Baltic Sea transparency from ships and satellites: centennial trends

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ABSTRACT: Water transparency can be measured with optical instruments and estimated with satellite sensors, but such measurements have been widely available for only a few decades. Estimates of water transparency using a white disk called a Secchi disk have been made for over a century and can be used to estimate long-term trends. However, historic in situ measurements of the Secchi depth (Zsd) were irregular in space and time and are difficult to interpret in regular time series due to biases introduced by changing locations and the timing of measurements. Satellite data time series, on the other hand, have consistent resolution in both space and time but cover too short a time to resolve climate-scale trends. We normalized historic Zsd measurements in the Baltic Sea with a satellite-derived mean climatology at 5 d temporal and 4 km spatial resolutions and created a merged time series of Zsd for the last century. The mean Zsd in the Baltic Sea from 1927–2020 decreased by 4.2 ± 0.6 m at a rate of 0.045 ± 0.06 m yr⁻¹. Most of the change happened before 1987, and a further decrease was evident primarily in the satellite data during the 1998–2008 period. After 2008, no significant trend in Zsd and or the coefficient of diffuse light attenuation was detected in the Baltic Sea. However, in some sub-basins of the Baltic Sea, the decrease in Zsd continued even after that. The decrease in spectral water transparency in recent decades was highest in the 412 nm band, indicating an increase in the concentration of chromophoric dissolved organic matter.

KEY WORDS: Water transparency · Baltic Sea · Eutrophication · Secchi depth · Light attenuation · k₄₉₀ · CDOM · Chromophoric dissolved organic matter · Climate variability

1. INTRODUCTION

The Baltic Sea is a large, semi-enclosed sea that has been under intense anthropogenic influence for many decades. Signs of offshore eutrophication, such as increased nutrient concentrations, were recognized in the Baltic Sea as early as the 1960s (e.g. Fonselius 1969, Elmgren 1989, Savchuk 2018). Even though the Baltic Sea is one of the best studied oceanographic regions in the world, most historic ship-based measurements were sporadic, sparse in space, and too infrequent to resolve the natural variability. Water transparency is an important ecological variable that directly affects processes such as primary production, solar bleaching of organic material, phytoplankton physiology, and behavior of zooplankton and fish. Water transparency can be measured with optical instruments and estimated with satellite sensors, but has also been estimated for over a century by using a simple white disk (Preisendorfer
The depth of disappearance of the disk is called the Secchi depth ($Z_{sd}$). While $Z_{sd}$ is a rather crude measurement, its advantage is the large number of measurements available, going back over 100 yr. Several previous studies (Launainen et al. 1989, Sandén & Håkansson 1996, Fleming-Lehtinen & Laamanen 2012, Dupont & Aksnes 2013) have shown that the water transparency in the Baltic measured with $Z_{sd}$ has decreased significantly in recent decades. However, shipborne measurements were always sporadic and inconsistent in space and time and the variability in measured $Z_{sd}$ is huge. Water transparency is sporadically reduced by river outflow plumes, particle resuspension events near the coasts and on shallow off-shore banks, and phytoplankton blooms. Quasi-regular events such as the phytoplankton spring bloom and the cyanobacteria summer bloom also severely curtail $Z_{sd}$. All these events typically last from days to weeks or even longer. Dupont & Aksnes (2013) fitted an empirical relationship between $Z_{sd}$ and the distance to coast and bottom depth and removed the mean effect of those variables from $Z_{sd}$. However, these effects are not spatially or temporally uniform. Seasonal effects caused by quasi-regular events such as the phytoplankton spring bloom and the cyanobacteria summer bloom clearly affect water transparency (e.g. Kahru & Elmgren 2014, Kahru et al. 2016a). Here, we removed both the mean spatial and seasonal variability in $Z_{sd}$ by subtracting satellite-derived mean $Z_{sd}$ climatology from individual in situ $Z_{sd}$ measurements. Satellite data time series have high and consistent resolution in both space and time but are too short to resolve climate-scale variability. We used satellite-derived mean $Z_{sd}$ climatology at 5 d temporal and 4 km spatial resolutions and normalized historic $Z_{sd}$ measurements by subtracting the seasonal (with 5 d resolution) mean value of the nearest 4 km pixel from each in situ $Z_{sd}$ measurement. We then compared in situ and satellite time series and merged them. The goal of this study was to create the best possible time series of $Z_{sd}$ using historic in situ measurements and modern era satellite measurements.

2. DATA AND METHODS

2.1. Satellite data

A number of models exist for calculating $Z_{sd}$ from optical inputs (e.g. Alikas & Kratzer 2017) but most are empirical in nature, which makes them less applicable to measurements not covered by the data sets used in the development of the algorithm. The algorithm of Lee et al. (2015), on the other hand, is based on a revised model of $Z_{sd}$ theory and adapts to the change in the spectral composition of light. It derives the $Z_{sd}$ at the estimated transparent window of the water column. Theoretical predictions of the model have been validated with $Z_{sd}$ measurements for over 90 yr (Lee et al. 2018).

The primary source of satellite data used here was the ESA Ocean Colour Climate Change Initiative (OC-CCI) version 5.0 (Sathyendranath et al. 2019; https://esa-oceancolour-cci.org/). OC-CCI data are available from September 1997 to the end of June 2020 and are merged from multiple ocean color sensors: SeaWiFS (1997–2010), MERIS (2002–2012), MODIS-Aqua (2002–2020), VIIRS-SNPP (2012–2020), and OLCI-A (2017–2020). The main goal of the ESA-CCI data set was to produce a compatible time series by removing inter-sensor differences. Time series from individual sensors cover only portions of the whole time series, are often processed with different methods, and are less suitable for estimating long-term trends. At high latitudes, ocean color data cannot be obtained during the winter season due to the low sun elevation (Kahru et al. 2016b). Frequent cloud cover further reduces the availability of ocean color data. Therefore, north of the southernmost Baltic, satellite ocean color data are not available for the winter season. In ocean optics, the common measure of water transparency is the coefficient of diffuse light attenuation at 490 nm ($k_{d490}$). This is also a standard product in many satellite data sets, including OC-CCI. We applied the Lee et al. (2015) $Z_{sd}$ algorithm to OC-CCI daily remote sensing reflectance data sets of the 6 spectral bands (412, 443, 490, 510, 560, 665 nm) at about 4.5 km spatial resolution. As part of the Lee et al. (2015) algorithm, we computed the coefficient of diffuse light attenuation ($k_d$) for the 6 spectral bands at the same spatial and temporal resolutions and found the spectral band with minimal $k_d$. The calculations were implemented in the application ‘wam_zsd’, which is part of the ‘Wimsoft’ package (https://www.wimsoft.com/). We also evaluated the empirical Alikas & Kratzer (2017) Baltic $Z_{sd}$ algorithm against in situ $Z_{sd}$ data, but it appeared less accurate in retrievals and was therefore not used further.

2.2. In situ data

Aarup (2002) and Fleming-Lehtinen & Laamanen (2012) assembled data sets consisting of tens of thou-
sands of *in situ* $Z_{sd}$ measurements from both the North and Baltic Seas for 1903–2009. Additional $Z_{sd}$ measurements were extracted from ICES and other sources until early 2016 (HELCOM 2018). A relatively small number of measurements (332 out of 28141) missed the day of the month and were assigned the middle day of the respective month. This change did not have any significant effects on the results. Early $Z_{sd}$ measurements were made using a viewer (see Fig. 2 in Fleming-Lehtinen & Laamanen 2012), while measurements from 1957 onward were not. Following Fleming-Lehtinen & Laamanen (2012), the early data were transformed with a simple empirical correction according to the formula proposed by Launiainen et al. (1989).

*In situ* $Z_{sd}$ measurements were converted to $Z_{sd}$ anomalies by subtracting the satellite-derived mean $Z_{sd}$ value (1997–2020) of the nearest pixel on a 4 km grid of the respective 5 d period of the annual cycle (see Section 2.3). As satellite data are unreliable adjacent to the coast, we used the HELCOM open-sea regions (Table 1, Fig. 1) that exclude coastal areas approximately 4 km from the coast. This division was also used by Fleming-Lehtinen & Laamanen (2012). The number of available *in situ* $Z_{sd}$ anomalies was also reduced by the lack of corresponding satellite data during the winter season due to low sun elevation and/or persistent cloudiness. The total number of *in situ* $Z_{sd}$ measure-

| HELCOM ID | Assessment unit | Code | No. of Secchi measurements |
|-----------|-----------------|------|-----------------------------|
| SEA-001   | Kattegat        | KAT  | 4477                        |
| SEA-002   | Great Belt      | B    | 725                         |
| SEA-003   | The Sound       | S    | 134                         |
| SEA-004   | Kiel Bay        | KB   | 687                         |
| SEA-005   | Bay of Mecklenburg | BM | 738                        |
| SEA-006   | Arkona Basin    | AB   | 2667                        |
| SEA-007   | Bornholm Basin  | BB   | 4329                        |
| SEA-008   | Gdansk Basin    | GD   | 1284                        |
| SEA-009   | Eastern Gotland Basin | EGB | 3258                      |
| SEA-010   | Western Gotland Basin | WGB | 1953                      |
| SEA-011   | Gulf of Riga    | GR   | 1552                        |
| SEA-012   | Northern Baltic Proper | NBP | 960                        |
| SEA-013A  | Gulf of Finland Western | GFW | 904                        |
| SEA-013B  | Gulf of Finland Eastern | GFE | 708                        |
| SEA-014   | Åland Sea       | AS   | 1805                        |
| SEA-015   | Bothnian Sea    | BS   | 195                         |
| SEA-016   | The Quark       | Q    | 1183                        |
| SEA-017   | Bothnian Bay    | BBay | 582                         |
| Total     |                 |      | 28141                       |

Table 1. HELCOM open-sea regions and the number of *in situ* Secchi depth ($Z_{sd}$) measurements converted to $Z_{sd}$ anomaly. See Fig. 1 for a map

Fig. 1. Study areas in the Baltic Sea showing (A) the entire Baltic Sea HELCOM open sea area (dark gray) and (B) the 18 sub-regions: Kattegat (K), Great Belt (B), The Sound (S), Kiel Bay (KB), Bay of Mecklenburg (BM), Arkona Basin (AB), Bornholm Basin (BB), Gdansk Basin (GD), Eastern Gotland Basin (EGB), Western Gotland Basin (WGB), Gulf of Riga (GR), Northern Baltic Proper (NBP), Gulf of Finland Western (GFW), Gulf of Finland Eastern (GFE), Åland Sea (AS), Bothnian Sea (BS), the Quark (Q), and Bothnian Bay (BBay)
ments converted to $Z_{sd}$ anomalies during 1903–2016 was reduced from 37491 to 28141 by excluding measurements from coastal zones and those with no matching satellite 5 d climatology value. The spatial and temporal distributions of these data were uneven (Fig. 2), with a major gap from 1940 to 1956. Individual $Z_{sd}$ anomaly values were pooled over monthly and annual periods.

Time series of the mean, median, and other statistics were calculated for the whole Baltic Sea and each of the 18 regions (Table 1, Fig. 1B), with an emphasis on the annual time series.

### 2.3. Normalization of $Z_{sd}$ data

Satellite measurements over more than 23 yr (1997–2020) were used to create $Z_{sd}$ and $k_d$ mean climatologies (i.e. mean seasonal cycles) with 5 d temporal and 4.5 km spatial resolution. Daily data sets were composited over 5 d periods by averaging valid pixel values (i.e. the composited value is the mean of 1–5 valid values). During cloudy periods that still left many missing pixel values, missing pixels in 5 d composites with valid values in the previous and following 5 d composites were filled with linear interpolation. Corresponding 5 d periods over all available years were averaged to produce mean maps of satellite-derived $Z_{sd}$ for each of the 73 five-day periods over 1 yr. These 73 data sets, therefore, consist of the mean pixel values for year days 1–5, 6–10, 11–15, etc. The mean annual cycle for each pixel is made up of the 73 five-day values. However, due to low sun elevation in winter and persistent cloudiness, some of the winter 5 d climatology values were missing. The median number of valid climatology values for the whole Baltic Sea was 57 (63 after interpolation) and decreased from south to north. As mentioned in Section 2.2, due to the missing satellite climatology values in winter, the number of calculated $Z_{sd}$ anomaly values was reduced compared to the number of available in situ measurements.

Anomalies of in situ $Z_{sd}$ were created by subtracting the respective climatology value of the nearest pixel in space and the nearest 5 d period corresponding to the date of the measurement. This normalization of the numerous but spatially and temporally irregular historic samples from $Z_{sd}$ to $Z_{sd}$-anomaly made measurements in different areas (with different means) more comparable. The same procedure was applied to satellite data by subtracting the climatology value from the 5 d $Z_{sd}$ composites. In situ $Z_{sd}$ anomalies and 5 d satellite $Z_{sd}$ anomalies were averaged over monthly and annual periods to obtain annual $Z_{sd}$ anomalies for each of the 18 regions and the whole study area.

A piecewise linear fit routine with automated breakpoint detection following Owens & Wong (2009) and Cabanes et al. (2016) was applied to the $Z_{sd}$ anomaly time series for the entire Baltic Sea.

### 3. RESULTS

#### 3.1. Validation of satellite estimates

The Lee et al. (2015) $Z_{sd}$ model has been applied in a number of regions (e.g. Shang et al. 2016, Liu et al. 2020a,b). We did not attempt a rigorous verification with high-resolution satellite match-ups within a short period (e.g. 1 h). Instead, we performed a general validation of the satellite $Z_{sd}$ data sets at daily and 4.5 km resolutions. We recognize that there can be considerable variability within each 4.5 km pixel. We found 3130 same-day matchups and used the average pixel value in a 3 × 3 pixel window centered at the in situ measurement. Match-ups with high pixel-to-pixel variability [(max. – min.)/min. > 0.5]) and less than 5 valid pixels out of 9 were excluded. The accuracy of the satellite estimates was quite good ($R^2 = 0.61$; Fig. 3A) considering the pixel-to-pixel and within-pixel variability. Subsets of match-ups in each of the 18 sub-areas showed no evidence for differences in the relationships (Fig. 3C,D). As the independent variable (in situ $Z_{sd}$) is also known with an error, the relationships between in situ and satellite $Z_{sd}$ (Fig. 3) were evaluated using both the ordinary least squares (OLS) linear regression and a Type II reduced major axis linear regression (York et al. 2004). While the OLS regression was always <1, overestimation at the low end and underestimation at the high end are expected due to the spatial averaging of small-scale extremes by the bigger footprint of satellite measurements. We conclude that satellite estimates of $Z_{sd}$ are reasonably accurate estimates of in situ $Z_{sd}$.

#### 3.2. Satellite time series of $k_d$ and $Z_{sd}$ for the whole Baltic Sea region

Averaged over the whole Baltic Sea area (Fig. 1A), the satellite-derived time series showed an increasing trend in $k_d$ and a decreasing trend in $Z_{sd}$ (Fig. 4). The slope of the trend over the 1998–2020
Fig. 2. Distribution of in situ Secchi depth measurements per decade from 1903–2016, except 1940–1949 (no measurements)
While matchups of satellite \( Z_{sd} \) retrievals against \textit{in situ} measurements (Fig. 3) did not show a significant mean bias, some bias may still exist for certain areas (e.g. coastal versus offshore), high versus low \( Z_{sd} \) values, or for certain meteorological or oceanographic conditions. An additional source of discrepancy between monthly and annual averages of \textit{in situ} and
satellite estimates is the difference in sampling pattern and frequency. While satellite averages are based on thousands of pixels that are spread relatively uniformly in space and time (constrained by light and clouds), in situ averages are based on relatively small numbers of measurements that are not uniformly distributed in space and time and are likely to be biased compared to the ideal mean. Satellite estimates produce ‘cleaner’ (i.e. less variable) time series due to a larger number of measurements and allow more reliable trend detection. However, they too are not ideal and contain various errors. The satellite retrieval error and its dependence on various conditions are unknown, and sampling is also limited by clouds and sun elevation. For long-term trend estimates, we need to combine both in situ and satellite estimates. When comparing annual averages of in situ and satellite $Z_{sd}$ anomalies (Fig. 5), the satellite-derived annual averages typically appear lower than the in situ annual averages. The source of this discrepancy is most likely the difference in sampling patterns but could also be the satellite retrieval bias. In order to make the satellite time series compatible with historic $Z_{sd}$ data, we...
adjusted the satellite time series by their mean bias. We calculated the mean bias between satellite and in situ annual averages during the overlapping period in each of the 18 regions and added that to the satellite-derived annual values (Fig. 5). For example, the mean bias during the overlapping period (1997–2014) for the Bornholm Basin annual time series was 0.42 m (satellite underestimation); therefore, 0.42 was added to the satellite-derived time series to create the mean-adjusted satellite time series. The merged annual satellite and in situ time series combined in situ values (until 1997) with the mean-adjusted satellite values (1998–2020).

3.4. Merged satellite and in situ time series of $Z_{sd}$

The earliest in situ $Z_{sd}$ data averaged over the whole Baltic Sea area (Fig. 6) showed a puzzling increase of $Z_{sd}$ anomaly at about 0.29 m yr$^{-1}$ from 1903–1912. We have no explanation for this increase. While the numbers of Secchi disk measurements in the early years were lower than in many later years, there were 216 $Z_{sd}$ anomaly measurements from 1903–1905 and a total of 829 measurements from 1903–1911. In order to test if the increase in 1903–1912 could have been due to a particular spatial or temporal sampling pattern, we sampled 9 yr of 5 d satellite composites at the same locations and same dates as for the period 1903–1912 but for different sequences of years (1998–2006, 1999–2007,…, 2012–2020). None of the individual time series showed a significant increase, and the estimated slope of the 15 satellite time series was between −0.17 and 0.12 m yr$^{-1}$. Therefore, we assume that the increase in $Z_{sd}$ in 1903–1912 was due to unknown natural variability. Regionally, indications of increasing $Z_{sd}$ from the 1900s to about 1912 can be seen in the East Gotland Basin, West Gotland Basin, and Northern Baltic Proper.

A piecewise linear breakpoint detection analysis (Owens & Wong 2009, Cabanes et al. 2016) applied to the merged satellite–in situ time series of 1903–2020 detected 3 breakpoints and 4 segments: a period of increase with a slope of 0.29 m yr$^{-1}$ for 1903–1912 (total change: +2.5 m), a flat period (slope of 0.00 for 1912–1927), a period of significant decrease with a slope of −0.05 for 1927–1987 (total change: −3.24 m), and lastly a period of slight decrease with a slope of −0.01 for 1987–2020 (total change: −0.40 m). The decreasing trend of $Z_{sd}$ during 1927–2020 estimated with the least squares linear regression had a slope of −0.045 m yr$^{-1}$ (95% confidence limits: −0.051 to −0.039 m yr$^{-1}$) and resulted in a total decrease of $Z_{sd}$ by 4.2 m (Table 2) (95% confidence limits: −3.6 to −4.8 m). When calculated for the full period (1903–2020), the slope was −0.032 m yr$^{-1}$ (95% confidence limits: −0.038 to −0.027 m yr$^{-1}$).

We characterized the long-term dynamics of $Z_{sd}$ anomaly in the Baltic Sea area and in the 18 HELCOM sub-regions by changes over 3 overlapping periods: the full time series (1903–2020), the period of satellite data availability (1998–2020), and the most recent period after 2008 (Table 2). The full time period may start on a different year, as the start year of the availability of historic $Z_{sd}$ data was not 1903 for all regions. The in situ $Z_{sd}$ data in the Baltic Sea area showed a drastic decrease until 1986–1987 and no significant change after that. Satellite data starting in 1997/1998 showed a new period of significant decrease from 1997/1998–2008 (Fig. 6). Therefore, while the tapering of the decrease in $Z_{sd}$ is clear, the start of the recent period of no significant reduction is either 1987 or 2008. Furthermore, in some regions

![Fig. 6. Time series of the annual Secchi depth ($Z_{sd}$) anomaly for the whole Baltic Sea estimated by in situ (black open circles) and mean-adjusted satellite (red line) measurements. The merged satellite–in situ time series has 3 breakpoints (1912, 1927, and 1987; black arrows) detected with automatic breakpoint detection. The slopes of the 4 segments for the combined satellite–in situ data (1903–2020) are 0.29 m yr$^{-1}$ for 1903–1912, 0.00 m yr$^{-1}$ for 1912–1927, −0.05 m yr$^{-1}$ for 1927–1987, and −0.01 m yr$^{-1}$ for 1987–2020](image-url)
the changes did not stop in 2008 (Fig. 7, Table 2). Qualitatively, we can characterize all regions by the signs of change during the 3 periods (full period until 2020, satellite data period 1998–2020, and 2008–2020). For example, Eastern Gotland Basin with ‘− − −’ shows a decrease in all 3 periods but...
Bothnian Bay, with ‘− + +’, shows a long-term decrease but an increase during the 2 latest periods (last column of Table 2). In the long term, the $Z_{Sd}$ anomaly decreased significantly in almost all of the sub-areas except the Sound, the Bay of Mecklenburg, and the Arkona Basin, where the change was not statistically significant. In the satellite data period, the decrease in $Z_{Sd}$ was significant in 10 sub-areas and not significant in 7 sub-areas. In only one sub-area, the Bothnian Bay, did $Z_{Sd}$ actually increase during the satellite data period. During the last decade (since ~2008), the long-term decrease in $Z_{Sd}$ had mostly ceased, with a few exceptions. In a group of adjacent areas—the Eastern Gotland Basin, Northern Baltic Proper, Western Gulf of Finland, and Bothnian Sea—the trend of decreasing $Z_{Sd}$ anomaly continued after 2008.

The total decrease in $Z_{Sd}$ over the full measurement period was highest in Western Gotland Basin ($−5.3 ± 1.5$ m), Eastern Gotland Basin ($−4.7 ± 1.3$ m), and Western Gulf of Finland ($−4.6 ± 0.9$ m). The significant increase in $Z_{Sd}$ in the Bothnian Bay after 2016 (Fig. 7D) is either related to some unexplained interannual variability or truly represents an increase in water transparency happening in the Bothnian Bay due to the shorter residence time of the water mass and reduced nutrient loads there (Håkanson & Lindgren 2010). In either case, this location needs further study.

### 3.5. Spectral $k_d$ anomalies

Increasing $k_d490$ (Fig. 4A) and decreasing $Z_{Sd}$ (Figs. 4B & 5–7) are evidence that the water transparency in the Baltic Sea has been decreasing, most likely at least since the 1920s. However, what is not clear are the primary factors causing the decrease in water transparency. We can get some clues by comparing the rates of change (m$^{-1}$ yr$^{-1}$) of the different spectral bands of $k_d$. Values of $k_d$ were computed at 6 spectral bands (412, 443, 490, 510, 560, 665 nm) according to Lee et al. (2015). While satellite data for these calculations are available from late 1997–2020, early data (1997–2002) were only available from a single sensor (SeaWiFS). It appeared that the early period was noisy, probably due to the lower signal-to-noise ratio of SeaWiFS compared to other sensors (Hu et al. 2012). We therefore estimated the trends in spectral $k_d$ for the period 2003–2020, when merged data from 3–4 satellite sensors were available (Fig. 8). While these estimates show the different

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**Fig. 8.** Slope of the linear change in time of the spectral light attenuation coefficient for the 6 wavelengths in the Baltic Sea in different regions (2003–2020): (A) Baltic Sea area (with 95% confidence limits); (B) Arkona Basin (AB), Bornholm Basin (BB), Eastern Gotland Basin (EGB), and Western Gotland Basin (WGB); (C) The Quark (Q), Gulf of Riga (GR), Gulf of Finland West (GFW), and Gulf of Finland East (GFE); and (D) Great Belt (B) and the Sound (S).
rates of change in different spectral bands of light during the last 18 yr (2003−2020), they do not necessarily mean that similar rates of change applied to earlier periods. When averaged over the whole Baltic Sea, \( k_d \) has increased in all spectral bands, but the change has been most rapid at 412 nm, followed by 443 nm (Fig. 8A). While the confidence limits are rather wide, particularly at 443 nm, the shapes of the rates of spectral increases in \( k_d \) were similar in most regions of the Baltic with only slight variations (Fig. 8B). The highest rates of change were observed in the Quark and Gulf of Riga, followed by the Gulf of Finland (Fig. 8C). In contrast to the Western Gulf of Finland and most other areas, the Eastern Gulf of Finland showed the fastest rate of change in the 443 nm band, indicating a growing role of phytoplankton (Fig. 8C). Surprising differences were observed between the Danish straits, with the Sound showing the fastest rate of change in the 665 nm band (Fig. 8D). In conclusion, in most areas, the increase in light attenuation has been strongest in the 443 nm band, extending the Lee et al. (2015) (SGLI) while applying the same algorithm. A method for the smaller bays and inlets. Increasing the spatial resolution to 1 km is straightforward with most ocean color sensors and even to 350 m (OLCI) or 250 m (SGLI) while applying the same algorithm. A method extending the Lee et al. (2015) \( Z_{sd} \) algorithm to the high-resolution satellite sensors with different spectral bands (OLI: 30 m on Landsat; MSI: 10 m on Sentinel-2) was recently developed by Pitarch & Vanhellemont (2021). Ship-borne sampling is expensive and time-consuming and may not represent the spatial and temporal variability near the coast. Instead of ships, automated measurements from sensors mounted on BGC-Argo floats (Jemai et al. 2021) or buoys can provide high-resolution time series to resolve that variability.

The trend of decreasing water transparency in the Baltic Sea has been demonstrated in several previous studies (Launiainen et al. 1989, Sandén & Håkansson 1996, Fleming-Lehtinen & Laamanen 2012, Dupont & Aksnes 2013) and is related to increased nutrient loads (e.g. Fleming-Lehtinen & Laamanen 2012). Our trend estimates for the whole Baltic Sea from the merged shipborne–satellite time series of about \(-0.04 \text{ m yr}^{-1}\) are close to previous estimates. The trend from satellite data alone (1998−2020) was \(-0.037 \text{ m yr}^{-1}\). We have no explanation for the observed increase in the average \( Z_{sd} \) in the Baltic Sea from 1903 to the mid-1920s. The tapering of the \( Z_{sd} \) decreasing trend after 1987 is evident in some areas and has also been noted before (Fleming-Lehtinen & Laamanen 2012). The timing of the flattening of the \( Z_{sd} \) trend is not certain. While satellite data (1998−2020) show no significant change after 2008, earlier in situ data show flattening of the trend already after 1986−1987, i.e. before the availability of
satellite data. This is probably related to multi-year fluctuations in $Z_{sd}$ caused by changes in river inflows, winds, currents, and other factors. The period 1986–1987 with $Z_{sd}$ minima was also notable for an almost complete absence of cyanobacteria accumulations (Kahru & Elmgren 2014) due to cold and rainy summers. While the decrease in $Z_{sd}$ in the Baltic Sea area and most of its sub-regions ceased at about 2008, the decrease continued even after that in some central Baltic Sea regions (Eastern Gotland Basin, Northern Baltic Proper, Western Gulf of Finland, and Bothnian Sea).

Satellite-detected changes in spectral light attenuation indicate that the strongest increase has been in bands affected by light absorption by CDOM (412 nm) and phytoplankton (443 nm). While $Z_{sd}$ is determined by light attenuation in the maximum transparency window (560 nm band in the Baltic Sea), the increase in CDOM and phytoplankton concentrations also gives an increase in $k_d$ at 560 nm that reduces $Z_{sd}$. We can therefore conclude that the decadal decrease in $Z_{sd}$ in the Baltic Sea was caused primarily by a combination of increasing CDOM and phytoplankton biomass.

5. CONCLUSIONS

A method of normalizing sparse historic shipboard measurements with modern satellite data was applied to a large archive of in situ measurements of $Z_{sd}$ in the Baltic Sea. Time series of the merged in situ–satellite estimates for 1927–2020 showed a trend of decreasing $Z_{sd}$ with a mean slope of $-0.045 \pm 0.06 \text{ m yr}^{-1}$. The mean $Z_{sd}$ decreased from 1927–2020 by 4.2 $\pm$ 0.6 m. While the decreasing trend has tapered off in most areas, the decrease in $Z_{sd}$ is still continuing in several major regions. During the period of satellite observations, light attenuation has increased the most in the spectral bands affected predominantly by CDOM (412 nm) and phytoplankton (443 nm).

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