Environmental Research Letters

PAPER

Satellite and airborne remote sensing of gross primary productivity in boreal lakes

Catherine Kuhn, Matthew Bogard, Sarah Ellen Johnston, Aji John, Eric Vermote, Rob Spencer, Mark Dornblaser, Kim Wickland, Rob Striegl and David Butman

1 Department of Forestry and Environmental Science, University of Washington, 4000 15th Avenue NE, Seattle, WA 98195-2100, United States of America
2 Florida State University, Tallahassee, United States of America
3 Department of Biology, University of Washington, Seattle, Washington, United States of America
4 NASA Goddard Space Flight Center, GSFC Code 619, Greenbelt, MD 20771, United States of America
5 U.S. Geological Survey, Boulder, United States of America
6 Department of Civil and Environmental Engineering, University of Washington, Seattle, Washington, United States of America

E-mail: ckuhn@uw.edu

Keywords: freshwater ecosystems, Google Earth Engine, boreal, gross primary productivity, Landsat-8, Sentinel-2, lake color, remote sensing, shallow lakes

Supplementary material for this article is available online

Abstract

In terrestrial and marine ecosystems, remote sensing has been used to estimate gross primary productivity (GPP) for decades, but few applications exist for shallow freshwater ecosystems. Here we show field-based GPP correlates with satellite and airborne lake color across a range of optically and limnologically diverse lakes in interior Alaska. A strong relationship between in situ GPP derived from stable oxygen isotopes ($\delta^{18}$O) and space-based lake color from satellites (e.g. Landsat-8, Sentinel-2 and CubeSats) and airborne imagery (AVIRIS-NG) demonstrates the potential power of this technique for improving spatial and temporal monitoring of lake GPP when coupled with additional field validation measurements across different systems. In shallow waters clear enough for sunlight to reach lake bottoms, both submerged vegetation (macrophytes and algae) and phytoplankton likely contribute to GPP. The stable isotopes and remotely sensed shallow lake color used here integrate both components. These results demonstrate the utility of lake color as a feasible means for mapping lake GPP from remote sensing. This novel methodology estimates GPP from remote sensing in shallow lakes by combining field measurements of oxygen isotopes with airborne, satellite and CubeSat imagery. This use of lake color for providing insight into ecological processes of shallow lakes is recommended, especially for remote arctic and boreal landscapes.

1. Introduction

Northern high latitudes are warming at twice the global average rate (Overland et al 2019), driving widespread changes to terrestrial ecosystem structure and function (Pastick et al 2019, Wang et al 2019), including to gross primary productivity (GPP) (Myneni et al 1997, Goetz et al 2005, Beck and Goetz 2011). GPP is the rate primary producers convert inorganic carbon to biomass via photosynthetic pathways. Quantifying GPP can provide crucial insights into ecosystem functioning by establishing rates of food web carbon (C) uptake and energy flows. Satellite remote sensing is a means to observe freshwater ecosystems at global scales. Satellite indices for productivity have been well-established for terrestrial (Tucker 1979, Pettorelli et al 2005) and marine (Antoine et al 1996, Lee et al 2015) systems from the red and near-infrared bands. While inland water remote sensing research has accelerated (Matthews 2011, Palmer et al 2015, Dörnhöfer and Oppelt 2016, Mouw et al 2017, Topp et al 2020), a comprehensive approach to efficiently map the spatial distribution of GPP for shallow lakes, which are globally abundant and concentrated in high northern latitudes (Downing et al 2006), has yet to emerge.
Past lake productivity studies used an approach adopted from oceanography that assumes phytoplankton drive GPP. Indices based on blue and green reflectance (Morel and Prieur 1977) are calculated to estimate phytoplankton biomass, which then drives net primary productivity models (Behrenfeld et al. 2005, Shuchman et al. 2013). Studies have primarily been limited to large water bodies (Bergamino et al. 2010, Shuchman et al. 2013, Youssef et al. 2014, Kauer et al. 2015, Fahrenstiel et al. 2016, Deng et al. 2017) and the method has even been applied for large (>1 km) lakes worldwide (Sayers et al. 2015). However, this model relies on the assumption that there is no influence from bottom-reflectance (i.e. that lakes are optically deep).

However, worldwide 99% of all lakes are small (Downing et al. 2006, Verpoorter et al. 2014) and average lake depth globally has been estimated to only be 3.9 m (Messager et al. 2016).

For these globally abundant small (<1 km) and shallow lakes (<10 m), the current method neglects benthic and littoral contributions to GPP from macrophytes and attached algae. Incorporating both benthic and pelagic processes into lake GPP models is crucial because macrophyte GPP rates exceed all other ecological communities including phytoplankton (Wetzel 2001) and can contribute 65%–98% of ecosystem production in shallow lakes (Jeppesen et al. 1998, Rautio and Vincent 2006).

A remote sensing method for mapping GPP is needed that can integrate phytoplankton and macrophytes. This is especially relevant for the shallow lakes that dominate northern latitudes because of their potential relevance to carbon cycling and aquatic food webs (Raymond et al. 2013, Wik et al. 2016, Stanley and Del Giorgio 2018). The majority of shallow water remote sensing studies have focused on deriving bathymetry and fractional cover of aquatic vegetation (Kutser et al. 2020). New field-based methods have emerged that account for contributions from phytoplankton and macrophytes in lakes (Bogard et al. 2017) but remote sensing techniques have not caught up despite repeated calls for consistent, global inland water quality products (Malthus et al. 2012) and the increasing availability of high-resolution satellite imagery.

This study describes a new approach for quantifying shallow lake GPP using high-resolution (<10 m) remote sensing and field measurements. We combine field observations of GPP derived from oxygen isotopes with high-resolution satellite imagery to estimate shallow lake GPP. We then assess this approach using independently collected field data and test the model across platforms. We also measured in situ properties including turbidity and absorbance to rule out their influence on results. Linking bottom-up field measurements of lake properties with top-down remote sensing provides a novel method to link in-lake ecosystem processes with spatially explicit data to investigate ecosystem function across arctic and boreal lakes.

2. Data and methods

2.1. Study area and field campaign overview
The Yukon Flats Basin is an extensive, 33 000 km² complex of low-lying lakes and wetlands inside the Yukon River Basin (figure 1). Dry, cold and underlain by discontinuous permafrost (Minsley et al. 2012, Rey et al. 2019), the region’s continental sub-arctic climate has an annual average temperature of ~−3 °C (Chen et al. 2014) with short, ice-free summers (April/May to September/October) (Gallant 1995). Over 30 000 lakes dot this semi-arid landscape (Heglund and Jones 2003). Despite abundant surface water, the area receives very little precipitation (250 mm) and lake water balances are dominated by evaporation (Anderson et al. 2013, 2019). Lakes are on the whole shallow and macrophyte-rich; historical surveys demonstrated that lake bottoms are carpeted with up to 80% coverage of aquatic vegetation (Glesne 1986).

Study lakes (n = 7) representative of the region were carefully selected based on results from historical surveys (Heglund and Jones 2003, Halm and Guldager 2012, Halm and Griffith 2014) and a 2016 field study (Bogard et al. 2019) to represent a gradient taking into consideration depth, pH, dissolved organic carbon (DOC) concentration, chlorophyll-a and chromophoric dissolved organic matter (CDOM) absorption (table S1).

Lakes were sampled by boat and/or floatplane (figures (a) and (b)) during a 2018 field campaign conducted as part of the National Aeronautics and Space Administration’s (NASA’s) Arctic-Boreal Vulnerability Experiment (ABoVE) for a suite of parameters (section 2.2, text s1).

2.2. Field and laboratory methods for lake GPP and color
Detailed chemical and optical measurements were collected from the center of each lake as well as in situ surface reflectance (Rₙ). Lake GPP was estimated using an oxygen isotope (δ¹⁸O) mass balance approach adapted from (Quay et al. 1995, Bocanik et al. 2012) as described in Bogard (2017) and text S1. For clarity, GPP derived from δ¹⁸O field measurements will be referred to hereafter as in situ GPP in contrast to satellite-derived GPP. Turbidity, CDOM absorbance and phytoplankton chlorophyll-a were also measured to determine their influence, if any, on lake color. CDOM is the proportion of dissolved organic matter that absorbs strongly in ultraviolet and visible wavelengths (detailed methods in text S1).

2.3. Satellite observations of lake color
The launch of commercial small satellites with daily return times and the increasing availability of hyperspectral imagery through large-scale campaigns such
as NASA ABoVE has sparked interest in finer spatiotemporal analysis. In this study, we capitalize on the strengths of three different satellites: Landsat-8, Sentinel-2 and CubeSats (Planet, Inc). The sensors on-board Landsat-8 (L8), Sentinel-2 (S2) and PlanetScope (PS) all possess bands in the visible and near-infrared (VNIR) with varying spatial and temporal resolutions (figure 2). We also incorporate hyperspectral airborne imagery from AVIRIS-NG (figure 2).

As part of the ABoVE campaign, AVIRIS-NG imagery was acquired on July 22, 2018. Level-2 (L2) atmospherically corrected \( R_s \) (Bue et al 2015) was downloaded from https://avirisng.jpl.nasa.gov/dataportal/. Sentinel-2 acquisitions were identified and downloaded from the U.S. Geological Survey Earth Explorer (https://earthexplorer.usgs.gov/) and atmospherically corrected using the Land Surface Reflectance Code (LaSRC) (Vermote et al 2016). Sentinel-2 images were also corrected using the dark spectrum fitting (DSF) algorithm available in ACOLITE (Python Version 20 190 326.0), which is an open-source atmospheric correction tested successfully in coastal waters (Vanhellemont 2019). PlanetScope Level-2 products were identified using the Planet Labs API (Planet 2017) and a cloud-native, scalable workflow called SWEeP (John et al 2019). No cloud-free Landsat overpasses occurred during or close in time to field operations.

To utilize long-term Landsat records, we also calculated Landsat growing season composites, which is the per-pixel median greenness over the growing season (June, July and August). A common remote sensing tool used to quantify terrestrial productivity (Roy et al 2010), growing season composites provide a continuous, stable record of seasonal lake color. While Landsat overpasses are infrequent (16 d) compared to Planet (≈daily), the Landsat program has the longest global record of Earth observation with acquisitions initiated in the mid-1980s (Lymburner et al 2016), making it a powerful tool for historical analysis. For L8 composites, Collection 1 Level 2 \( R_s \) was accessed using Google Earth Engine. To generate seasonal composites, per-pixel median greenness was calculated from all cloud-free images acquired during the growing season (June 1–September 30) over the study area. With the exception of ACOLITE, all \( R_s \) products described above are derived using 6 SV-based approaches (Vermote et al 2006). For brevity only those results are shown in the main text, but ACOLITE results are given in figures S1–2 (available at stacks.iop.org/ERL/15/105001/mmedia), table S3.

2.4. In situ surface reflectance validation data
In order to verify in situ lake color, \( R_s \) (350–2500 nm) was measured at each lake center in 2018 (\( n = 7 \)) using an ASD FieldSpec 4 High Resolution Spectroradiometer (3 nm and 8 nm resolution in VNIR and SWIR) (text S2). Above-water, in situ lake \( R_s \) was collected 3–5 d prior to overpasses because same-day in situ validation was not possible due to weather delays.

2.5. Combining field and satellite observations
Lake color was extracted for each sampling location from PlanetScope, Sentinel-2, Landsat-8 and AVIRIS scenes for each lake (\( n = 7 \)) using Google Earth Engine (Gorelick et al 2017). A 3 × 3 pixel-wise box centered on field GPS coordinates was drawn for each
lake and the median $R_s$ within each box was extracted from the image in order to reduce bias introduced by spatial sampling (Pahlevan et al. 2016). In the case of scenes overlapping above a site, the median value between scenes was extracted. Since sampling was done at lake centers, all selected pixels were open water. A restrictive F-mask filter was also used to confirm selected pixels were water (Zhu et al. 2015).

Lake color from each respective platform was then regressed against in situ GPP ($n=7$) using a reduced major axis (RMA) type II regression (Python package plyr2, (Haëntjens 2018)). This same workflow was also used to extract lake color from Landsat seasonal composites (section 2.3) for the 2016 samples ($n=24$). The regression model was used to create satellite-derived maps of GPP by taking the regression equation derived from the GPP ~ greenness relationship observed in the 2018 field campaign and applying it on a per-pixel basis to Sentinel-2 imagery using the green band as the model input.

### 2.6. Comparing surface reflectance across sensors

In order to make hyperspectral lake color comparable to multi-spectral observations, in situ and AVIRIS-NG $R_s$ was spectrally convolved to Sentinel-2 wavelengths as in (Pahlevan et al. 2017): 

$$R_{rs}(\lambda_j) = \frac{\sum_{i=1}^{n} R_s(\lambda_i) \cdot \text{RSR}(\lambda_i)}{\sum_{i=1}^{n} R_s(\lambda_i)}$$

where:

- $R_s(\lambda_i)$: band center wavelength
- $n$: total number of hyperspectral band centers ($i$)
- RSR: spectral response factor

Median absolute percent different (MAPD) was used to compare sensor $R_s$: 

$$\text{MAPD} = \text{median} \left( \frac{\text{abs}(x - y)}{x} \right) \cdot 100$$

where $x$ is sensor 1 and $y$ is sensor 2. For decadal time series analysis (figure 4), the non-parametric Mann–Kendall estimator and Sen’s Slope were used to determine whether there was a positive or negative trend in lake greenness and its significance. Thiel–Sen Slope was calculated using the Scipy Python-based scientific computing package (Virtanen et al. 2020) and significance of the slope was determined using a Mann–Kendall test (Hirsch et al. 1982).

### 3. Results and discussion

#### 3.1. In situ lake GPP

*In situ* median GPP rates (table 2) were high at 9.72 mg O$_2$ m$^{-2}$ d$^{-1}$ and spanned a wide range (interquartile range = 6.25 to 10.50 mg O$_2$ m$^{-2}$ d$^{-1}$). *In situ* GPP is on the same order of magnitude as other free-water techniques estimating GPP (Solomon et al. 2013). The rates observed here are higher than more dilute and often deeper boreal lakes (Ask et al. 2012, Deininger et al. 2017) and are consistent with the high productivity observed in shallow, macrophyte-rich lakes found in the northwestern Siberia lowlands (Manasypov et al. 2014) and shallow lakes in the Mackenzie Delta (Squires et al. 2009, Tank et al. 2009).
3.2. Controls on lake color

Other influences on lake color must be ruled out in order to avoid applying this empirical method over-ambitiously. To this end, we characterized variables (table 2) known to influence lake color, including phytoplankton pigments, CDOM and turbidity (Aurin and Dierssen 2012). We observed relatively low phytoplankton biomass based on HPLC Chl-a pigment analysis (median = 3.4 m$^{-1}$, interquartile range = 2.4–5.9 µg l$^{-1}$) (table 1). Overall, this is consistent with a previous study of 129 Yukon Flats lakes (table S1) showing Chl-a was lower than expected based on nutrient availability (Heglund and Jones 2003). The relatively clear waters and high GPP observed here in the presence of low phytoplankton biomass suggest macrophyte production is driving lake GPP (Genkai-Kato et al 2012). One exception was YF17, where field observations of a bloom were confirmed by high HPLC-derived Chl-a (83.3 µg l$^{-1}$).

The majority of lakes were shallow (median depth of 1.6 m) (table 1), with light extending to epiphytic periphyton and aquatic macrophytes. One lake was >10 m deep; the depth, low GPP and low Chl-a (table 2) of this lake provided an end-point representative of the gradient in the area. Other studies have established that submerged and floating macrophytes reflect in the green (560 nm) and near-infrared (850–880 nm) (Silva et al 2008, Oyama et al 2015, Palmer et al 2015, Dogliotti et al 2018). The shallow depths of these relatively clear lakes, as inferred by low turbidities (<1 FNU in most cases) could allow signals from macrophytes and periphyton to reach the surface (Mobley et al 2020). Given the low Chl-a, low turbidities and the observed presence of macrophytes within the water column we suggest that overall, phytoplankton production is not a significant component of the optical signature.

A second influence on lake color is absorption of light by CDOM. CDOM can interfere with the remote sensing of GPP in two ways. CDOM absorbs green light, so high CDOM has the direct effect of masking green light reflected from photosynthetic pigments (Carder et al 1989). Indirectly, CDOM can shade out aquatic producers, thus having the ecological impact of reducing GPP (Ask et al 2012, Seekell et al 2015). In order to rule out this influence, CDOM data were collected at each site. CDOM values (table 2) in sampled lakes were low (a440, median = 1.13 m$^{-1}$, interquartile range = 0.78–1.82 m$^{-1}$), showing that lakes are relatively clear despite their high DOC (10.2 to 25.6 mg l$^{-1}$) (table 2). Our findings are consistent with other studies in semi-arid aquatic ecosystems (Osburn et al 2011, Bogard et al 2019, Kellerman et al 2019) that show low CDOM despite high DOC. While coupling between DOC and CDOM has been demonstrated at global scales (Massicotte et al 2017), CDOM-DOC decoupling in these semi-arid landscapes is hypothesized to result from decreased hydrologic connectivity which reduces terrestrial organic carbon subsidies as aromatic carbon compounds to aquatic ecosystems, resulting in clearer lakes than otherwise expected (Johnston et al 2020).

Finally, lake color can be influenced by scattering from sediment during periods of hydrologic connectivity to surface waters or during lake turnover. However, turbidity across lakes was low (<1 FNU) (table 2) with the exception of YF17, where the previously noted algal bloom drove turbidity up to 35 FNU. Taken together, these results indicate the

---

Table 1. Sampling dates, coordinates and physical properties of study lakes sampled in situ in July 2018 for GPP, reflectance, dissolved organic matter composition and chlorophyll-a among others (section 2.2, text s1).

| Lat!ude | Longitude | Date Sampled | Depth (m) | Surface Area (km$^2$) |
|---------|-----------|--------------|-----------|------------------------|
| Boot (B)  | 66.07404 | 146.27066 | 7/18/18 | 22.0 | 0.73 |
| Canvasback (CB) | 66.38303 | 146.35489 | 7/19/18 | 1.4 | 2.83 |
| Greenpepper (GP) | 66.09209 | 146.73557 | 7/18/18 | 10.3 | 0.97 |
| Ninemile (NM) | 66.18285 | 146.66376 | 7/17/18 | 1.8 | 3.33 |
| Scoter (SC) | 66.24241 | 146.39896 | 7/17/18 | 4.5 | 4.56 |
| YF17 (Y17) | 66.32072 | 146.27431 | 7/17/18 | 1.6 | 1.75 |
| YF20 (Y20) | 66.63715 | 145.77278 | 7/17/18 | 1.3 | 0.59 |

Table 2. Limnological conditions for Yukon Flats sites sampled in 2018. Values given represent the means and, when more than two replicates were collected, standard deviations of the replicates are given as well.

| pH | Turbidity (FNU) | Chl-a (µg l$^{-1}$) | GPP (g O$_2$ m$^{-2}$ d$^{-1}$) | a440 (m$^{-1}$) | DOC (mg l$^{-1}$) |
|----|----------------|-------------------|------------------|----------------|----------------|
| Boot (B) | 8.31 ± 0.54 | 2.7 ± 0.05 | 3.0 | 1.2 ± 0.12 | 19.2 ± 0.21 |
| Canvasback (CB) | 9.55 ± 0.96 | 2.26 ± 0.01 | 10.7 | 2.41 ± 0.17 | 29.83 ± 0.22 |
| Greenpepper (GP) | 9.02 ± 0.96 | 4.1 ± 0.04 | 6.2 | 0.42 ± 0.03 | 32.82 ± 0.40 |
| Ninemile (NM) | 9.46 ± 0.05 | 6.5 ± 0.00 | 9.7 | 1.09 ± 0.31 | 27.64 ± 0.07 |
| Scoter (SC) | 8.93 ± 0.00 | 7.1 ± 0.05 | 6.3 | 0.47 ± 0.20 | 19.46 ± 0.08 |
| YF17 (Y17) | 9.82 ± 35 | 83.3 ± 0.33 | 14.6 | 2.42 ± 0.59 | 35.65 ± 0.54 |
| YF20 (Y20) | 10.24 ± 0.78 | 1.26 ± 0.4 | 10.3 | 1.09 ± 0.83 | 10.17 ± 0.14 |
clear and shallow nature of these macrophyte-rich lakes creates favorable conditions for the remote sensing of benthic properties.

3.3. **Linking in situ GPP to Sentinel-2 lake color**

Lake color from satellite and airborne sensors was regressed against 2018 *in situ* GPP (mg O$_2$ m$^{-2}$ d$^{-1}$) ($n = 7$), revealing a strong, positive correlation between greenness and GPP (figure 3(a), $p$-value < 0.05). We then applied this regression pixel-wise to Sentinel-2 imagery to create spatially-explicit GPP maps (figures 3(b) and (c)) for each lake. Modeled, S2 GPP ranged from 3.9 ± 1.14 mg O$_2$ m$^{-2}$ d$^{-1}$ in the deep, upland Boot Lake to 14.21 ± 6.42 mg O$_2$ m$^{-2}$ d$^{-1}$ in shallow, eutrophic YF17.

3.4. **Independent evaluation with Landsat**

The relationship was then evaluated using a separate dataset from a 2016 field campaign that had been withheld for independent testing (figure 4). As same-week images were not available, we instead regressed seasonal L8 composites against 2018 *in situ* GPP ($n = 7$) and 2016 *in situ* GPP ($n = 17$) (Bogard et al 2019). The correlation between greenness and *in situ* GPP was maintained across both models.

The L8 seasonal composites produced a slightly stronger relationship (type 2 major axis regression: $y = 385.81x - 0.45; r^2 = 0.69; p = 2.60 \times 10^{-4}; n = 24$) than the Sentinel-2 same-week model. This likely results from the smoothing of short-term variability from the composite and the relative stability of oxygen pools (Bogard et al 2017) in these shallow lakes on seasonal scales. The separate models provide an independent check against each other, further substantiating the robustness of this approach across sensors and years.

The use of Landsat allows us to tap into the powerful historical imagery available through the Landsat archive in order to detect decadal (Wang et al 2014, Lymburner et al 2016) and seasonal (Kallio et al 2008) trends in lake color. Lake greenness computed for Scoter Lake (figure 5) showed a decline from 1984 to 2018. Field studies suggest that declines in greenness could result from increased CDOM absorption resulting from thermokarst processes for lakes with higher absorption (Wauthy et al 2018), increases in depth (Duguay and Lafleur 2003), or increased sediment loading during periods of surface water connectivity (Vonk et al 2015). Subsequent research combining these techniques with paleolimnology (Pienitz et al 1999, Bouchard et al 2017) and radiocarbon (Rühlman et al 2003) data has the potential to unveil past lake processes, although more testing is required to establish mechanistic links between these processes and lake color across more diverse ecosystems.

3.5. **AVIRIS-NG, PlanetScope and *in situ* $R_s$**

Surface reflectance from different sensors showed the greatest agreement in the green band.

Using high-resolution PlanetScope and AVIRIS-NG $R_s$ (table S2), Sentinel-2 and *in situ* $R_s$ (figures 6, S1-2), we compared $R_s$ and respective model performance using 2018 *in situ* GPP. Analyzing agreement between the blue, green, red and NIR bands, we found the best agreement in the green (MAPD median = 29%, interquartile range 8%–53%) (figure S1-2, text S3-4).

Green $R_s$ is less subject to inter-sensor differences (Pahlevan et al 2018) and calibration errors between Landsat sensors (Vogelmann et al 2016). S2’s green $R_s$ has been successfully ground-truthed over small thermokarst lakes and ponds by Freitas et al (2019) and green $R_s$ is also less impacted than NIR by particulates (Wang and Philpot 2007). Green $R_s$ also has the major advantage of being measured by almost every spectral remote sensing platform, dating back to early Landsat (Dwyer et al 2018) and including the upcoming Plankton Aerosol, Cloud,
Figure 4. Scatter plot using L8 composites ($R_s; 560$ nm) and in situ GPP from 2016 and 2018 ($g$ O$_2$ m$^{-2}$ d$^{-1}$) ($n = 24$). The 2016 in situ GPP is the average of June and September; 2018 in situ GPP was collected once during July. The 2016 (shown in blue, $n = 17$) and 2018 (shown in green, $n = 7$) $R_s$ was calculated from June to September composites (see text for full description). The S2 model from figure 1(d) ($n = 7$) is shown in grey for comparison. L8 regression model and coefficients of determination ($r^2$) are given in inset. Scene IDs can be found in table S2.

Figure 5. Landsat time series of greenness for Scoter Lake. Black dots represent median growing season greenness at the sampling location. The red line is the Thiel–Sen slope ($y = -0.00023x + 0.61$) with the $p$-value from the Mann–Kendall significance test given top left. Grey shading depicts launch of Landsat-7, after which two Landsat sensors have continuously been in orbit. Green shading represents time period of ABoVE field campaigns.

Ocean Ecosystem (PACE) Mission (Werdell et al 2019). Finally, previous studies have shown greenness covaries with both phytoplankton (O’Reilly et al 1998, O’Reilly and Werdell 2019) and macrophytes (Hestir et al 2015). In light of the larger disagreements between sensors detected in the NIR (text S4), these results suggest that green $R_s$ may be a stable, sensor-agnostic quantity suitable for GPP modeling across a range of spectral, spatial and temporal resolutions.
3.6. GPP model results for green and red-edge bands across sensors

In situ GPP (mg O₂ m⁻² d⁻¹) corresponded with greenness (table 3, figures S3–4). The strongest correlation was between in situ GPP and in situ Rs (r² = 0.68; p-value < 0.05) and CubeSat Rs (r² = 0.78; p-value < 0.05). This could be due to two factors. First, in situ Rs was collected simultaneous to in situ GPP, in contrast to the overpasses 2–5 d later. However, unlike dynamic river and coastal systems, processes in these lakes vary on seasonal and annual scales. For example, high-frequency daily observations of dissolved oxygen collected from May to September (Bogard et al 2019) show consistently positive rates of net production driven by intense plant growth was sustained throughout most of the growing season. Johnston et al (2020) also showed diel dissolved organic matter composition and optical properties changed minimally over a 3 d period. A second reason for the stronger performance of PlanetScope and the in situ sensor’s performance could be because of their finer spatial resolution relative to other sensors (10–30 m).

While restricting the time difference between field and satellite observations can improve model uncertainty in dynamic river systems (Kuhn et al 2019), albeit time differences of up to 3 to 5 d have been used successfully in several lake studies (Kloiber et al 2002, Chipman et al 2004, Olmanson et al 2008, Boucher et al 2018). Shorter time differences are ideal, yet given the temporal stability of the dissolved oxygen pool and water color over several days in these lakes, we are confident that these results are representative and provide important insights, particularly given the lack of comparisons of surface reflectance over inland waters (Maciel et al 2020).

A second advantage of Sentinel-2 over Landsat-8 is the addition of red-edge bands suitable for mapping vegetation. An even stronger correlation than with greenness was observed between GPP and the red-edge band (704 nm) (table 3, S3). Models improved by an average of 16% (table 3) due to the strong red-edge reflectance of macrophytes. This suggests that, when available, red-edge bands may be the strongest candidate for modeling GPP in these shallow lake ecosystems whose GPP is driven by both macrophytes and phytoplankton. This finding has implications for future missions as red-edge bands with narrower bandpasses are increasingly being added to, for example, Planet Lab’s next-generation Dove satellites.
Table 3. Regression results between July 2018 $R_s$ and in situ GPP fitted using a Type II regression model using the green (560 nm) and the red-edge (704 nm) bands from each sensor. The empty row results from PlanetScope lacking a red-edge band. All $p$-values were $<0.05$ (table S3) and individual scatterplots are provided in figures s3 and s4.

| Green ($\sim$560 nm) | Red-edge ($\sim$704 nm) |
|----------------------|-------------------------|
|                      | Slope | Intercept | $r^2$ | Slope | Intercept | $r^2$ |
| S2 TOA               | 478.91| -22.46    | 0.30  | 478.91| -22.46    | 0.56  |
| S2 LaSRC             | 446.18| -5.93     | 0.53  | 446.18| -5.93     | 0.62  |
| PlanetScope          | 413.39| -6.65     | 0.78  | NA    | NA        | NA    |
| AVIRIS-NG            | 607.19| -4.51     | 0.40  | 607.19| -4.51     | 0.74  |
| ASD Field Spec       | 146.86| 4.43      | 0.68  | 146.86| 4.43      | 0.80  |

While the green band is suitable for historic analysis, these findings encourage red-edge based algorithm development due to the strong signal in these shallow arctic and boreal lakes.

The correlation between green and NIR bands with in situ GPP across sensors and sites indicates their potential as a simple GPP proxy for shallow lakes with low turbidity and CDOM. For context, global ocean models typically only explain 40% of water-column-integrated primary production (Siegel et al 2001). The strength of this relationship between lake color and in situ GPP for both 2016 and 2018 datasets suggests potential for the development of a remote sensing modeling framework for shallow lake GPP.

4. Conclusions

This study provides evidence of a simple empirical relationship between lake color and GPP for shallow, relatively clear boreal lakes using in situ field data paired with remote sensing. We use a novel approach that pairs oxygen isotopes with satellite imagery. Both techniques integrate pelagic and benthic processes from phytoplankton and macrophytes in shallow waters (Wetzel and Hough 1972, Jackson 2003). Summertime CO$_2$ drawdown in shallow lakes has been linked to macrophyte growth, highlighting the potentially important role of macrophytes in lake carbon cycling (Tank et al 2009, Vesterinen et al 2016). Shallow lakes are abundant worldwide and therefore the ability to integrate benthic and pelagic GPP is crucial for capturing whole ecosystem GPP.

In terrestrial systems, NDVI has been widely adopted as a useful, albeit imperfect, proxy for vegetation biomass (Rouse 1974). NDVI has transformed our understanding of landscape change in remote northern regions (Jia et al 2003, Goetz et al 2005, Bhatt et al 2013, Ju and Masek 2016, Sulla-Menashe et al 2018), yet no such metric has been adopted for shallow lakes. This study provides initial evidence of the green band as a potential simple index for mapping GPP in shallow, light-filled, and highly productive northern lakes. We then confirmed this relationship using Landsat-8 and compare results from other sensors including AVIRIS-NG and PlanetScope. This study demonstrates green and red-edge bands from Sentinel-2, Landsat-8, AVIRIS-NG and PlanetScope can be used to map GPP when constrained with appropriate field data. More detailed in situ measurements of lake color and biogeochemistry across optically diverse systems are needed to further test this finding. Advances in field data collection needs to be prioritized for algorithm development across the circumpolar north.

In the Yukon Flats, warming and thawing has led to lake area decline (Jepsen et al 2013, 2016). Surveying all 30 000 lakes in this region is not feasible yet the area is predicted to undergo drastic hydrologic changes linked to increasing permafrost thaw (Walvoord and Striegl 2007, Walvoord et al 2012). Our findings suggest further work developing remote sensing algorithms for GPP could advance lake monitoring at scales useful for climate science and ecosystem management.

Acknowledgments

This research was supported by a NASA Earth and Space Science Fellowship (NESSF) awarded to CDK. Data collection was also supported by NASA-ABoVE Project 14-14TE-0012 (awards NNH16AC03I and NNX15AU14A) and the U.S. Geological Survey (USGS) Land Carbon Program. Sample collection was made possible by the expert flights in and out of lakes by Jim Webster (Webster’s Flying Service). We thank the Remote Sensing and Geospatial Analysis Laboratory (RSGAL) lab for the use of the ASD Field Spectrometer. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. We also thank three anonymous reviewers for their constructive comments.

Data availability statement

Any data that support the findings of this study are included within the article.

ORCID iDs

Catherine Kuhn @ https://orcid.org/0000-0002-9220-630X
Matthew Bogard  https://orcid.org/0000-0001-9491-0328
Sarah Ellen Johnston  https://orcid.org/0000-0002-6237-0379
Aji John  https://orcid.org/0000-0002-4401-1401
Rob Spencer  https://orcid.org/0000-0003-0860-4717
Mark Dornblaser  https://orcid.org/0000-0002-6298-3757
Kim Wickland  https://orcid.org/0000-0002-6400-0590
Rob Stiegl  https://orcid.org/0000-0002-8251-4659
David Butman  https://orcid.org/0000-0003-3520-7426

References
Anderson L, Birks J, Rover J and Guldager N 2013 Controls on recent Alaskan lake changes identified from water isotopes and remote sensing Geophys. Res. Lett. 40 3413–8
Anderson L, Edwards M, Shapley M D, Finney B P and Langdon C 2019 Holocene thermokarst lake dynamics in northern Interior Alaska: the interplay of climate, fire, and subsurface hydrology Front. Earth Sci. 7
Antoine D, André J and Morel A 1996 Oceanic primary production: 2. estimation at global scale from satellite (coastal zone color scanner) chlorophyll Glob. Biogeochem. Cycles 10 57–69
Ask J, Karlsson J and Jansson M 2012 Net ecosystem production: 2. estimation at global scale from satellite (coastal zone color scanner) chlorophyll Glob. Biogeochem. Cycles 26
Aurin D A and Dierssen H M 2012 Advantages and limitations of ocean color remote sensing in CDOM-dominated, mineral-rich coastal and estuarine waters Remote Sens. Environ. 125 181–97
Beck P S A and Goetz S J 2011 Satellite observations of high northern latitude vegetation productivity changes between 1982 and 2008: ecological variability and regional differences Environ. Res. Lett. 6 45501
Behrenfeld M J, Boss E, Siegel D A and Shea D M 2005 Carbon-based ocean productivity and phytoplankton physiology from space Global Biogeochem. Cycles 19
Bergamino N et al 2010 Spatio-temporal dynamics of phytoplankton and primary production in Lake Tanganyika using a MODIS based bio-optical time series Remote Sens. Environ. 114 772–80
Bhatt U et al 2013 Recent declines in warming and vegetation greening trends over pan-Arctic Tundra Remote Sens. 5 4229–54
Bocanovic S A, Schiff S L and Smith R E H 2012 Plankton metabolism and physical forcing in a productive embayment of a large oligotrophic lake: insights from stable oxygen isotopes Freshwater Biol. 57 481–96
Bogard M J et al 2019 Negligible cycling of terrestrial carbon in many lakes of the arid circumpolar landscape Nat. Geosci. 12 180–5
Bogard M J, Vachon D, Sr.-Gelais N F and Del Giorgio P A 2017 Using oxygen stable isotopes to quantify ecosystem metabolism in northern lakes Biogeochemistry 133 347–64
Bouchard F et al 2017 Paleolimnology of thermokarst lakes: a window into pastaermofrost lake evolution Arct. Sci. 3 91–117
Boucher J, Weathers K C, Norouzi H and Steele B 2018 Assessing the effectiveness of Landsat 8 chlorophyll a retrieval algorithms for regional freshwater monitoring Ecol. Appl. 28 1044–54
Bue B D, Thompson D R, Eastwood M, Green R O, Gao B-C, Keymeulen D, Sarture C M, Mazer A S and Luong H H 2015 Real-time atmospheric correction of AVIRIS-NG imagery IEEE Trans. Geosci. Remote Sens. 53 6419–28
Carder K L, Steward R G, Harvey G R and Ortner P E 1979 Marine humic and fulvic acids: their effects on remote sensing of ocean chlorophyll Limnol. Oceanogr. 34 68–81
Chen M, Rowland J C, Wilson C J, Altman G L and Brumby S P 2014 Temporal and spatial pattern of thermokarst lake area changes at Yukon Flats, Alaska Hydrol. Processes 28 837–52
Chipman J W, Lillesand T M, Schmalz J E, Leple J E and Northem M J 2004 Mapping lake water clarity with Landsat images in Wisconsin, USA Can. J. Remote Sens. 30 1–7
Deininger A, Faithfull C L and Bergstrom A 2017 Phytoplankton response to whole lake inorganic N fertilization along a gradient in dissolved organic carbon Ecology 98 982–94
Deng Y, Zhang Y, Li D, Shi K and Zhang Y 2017 Temporal and spatial dynamics of phytoplankton primary production in Lake Taihu derived from MODIS data Remote Sens. 9 195
Dogliotti A, Gossin J, Vanhellemont Q and Ruddick K 2018 Detecting and quantifying a massive invasion of floating aquatic plants in the Río de la Plata turbid waters using high spatial resolution ocean color imagery Remote Sens. 10 1140
Dörnhöfer K and Oppelt N 2016 Remote sensing for lake research and monitoring – recent advances Ecol. Indic. 64 105–22
Downing J A et al 2006 The global abundance and size distribution of lakes, ponds, and impoundments Limnol. Oceanogr. 51 2386–97
Duguay C R and Laffite P M 2003 Determining depth and ice thickness of shallow sub-Arctic lakes using space-borne optical and SAR data Int. J. Remote Sens. 24 475–89
Dwyer J et al 2018 Analysis ready data: enabling analysis of the Landsat Archive Remote Sens. 10 3636
Fahnenstiel G L, Sayers M J, Shuchman R A, Yousef F and Pothoven S A 2016 Lake-wide phytoplankton production and abundance in the Upper Great Lakes: 2010–2013 J. Great Lakes Res. 42 619–29
Freitas P, Vieira G, Canário J, Folhas D and Vincent W 2019 Identification of a threshold minimum area for reflectance retrieval from thermokarst lakes and ponds using full-pixel data from Sentinel-2 Remote Sens. 11 657
Gallant A L 1995 Ecoregions of Alaska No. 1567 (Washington, DC: US Government Printing Office)
Genkai-Kato M, Vadeboncoeur Y, Liboriussen L and Jeppesen E 2012 Benthic–planktonic coupling, regime shifts, and whole-lake primary production in shallow lakes Ecology 93 619–31
Glesne R S 1986 Lake fishery habitat survey and classification on Ecoregions of Alaska No. 1567 (Washington, DC: US Government Printing Office)
Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D and Gore M 2017 Google earth engine: planetary-scale data from Sentinel-2 Remote Sens. 11 64–81
Haintjens N 2018 Pyflx 0.1.0 PyPl available at: https://pypi.python.org/pypi/pyflx/
Halm D R and Griffith B 2014 Water-quality Data from Lakes in the Yukon Flats, Alaska, 2010–2011 USGS Open File Report 1181 (Reston, VA: US Geological Survey)
Halm D R and Guldager N 2012 Water-quality Data of Lakes and Wetlands in the Yukon Flats, Alaska, 2007–2009 (Reston, VA: US Geological Survey)
Heglund P J and Jones J R 2003 Limnology of shallow lakes in the Yukon Flats National Wildlife Refuge, Interior Alaska Lake Reservoir Manage. 19 133–40
Hestir E L et al 2015 Measuring freshwater aquatic ecosystems: the need for a hyperspectral global mapping satellite mission Remote Sens. Environ. 167 181–95
Hirsch R M, Slack J R and Smith R A 1982 Techniques of trend analysis for monthly water quality data Water Resour. Res. 18 107–21
Jackson L J 2003 Macrophyte-dominated and turbid states of shallow lakes: evidence from Alberta lakes Ecosystems 6 213–23
Jeppesen E et al 1998 Impact of submerged macrophytes on fish-zooplankton interactions in lakes The Structuring Role of Submerged Macrophytes in Lakes (Berlin: Springer) pp 91–114
Jeppesen S M, Voss C I, Walvoord M A, Rose J R, Minsley B J and Smith B D 2013 Sensitivity analysis of lake mass balance in discontinuous permafrost: the example of disappearing Twelvemile Lake, Yukon Flats, Alaska (USA) Hydrogeol. J. 21 185–200
Jeppesen S M, Walvoord M A, Voss C I and Rover J 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Jia G J, Epstein H E and Walker D A 2003 Greening of arctic Environ. Res. Lett. 2014 Thermokarst lake waters across the permafrost zones pp 5234–7
Johnston S E 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Jepsen S M, Voss C I and Rover J 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Jepsen S M, Voss C I and Rover J 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Jepsen S M, Walvoord M A, Voss C I and Rover J 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Jepsen S M, Walvoord M A, Voss C I and Rover J 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Jepsen S M, Walvoord M A, Voss C I and Rover J 2016 Effect of permafrost thaw on the dynamics of lakes recharged by ice-jam floods: case study of Yukon Flats, Alaska Hydrolog. Processes 30 1782–95
Ju J and Maske J G 2016 The vegetation greenness trend in Canada and US Alberta from 1984–2012 Landsat data Remote Sens. Environ. 176 1–16
Kallio K, Attila J, Härmä P, Koponen S, Pulliainen J, Hyttinen U-M and Pyhälähti T 2008 Landsat ETM+ images in the estimation of seasonal lake water quality in boreal river basins Environ. Manage. 42 511–22
Kauer T, Kutser T, Arst H, Danckaert T and Noges T 2015 Modelling primary production in shallow well mixed lakes based on MERIS satellite data Remote Sens. Environ. 163 253–61
Kellerman A M et al 2019 ‘Fundamental drivers of dissolved organic matter composition across an Arctic effective precipitation gradient’ Limnol. Oceanogr. 10 1–18
Kloiber S M, Brezonik P L, Olmanson L G and Bauer M E 2002 A procedure for regional lake water clarity assessment using Landsat multispectral data Remote Sens. Environ. 82 38–47
Kuhn C et al 2019 Performance of Landsat-8 and Sentinel-2 surface reflectance products for river remote sensing retrievals of chlorophyll-a and turbidity Remote Sens. Environ. 224 104–18
Kutser T et al 2020 Remote sensing of shallow waters – A 50 year retrospective and future directions Remote Sens. Environ. 240 111169
Lee Z, Marra J, Perry M J and Kahrui M 2015 Estimating oceanic primary productivity from ocean color remote sensing: A strategic assessment J. Mar. Syst. 149 50–59
Lymburner L, Botha E, Hestir E, Hruschka M, Dekker A and Malthus T 2016 Landsat 8; providing continuity and increased precision for measuring multi-decadal time series of total suspended matter Remote Sens. Environ. 185 108–18
Maciel D A, Novo E M L M, Barbosa C C F, Martins V S, Flores Júnior R, Oliveira A H, Sander De Carvalho L A and Lobo F D I 2020 Evaluating the potential of CubeSats for remote sensing reflectance retrieval over inland waters Int. J. Remote Sens. 41 2807–17
Malthus T J, Hestir E L, Dekker A G and Brando V E 2012 The case for a global inland water product quality 2012 IEEE Int. Geoscience and Remote Sensing Symp. (Piscataway, NJ: IEEE) pp 5234–7
Manasypov R M, Pokrovsky O S, Kirpotin S N and Shirokova L S 2014 Thermokarst lake waters across the permafrost zones of western Siberia Cryosphere 8 1177–93
Massicotte P, Asmaul E, Stedmon C and Markager S 2017 Global distribution of dissolved organic matter along the aquatic continuum: across rivers, lakes and oceans Sci. Total Environ. 609 180–191
Matthews M W 2011 A current review of empirical procedures of remote sensing in inland and near-coastal transitional waters Int. J. Remote Sens. 32 6855–6899
Messager M L, Lehner B, Grill G, Nedeva I and Schmitt O 2016 Estimating the volume and age of water stored in global lakes using a geo-statistical approach Nat. Commun. 7 13603
Minsley B J et al 2012 Airborne electromagnetic imaging of discontinuous permafrost Geophys. Res. Lett. 39 L02503
Mobley C, Boss E and Roesler C 2020 NASA Ocean Optics Web Book 2020th edn. Edited by N. grant NNX14AQ49G
Creative Commons available at: https://oceanopticsbook.info/view/references/publications
Morel A and Prieur L 1977 Analysis of variations in ocean color&rsquo; s 2019 Limnol. Oceanogr. 22 709–22
Mouw C B et al 2017 A consumer’s guide to satellite remote sensing of multiple phytoplankton groups in the global ocean Front. Mar. Sci. 4 41
Myneni R B, Keeling C D, Tucker C J, Asrar G and Nemani R R 1997 Increased plant growth in the northern high latitudes from 1981 to 1991 Nature 386 698
O’Reilly J E, Maritorena S, Mitchell B G, Siegel D A, Carder K L, Garver S A, Kahrui M and McClain C 1998 Ocean color chlorophyll algorithms for SeaWiFS J. Geophys. Res. 103 24937–53
O’Reilly J E and Werdell P J 2019 Chlorophyll algorithms for ocean color sensors-OC4, OCS & OC6 Remote Sens. Environment 229 32–47
Olmanson L G, Bauer M E and Brezonik P L 2008 A 20-year Landsat water clarity census of Minnesota’s 10,000 lakes Remote Sens. Environment, 112 4086–97
Osburn C L, Wigdahl C R, Fritz S C and Saros J E 2011 Dissolved organic matter composition and photoactivity in prairie lakes of the US Great Plains Limnol. Oceanogr. 56 2371–90
Overland J E et al 2019 Ivory gull: status, trends and new knowledge Arctic Report Card 2019 (Silver Spring, MD: NOAA)
Overland J E and Wang M 2005 The Arctic climate paradox: the recent decrease of the Arctic Oscillation Geophys. Res. Lett. 32
Oyama Y, Matsuishi B and Fukushima T 2015 Distinguishing surface cyanobacterial blooms and aquatic macrophytes using Landsat/TM and ETM+ shortwave infrared bands Remote Sens. Environment. 157 35–47
Pahlevan N, Balasubramanian S, Sarkar S and Franz B 2018 Toward long-term Aquatic science products from heritage landsat missions Remote Sens. 10 1337
Pahlevan N, Sarkar S and Franz B A 2016 Uncertainties in coastal ocean color products: impacts of spatial sampling Remote Sens. Environment, 181 114–26
Pahlevan N, Smith B, Binding C and O’Donnell D M 2017 Spectral band adjustments for remote sensing reflectance spectra in coastal/inland waters Opt. Express 25 28650–67
Palmburner L, Botha E, Hestir E, Arst H, Noges T, Sander De Carvalho L A and Lobo F D I 2015 Remote sensing of inland waters: challenges, progress and future directions Remote Sens. Environment. 157 1–8
Pastick N J, Jorgenson M T, Goetz S J, Jones B M, Wylie B K, Minsley B J, Genet H, Knight J F, Swanson D K and Jorgenson J C 2019 Spatiotemporal remote sensing of ecosystem change and causation across Alaska Global Change Biol. 25 1711–89
Pietracci N, Vilj J O, Mysterud A, Gaillard J-M, Tucker C J and Stenseth N C 2003 Using the satellite-derived NDWI to assess ecological responses to environmental change Trends Ecol. Evol. 20 503–10
Pienitz R, Smol J P and Macdonald G M 1999 Paleoecological reconstruction of Holocene climatic trends from two boreal treeline lakes, Northwest Territories, Canada Arct. Antarct. Alp. Res. 31 82–95
