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Assessment of using spaceborne LiDAR to monitor the particulate backscatter coefficient on large, freshwater lakes: A test using CALIPSO on Lake Michigan

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The Cloud-Aerosol LiDAR and Infrared Pathfinder Satellite Observation (CALIPSO) satellite was launched in 2006 with the primary goal of measuring the properties of clouds and aerosols in Earth's atmosphere using LiDAR. Since then, numerous studies have shown the viability of using CALIPSO to observe day/night differences in subsurface optical properties of oceans and large seas from space. To date no studies have been done on using CALIPSO to monitor the subsurface optical properties of large, freshwater-lakes. This is likely due to the limited spatial resolution of CALIPSO, which makes the mapping of subsurface properties of regions smaller than large seas impractical. Still, CALIPSO does pass over some of the world's largest, freshwater-lakes, yielding important information about the water. Here we use the entire CALIPSO data record (approximately 15 years) to measure the particulate backscatter coefficient (b_{bp} , m^{-1}) across Lake Michigan. We then compare the LiDAR derived values of b_{bp} to optical imagery values obtained from MODIS and to *in situ* measurements. Critically, we find that the LiDAR derived b_{bp} aligns better in non-summer months with *in situ* values when compared to the optically imagery. However, due to both high cloud coverage and high wind speeds on Lake Michigan, this comes with the caveat that the CALIPSO product is limited in its usability. We close by speculating on the roll that spaceborne LiDAR, including CALIPSO and other satellites, have on the future of monitoring the Great Lakes and other large bodies of fresh water.

KEYWORDS

CALIPSO, MODIS, lidar, particulate backscatter coefficient (b bp), great lakes

1 Introduction

The particulate backscatter coefficient, or b_{bp} (m^{-1}), is a central inherent optical property that gives important insight into ecological processes that happen in large bodies of water. Specifically, b_{bp} has been used as a proxy for particulate organic carbon in regions where inorganic material concentrations are low (Cetinić et al., 2012). Through this connection, on the global oceans b_{bp} has been used to quantify global carbon stocks (Loisel et al., 2001; Stramski et al., 2008; Behrenfeld et al., 2013; Martinez-Vicente et al., 2013), track the vertical migrations of ocean animals (Burt and Tortell, 2018; Behrenfeld et al., 2019), quantify primary production (Behrenfeld et al., 2005; Westberry et al., 2008; Schulien et al., 2017), and can be used to potentially monitor the overall health of water environments. Typically, b_{bp} has been sampled

globally on the open oceans *via* two methods. First, by way of *in situ* collected measurements from ship (Concannon and Prentice, 2008; Dickey et al., 2011), aircraft (Hair et al., 2016; Churnside et al., 2017; Churnside and Marchbanks, 2019), and float surveys (Bittig et al., 2021). Second, by using ocean color data derived from optical imagery satellites such as the MODerate-resolution Imaging Spectroradiometer (MODIS), in which a gridded b_{bp} product is created (Mélin, 2011; Blondeau-Patissier et al., 2014). Both of these methods have paved the path of b_{bp} monitoring over the last 20 years.

While *in situ* sampling and passive sensors are able to provide b_{bp} , they are not without drawbacks. *In situ* measurements *via* ship and aircraft are costly and the network of ARGO floats is limited in its spatial coverage. Likewise, MODIS derived b_{bp} can only be collected in the daytime and can have errors associated in excess of 50% (Hostetler et al., 2018; Jamet et al., 2019). These drawbacks gave rise to a new era of b_{bp} collection: LiDAR based satellites (Hostetler et al., 2018; Bisson et al., 2021). The Cloud-Aerosol LiDAR and Infrared Pathfinder Satellite Observation (CALIPSO) satellite was launched in 2006 with the primary goal of measuring the properties of clouds and aerosols in Earth's atmosphere using LiDAR (Winker et al., 2009; 2010). However, over the 15 years lifespan of the satellite, secondary uses were identified including its ability to obtain b_{bp} , which was first done a decade ago (Behrenfeld et al., 2013). Since then, numerous studies have been done using CALIPSO and other LiDAR based satellites as a way of collecting b_{bp} (Lu et al., 2014; 2016; 2020; Behrenfeld et al., 2016; 2019; Bisson et al., 2021).

Most studies which have obtained b_{bp} from CALIPSO have done so on the global oceans, though there have been studies done on a more localized scale (Dionisi et al., 2020). To date however, none have been done in a large freshwater environment. This is likely due to the spatial resolution of CALIPSO satellite tracks, which are spaced at ≈ 150 km apart. On the global oceans this is an acceptable resolution for binning the data into 2° by 2° boxes, such as in Behrenfeld et al. (2019). However on study regions similar in size to the Great Lakes, this would be ineffective as one bin would span the entire basin of a lake. Another likely reason that CALIPSO has not been used to study large lakes is the need for high resolution (in both time and space) wind speed measurements, which play a large roll in the calculation of b_{bp} (Behrenfeld et al., 2013; Hu and Zhai, 2016).

Inland, freshwater lakes can also be optically complex (case 2, (Morel and Prieur, 1977) when compared to marine environments (case 1, (Palmer et al., 2015)). This stems mainly from differences in concentrations of optically active constituents (OAC) compared to sections of the global oceans (Morel and Prieur, 1977; Gons et al., 2008; Mouw et al., 2015). Likewise, the specific biological makeup of phytoplankton assemblages can differ substantially between freshwater and marine environments (Elser and Hassett, 1994). In addition, changes in the vertical distribution of particulate assemblages can vary substantially on freshwater lakes when compared to their marine equivalent (Scofield et al., 2020). These phenomenon present their own set of challenges and are unique to the freshwater remote sensing world.

Drawbacks aside, CALIPSO does make passes over some of the worlds largest freshwater lakes, specifically Lake Michigan in the United States. While it is impossible to map trends across the entire lake using CALIPSO, it is possible to map trends across individual, satellite flyover tracks. In the scope of Great Lakes ecosystem, b_{bp} is important to the monitoring of overall lake health. Decreases in b_{bp} over a 14 year period on Lakes Michigan

and Huron have been tied to the effect of dreissenid mussels, phosphorus abatement, and climate change on the lakes (Yousef et al., 2017). In addition, b_{bp} has been monitored and used on the lakes as a metric to assess particulate assemblages and better regulate optical signal remote sensing. As the fishing industry on the Great Lakes is upwards of a \$7 billion per year trade, being able to remotely sense/monitor the health of the ecosystem through b_{bp} would be extremely valuable (Roth et al., 2012).

Because of high resolution wind speed forecasting obtained from the National Oceanic and Atmospheric Administration (NOAA)'s Great Lakes Coastal Forecasting System (GLCFS) (NOAA, 2022), we are able to obtain b_{bp} from CALIPSO across the lake. Likewise, because of both NOAA cruises over the last decade and because of recent advances in using MODIS to obtain b_{bp} (Shuchman et al., 2013), we are able to compare the results obtained from CALIPSO to others sampled over similar time periods and locations. Here we show a method of obtaining LiDAR derived b_{bp} on large, freshwater lakes and the challenges associated with it. We then compare these results to both *in situ* values and results obtained through passive sensors. We close by speculating on the roll that LiDAR obtained b_{bp} can play in the future of Great Lakes remote sensing.

2 Materials and methods

2.1 CALIPSO b_{bp}

Data used in deriving b_{bp} from CALIPSO comes from NASA/CNES's LiDAR Level 1B profile data, Version 4–10 product (Winker et al., 2009). For the majority of this assessment, we followed Behrenfeld et al. (2013), implementing changes that have come about over the last decade to improve the reliability of the results (Lu et al., 2013; 2014; 2021b; Bisson et al., 2021). A schematic of how b_{bp} is derived from CALIPSO is shown in Figure 1. For the scope of this analysis, b_{bp} refers to the backscatter sampled at 532 nm. At every point along the satellite track, the co-polarized and cross-polarized channel returns are extracted. A cross-talk correction between the two channels is implemented and the transient response from the surface is removed (Lu et al., 2014; 2021b). The corrected signal is then used to calculate a depolarization ratio (δ_p) between the two channels for the first three bins below the surface of the water. Following this, a series of filtering is done to eliminate signals that would result in a contaminated result. Implementation of this filtering is as follows, as was done in Dionisi et al. (2020):

- 1) Removal of signal that is, flagged as saturated in the data product.

Lu et al. (2018) implemented a signal saturation flag to the CALIPSO data product. Here, we only consider data that is, not saturated in any way, and ignore data that is, flagged as possibly saturated or certainly saturated as this signal would not yield reliable results.

- 2) Removal of signal that had cloud coverage.

Clouds are identified through two sources. First, if the water surface peak from the LiDAR return is not within 120 m of the actual surface (derived from the Digital Elevation Model (DEM) flag on the CALIPSO data), then the signal is considered to be polluted by clouds. Second, if the integrated attenuated backscatter (IAB) for the entire LiDAR return is greater than a threshold value

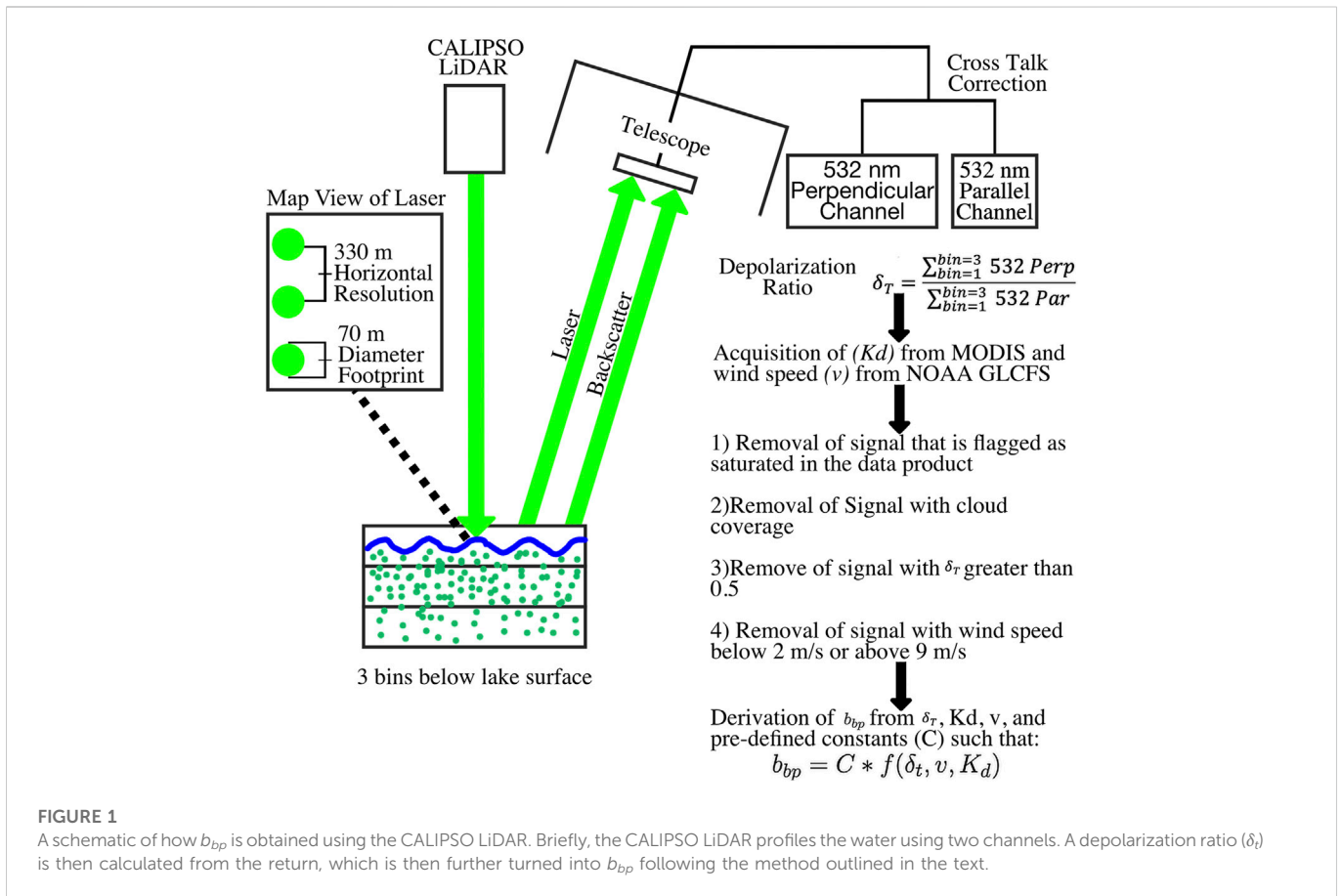


TABLE 1 A listing of the constants used to derive b_{bp} from CALIPSO channel returns. Further information on the derivation can be found in Behrenfeld et al. (2013).

Variable name	Variable value	Reference
Below-surface depolarization ratio (δ_w)	0.1	Voss and Fry (1984), Kokhanovsky (2003)
CALIOP's off-nadir pointing angle (θ)	3°	Winker et al. (2009)
Water surface transmittance (t)	0.98	Gilman and Garrett (1994)
CALIPSO to MODIS wavelength conversion ($b(\pi)/b_{bp}$)	0.32	Bisson et al. (2021)

(0.017sr⁻¹), then the signal is considered contaminated by clouds (Dionisi et al., 2020).

3) Removal of the signal where the depolarization ratio (δ_t) exceeded 0.5.

Realistic values of the depolarization ratio (δ_t) certainly would be below 0.5 (Dionisi et al., 2020). As such, all data returns with a depolarization ratio greater than 0.5 are not considered.

4) Removal of the signal where the wind speed is less than 2 m/s and greater than 9 m/s.

Low wind speeds (less than 2 m/s) result in signal saturation and high wind speeds (greater than 9 m/s) result in turbid waters. As each of these cases would result in an unreliable signal, they are therefore not considered.

After preliminary filtering of the signal, we were able to start the calculation of b_{bp} . This was done through the use of parameters taken from Behrenfeld et al. (2013), Bisson et al. (2021), and though two

dynamic variables. A listing of the constants and values are shown in Table 1. The first dynamic variable used in deriving b_{bp} is the diffuse attenuation coefficient for downwelling irradiance (K_d), which is obtained from MODIS optical imagery. Specifics surrounding the acquisition of K_d are shown in Section 2.2. We chose to directly use the MODIS derived K_d measurements rather than using the empirical relationship for K_d in Bisson et al. (2021) because we are analyzing a freshwater environment. As such, the relationship between MODIS K_d and the depolarization ratio (δ_t) may be different. However, it is likely that using either method will result in a very similar result, as the K_d used in Bisson et al. (2021) is still derived from MODIS via an empirical relationship.

The second and most important dynamic variable in the derivation of b_{bp} from CALIPSO is water surface wind speed (v). Wind speed is used in deriving wave height (Cox and Munk, 1954; Hu et al., 2008), which is directly used in calculating b_{bp} from the

depolarization ratio (δ_i). For every point along the CALIPSO tracks, we used a dynamic wind speed obtained from NOAA GLCFS (NOAA, 2022). The high temporal resolution of the wind speed model allowed us to have wind speed measurements down to the same hour of each CALIPSO flyover. High winds will result in waves that make the water too turbid to obtain reliable b_{bp} measurements and low wind speeds can result in signal saturation (Behrenfeld et al., 2013). As such, we implemented a filter by removing all measurements that had a wind speed greater than 9 m/s and less than 2 m/s (Dionisi et al., 2020), as is shown in the pre-processing steps. Thus, we can now define b_{bp} as a function of the depolarization ratio (δ_i), wind speed (v), the attenuation coefficient for downwelling irradiance (K_d), and the combination of previously defined constants (C) following the relationship shown in Behrenfeld et al. (2013) as:

$$b_{bp} = C * f(\delta_i, v, K_d) \quad (1)$$

2.2 MODIS b_{bp} and K_d

Level 2 MODIS imagery intersecting Lake Michigan was downloaded through the NASA Ocean Biology Processing Group (OBPG; <https://oceancolor.gsfc.nasa.gov/>). Each image was processed using the Color Producing Agents Algorithm (CPA-A; Shuchman et al. (2013)) in order to derive estimates of chlorophyll-a concentration, suspended minerals concentration, and CDOM (Colored Dissolved Organic Matter) absorption. Using these three estimates, bulk absorption and bulk backscatter coefficients were derived for the following MODIS bands: 412, 443, 488, 531, 547, and 667 nm. At the same bands, b_{bp} was computed from the bulk backscatter by removing the backscatter due to pure water (coefficients derived from Morel et al. (1974)). The diffuse attenuation coefficient (K_d) at the above wavelengths was estimated using a method outlined in Lee et al. (2005), which uses the bulk absorption and backscatter coefficients as well as the solar zenith angle.

Yearly average images were also computed for both b_{bp} and K_d . First, daily average images were generated by computing the mean of overlapping pixels within all satellite images from a given day. The yearly average images were then computed as the mean of all daily images within that year.

2.3 In situ b_{bp}

In situ b_{bp} was sampled by the National Oceanic and Atmospheric Administration's Great Lakes Environmental Research Laboratory (NOAA GLERL). This was done primarily in the spring (March-May) and summer (June-August), with a scattering of samples in the fall (September- November), at several stations on Lake Michigan between 2015 and 2019. Observations of b_{bp} were derived from data collected by a WET Labs BB9 sensor, which measures volume scattering coefficients at 9 wavelengths (412, 440, 488, 510, 532, 595, 650, 676, and 715 nm). During sampling, the BB9 is mounted in a package along with other sensors including a WET Labs ac-s, Sea-Bird CTD, and WET Labs fluorometer. Packaging these sensors provides concurrent measurements of salinity, temperature, and absorption which are necessary for processing BB9 data to b_{bp} . The

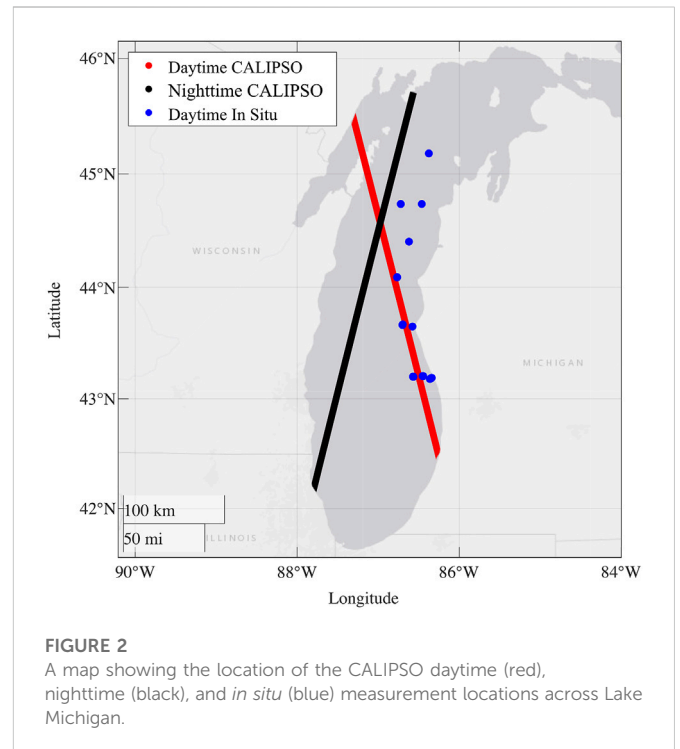


FIGURE 2
A map showing the location of the CALIPSO daytime (red), nighttime (black), and in situ (blue) measurement locations across Lake Michigan.

package was deployed vertically through the water column using a crane.

Using the WAP software package (WET Labs), ac-s, CTD, and BB9 data were converted from binary data to text files, and BB9 data were processed to b_{bp} using protocols outlined in Zaneveld et al. (2003). First, the total volume scattering function (β_t) is corrected using the coincident total absorption (a_t) measurements from the ac-s after having been re-sampled to the BB9 wavelengths. Next, the volume scattering function of the water (β_w) was calculated according to Boss and Pegau (2001), utilizing the coincident CTD-measured temperature and salinity. The particulate fraction of the volume scattering function (β_p) is calculated as the difference between β_t and β_w . b_{bp} is then computed according to the following equation using a χ factor of 1.1 (Sullivan et al., 2013):

$$b_{bp} = 2\pi * \chi * \beta_p \quad (2)$$

Finally, the b_{bp} data is binned to 1 m with the vertical profiles then averaged between 0 and 50 m below the water surface.

2.4 Study regions

For the scope of this assessment, we chose to limit our study to only Lake Michigan rather than any of the other Great Lakes. This was done purposefully for a two main reasons. First, the way the CALIPSO flyovers were oriented coincided very well with the geometry of the lake. For Lake Michigan, the satellite had two unbroken and intersecting day/night tracks that spanned a few degrees of latitude (Figure 2). This match up allowed us to effectively preform our analysis even with the limited spatial coverage of the CALIPSO satellite. Secondly, the distribution of in situ sampled b_{bp} values was the highest in Lake Michigan. This distribution of samples

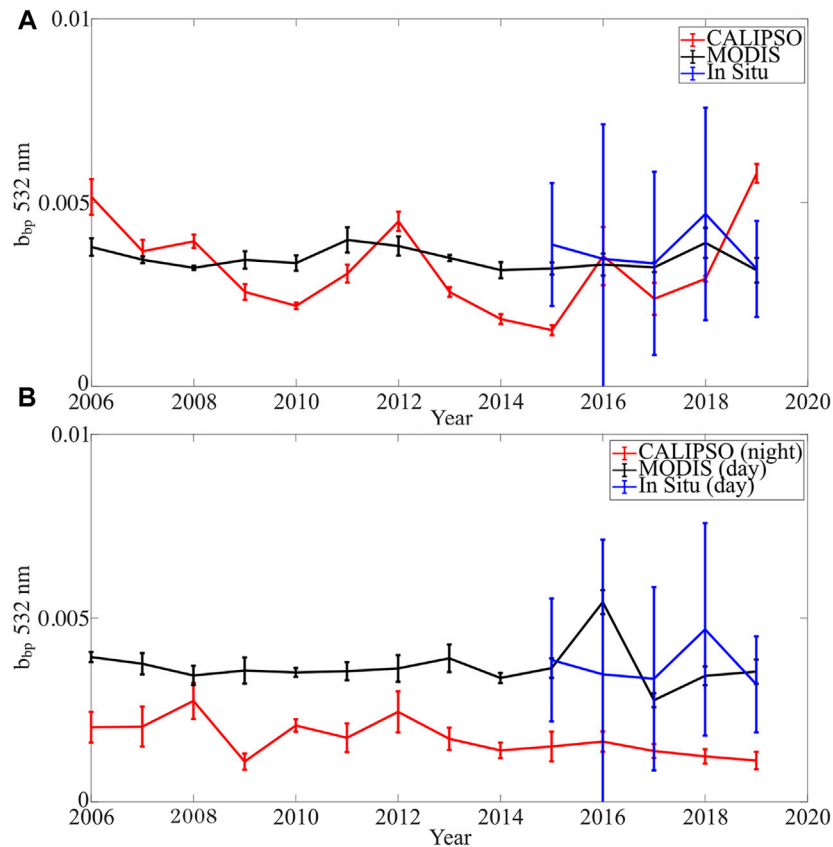


FIGURE 3

(A) Yearly b_{bp} daytime average across Lake Michigan for CALIPSO (red), MODIS (black), and *in situ* (blue). (B) Yearly b_{bp} nighttime average across Lake Michigan for CALIPSO (red), MODIS (black), and *in situ* (blue). Here, MODIS and *in situ* values are still sampled in the daytime. Error bars for (A) and (B) represent 95% confidence. Intervals. Here, MODIS derived values are different across the lake because the daytime and nighttime CALIPSO tracks differ spatially.

along similar lines of latitude to that of the CALIPSO tracks allowed us to compare our derived product effectively. A map of both of the CALIPSO tracks used in this survey along with the locations of all *in situ* sampling stations is shown in Figure 2.

3 Results

3.1 Yearly average b_{bp} on Lake Michigan

As a first test of the ability to derive b_{bp} from CALIPSO, we computed an average b_{bp} across the entire lake for every year in the data record. We did this for both the daytime and nighttime CALIPSO tracks. To ascertain how this value compared to other measurements of b_{bp} , we took a yearly average b_{bp} for the MODIS data at the same location as the CALIPSO data. In conjunction with CALIPSO and MODIS, we also calculated a yearly average b_{bp} for the *in situ* data across the entire lake. We compared the three metrics in Figure 3A (daytime) and Figure 3B (nighttime). As MODIS is unable to sample at nighttime and as there is no documented nighttime b_{bp} samples on Lake Michigan, the nighttime b_{bp} from CALIPSO is compared to daytime measurements.

Our results for the daytime flyovers showed more yearly variability in the CALIPSO b_{bp} than the MODIS b_{bp} (Figure 3A). However, over the course of the 15 year period, there was no discernible trend in b_{bp}

(p -value > 0.05). The 95% confidence bounds for the CALIPSO b_{bp} were similar to that of the MODIS derived results, and much smaller than the bounds on the *in situ* sampling. These results also held for the nighttime CALIPSO results (Figure 3B). However, the nighttime results are systematically lower for every year in the record when compared to their daytime counterparts and the MODIS/*in situ* data.

3.2 Seasonal b_{bp} across Lake Michigan

Both cloud cover and high wind speeds limited the return rate of usable CALIPSO data and therefore did not allow us to resolve seasonal trends across the lake on a yearly basis. However, because trends across the 15 years time period of the CALIPSO, MODIS, and *in situ* data were largely unchanged (relative to the standard error of the *in situ* measurements), we felt justified in combining the entire time record into a seasonally divided data set and then evaluating this data set spatially across the lake. We did this for both the daytime and nighttime measurements. To start, the daytime measurements across Lake Michigan are shown in Figure 4A. These results are divided up into four seasons: Spring (March through May), Summer (June through August), Fall (September through November) and Winter (December through February).

At a first order evaluation, for the spring, summer, and fall we see very good coherence between all three methods of collecting Daytime

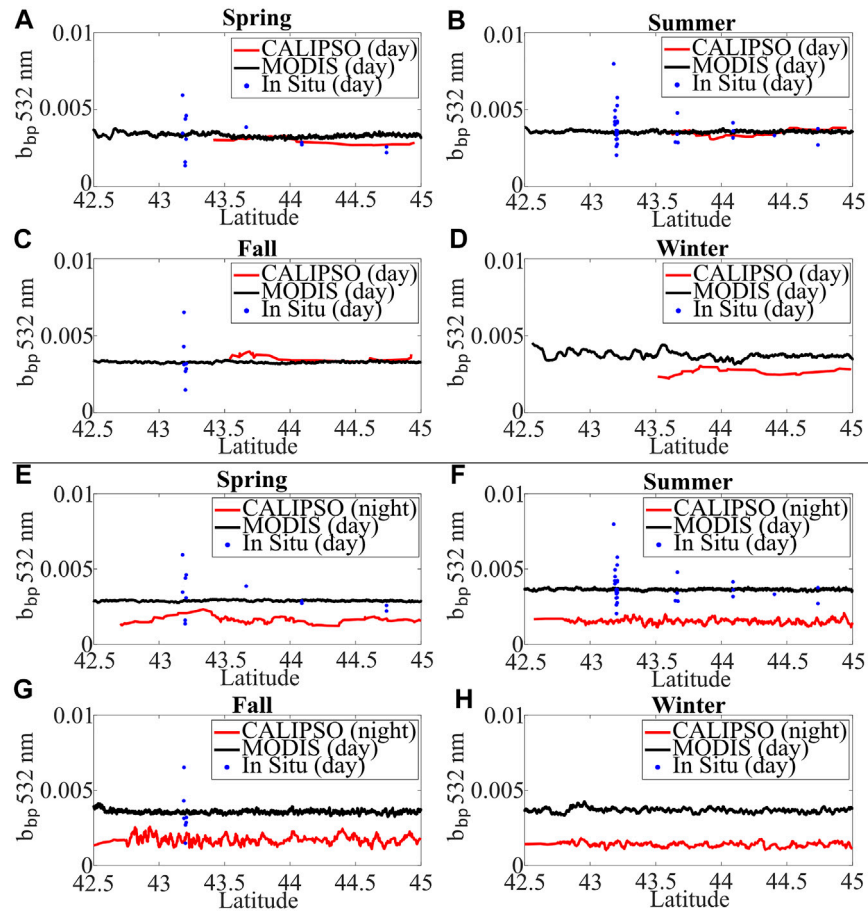


FIGURE 4

(A–D) Daytime, seasonal measurements for CALIPSO (red), MODIS (black), and *in situ* (blue) values of b_{bp} . (E–H) Nighttime, seasonal measurements for CALIPSO (red), MODIS (black), and *in situ* (blue) values of b_{bp} . Once again, MODIS and *in situ* values are still sampled in the daytime. Large variations in *in situ* values can be partially attributed to differences in sampling longitude.

b_{bp} (Figure 4A). In the winter, we see a much larger divergence between measurements, which is not surprising in that the MODIS result is not well calibrated for winter. This could be related to one or more of the following potential issues. First, the CPA-A, which is used to generate the MODIS b_{bp} estimates, is calibrated based on *in situ* measurements throughout the lakes (Shuchman et al., 2013). However, because our *in situ* dataset does not include any measurements collected in winter, it is unclear how suitable the current calibration is during the winter season. Second, the CALIPSO result may also be influenced by ice in the lake. With these issues in mind, CALIPSO may be able to supplement non-existent winter sampling campaigns if validation of the result could be performed. The nighttime measurements from CALIPSO again show systematically lower response across all sections of the lake when compared to the daytime sampled results (Figure 4B). The usable data retrieval rate of the nighttime measurements was also nearly an order of magnitude higher than that of the daytime (7% vs. 1%).

Also of note is the lack of CALIPSO daytime data between 42.5° and 43.5° latitude. This likely is a direct result of the optical complexity of the waters of Lake Michigan in this region. Satellite optical imagery frequently shows the existence of sediment plumes in this part of the lake (Lohrenz et al., 2004; Vanderploeg et al., 2007), which may be

resulting in a CALIPSO return that is, flagged as contaminated (for one or more of the previously shown filtering steps). Likewise, this part of the CALIPSO track is mostly nearshore, which further increases the optical complexity of the water and may result in further signal loss. This is also related to the large variability of *in situ* values in these optically complex waters, which are likely to have more variability in their b_{bp} relative to portions of the lake that are more spatially consistent.

3.3 Comparison of CALIPSO vs. MODIS daytime b_{bp}

To a higher level analysis of the daytime results, there is some smaller scale divergence across the lake between the CALIPSO and MODIS measurements. This is especially prevalent in the spring time (Figure 4A). Taking the *in situ* values as being ground truth, we next compared the daytime CALIPSO and MODIS b_{bp} results to their closest measurement spatially on a seasonal basis, taking a median percent error for each season and instrument. We did this for both the spring and the summer separately (when *in situ* measurements were available) and then also combined the results across all seasons (Figure 5).

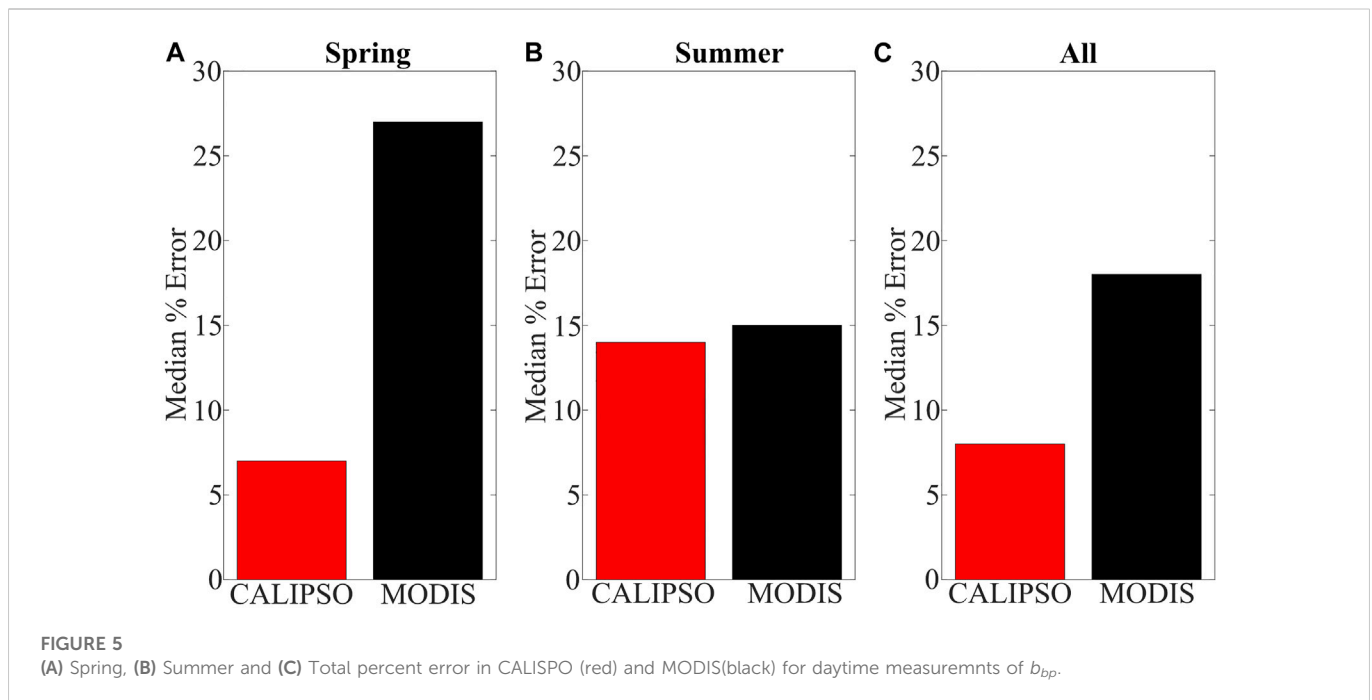


FIGURE 5
(A) Spring, (B) Summer and (C) Total percent error in CALIPSO (red) and MODIS (black) for daytime measurements of b_{bp} .

We found that CALIPSO derived b_{bp} showed better agreement relative to the *in situ* sampling than the MODIS derived b_{bp} . This was especially true in the springtime where the CALIPSO b_{bp} had a median percent error of 7% and the MODIS b_{bp} had a median percent error of 27%. In the summer, both instruments were nearly the same in their performance, with the CALIPSO (14% error) only slightly outperforming the MODIS (15% error). Finally, taken together regardless of season, CALIPSO (8%) was closer to *in situ* values than MODIS (18%).

4 Discussion

4.1 Weather dependent return rate of CALIPSO

Our results indicate that CALIPSO can retrieve a reliable b_{bp} signal on a large, freshwater lake. However, deriving trends with a higher resolution than yearly across the entire lake or seasonally across the entire data record is impractical using the CALIPSO data. This is due to a weather dependent return rate of usable CALIPSO backscatter data across the lake. For daytime measurements, the amount of good measurements after filtering is around 1%. This improves substantially for the nighttime measurements where the amount of usable data climbs to approximately 7%. However, even at 7% retrieval, the limited spatial coverage of CALIPSO prevents a more in depth analysis.

Reasons for the low usable data percentage of CALIPSO on the Great Lakes stems mostly from two sources. First, average wind speeds on Lake Michigan are generally around 6 m/s, with values varying both spatially and temporally (Li et al., 2010). Due to turbid waters at high wind speeds and to signal saturation at low wind speeds, a range of wind speeds of between 2 m/s and 9 m/s is required in order to reliably derive b_{bp} from CALIPSO (Behrenfeld

et al., 2013). Many of the CALIPSO flyovers on Lake Michigan take place when the wind speed is greater than the maximum allowed wind speed, resulting in a considerable loss of data. The second major source of data loss comes from the cloud coverage on the great lakes, where the percentage of cloud free days is less than 50% (Ju and Roy, 2008). Clouds prevent reliable retrieval of the signal from CALIPSO and therefore result in a null measurement.

A final note on the return rate of usable data from CALIPSO is the substantially higher retrieval rate in the nighttime hours to that of the daytime hours (7% vs. 1%). This is likely due to the behavior of clouds on wind speeds on Lake Michigan between the daytime and the nighttime. In the daytime, temperature gradients between the lake and the land produce high winds, an effect which may be diminished in the nighttime when temperature gradients are much less steep (Laird et al., 2001). This could result in both less cloud coverage and lower wind speeds on the lake in the evening hours, resulting in a higher data usability rate.

4.2 Substantial day/night difference in CALIPSO b_{bp}

As the usable data retrieval rate for nighttime measurements is higher for CALIPSO, it would be advantageous to use nighttime measurements of b_{bp} to further monitor the Great Lakes. However, our results indicate that there is a substantial offset in nighttime b_{bp} across all years (Figure 3B) and seasons (Figure 4B). This offset is sometimes more than 50% lower than the closest daytime measurement. Theory on the open ocean suggests that the nighttime measurement should be intrinsically 10% lower due to the diurnal size differences in particulates (Kheirredine and Antoine, 2014; Behrenfeld et al., 2019). This difference could be exacerbated in the freshwater ecosystem where zooplankton and phytoplankton are stoichiometrically distinct compared to their

marine equivalent, and therefore could have much different and more amplified diurnal difference to their combined back-scattering (Elsner and Hassett, 1994).

The challenge with validating the nighttime CALIPSO measurements is the lack of other sources of nighttime b_{bp} to compare it to. MODIS can only sample in the daytime as it is an optical instrument and there has not yet been any effort to sample b_{bp} in the nighttime across the Great Lakes. Because all current and future LiDAR based satellites will sample in the nighttime, and because the retrieval rate of usable data for nighttime measurements is nearly an order of magnitude better than daytime measurements, future sampling efforts across the Great Lakes should be gauged to have a nighttime component. This would serve to validate any future spaceborne LiDAR derived b_{bp} measurements.

4.3 CALIPSO b_{bp} as compared to MODIS b_{bp}

Our results indicated that daytime derived CALIPSO b_{bp} aligned better with the *in situ* sampling when compared to MODIS derived b_{bp} . This was especially true in the springtime where CALIPSO measurements were more than 20% closer to the *in situ* values than MODIS measurements. However, in the summer months CALIPSO was only slightly closer than MODIS, with a difference between them of less than 1%. This result is in line with previous studies on the global oceans, where CALIPSO performed better than MODIS when compared to *in situ* data gathered by the network of ARGO floats (Bisson et al., 2021). However, it should be noted that *in situ* sampling is quite variable and further analysis would be needed to further examine the performance of the CALIPSO measurements to MODIS measurements. For example, *in situ* measurements of b_{bp} on Lake Michigan are taken only periodically (usually twice a year) and only at one particular section of the lake. These sampling campaigns also are done *via* shipborne collection, which are intrinsically time consuming. To set up a more consistent and more efficient sampling campaign, it would be advantageous to establish a system of floats (similar to the open ocean) that could collect *in situ* values of b_{bp} regularly throughout the year. This would vastly improve the analysis.

The difference in reliability between the spring and summer for MODIS is likely due the summer biasing of the b_{bp} derivation from optical imagery. MODIS derived b_{bp} is calculated, in part, by using *in situ* values to calibrate the method. Most of the *in situ* sampling that is, used to calibrate the MODIS derived product comes from summertime measurements. This results in a heavy biasing towards the summer months which yields a summertime MODIS b_{bp} that aligns better with *in situ* measurements and a springtime MODIS b_{bp} that diverges. Moreover, there is very little difference in coherence between seasons for CALIPSO because CALIPSO derived b_{bp} is independent of *in situ* sampling campaigns.

4.4 The future of CALIPSO and LiDAR in large lake monitoring

Here, we derived b_{bp} from a spaceborne, LiDAR based, satellite on a large freshwater lake. We found that b_{bp} derived

in this manner matches well with *in situ* sampled and MODIS derived b_{bp} values. We also found that the LiDAR derived values tend to be closer than the MODIS derived values when compared to the *in situ* values, however variability in the *in situ* sampling may be biasing this relationship. That said, the practicality of CALIPSO derived b_{bp} is limited on the Great Lakes due to three main reasons:

1) The weather dependent retrieval rate of daytime measurements is less than 1%, which makes monitoring small scale trends nearly impossible.

2) The spatial coverage of CALIPSO is limited in the scope of the Great Lakes, where the satellite only makes a few flyovers across repeat tracks.

3) CALIPSO, after 15 years in service, is nearing the end of its usable life and therefore further data that will be acquired by the satellite is likely minimal.

With these drawbacks in mind, the usability of CALIPSO derived b_{bp} on the Great Lakes likely lies in its ability to supplement *in situ* measurements, which are used to validate the gridded b_{bp} MODIS products. Previously, we stated that CALIPSO was more in line with *in situ* measurements than MODIS, especially in the springtime. This is due to summer biasing which is related to the heavy summer distribution of *in situ* measurements. However, CALIPSO derived results may be able to serve as proxy "*in situ*" b_{bp} values. This would greatly supplement current sampling efforts and improve MODIS derived b_{bp} products.

Even with CALIPSO coming to an end, the future of spaceborne LiDAR derived b_{bp} on the Great Lakes is still bright. Recent studies on the global have used a new LiDAR based satellite that was launched in 2018, ICESat-2, to calculate b_{bp} both as an along track variable and as a function of water depth (Lu et al., 2020; 2021b; a). With considerably higher spatial coverage than CALIPSO and the ability to profile b_{bp} at depth, ICESat-2 could provide valuable information about water quality on the Great Lakes. With that in mind, we believe that spaceborne LiDAR will be a major component of monitoring efforts on the Great Lakes over the next 10 years.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

RW analyzed data and drafted the manuscript. MS and RS conceived the idea. KB processed the MODIS and *in situ* data. All authors contributed to the article and approved the submitted version.

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