DEVELOPING A MODEL TO ESTIMATE FRESHWATER GROSS PRIMARY PRODUCTION USING MODIS SURFACE TEMPERATURE OBSERVATIONS

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Abstract. Lakes contribute to local and regional climate conditions, cycle nutrients, and are viable indicators of climate change due to their sensitivity to disturbances in their water and airsheds. Utilizing spaceborne remote sensing (RS) techniques has considerable potential in studying lake dynamics as it allows for coherent and consistent spatial and temporal observations, and, ultimately, estimates of lake functions without in situ measurements. However, in order for RS products to be utilized in this way, algorithms that relate in situ measurements to RS data must be developed. Estimates of lake metabolic rates are of particular scientific interest since they are indicative of lakes' roles in carbon cycling and ecological function. There have been recent advances in modeling lake metabolism using high frequency sensor data. However, to date, there are few existing algorithms relating remote sensing products to in-lake estimates of metabolic rates. Here we use satellite surface temperature observations from Moderate Resolution Imaging Spectroradiometer (MODIS) product (MYD11A2) and published in-lake gross primary production (GPP) estimates for eleven globally distributed lakes during a one-year period to produce a univariate quadratic equation model/algorithms. Statistical analyses reveal significant positive relationships between MODIS temperature data and the previously modeled in-lake GPP. Lake-specific algorithms with MODIS temperature such as those for Lake Mendota (USA), Rotorua (New Zealand), and Rotoiti (New Zealand), showed stronger relationships than the general combined model using all lakes (n = insert number of lakes used), pointing to local influences. The 'global' algorithm we developed was validated using lakes whose GPP was estimated during an equivalent one-year time period but not utilized in the model, and showed a strong relationship (R2=0.76). These validation data suggest that our 'global' algorithm has a potential to predict lake GPP on a global scale.

INTRODUCTION

Lakes provide a multitude of ecosystem services such as supplying water for human use, supporting habitat for biodiversity, and regulating local and regional climate (Postel 2000, Bronmark and Hanson 2002, Krinner 2003). Although lakes cover a small global area, this area is larger than originally thought by the scientific community (Downing et al. 2006), and there are more than 117 million lakes around the globe (Verpoorter et al. 2014). Currently, many if not most of these lakes are threatened by problems such as increased nutrient load, pollution, acidification, and invasive species (Tranvik et al. 2009). Sensitive to these types of inputs, lakes are considered indicators of ecosystem health and sentinels of climate change (Williamson et al. 2009). Studying lakes and their biogeochemical interactions has the potential to reveal many mechanisms behind ecosystem processes.

Lakes play an important role in the global carbon cycle. Carbon is constantly exchanged between lakes, atmosphere, and land. Twice as much carbon flows into inland aquatic systems from the land as flows from the land to sea (Cole et al. 2007). At the landscape level, lake ecosystems cycle carbon by receiving terrestrial carbon and producing organic carbon as a result of primary productivity (Tranvik et al. 2009).

They also have the capacity to act as both sinks and sources of CO_2 depending on available nutrients and food web structure (Schindler et al. 1997). Nutrient loading as a result of land use (e.g., agriculture) in lake catchments has been identified as a primary influence on eutrophication (increased productivity) and climate change can further impact increased productivity and nutrient cycling (Blenckner et al. 2002). Climate change will likely impact various biomes in differing ways, as decreased productivity triggered by climate change has been recorded as well as increased (O'Reilly et al. 2003). As a result, the scientific community is interested in understanding lake metabolism (gross primary productivity and respiration (Solomon et al. 2013) as an integrated measure of lake function. Lake ecosystem gross primary productivity, or the rate at which organic matter is synthesized in a given time period, is of particular importance since inland aquatic waters constitute a small portion of the Earth's surface, yet are highly productive (Likens 1975). Primary producers within lake ecosystems often include phytoplankton, macrophytes, and periphyton (Dodson et al. 2000), and these organisms and their metabolic rates can be affected by disturbances such as nutrient loading and climate change (Mooji et al. 2005, Solomon et al. 2013). Thus, understanding the processes that contribute to lake metabolism can help further elucidate mechanisms driving a changing global carbon budget.

Understanding ecosystem-level processes such as lake metabolism and how it responds to disturbances such climate change requires frequent, long-term data collected on large spatial scales (Williamson et al. 2009). Currently, this is difficult to do given the small temporal and spatial scales and varied methods carried about in many lake studies (Palmer et al. 2015). Traditionally, lake metabolism is measured using bottle methods wherein water samples at different irradiance levels are captured in chambers and respiration and production are measured using elemental tracers such as carbon 14 (Staehr et al 2010). Generally daily values of gross primary production are derived from measurements taken per hour and then multiplied by day length (Morin et al. 1999). Such methods have limitations in that it is difficult to scale measurements and findings up to the ecosystem level due to uncertainty in container measurements (Bender et al. 1987), among other things. Recently, metabolism has been estimated using high frequency data from sensors suspended from in-lake buoys (e.g., www.gleon.org, Solomon et al. 2013, Richardson et al. 2016).

While it is difficult to manually carry out sampling across large spatial scales, remote sensing provides an opportunity to upscale and obtain indices of water quality parameters from local to global scales (Tyler et al. 2016, Xiao et al. 2008). Applying remote sensing to lake studies is relatively novel, given that remote sensing technology has been historically developed primarily to gather information from land and ocean surfaces (Palmer et al. 2015). However, there is an increasing need for using remote sensing to infer lake ecological functions as well as for monitoring as evidenced by several governmental agencies funding national lake monitoring projects that utilize remote sensing (Drusch et al. 2012). Again, this is, in part, because changes in lakes are indicative of larger ecosystem and climatic changes. In addition, several of the newly launched sensors such as Landsat 8 operate at spatial and temporal resolutions that can be used for inland waters (Pahlevan et al. 2014).

One sensor that is particularly useful for time series analysis is the MODerate Resolution Imaging Spectroradiometer (MODIS). MODIS is one of the instruments onboard NASA's Earth Observing System (EOS) satellites, Terra (AM) and Aqua (PM). It has a temporal resolution of 1-2 days that is useful for time series analyses. MODIS has a spatial resolution ranging from 250 m to 1km, and 36 spectral channels or bands that provide information about conditions in the water, land, and atmosphere (Table 1). In addition, it is one of the few sensors to have publically available data from the Earth Science Distributed Archive Centers from its inception in 2002 (Engel-Cox 2004). There are 44 processed data sets or products available on the DAAC, but region-specific algorithms may need to be applied to these data to acquire desired measurements. Data products are provided for atmosphere, land, ocean, and cryosphere, (Table 2) but none exist for freshwater aquatic systems.

While the capability of satellite sensors to retrieve information from inland waters is limited due to the need for hyperspectral data that may not be available at needed spatial resolutions, many studies have successfully applied water constituent retrieval algorithms and obtained promising results (Kutser et al. 2009). For example, in-lake chlorophyll a has been successfully estimated using remote sensing (Gitelson et al. 2008, Dall'Olmo et al. 2006), although accuracy levels vary for each study. A major obstacle in applying remote sensing to lake ecology involves developing specific water constituent retrieval algorithms. There is currently no universal algorithm given the optical complexity of inland waters and thus many studies make use of products developed for studying ocean waters (Tyler et al. 2016), whether or not the systems under study are marine.

A crucial aspect of applying remote sensing techniques to inland water pattern and process detection includes the development of algorithms that relate remote sensing products to in-lake measurements. There are various types of algorithms, such as those depending on band ratios derived from statistical relationships, algorithms based on physics-based optical models, and those depending on machine learning approaches (Morel and Priuer 1977, Werdell et al. 2013, Kiener and Yan, 1998). Algorithms using band ratios must be modified to incorporate regional environmental differences, but are generally applicable to a variety of lakes (Tyler et al. 2016). It must be noted that no studies have been conducted on relating remote sensing data to freshwater GPP estimates, making this project novel in methods and interdisciplinary approach (Fig 1).

The overarching question under which this research sits is: How can remote sensing be applied to better understanding lake ecosystem processes? Specifically,

- What is the relationship between remote sensing data and in-lake lake estimates of metabolism, specifically GPP?
- Does MODIS surface temperature data correlate well with either individual, in-lake GPP estimates for lakes that span large geographic extents as well as trophic states?
- Can a robust 'global' algorithm, which includes many lakes from around the world, be identified?

SITE DESCRIPTION

The ten lakes included in this study are a subset of the twenty-five lakes used in a previous study that examined in-lake metabolism through modeling gross primary productivity and respiration (Solomon et al. 2013). The study utilized high frequency sensor data to build the metabolism models. These lakes are part of the Global Lake Ecological Observatory Network (GLEON; www.gleon.org), in which high frequency and high resolution sensors are used to understand how lakes function in the face of global environmental change. Sensors are used to obtain dissolved oxygen (DO), water temperature, wind speeds, and other lake characteristic measurements. The lakes used in this study are as follows: Lake Balaton, (Hungary), Lough Feeagh (Ireland), Kentucky Lake, (Kentucky USA), Lake Mendota (USA), Müggelsee Lake (Germany), Lake Pontchartrain (Louisiana, USA) Lake Rotoiti (New Zealand), Lake Rotorua, (New Zealand), Sunapee Lake, (New Hampshire, USA), Lake Taihu (China), and Trout Lake (USA) (Table 3). The lakes vary in size, geographic location, and trophic state.

DATA & METHODS

In-lake data: In-lake gross primary production estimates (mg O_2/L/d) for GLEON lakes were obtained from the Solomon et al. 2013 paper (via C. Solomon). These GPP estimates were derived by analyzing changes in dissolved oxygen as measured by the in-lake buoys. Of the twenty-five GLEON lakes from Solomon's 2013 study, 11 lakes had an area over 1 km^2 and were therefore large enough to be detected using the MODIS sensor and consequently analyzed in this study.

MODIS data: Four MODIS products were initially explored in order to determine potential relationships between these products and the in-lake modeled GPP estimates. These products were: Surface Temperature and Emissivity, (MYD11A2), Vegetation Indices (MYD13A2), Surface Reflectance (MYD09A1), and Terrestrial Gross Primary Production (MYD17A2). Note that the MYD17A2 product estimates terrestrial GPP using eddy flux towers and does not incorporate aquatic GPP. Initial tests revealed strong relationships only between in-lake modeled GPP and the surface temperature observations; the MYD11A2 product was therefore selected as the main focus for this investigation.

Surface temperature observations were obtained from NASA's Reverb metadata discovery tool. The MODIS Aqua surface temperature product (MYD11A2) data were downloaded for each lake for time periods corresponding to the in-lake modeled GPP. The MYD11A2 is a ground-truth validated product containing Global land surface temperature (LST) and emissivity 8-day data compiled from daily 1 km resolution photos. The data are stored on a 1 km sinusoidal grid as average values of clear-sky surface temperature in the 8-day period. The retrieved hdf files were processed in MATLAB (r2016a) by running scripts to extract daytime LST data. Pixel indexing ensured that the point of MODIS observation was within the lake area. The daily in-lake GPP estimate values were compiled into 8-day average values in order to be comparable to the 8-day average LST values. The emissivity data, representing how well the surface could radiate thermal energy, were constant values throughout the time period of the study and not used.

The coordinates of the data points utilized in this study were cross-referenced using Google Maps to ensure that temperature outputs were from the lake instead of nearby land. One lake in particular, Lake Feeagh, could not be included in the analysis because the pixel location of the satellite data retrieval was not in the water body and in fact on nearby land. Consequently, surface temperature readings represented ground temperature, not lake water temperature.

The data were screened for invalid outputs and temperature values of 0 were removed. Linear regression modeling was employed to determine the relationship between temperature and GPP for each of the individual 10 lakes, and best-fit curves were generated. In addition, the data for the 10 lakes were compiled and a general combined 'Global' model was determined using linear regression.

For validation of the general combined model, modeled GPP data from Lake Acton (another lake in the GLEON metabolism study) using the MODIS LST data for a one-year period. Lake Acton was the only lake used for validation because it was the only remaining in the Solomon et al. (2013) paper (hence containing identically calculated GPP values) large enough to be captured by the 1-km MODIS sensor.

RESULTS

It is important to note that the in-lake modeled GPP peak values ranged from 0.4 to 25 mg O2 L/d, and some lakes displayed stronger seasonal patterns of GPP than others (Solomon et al. 2013). This daily variation of GPP values was muted in the calculation of 8-day averaged values of GPP and led to the creation of several outliers.

It is also important to note that the in-lake modeled GPP displayed a wide ranged of values from 0.4 to 25 mg O2 L/d; some lakes were oligotrophic (low productivity) and others were eutrophic (high productivity). Further, some lakes displayed stronger seasonal patterns of GPP than others (Solomon et al. 2013). In addition, day-to-day spikes in GPP values not apparent when looking at 8-day averaged values of GPP and could have led to potential outliers (for example two unusually high GPP values could drive up the 8-day average value).

Regression analysis showed MODIS Surface Temperature observations correlated positively with the in-lake modeled GPP (R^2=0.27)(Figure 3). The data were screened for invalid outputs and temperature values of 0 were removed. The best-fit model for all combined lake data is the univariate quadratic equation $y=0.0046x^2 - 0.038x + 0.23$ ($p < 0.001$). Individually, most of the lakes displayed stronger correlations between modeled GPP and MODIS surface temperature than the general combined model (Table 2). The three lakes with individual best-fit quadratic univariate models include Kentucky, Rotorua and Rotoiti. Two of these lakes are in the temperate zone of the Southern Hemisphere and one is in the Northern Hemisphere temperate zone. The quadratic equation best fitting Kentucky Lake was $y=0.119x^2-0.1912x+ 0.8123$, and its coefficient of determination was $R^2 = 0.59$ ($p < 0.001$). The quadratic model for Lake Rotorua was best described with the equation $y = 0.0041x^2-0.0546x + 0.4763$, with an R^2 of 0.71 ($p < 0.001$). Lake Rotoiti had a best-fit model with an equation y=-94.191x2 + 285.18x - 214.76 and an R^2 of 0.58021 ($p<0.001$). Six of the remaining lakes had R^2 values higher than that of general combined model, with the exception of Trout Lake, which had a model fit equation of y = 24.405x2 - 71.03x + 51.75 that was not statistically significant (Table 4).

The resulting quadratic equation from the combined general model was used to estimate Lake Acton's GPP from the downloaded MODIS surface temperature data. The new, MODIS-derived estimated GPP values were correlated with Solomon et al.'s (2013) previously in-lake modeled GPP values. The data were fit to a linear line with the equation y = 3.9619x - 2.879 and R2=. 7603(p=0.00021784) (Figure 6).

DISCUSSION

The results of this study yield several interesting findings. First, the relationship between in-lake modeled GPP for lakes of a wide global distribution and satellite surface temperature observations points to the potential for the creation of a global aquatic freshwater GPP product. In addition, the temperature-GPP relationship has possible biological and ecological mechanistic explanations behind it.

The ecological reasoning for why temperature and gross primary production seem to be positively related is complex. On a cellular level, metabolic rates are influenced by temperature. Analysis of ice cores from the Vostok Lake suggest that there is no temperature minimum for metabolic processes to be carried out by phytoplankton and unicellular organisms, and that metabolism increases with increases in temperature (Price and Sowers 2004). In terms of limnological metabolism, lake respiration is temperature dependent on a cellular level, but an increasing number of variables lead to increased variation when scaled up to the ecosystem level (Yvon-Durocher 2010).

Temperature Dependence of Respiration

The GPP values in the Solomon et al. 2013 paper were derived by multiplying the average rate of photosynthesis per unit of photosynthetically active radiation (PAR). Ecosystem respiration, or the sum of the respiration of living organisms in the system, was also calculated in this study and when subtracted from the GPP values, yields NPP or Net Primary Production. Note that collectively, ecosystem level GPP and respiration constitute ecosystem metabolism (Solomon et al. 2013). In this case of this study, it is difficult to isolate respiration from GPP and assert that the temperature dependence of respiration (a potential component of GPP estimates) is responsible for the correlation between temperature and GPP. Further analysis in comparing Solomon et al. (2013) respiration rates with the MODIS temperature output could help to determine drivers of the relationship.

Physical and Biological Lake Properties Relating to Lake Temperature

The relationship between remotely sensed lake temperature and GPP could also potentially be explained by the physical properties of lakes. For example, GPP is coupled influenced by in-lake properties such as bathymetry, morphometry, depth, and catchment conditions, factors also influencing lake temperature (Carpenter et al. 2005, Staehr et al. 2012). Studies also show that temperature is the best predictor of chlorophyll biomass (Staehr et al. 2007), and chlorophyll biomass is, essentially, gross primary production. A study conducted on Lake Mendota (one of the lakes included in this study) suggested that algal-macrophyte interactions were controlled by lake morphometry and temperature (Carpenter et al. 2005), and it can be inferred that algae and macrophytes are organisms that contribute to lake GPP. In addition, nutrient inputs and algal productivity are influenced by lake properties such as depth (Staehr and Jensen 2007). The models for individual lakes had stronger R^2 than the 'global' model, which suggests that individual lake watershed characteristics have an impact on GPP. Examining the area: volume ratio of the watershed may further elucidate GPP dynamics. Lake size also plays an important role in in-lake productivity and its heterogeneity. Lake Taihu is known to have different concentrations of chlorophyll a in different parts of the lake, given its impressive size of 2338 km^2 (Zhang and Liu 2007). In this sense, remote sensing could help to provide GPP measurements of large lakes that would be time consuming to obtain in situ.

Impact of In-Lake Processes

In addition to physical properties of lakes, storms and microstratification are two factors that can be considered when trying to understand the drivers behind GPP and the reasoning for the spread in the individual lake models, however these drivers would be difficult to discern from remotely sensed data. Microstratification occurring in lakes has been shown to correlate to lower values of GPP and respiration (Coloso et al. 2011). Given that microstratification was not something that was measured or considered in any of the individual lakes, it cannot be said whether or not it occurred, and/or if disruptions to microstratification are responsible for data outliers. Storm-induced destratification and subsequent changes in algal communities has been documented in Lake Balaton, Hungary (Padisák et al. 1990), and such potential losses of algal species can alter GPP rates. Daily changes in GPP that could have been potentially caused by storms were not captured in this study since the GPP values were averages of 8-day time periods. If MODIS could provide daily LST observations, these could be correlated with daily GPP estimates and perhaps outliers could be more easily revealed.

The relationship between GPP and temperature that was confirmed by this study is important since long-term temperature changes can even lead to shifting or mixing regimes such from polymictic to dimictic or dimictic to monomictic (Boehrer and Schultze 2008, Livingstone 2008). Being able to obtain changing GPP measurements could help predict shifting regimes and ultimately stop adverse changes before they occur.

Challenges and Opportunities

While producing some promising results, this is a first step toward building a GPP product for lakes. A few of the challenges and opportunities are listed below. One primary challenge is the limited spatio-temporal inference of remote sensing. For example, the LST output only retrieves surface temperatures of the water body. Some amount of gross primary production occurs beneath the surface (Carignan et al. 1998), and utilizing only surface temperatures might affect the certainty of the model of below surface GPP that is occurring. In addition, surface temperature observations are 8-day composites of daily images, and currently no MODIS surface temperature and emissivity product at the correct spatial resolution produces daily LST outputs. Daily surface temperatures are available at coarser resolution and downscaling techniques may resolve this issue. Correlating daily GPP values to daily temperature values could reveal more fine-scale patterns.

The variation in the results that could not be explained by the general model or the individual lake models can perhaps be attributed to the uncertainty in the GPP values resulting from Solomon et al.'s (2013) work. For example, Solomon et al. attribute uncertainty in their model to ecological variation among other considerations. This same ecological variation could be contributing to the spread in the data points when being fit to the model. Furthermore, for each of the lakes, there are several days throughout the one-year time period in which there are no estimated GPP values. As a result, several 8 day time periods had no corresponding GPP values, leading to fewer data points. In addition, Trout Lake had GPP values ranging from only 9.79 x 10^{-13} mg O_2/L/d to 0.43 mg O_2/L/d; it was the only lake for which no real correlation existed between GPP measurements and MODIS temperature output. This could be because these GPP values were far too small and there is in fact a threshold of GPP measurements below which relationships between the two variables cannot be determined. This could potentially mean that the general model would have difficulty in predicting extremely low values of GPP, but it is generally well-suited predict moderate and higher levels of GPP.

Model Improvement

Currently, the general model has been validated with only Acton Lake because there was only one available lake from the 2013 Solomon et al. study that was not included in our general model but still big enough to be located by the MODIS sensor. Testing the model with more lakes with identically calculated GPP values could further validate the robustness of the general model.

Future Product Development

Despite uncertainty due to ecological variation amongst lakes and logistical difficulties with the state of technology of remote sensing, the results of this study point to great potential for applying remote sensing technologies to ecosystem-scale lake metrics of lake function. The fact that the general model can explain 27% of the variation in the data is promising since the lakes are globally distributed and have a range of ecological and physical properties. A number of previous lake remote sensing studies reveal that their algorithms are better suited for regional prediction of lake indices (Dörnhöfer and Oppelt 2016, Woelmer et al. 2016) and while this may be currently true for the GPP model, future improvements could result in a good global predictor. Currently, there is no freshwater GPP MODIS product, and it is possible that creation of a more robust algorithm that takes into consideration certain ecological parameters could lead to such a product. Interestingly, the MODIS product for terrestrial gross primary production calculates GPP as the total organic carbon accretion in the ecosystem in a given time period (Source: MODIS product development PDF), which is conceptually different from the photosynthetic rates that were used to obtain GPP values from Solomon et al. (2013). Since NEP and organic carbon accumulation are not always equivalent in aquatic systems (Lovett et al. 2006), it is important that future aquatic GPP products or algorithms produce estimates of GPP that are consistent with current limnological standards. In addition, the dates for which lake GPP was analyzed include summer months, when GPP is often at its peak. Lakes' GPP have seasonal variation, with low concentration of chlorophyll a in the winter (Zhang and Liu 2007). An aquatic GPP product could allow for prediction of GPP levels during all seasons (excluding ice-on periods), which, over long-term analysis can reveal broad patterns about GPP fluctuations. Ultimately, this preliminary study suggests that remote sensing can be used for global-scale understanding of lake metabolism and ecosystem processes.

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APPENDIX

TABLE 1. List of bands available from the MODIS sensor and the type of information they collect. Information on MODIS bands from were obtained from https://lpdaac.usgs.gov/ maintained by the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, [2014].

BAND	PRIMARY USE
1	Land/Cloud Aerosol Boundaries
2	
3	
4	Land/Cloud/Aerosol Properties
5	
6	
7	
8	Ocean Color/Phytoplankton/Biogeochemistry
9	
10	
11	
12	
13	
14	
15	
16	
17	Atmospheric Water Vapor
18	
19	
20	
21	
22	
23	
24	Atmospheric Temperature
25	
26	Cirrus Cloud/Water Vapor
27	
28	
29	Cloud Properties
30	Ozone
31	Surface/Cloud Temperature
32	
33	Cloud Top Altitude
34	
35	
36	

TABLE 2. List and specifications of MODIS Aqua products available for use and download.

Name	Dataset	Product	Pixel Size	Temporal Granularity
MYD09A1	Aqua MODIS	Reflectance	500	Composites
MYD09CMG	Aqua MODIS	Reflectance	5600	Daily
MYD09GA	Aqua MODIS	Reflectance	500, 1000	Daily
MYD09GQ	Aqua MODIS	Reflectance	250	Daily
MYD09Q1	Aqua MODIS	Reflectance	250	Composites
MYD11_L2	Aqua MODIS	Temperature and Emissivity	1000	5 Minute
MYD11A1	Aqua MODIS	Temperature and Emissivity	1000	Daily
MYD11A2	Aqua MODIS	Temperature and Emissivity	1000	Composites
MYD11B1	Aqua MODIS	Temperature and Emissivity	5600	Daily
MYD11C1	Aqua MODIS	Temperature and Emissivity	5600	Daily
MYD11C2	Aqua MODIS	Temperature and Emissivity	5600	Composites
MYD11C3	Aqua MODIS	Temperature and Emissivity	5600	Monthly
MYD13A1	Aqua MODIS	Vegetation Indices	500	Composites
MYD13A2	Aqua MODIS	Vegetation Indices	1000	Composites
MYD13A3	Aqua MODIS	Vegetation Indices	1000	Monthly
MYD13C1	Aqua MODIS	Vegetation Indices	5600	Composites
MYD13C2	Aqua MODIS	Vegetation Indices	5600	Monthly
MYD13Q1	Aqua MODIS	Vegetation Indices	250	Composites
MYD14	Aqua MODIS	Thermal Anomalies and Fire	1000	5 Minute
MYD14A1	Aqua MODIS	Thermal Anomalies and Fire	1000	Daily
MYD14A2	Aqua MODIS	Thermal Anomalies and Fire	1000	Composites
MYD15A2	Aqua MODIS	Leaf Area Index and Fractional Photosynthetically Active Radiation	1000	Composites
MYD17A2	Aqua MODIS	Gross Primary Productivity	1000	Composites

Information on MODIS products were obtained from https://lpdaac.usgs.gov/ - maintained by the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, [2014].

TABLE 3. Denotes characteristics of the eleven lakes analyzed in this study. These lakes are a subset of 25 lakes in a GLEON global lake study (Solomon et al. 2013). The 'Dates' category refers to the dates for which data was collected on a daily basis.

Lake Name	Country	Dates	Area (km^2)	Latitude	Longitude	Trophic Status
Balaton	Hungary	6/13/2008-10/11/08	38	46.717	17.245	Oligotrophic
Kentucky	USA	1/1/2008-12/30/08	970	36.739	-88.109	Mesotrophic
Pontchartrain	USA	3/21/2008-12/31/08	1603	30.316	-90.283	Oligotrophic-mesotrophic
Rotorua	New Zealand	7/13/2007-7/12/08	79.8	-38.066	176.266	Eutrophic
Sunapee	USA	5/1/2008-10/30/08	16.7	43.383	-72.033	Oligotrophic
Taihu	China	10/9/2007-10/30/08	2338	31.287	120.202	Eutrophic
Muggelsee	Germany	3/11/2008-12/7/08	7.46	52.438	13.648	Eutrophic
Mendota	USA	7/10/2008-11/3/08	39.4	43.099	-89.652	Oligotrophic
Rotoiti	New Zealand	7/25/2008-7/23/2009	34.6	-38.039	176.428	Eutrophic
Trout	USA	5/30/2008-11/10/08	16.1	46.029	-89.665	Oligotrophic

Trophic status key: *Oligotrophic*: low nutrient, clear lake. *Mesotrophic:* moderate level of dissolved nutrients. *Eutrophic:* nutrient rich lake, with abundance of plant life.

TABLE 4. Results of regression analysis of MODIS LST output versus in-lake modeled GPP. Shows the coefficient of determination and significance level for each individual lake general regression model.

Regression Analysis of MODIS LST Output v In-Lake Modeled GPP			
Lake Name	Country	R^2	P-value
Balaton	Hungary	0.31	0.097
Feeagh	Ireland	0.37	< 0.001
Kentucky	USA	0.59	< 0.001
Mendota	USA	0.55	0.005
Muggelsee	Germany	0.33	0.001
Pontchartrain	USA	0.35	< 0.001
Rotoiti	New Zealand	0.58	< 0.001
Rotorua	New Zealand	0.71	< 0.001
Sunapee	USA	0.44	0.002
Taihu	China	0.52	< 0.001
Trout	USA	0.05	0.966

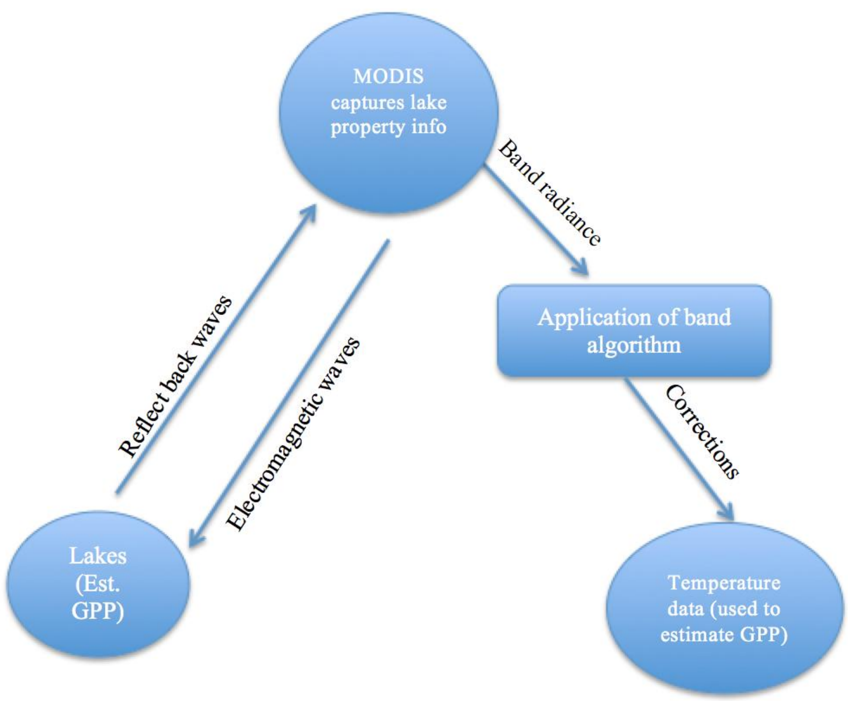

FIGURE 1. Conceptual model showing how information about lakes can be retrieved from remote sensing.

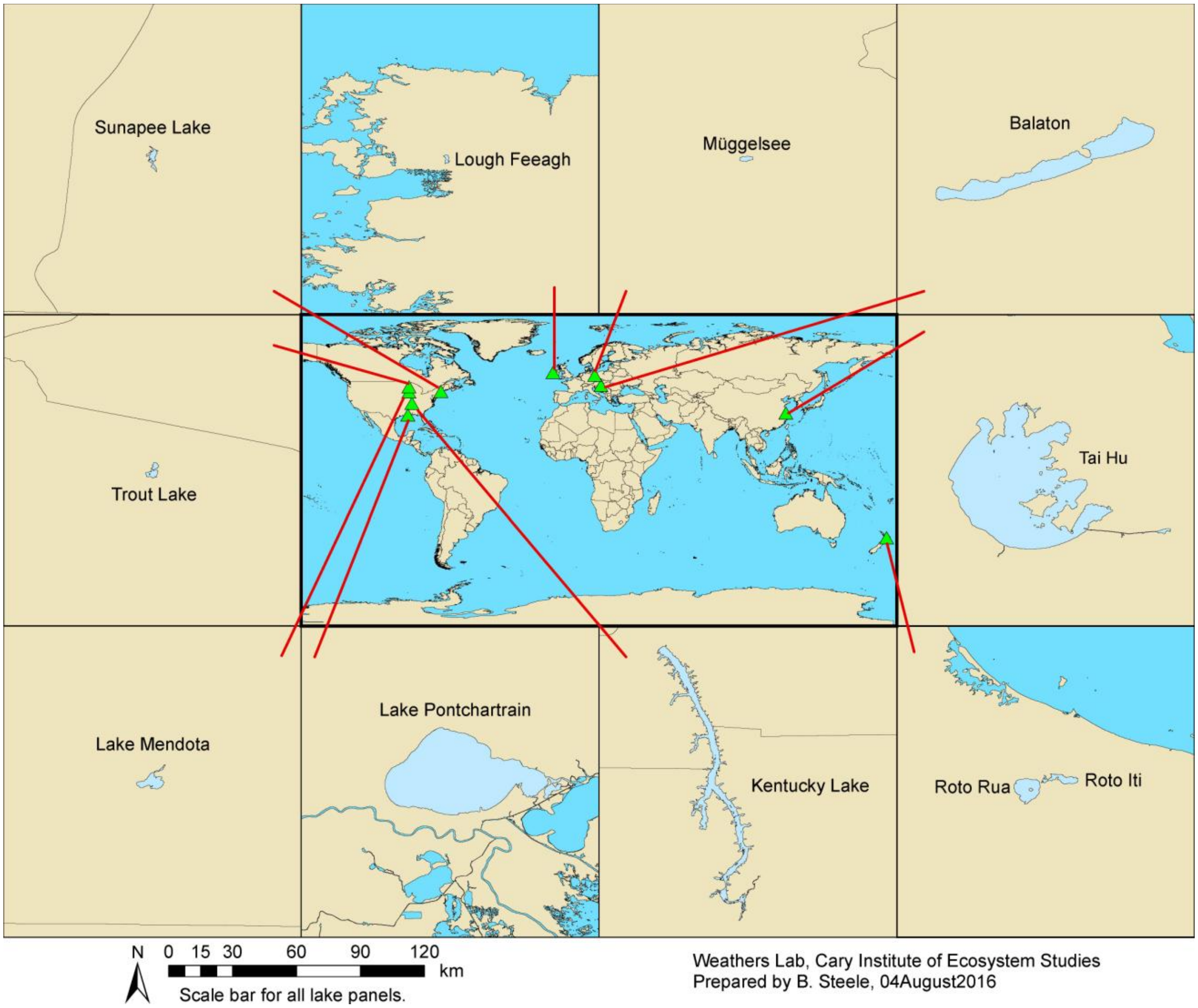

FIGURE 2. Map illustrating the global locations, size, and shapes of each of the lakes included in this study.

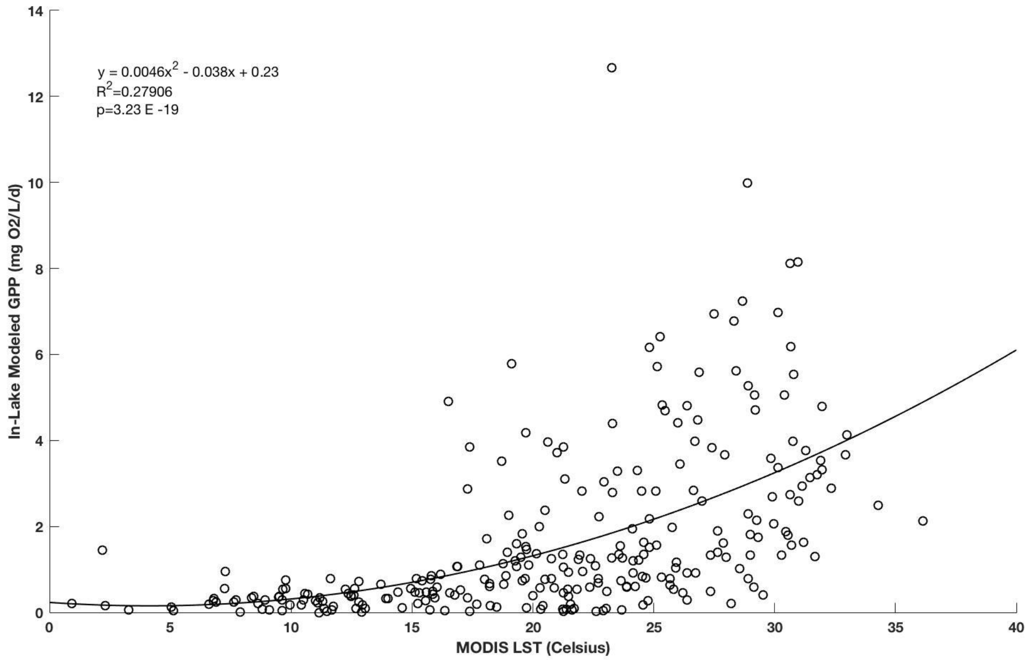

FIGURE 3. Quadratic model fit for all lakes' GPP predicted from MODIS temperature output. (N=263, p=3.23 E -19).

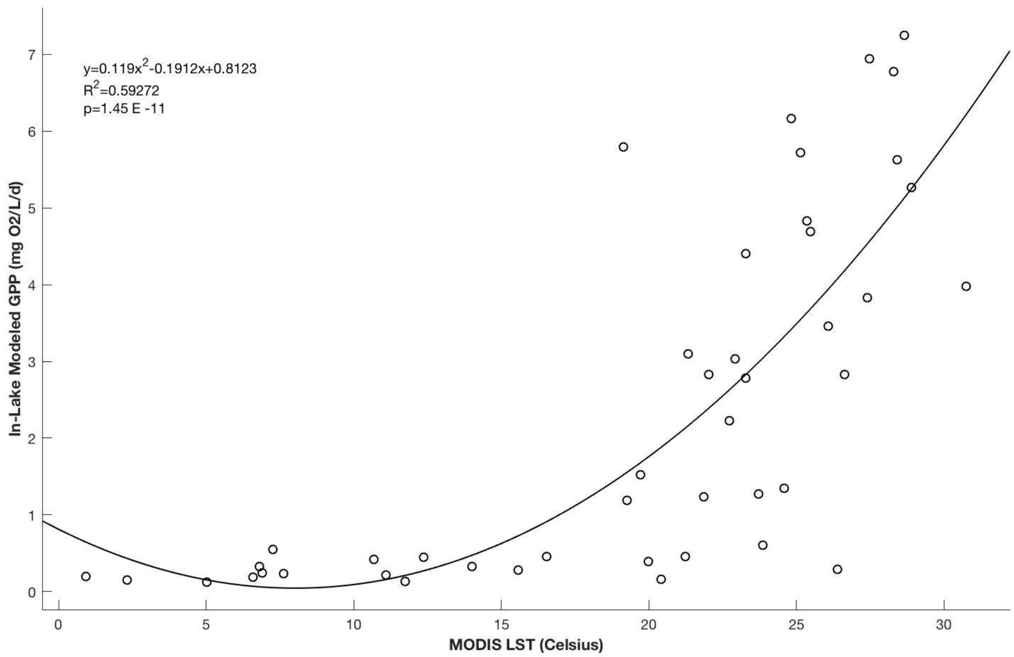

FIGURE 4. Quadratic model fit for Kentucky Lake GPP predicted from MODIS temperature output. (N=45, p=1.45 E -11).

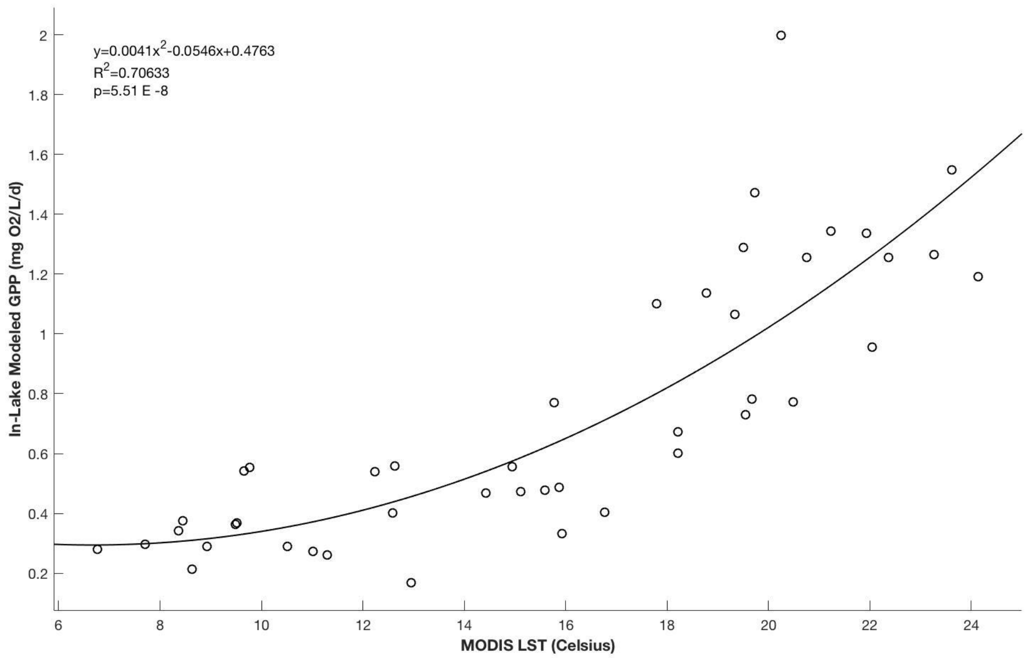

FIGURE 5. Quadratic model fit for Lake Rotorua GPP predicted from MODIS temperature output. (N=44, p=5.51 E -8).

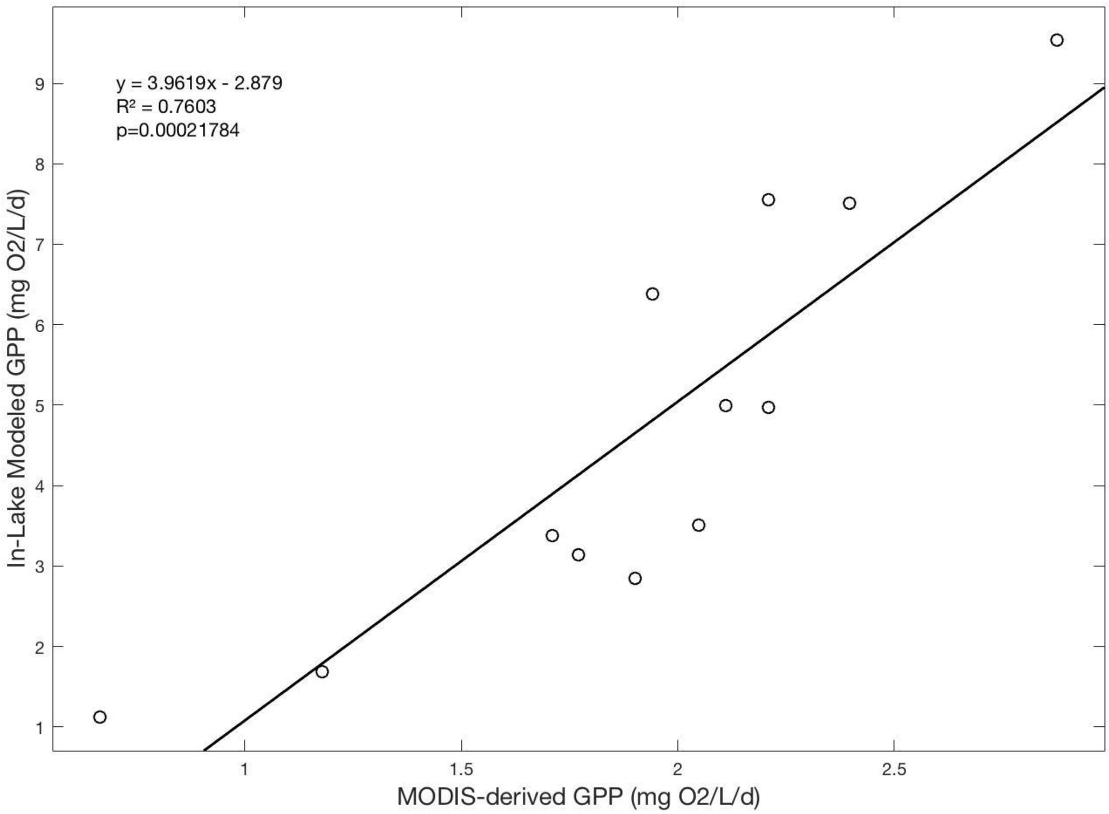

FIGURE 6. Linear model fit for Lake Acton GPP predicted from MODIS-derived GPP 'Global Model'. (N=12, p=. 00021784).