Trends in Winter Light Environment Over the Arctic Ocean: A Perspective From Two Decades of Ocean Color Data

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Abstract The last few decades have seen a decrease in Arctic ice cover, leading to changes in the structure and function of marine ecosystems. Yet sustained long-term observations of the marine environment are difficult to acquire. Harsh environments limit in situ measurements, while low light and high solar angles hinder ocean color observations from satellite. Here we use masks of valid-invalid ocean color pixels to diagnose ocean conditions and find strong positive trends in the Arctic open-water season close to the ice sheet, generally consistent with sea ice products from satellites. The North East Atlantic with no seasonal ice cover shows weaker, but significant trends indicative of decreasing winter cloud cover. Decreases in both sea ice and cloud cover will increase light availability at the sea surface and potentially enhance phytoplankton growth. Our method allows the winter light conditions to be studied at temporal and spatial scales relevant for phytoplankton dynamics.

1. Introduction

The climate of the Arctic Ocean is changing rapidly (Maksym, 2019; Meier et al., 2014), with the region experiencing among the highest warming trends on the planet and a rapid decrease over the last few decades in the extent of both the seasonal and multiyear sea ice coverage (Johannessen et al., 2004; Maksym, 2019; Meier et al., 2007). The decline in Arctic sea ice cover has been attributed to a combination of factors such as increased advection of warm water into the region (Shimada et al., 2006; Steele & Boyd, 1998), increased export of ice through Fram Strait from changes in the atmospheric circulation (Maslanik et al., 2007; Rigor & Wallace, 2004), and increased Arctic temperatures (Polyakov et al., 2010; Rothrock, 2005). The mechanistic connection between declining ice extent and increasing temperatures in the Arctic has also been investigated (Screen & Simmonds, 2010).

These rapid changes in the physical environment have been reported to affect the structure and function of Arctic marine ecosystems in far-reaching ways (Post et al., 2013): Several studies suggest a significant increase in phytoplankton biomass and biological production in the region (Arrigo et al., 2008; Kahru et al., 2016; Mélin et al., 2017); annual phytoplankton bloom maxima are now occurring earlier in the season (Kahru et al., 2010); and increased occurrences of secondary fall blooms have been reported in many areas where a single bloom per year used to be the norm (Ardyna et al., 2014). Such changes in magnitude and timing of phytoplankton blooms can potentially have profound consequences for the food chain and the carbon cycle (Kahru et al., 2010; Post et al., 2013).

Key to many of the changes in the phenology of marine organisms are the modifications in the Arctic ice cover and in the extension of the open-water season. Biofeedback mechanisms that can in turn impact the ice dynamics of the region have also been highlighted (Goosse et al., 2018; Lengaigne et al., 2009; Park et al., 2015), emphasizing the need to study phytoplankton phenology and ice dynamics as a coupled problem. Many marine organisms native to high latitudes have adapted their seasonal cycles to the dynamic interface between ice and water and are particularly vulnerable to the drastic changes in sea ice cover currently seen (Smetacek & Nicol, 2005). Changes in the ice-free open-water season also have consequences for physical processes such as air-sea exchange of momentum, energy, and material. They have a profound effect on the albedo of the sea surface, and on penetration of solar radiation into the water, which in turn influences the heat budget of the upper layers of the water body, and the rate of photosynthesis by phytoplankton in the water.
Although it is indisputable that polar regions are changing rapidly, detailed information on the Arctic environment is still difficult to acquire, especially when the requirement is for sustained, long-term observations at high spatial and temporal resolution. Harsh environmental conditions, difficulty of access, and lack of infrastructure hamper in situ observations. Low light and adverse viewing geometries, together with ice cover and cloud cover, limit the coverage of satellite-derived ocean color products such as chlorophyll concentration. Microwave remote sensing techniques to detect sea ice can be used to interpret observed changes in the Arctic phytoplankton (Ardyna et al., 2014; Kahru et al., 2010) and do not suffer from the same limitations as ocean color products under cloudy conditions, but the spatial scales (∼25–50 km compared with 1–4 km for OC-CCI) at which such information is available might not always be compatible with the characteristic scales associated with biological processes. Nor does it tell us whether there are changes in the light field in the ocean, arising from potential variability in cloud cover.

In this paper we explore the use of ocean color products to track trends in the open-water season in the Arctic. We compare observed trends with those in sea ice extent from microwave measurements and show the general consistency in the two fields. In areas of high-latitude North Atlantic, we see weaker, but significant trends in persistent cloud cover, which could be enhancing light conditions favorable for phytoplankton growth. Because these trends are extracted from ocean color data, compatibility with temporal and spatial scales at which phytoplankton dynamics are studied is assured. The work demonstrates a new use of ocean color data where the flagging of pixels as water, ice, or cloud can be exploited.

2. Materials and Methods

2.1. OC-CCI Data

We use satellite-derived chlorophyll products at 4 km resolution from Version 3.1 of the Ocean Colour Climate Change Initiative (OC-CCI, Mélin et al., 2017; Sathyendranath et al., 2018, 2019). OC-CCI merges data from the Sea-viewing Wide-Field-of-view Sensor (SeaWiFS), the Aqua Moderate-resolution Imaging Spectroradiometer (MODIS-Aqua), the MEdium spectral Resolution Imaging Spectrometer (MERIS), and the Suumo-NPP Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) into a unified product. SeaWiFS operated from September 1997 until December 2010 and MERIS from March 2002 to May 2012, MODIS-Aqua was launched in May 2002, and VIIRS in October 2011; both are still operational as of December 2019. Data from the different instruments are merged after band-shifting normalized remote-sensing reflectance ($R_{rs}$) to the spectral bands of SeaWiFS and correcting for intersensor biases. Atmospheric correction is performed using POLYMER v3.5 (Steinmetz et al., 2011) for MERIS and MODIS-A, and NASA/L2Gen 7.3 for SeaWiFS and VIIRS. All individual grid cells are classified optically using a fuzzy-logic approach (Jackson et al., 2017; Moore et al., 2009, 2012) and a combination of the best chlorophyll algorithms for each class is used along with class membership at each pixel to generate chlorophyll at each pixel. The spatial mapping follows NASA protocol for Level 3 processing by considering a 4-km bin as valid if there is at least a single 1 km valid pixel from at least one sensor, and taking the mean if more than one value is valid. The resulting time series for the period 1997 to 2018 is designed to be internally consistent (all radiometric products band-shifted to a common set of bands corresponding to SeaWiFS) and stable (corrected for intersensor bias) (Sathyendranath et al., 2019).

A unique feature of OC-CCI Version 3.1 is that Level 2 flags for invalid data are applied differently from the NASA operational products. In particular, based on the performance of the POLYMER atmospheric correction algorithm, data are not automatically flagged as invalid if the solar zenith angle at the time of satellite overpass is high. NASA/L2Gen originally flagged chlorophyll data if solar zenith angles were above 70° but have increased the limit to 75° in recent years (Bailey & Werdell, 2006; Gordon et al., 1988). This exclusion is due to the limitation of atmospheric correction algorithms assuming a plane-parallel geometry where extreme viewing and solar geometries are expected to introduce high errors in retrieved chlorophyll values. Although such a potential degradation would be a concern when using the chlorophyll products, it is not a problem when the data are used only to assess whether the satellite detected water (which in turn implies absence of clouds and ice over the pixel). We have tested potential effects of blending different atmospheric correction algorithms, as was the case with the OC-CCI v3.1 product used here, by performing the trend analysis on only MODIS data and on an experimental, unpublished OC-CCI data set where POLYMER is used for all instruments. The results are consistent with the ones presented here.
2.2. Sea Ice CCI Data

Sea ice trends are based on version 2.1 of the EUMETSAT OSI SAF and ESA CCI sea ice concentration climate data records (Sea Ice CCI Lavergne et al., 2019). The sea ice concentration products are based on medium resolution passive microwave satellite data over the polar regions. Sea Ice CCI is based on observations from two Advanced Microwave Scanning Radiometer (AMSR-E Wentz, 2013 and AMSR2; Maeda et al., 2016) sensors. We use the Sea Ice CCI product with a 50 x 50 km spatial resolution and daily coverage from June 2002 to October 2011 and July 2012 to May 2017. A pixel is defined as ice-free when the ice coverage is 0%.

2.3. Photosynthetically Available Radiation

Photosynthetically Available Radiation (PAR) is defined as the quantum energy flux from the Sun in the 400–700 nm range. We use the NASA/MODIS 24-hr averaged product as measured at the sea surface with the unit Einstein (E) m⁻² day⁻¹ (Frouin & Pinker, 1995; Frouin et al., 2012; NASA Ocean Biology Processing Group, 2017). The product is based on subtracting the solar energy reflected by the ocean-atmosphere system and that absorbed by the atmosphere from the solar irradiance at the top of the atmosphere. The PAR model uses plane-parallel theory and assumes that the effects of clouds and clear atmosphere can be decoupled. It is unnecessary to distinguish between clear and cloudy regions within a pixel, thereby avoiding the need for the often-arbitrary assumptions about cloudiness distribution (Frouin & Pinker, 1995; Frouin et al., 2012).

2.4. Start, End, and Duration of Clear-Sky, Open-Water Season in the Arctic

For each year in the time series, and for every pixel at 4 km resolution, we interrogate the data set to find the first day ($T_s$) (in Day of Year) when a valid chlorophyll value appears in the data set. Valid data are provided in Figure 1. First and last day in the Boreal year (Jan-Dec) when valid chlorophyll observations occur in the Northern Hemisphere, based on OC-CCI data from 1 January 1998 to 31 December 2018. Panel (a) shows the minimum values of $T_s$ in each pixel. Panel (b) shows the median values, and (c) the maximum. Panels (d)–(f) are analogous plots for $T_e$ with panel (d) showing minimum, panel (e) median, and panel (f) the maximum values.
only when the pixel has not been masked due to adverse viewing conditions such as ice or cloud cover, or unfavorable viewing geometry. A valid pixel therefore implies that the satellite sensor has detected open water with clear skies. The domain of interest is from 45°N to 84°N. No data are available north of 84°N due to the permanent ice cap. We also note the last day in the year when there is a valid chlorophyll value in the data set, denoted as \(T_e\), which represents the end of the open-water season with cloud-free conditions. For each year, the open-water duration for the pixel is computed as \(D = T_e - T_s\). The ice-free conditions are inferred from the microwave ice data in an analogous fashion, using information on when ice-free pixels are detected for the first and last time in a year.

2.5. Statistical Analysis

Trends in the data are identified by calculating the linear least squares regression for each grid cell using the Python Scipy Linregress function (Virtanen et al., 2019) with Year as independent variable and \(T_s\), \(T_e\), and \(D\) as dependent variables. We treat the resulting slopes as estimates of linear trends and follow the protocol suggested by Santer et al. (2000, 2008) to compensate for possible overestimations of statistical significance from autocorrelations between successive data points.

3. Results

The baseline data for \(T_s\) (time in Day of Year when a valid chlorophyll datum first occurs in the OC-CCI product set, for each year at a pixel) and \(T_e\) (time in Day of Year when a valid chlorophyll datum is noted for the last time, for the same year in the OC-CCI product set at the same pixel) are shown in Figure 1. Minimum values for \(T_s\) are 1 January for all pixels south of 52°N, whereas the maximum is as late as October, and occurs in the ice-dominated region between the permanent ice cap and Bering Straight. The maximum \(T_e\) value south of 52°N is 31 December (Day of Year = 365 or 366) while the lowest \(T_e\) values (late May) are found close to the permanent ice sheet. Note that the maximum in \(T_s\) can be later than the minimum \(T_e\) in a given grid cell if they occur in different years.

We calculate the number of days (\(D\)) with clear-sky, open-water conditions each year by subtracting \(T_e\) from \(T_s\). Figure 2 shows the minimum, median, and maximum values of \(D\) for each grid cell during the time period 1998–2018. We find similar spatial patterns as in 1, only even more accentuated. The domain of interest can be broadly divided into three areas: waters south of 52°N where the maximum inferred period is 365 (or 366) days, or the whole year. In this domain, neither ice cover nor unfavorable viewing geometries associated

![Figure 2. Duration \(D\) calculated as difference between the first and last days in a year when valid chlorophyll observations are recorded in the Arctic region. Panel (a) shows the minimum value for \(D\) in each grid cell over time period 1998–2018, panel (b) the median, and panel (c) the maximum. The insert shows the zonal maximum of \(D\), gray dotted line indicates 52° latitude.](image-url)
with low-light preclude detection of open-water, and only cloudiness causes variability in inferred $D$. The area north of 52°N and outside the maximum extent of sea ice coverage shows a gradual meridional decrease in $D$, whereas areas of seasonal ice coverage have significantly shorter duration $D$. The region of seasonal ice cover includes Hudson Bay, the Canadian Arctic Archipelago, the Siberian shelf, and the east coast of Greenland.

Our analysis has established the effective southern boundary of winter degradation in ocean color satellite coverage. The systematic, latitudinal decrease in maximum $D$, minimum $T_s$, and maximum $T_e$ north of 52°N, but not to the south indicates that the satellite detection of open water is affected by adverse viewing geometries in winter at latitudes only north of 52°N (see insert in Figure 2). While of general interest, these results do not affect our findings since viewing geometries remain the same for any satellite from one year to the next. Trends in $D$ should not be affected by such absence of satellite data during low-light winter conditions.

Trends in $T_s$, $T_e$, and $D$ are calculated individually for each grid cell in the domain using ordinary least squares linear regression. The resulting maps of slopes, presented in Figures 3a–3c, show significant trends in most of the Arctic (slopes with $p$ values higher than 0.05 are masked). The strongest trends (up to 2 days per year) are mainly, as expected, in regions bordering the permanent ice cap that are experiencing rapid ice retreat. We also find significant, but weaker, trends in most of the north-east sub-Arctic Atlantic where no winter ice cover occurs. Most regions are shifting toward a longer clear-sky, open-water season with ice fringe regions changing fastest. The main exceptions are the Hudson Bay and the Canadian Arctic Archipelago where the trends are toward a longer season with ice cover. A notable region is the Celtic Sea, which shows strong significant increases in $D$ without being associated with sea ice.

Figure 3. Trends in $T_s$ (panel a), $T_e$ (panel c), and duration $D$ (panel b) between the $T_s$ and $T_e$, from Ocean Colour CCI products, computed as the slope of a linear regression, with year (1998–2018) as independent values and each of $T_s$, $T_e$, or $D$ as dependent values. The linear regression is performed independently on each grid cell. Effects of autocorrelation between successive data points are adjusted for, by applying the protocol suggested by Santer et al. (2000). Slopes (trends) where $p$ values are higher than 0.05 are masked. Panels (d)–(f) show the analogous slopes but for the Sea Ice CCI product.
The trends shown in Figures 3a–3c can be compared with corresponding slopes calculated for sea ice coverage using the Sea Ice CCI data product, for start, end, and duration of the open-water season, shown in Figures 3d–3f. We see that in regions of seasonal ice cover, trends in open-water season inferred from Sea Ice CCI (start, end, and duration) are in general agreement with trends in open-water, clear-sky conditions inferred from ocean color data, with stronger positive trends in the Siberian shelf, and negative trends in the Canadian Arctic Archipelago and the Hudson Bay. An exception is the Bering Strait where Sea Ice CCI shows a strong negative trend in the length of the ice-free season, whereas OC-CCI shows a positive trend.

We estimate PAR and Chlorophyll concentrations at Ts and Te to determine whether ambient conditions are favorable for phytoplankton growth at those times. Figure 4 shows that surface PAR ranges from 0 to 35 E m⁻² d⁻¹ at Ts and from 0 to 60 E m⁻² d⁻¹ at Te. Zonally averaged PAR is about 12 m⁻² d⁻¹ at both Ts and Te from 50°N to 67°N, whereas Ts experiences higher PAR further north. This pattern arises because Ts is heavily influenced by the last day of ice north of 67°N. Chlorophyll concentrations range between 0.1 and 10 mg m⁻³ for both Ts and Te with a median concentration of 0.6 mg m⁻³ for Te and 0.4 for Ts with no significant meridional variability.

4. Discussion and Conclusion

Our results show trends according to which winter conditions are now ending earlier in the season (Ts is occurring earlier in recent years) and winter conditions are starting later (Te occurring later in the year in...
recent years) for most of the Arctic, leading to a corresponding increase in open-water, cloud-free conditions (duration $D$). We also find weaker but significant trends toward longer $D$ at latitudes well below those with seasonal ice cover, suggesting decrease in winter cloud cover. The obvious cause of these trends is changes in persistent winter cloud cover: In eastern North Atlantic and eastern Arctic, poor-light winter conditions are ending earlier, and restarting later, in recent years. The effect of ice and persistent cloud cover is to reduce the light reaching the sea surface. Where the trends indicate that persistent cloud cover in winter is now reduced to a shorter period, conditions are favorable for more light reaching the sea surface earlier in the spring season, thereby extending the duration of enhanced light conditions favorable for phytoplankton growth.

Comparison of the results with microwave sea ice products showed consistency between the two products in general, though some small areas of discrepancies were also identified. These areas merit further investigation to identify the sources of discrepancy, which could help to improve the ocean color products or to interpret the results better. Given the complementarity of ocean color and microwave products, the potential exists for combining both microwave and ocean color information to generate a blended product that would exploit the best features of both. Microwave products are not hampered by low light or clouds, but ocean color provides higher spatial and temporal resolution commensurate with time and space scales relevant for phytoplankton dynamics. A blended product would use ocean color information, when available, to improve the resolution of sea ice products. Such improvements could also benefit practical applications such as navigation. The trends are stronger in the eastern Arctic than in the western, Canadian Arctic, where in fact, we see some opposite trends, with winter conditions lasting longer.

The indicators we have introduced here are compound indicators, in the sense that they indicate the combined effects of both ice and clouds on light reaching the sea surface at the start and the end of the winter season. Both clouds and ice hamper light reaching the sea surface, and thereby influence the growth conditions for phytoplankton in the water. The observed trends in ice-free regions indicate that changes in winter cloud conditions could be a hitherto underrecognized factor promoting earlier phytoplankton blooms and a longer season favorable for phytoplankton growth. These interesting results argue for the value of retaining information on cloud flags and ice flags when data from multiple sensors are merged to create long time series, as in the case of OC-CCI, or when information from multiple satellite passes are combined, to create composites over different time intervals. Such information, if retained and properly validated, would allow discrimination of the effects of ice and clouds. As noted earlier, such information is also of interest to many physical processes at the air-sea interface.

One outcome from our study is precise estimates of the start and end of the season observable by ocean color satellites, and the light availability at the start and end of the clear-sky, open-water season. Although it is quite challenging to determine when light is too low to allow net positive community production without a full understanding of the biological and physical conditions, it is possible to make some crude estimates. Several studies suggest that phytoplankton growth is generally light limited below 10 E m$^{-2}$ day$^{-1}$ and sustainable down to 1 E m$^{-2}$ day$^{-1}$ or lower (Behrenfeld & Boss, 2017; Cloern et al., 1995; Geider et al., 1986; Nicklisch et al., 2007; Spilling et al., 2015). From the light attenuation equation $I_z = I_0 e^{-K_d z}$ where $K_d$ is the attenuation coefficient for downwelling PAR, we see that mean PAR in the euphotic zone is about 20% of surface PAR. This suggests that surface PAR higher than 10 E m$^{-2}$ day$^{-1}$ has the potential to sustain growth, an inference that is supported by chlorophyll concentrations being typically higher than 0.1 mg m$^{-3}$ at $T_s$ and $T_c$. A significant portion of the region shows incident light levels greater than 10 E m$^{-2}$ day$^{-1}$ at $T_s$ and $T_c$ in our study, suggesting favorable growing conditions during times when ocean color retrievals are impeded. This inference only holds if there is no sharp change in light reaching the sea surface prior to $T_s$ or post $T_c$ because of change in ice or cloud. These findings have potentially significant implications for how primary production in the polar regions should be estimated from space.

The era of studying individual essential climate variables (ECVs, such as ocean color or sea ice) in isolation is over. There is clearly value in combining information from multiple sources to improve the information base on our planet, especially in the context of climate change. The analysis presented here opens the avenue for combining ocean color and microwave information to map ocean winter light conditions at temporal and spatial scales inaccessible to a single ECV. The results also show that useful information is contained in the cloud and ice masks in ocean color data. The utility of these masks would be further enhanced as algorithms to discriminate between ice and cloud improve.
Data Availability Statement

Data presented in the publication are archived at https://10.5281/zenodo.3967299.

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