.

Table 2
Agreement statistics for a cross comparison of average monthly Secchi disk depth (SDD) during overlapping satellite time periods (see also Fig. S3). Agreement statistics include Spearman rank correlation (r_s), mean absolute error (MAE) in m, and average bias in m; *n* indicates the sample size of coincident SDD estimates between Satellite #1 and Satellite #2.

Satellite #1	Satellite #2	Time period	*n*	r_s	Association[a]	MAE	Bias
Landsat 5	Landsat 7	1999–2011	6913	0.90	Very strong	0.44	−0.20
Landsat 7	Landsat 8	2013–2022	5685	0.91	Very strong	0.45	−0.18
Landsat 8	Landsat 9	2022	765	0.88	Very strong	0.52	0.22
Landsat 8	Sentinel-2	2017–2022	4766	0.91	Very strong	0.47	−0.04
Landsat 9	Sentinel-2	2022	784	0.85	Very strong	0.56	−0.13

[a] Spearman rank correlation was interpreted following Prion and Haerling (2014).

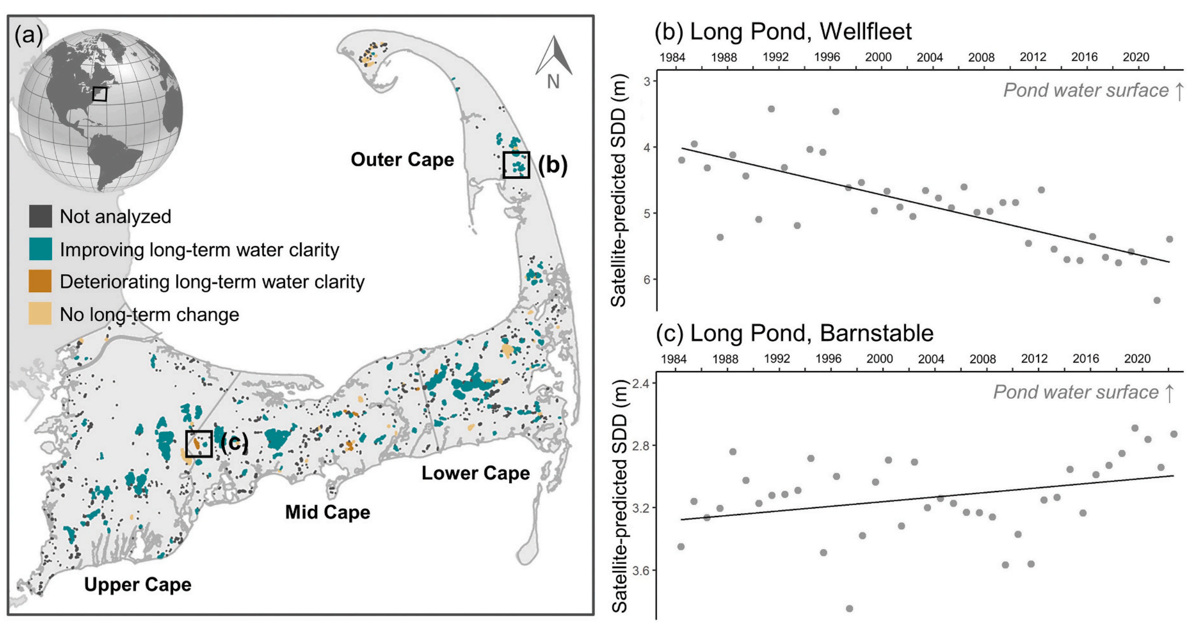

Fig. 6. Results of a long-term change assessment in satellite-estimated Secchi disk depth (SDD) from 1984 to 2022 for (a) 193 ponds across Cape Cod, (b) Long Pond in Wellfleet, and (c) Long Pond in Barnstable (village of Marstons Mills). Solid lines in (b) and (c) indicate the Theil-Sen slope accompanying the nonparametric Mann-Kendall test for trend. Note, the y-axes for (b) and (c) are reversed such that the pond water surface is at the top of the figure, meaning increasing SDD is shown as a downward trend and decreasing SDD is shown as an upward trend.

estimated SDD, indicating deteriorating water clarity. Of the 8 ponds with deteriorating long-term water clarity, 7 were located in the Mid Cape. For ponds with deteriorating long-term water clarity, percent change across the 39-year timeseries ranged from 6 to 16%. Ponds with improving long-term water clarity were more spatially distributed across the Cape, and percent change ranged from 1 to 67%. Fig. 6 shows a single timeseries for a pond with improving long-term water clarity conditions and a single timeseries for a pond with deteriorating long-term water clarity conditions. Satellite-estimated SDD for Long Pond in Wellfleet, located in the Outer Cape, increased by 43% over the 39-year timeseries from a depth of about 4 m in 1984 to a depth of nearly 6 m in 2022 (n = 39, $|tau|$ = 0.57, p-value <0.001; Fig. 6b). Conversely, satellite-estimated SDD for Long Pond in Barnstable (village of Marstons Mills), located in the Mid Cape, decreased by 9% over the 39-year timeseries from a depth of nearly 3.5 m in 1984 to just over 3 m in 2022 (n = 39, $|tau|$ = 0.21, p-value = 0.06; Fig. 6c).

Concurrent long-term weather observations indicated warmer and wetter conditions across 193 Cape Cod ponds from 1984 to 2022, as satellite-estimated SDD largely improved across these ponds (Fig. S4). Following global increases in both air temperature and precipitation, Cape Cod's average annual air temperature increased over 1 °C across the four decades of data assessed (n = 39, $|tau|$ = 0.40, p-value <0.001; Fig. S4a). Similarly, cumulative annual precipitation increased from 1984 to 2022 from approximately 1100 mm of precipitation in 1984 to 1300 mm in 2022 (n = 39, $|tau|$ = 0.26, p-value = 0.022; Fig. S4b).

3.4. Recent short-term changes in SDD

Of the 193 ponds considered, 44 were not assessed for differences in satellite-estimated SDD from 2021 to 2022 due to insufficient variability to confidently assess recent short-term change (Divine et al., 2018). Of the remaining 149 ponds, 96 indicated a statistically significant difference in satellite-estimated SDD from 2021 to 2022 (Table S8). Each of these ponds had a lower median satellite-estimated SDD in 2022 than in 2021, indicating deteriorating water clarity conditions. No ponds showed a short-term improvement in water clarity from 2021 to 2022, while 53 ponds had no statistically significant change in satellite-estimated SDD. Featured in Fig. 7 are Shawme Pond, Mashpee-Wakeby Pond, and Lower Mill Pond.

Shawme Pond, located in the Upper Cape, has seen an increase in algal blooms over the past decade according to the Town of Sandwich Board of Health, with algae growth in 2022 being particularly extensive (Devaney, 2022). The Mann-Whitney U test indicated that satellite-estimated SDD was substantially lower in 2022 than in 2021, indicating a deterioration in year-over-year water clarity (Fig. 7a; U = 913, N = 72, p-value = 0.002). In 2021, satellite-estimated SDD had a median of 2.76 m compared to a median of 2.33 in 2022. Mashpee-Wakeby Pond, also located in the Upper Cape, has seen significant degradation according to the Mashpee-Wakeby Pond Alliance, and the Mashpee Board of Health has issued several advisories for cyanobacterial blooms in recent years. Results of the Mann-Whitney U test support these observations, with substantially lower satellite-estimated SDD in 2022 compared to 2021 (Fig. 7b; U = 756, N = 69, p-value = 0.026). In 2021, satellite-estimated SDD had a median of 4.60 m, indicating clearer waters than the median of 4.29 m estimated for 2022. The Town of Brewster in the Lower Cape has seen a degradation in freshwater ponds according to the Brewster Ponds Coalition, with cyanobacterial blooms noted at several ponds, including Lower Mill Pond (Walsh, 2022). The Mann-Whitney U test again indicated that satellite-estimated SDD was substantially lower in 2022 compared to 2021 (Fig. 7c; U = 2031, N = 109, p-value = < 0.001). In 2021, median satellite-estimated SDD was 2.35 m, while in 2022, median satellite-estimated SDD was 2.02 m.

4. Discussion

Recent literature has suggested that water quality across Cape Cod has worsened (Devaney, 2022; Fraser, 2022; Walsh, 2022), and both Flavelle (2023) and Howes et al. (2022) noted deteriorating water quality in nearby coastal embayments. The APCC's 2022 State of the Waters report found that 90% of coastal embayments received an unacceptable water quality grade, an increase from 87% in 2021, 79% in 2020, and 68% in 2019, where APCC water quality grades consider several parameters in addition to water clarity (Gottlieb et al., 2023). Yet few datasets are available for assessing large-scale change for inland, freshwater systems. This study established a framework for assessing water clarity for nearly 200 Cape Cod ponds, representing 85% of the Cape's freshwater surface area, and provided the most comprehensive statistical assessment to date of long- and recent short-term change. Identifying ponds with changing water clarity allows for efficient resource prioritization and provides a complement to improve spatial and temporal coverage offered through traditional field-based monitoring.

Satellite imagery from both the Landsat Program and the Sentinel-2 mission were well-suited for characterizing SDD across Cape Cod. Corresponding r_s between satellite-estimated SDD and field-measured SDD were either "strong" or "very strong" for each satellite platform, and both MAE and bias indicated favorable agreement. Many studies have defined algorithms to predict SDD from satellite imagery, including from Landsat and Sentinel-2, and the random forest machine learning model

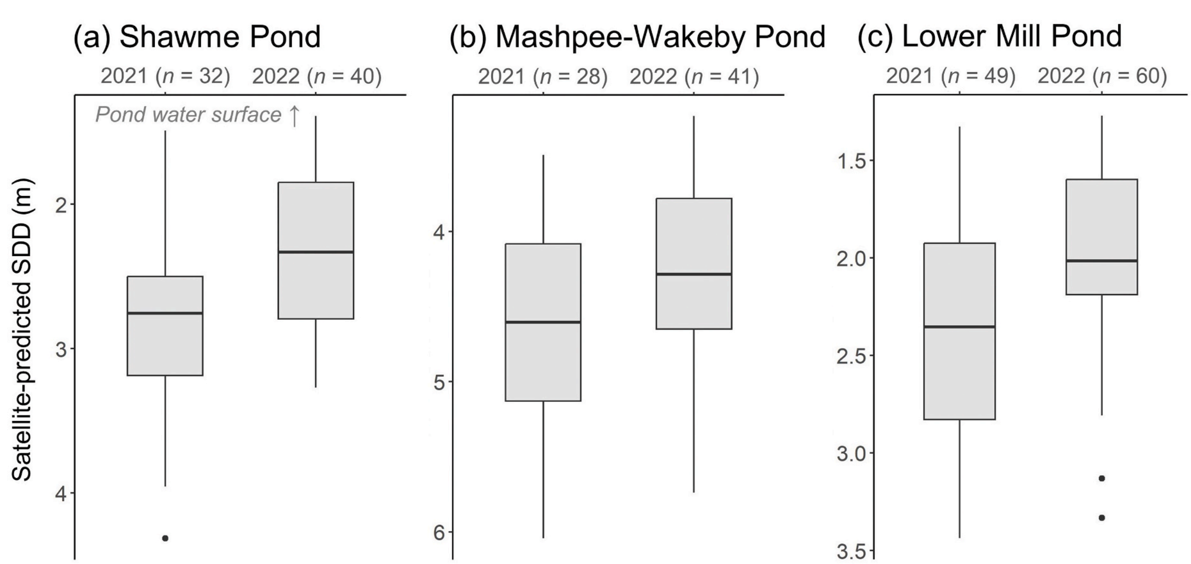

Fig. 7. Boxplots representing satellite-estimated Secchi disk depth (SDD) for the years 2021 and 2022 at (a) Shawme Pond, (b) Mashpee-Wakeby Pond, and (c) Lower Mill Pond. Note, the y-axes are reversed such that the pond water surface is at the top of the figure; n indicates the number of satellite images included in the distribution.

defined here provided similar predictive capacity. Keith et al. (2023) used Landsat 8 data to measure water clarity for nearly 300 locations across the United States, achieving a MAE of 0.92 m, and Page et al. (2019) leveraged both Landsat 8 and Sentinel-2 to predict SDD for lakes in Minnesota, yielding MAE between 0.25 and 0.67 m. Yet neither of these studies, nor any previously published algorithms, focus on the inland waters of Cape Cod. SDD algorithms tend to be highly regional as large-scale relationships are complicated by the nonlinear response of SDD to optical properties and both physical and chemical processes of different waters (Zhang et al., 2022a). The random forest machine learning model defined here represents the first algorithm specifically defined for inland Cape Cod waters, which are unique in their limnology given their glacial formation and relative isolation from other inland systems.

Using data from Landsat 5, 7, and 8, satellite data underpredicted SDD compared to field measurements at deeper field-measured SDD and slightly overpredicted SDD at shallower field-measured SDD. Thus, satellite imagery from these platforms should be interpreted with caution at SDDs deeper than approximately 7.5 m or shallower than approximately 1.5 m, and tracking improving or declining long- and recent short-term change at these depths can be challenging. While overestimation in satellite-predicted SDD at depths shallower than 1.5 m were consistent across satellite platforms, underestimation at depths deeper than 7.5 m primarily occurred for satellite observations from Landsat 5, 7, and 8, ranging from 1984 to present, and not for SDDs estimated from Landsat 9, ranging from 2021 to present, or Sentinel-2, ranging from 2015 to present.

Maximum pond depth was an important predictor variable in estimating SDD from satellite imagery, consistent with results presented in McCullough et al. (2012), but this limited the number of ponds available for analysis. Using data from either the Landsat Program or the Sentinel-2 mission, approximately half of the 883 ponds across the Cape can be monitored routinely. However, incomplete maximum pond depth data resulted in satellite-estimated SDD only being generated for 193 of these ponds (CCC, 2003). Additionally, only static maximum pond depth measurements were considered in this study, but maximum pond depth can fluctuate over time with water level and changes in pond bathymetry. While maximum pond depth was an important predictor variable, its inclusion can also stabilize resulting satellite-estimated SDDs over time since its value remains constant over an otherwise variable timeseries. The collection of additional maximum pond depth data across both space and time should be a primary focus of future field efforts, which would increase satellite data coverage for ponds across Cape Cod.

The temporal offset (*i.e.*, the number of days) between satellite image acquisition and field data collection had little impact on random forest machine learning model performance. This suggests that, generally, SDD across Cape Cod did not change drastically over sub-weekly time periods. Rather than coordinating field data collection for the same day of satellite overpass, management applications should instead focus on targeting ideal collection conditions. Dodds and Whiles (2010) noted that Secchi disks provide the most consistent measurements in calm, sunny, midday conditions. Allowing for a broader temporal offset between field data collection and satellite image acquisition also increases the number of observations available for both model development and agreement assessments.

Across Cape Cod ponds, median satellite-estimated SDD for 2022 ranged from 0.61 to 6.00 m. These results are well within the published range for the Cape. In Ahrens and Siver (2000) and Siver (2001), SDD was measured for 60 Cape Cod ponds from 1996 to 1998. Ponds averaged a SDD of 4.4 m, ranging from 0.3 to 9.4 m. Wagner et al. (2017) monitored 10 ponds across Cape Cod, finding summer SDD ranged from 0.5 to 7.8 m over the study period. Within the Cape Cod National Seashore, Smith et al. (2018a) noted SDDs ranging from 1.5 to 7.5 m across its 15 ponds. Here, satellite data suggested that ponds generally fell within the "suitable" or "eminently suitable" categories as defined in Smith and Davies-Colley (1992). The sole exception was the town of Provincetown, located in the Outer Cape. Median SDD for ponds across Provincetown for 2022 was 0.91 m, corresponding to the "unsuitable" category and consistent with results presented in Ahrens and Siver (2000) and Siver (2001). Provincetown ponds are notably different from other ponds across the Cape, unique in both their formation and characteristics. While most Cape Cod ponds are glacially formed, Provincetown ponds were formed after the stabilization of sand dunes when depressions within interdunal swales intersected groundwater (Giese et al., 2015; Oldale, 1976). These ponds are young for Cape Cod and are generally shallow, highly acidic, and nutrient-rich (CCC, 2021). Shallow SDDs may be a natural product of the ponds formation and characteristics, rather than the result of water quality stressors, but additional data is needed to differentiate drivers of SDD in these ponds.

A multi-decade assessment of water clarity suggested conditions are generally improving across relatively large ponds greater than 1 ha in surface area, with 77% of the 193 ponds analyzed increasing in satellite-estimated SDD from 1984 to 2022. Changes in satellite-estimated SDD were accompanied by decadal increases in air temperatures and cumulative precipitation. Smith et al. (2018a) assessed trends in field-measured SDD for the month of August across ponds in Cape Cod National Seashore, finding SDD either did not change or increased from 1996 to 2016. Through a similar analysis, Smith et al. (2018b) also found significant increases in the depths of 25% and 50% light transmission, which represent additional measures of water clarity, from 1999 to 2014 for nine ponds in Cape Cod National Seashore. Across the nation, Topp et al. (2021) found that water clarity has improved for United States' inland waters since 1984, including for the Northern Appalachians region where Cape Cod is located. And while many ponds in this study have improved in water clarity over the past 40 years, none demonstrated recent short-term improvements in water clarity from 2021 to 2022. Both long- and recent short-term change assessments offer unique perspectives for water quality management. Long-term change assessments provide baseline information and offer a range of historic water clarity conditions. Short-term change assessments benefit efficient resource prioritization; for example, ponds with deteriorating year-over-year water clarity may be a focus for additional field measurements the following monitoring season.

While long- and recent short-term change assessments presented here provide valuable information for Cape Cod, trend analyses in general should be interpreted with caution as they provide an incomplete evaluation of water quality conditions. For example, the Mann-Kendall test for trend, used here to assess long-term change, is designed to detect monotonic changes, meaning variables increased or decreased over the entire time period. If satellite-estimated SDD increased then decreased over time, or vice versa, it will not be captured as a statistically significant change. Additionally, long-term improvements in water clarity do not necessarily mean that water clarity conditions are favorable. Coffer et al. (2021) found significant reductions in satellite-estimated cyanobacterial abundance at Grand Lake, Ohio, but cyanobacterial blooms were still a consistent occurrence over the time period, and waters remain impaired (Jacquemin et al., 2023). Moreover, improving water clarity does not directly indicate improving water quality as some factors can have contrasting effects on water clarity and quality; for example, the species composition of submerged macrophytes can positively impact water clarity without improving its quality (Liu et al., 2020).

Analyzing drivers of water clarity was beyond the scope of this study, but has been reported elsewhere. Smith et al. (2018a) assessed the relationship between SDD and water quality constituents, physical pond features, shoreline housing densities, and wildlife occurrence for ponds in Cape Cod National Seashore. Only deep-water nutrient concentrations were related to SDD, where higher concentrations of total nitrogen and phosphorus led to lower SDD. Cape Cod's freshwater ponds and coastal estuaries are under stress from excess nutrients (WWW Document), and towns are responsible for managing nutrient inputs under Section 208 of the Clean Water Act. Many towns have a Comprehensive Wastewater Management Plan or other local nutrient management plans to address environmental impacts from septic systems and other nutrient sources, though the progress of those plans varies widely. Septic systems, stormwater runoff, and fertilizer are all sources of nitrogen and phosphorus loading to ponds, and while septic systems are the dominant source of nitrogen to fresh and coastal waters, the relative contribution of each source to phosphorus loading is less clear due to the lower mobility of phosphorus through soil. Detailed analyses focused on elucidating driving factors of water clarity are a focus of ongoing research efforts and will be presented in subsequent studies. Specifically, more comprehensive estimates of water clarity, such as those estimated via satellite imagery, may be combined with other geospatial data to better understand the connection between landscape features indicative of different phosphorus sources and corresponding water quality.

Consistent, large-scale estimates of SDD, such as those from satellite data, can be leveraged for understanding additional components of water quality across the Cape. The widely-used Carlson Trophic State Index can be calculated from some combination of SDD, chlorophyll-*a*, total phosphorus, or total nitrogen (Carlson, 1977). This index has been used by APCC to grade ponds across Cape Cod (Gottlieb et al., 2023). While satellite imagery is unable to detect nutrients, this study demonstrated that it can be used to estimate SDD across Cape Cod ponds, and studies have shown the ability to estimate chlorophyll-*a* concentration with both Landsat (Cao et al., 2020; Duan et al., 2008; Keith et al., 2023) and Sentinel-2 (Pahlevan et al., 2020; Woo Kim et al., 2022). Thus, satellite imagery may be used to complement field-based efforts for applying the Carlson Trophic State Index across broader scales than is currently feasible through field data alone.

This study offers the most temporally and spatially comprehensive management framework to date for monitoring water clarity across Cape Cod, but there are several limitations to consider. Only 193 ponds were analyzed, and conclusions are not fully representative of past or current conditions across the Cape. This assessment represented conditions at the center of each pond, but nearshore areas are where recreational use primarily occurs and where wind-driven algal blooms tend to accumulate (Gons et al., 2005). Only the monitoring season was considered, as this period represents when most field data were collected, but assessing water quality data for the entire year would provide a more holistic understanding of pond health for management prioritization. Additionally, both field and satellite data are not without error. Trees et al. (1985) found that error in field-based chlorophyll-*a* measurements can range from 30 to 60%, and field-measured SDD differs based on the time of day, angle of the sun, and weather conditions (Dodds and Whiles, 2010). SDD performs well in clear waters, but its magnitude tends to diminish in more turbid conditions (Zheng and DiGiacomo, 2022). Satellite data coverage is limited by clouds, Sun glint, snow, and ice cover, and are impacted by adjacency effects from neighboring land (Schaeffer et al., 2012). Here, a buffer of 10 m from the shoreline was removed before further analysis, but previous studies have indicated that adjacency effects can impact distances equivalent to up to four satellite pixels (Hestir et al., 2015), or up to 3 km offshore (H. Zhang et al., 2022).

5. Conclusions

This study defined a framework for assessing long- and recent short-term changes in SDD across Cape Cod, important for both local and regional management and efficient resource prioritization. While this study focused solely on Cape Cod, the same methods can be applied to other areas given the availability of local field data. This study advances satellite monitoring of water clarity across Cape Cod to NASA's ARL 6, which is reached upon "demonstration in relevant environment," and provides guidance for achieving ARL 7, reached upon the "use of application prototype in partner's decision making." NASA has also defined a "research to operations" and "operations to research" (R2O–O2R) framework (Cooley et al., 2022). R2O occurs when knowledge and technology are transferred between researchers and those that manage natural systems, while O2R occurs when decision-makers motivate and inform research efforts. The R2O–O2R framework consists of six iterative, linked processes. To date, this research has addressed the first four of these processes through iterative engagement and feedback from partners across Cape Cod: (1) Understand operational needs, (2) Build relationships and institutional buy-in, (3) Demonstrate technical feasibility, and (4) Identify resources available for transition. The remaining two processes, (5) Integrate into an operational system and (6) Sustained use in an operational system, are a primary focus of ongoing efforts. Similarly, the National Oceanic and Atmospheric Administration (NOAA) has defined nine readiness levels (RL) designed to assess the maturity of research and development projects for transition to operation. NOAA's RLs are grouped into Research (RL 1–2), Development (RL 3–5), Demonstration (RL 6–8), and Deployment (RL 9). To date, this research has achieved RL 6, "demonstrated prototype in a relevant environment." RL 7, "demonstrated prototype in an operational environment," is currently being implemented, and RLs 8 and 9 are a focus of future efforts. All processing scripts accompanying this analysis can be found at https://github.com/mmcoffer/Cape_Cod_SDD or https://doi.org/10.5281/zenodo.10675344.

CRediT authorship contribution statement

Megan M. Coffer: Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Nikolay P. Nezlin:** Conceptualization, Formal analysis, Software, Writing – original draft, Writing – review & editing. **Nicole Bartlett:** Conceptualization, Project administration, Writing – review & editing. **Timothy Pasakarnis:** Conceptualization, Data curation, Writing – review & editing. **Tara Nye Lewis:** Data curation, Writing – review & editing. **Paul M. DiGiacomo:** Funding acquisition, Resources, Supervision.

Declaration of competing interest

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

Data availability

Data is all open access, and processing scripts to query this data can be found at https://github.com/mmcoffer/Cape_Cod_SDD or https://doi.org/10.5281/zenodo.10675344.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.120334.

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