Remote Sensing of Global Lake Gross Primary Production

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ABSTRACT

Lakes contribute to local and regional climate conditions, cycle nutrients, and are indicators of climate change due to their sensitivity to disturbances in their air and watersheds. Spaceborne remote sensing (RS) techniques have promise for studying lake dynamics by allowing for consistent spatial and temporal observations and estimates of lake functions without *in situ* measurements. Recent advances in modeling lake metabolism use high frequency sensor data, but there are few existing algorithms that relate RS products to in-lake estimates of metabolic rates. I use satellite surface temperature observations from MODIS product MYD11A2 and published in-lake gross primary productivity (GPP) estimates for ten globally distributed lakes, with areas greater than 1 km^2 , varying trophic states and surrounding land cover to produce a univariate quadratic equation model. Statistical analyses reveal a significant positive relationship ($p<.00001$) between MODIS temperature data and in-lake GPP for the global model. I performed preliminary validation on the global model using a lake reserved from the data set (Lake Acton) resulting in a strong correlation (R^2=0.76) between MODIS-derived GPP and previously modeled values. Lake-specific algorithms such as those for Rotorua (NZ) and Kentucky (USA) had stronger relationships than the global model derived from all ten lakes, pointing to the influence of regional biological and physical characteristics of the lakes and their watersheds. Analyses of land cover type within lake watersheds and in-lake GPP revealed a positive correlation with forested land cover and GPP ($R=0.67$, $p=0.03$).Land cover type was incorporated into a separate model that was not statistically significant. These data suggest that it may be possible to predict GPP for lakes across a wide geographic region.

KEYWORDS

Remote sensing, GLEON, MODIS, global lakes, algal blooms, and management

INTRODUCTION

Lakes play an important role in the global carbon cycle, support habitat for biodiversity and regulate climate (Postel 2000, Bronmark and Hanson 2002, Krinner 2003). Although lakes cover a small global area, there more than 117 million lakes on the planet, they are disproportionately important (Verpoorter et al. 2014). At the landscape level, freshwater lake ecosystems cycle carbon by receiving and processing terrestrial carbon from their surrounding catchments as well as by fixing carbon via photosynthesis by biota within the lake (Tranvik et al. 2009). In addition to carbon, lakes also cycle nutrients including phosphorus and nitrogen (Cottingham et al. 2015)

Sensitive to inputs such as increased nutrient load, pollution, acidification, and invasive species, lakes are indicators of ecosystem health and sentinels of climate change (Williamson et al. 2009). For example, Lake Taihu in China is one of many large lakes experiencing increased productivity and cyanobacteria blooms (McCarthy et al. 2007). However, the mechanisms of how climate change will affect biological lake processes such as productivity are still not well understood. We know, nonetheless, that anthropogenic climate change caused by burning fossil fuels that release excess carbon into the atmosphere impacts the global carbon cycle by putting lakes at risk for increased productivity and nutrient cycling (Blenckner et al. 2002). Excessively productive lakes can lead to harmful algal blooms that, ultimately, can result in the death of lake fauna (Anderson et al. 2002). Despite their relatively small size, lakes can impact global productivity and the overall global carbon cycle more than previously thought by serving as both sources and sinks of carbon. This relatively disproportionate impact on global productivity is because twice as much carbon flows into inland aquatic systems from the land as flows from the land to sea (Cole et al. 2007). Increased global productivity could lead to changes in vegetation growth and consequently alter food webs (Carpenter et al. 1897, Nemani et al. 2003). In addition, changes in gross primary productivity (GPP) can result from differences in land cover types within the watershed, which contribute nutrients that get exported to freshwater systems (Gergel et al. 1996). In contrast, in-lake contributors to GPP include size, depth, and morphology (Carpenter et al. 2005).

Estimating GPP and respiration (lake ecosystem metabolism) has recently been used as a measure of function within lakes. Solomon et al. (2013) modeled daily estimates of respiration and gross primary productivity for the course of a full year in 25 globally distributed lakes. In these lakes respiration rates differed on a day-to-day basis, resulting from variability in GPP. This study created a spatially and temporally extensive database of modeled lake GPP and respiration that can be used, along with remotely sensed (RS) data to create models of ecosystem metabolism. Here, as a first step, I focus on building algorithms for predicting GPP in lakes.

What is the importance of examining the relationship of RS and in-lake modeled data to predict GPP? Understanding ecosystem-level processes and responses to disturbances such as climate change requires frequent, long-term data collected on large spatial scales (Williamson et al. 2009) and remote sensing offers the potential to make global estimates of productivity. Temporally frequent data are useful because productivity is highly variable on an annual basis and long-term analysis can help to detect patterns and changes. Yet obtaining such data is difficult given the small temporal and spatial scales and varied field methods carried about in many lake studies (Palmer et al. 2015). Traditional methods of bottle sampling cannot be scaled up to the ecosystem level because of uncertainty and the amount of physical labor required. Although the advent of sensors and sensor networks (see the Global Lake Ecological Observatory Network www.gleon.org) that collect high frequency data in lakes are an improvement, too few lakes have such equipment. For example, the Solomon et al. (2013) metabolism modeling project used dissolved oxygen measurements from GLEON's in-lake sensors. Here I suggest that the use of The MODerate Resolution Imaging Spectroradiometer (MODIS) sensor with its temporal resolution of 1 to 2 days, and a spatial resolution from 250 m to 1km may be, when coupled with in-lake data, a useful tool for expanding spatial and temporal estimates of lake GPP. Components of lake metabolism such as GPP and respiration can vary on a day-to-day and seasonal basis due to differences in light and nutrient availability (Solomon et al. 2013) and MODIS is a sensor that can capture these short-term changes. There have been studies conducted using the MODIS sensor that applied ocean techniques to inland waters, yet there are none that use it to estimate freshwater GPP and lake productivity.

How can remote sensing be applied to better understand lake ecosystem processes? Specifically, what is the relationship between remote sensing data and in-lake estimates of GPP? Objectives include testing for a relationship between MODIS surface temperature data and in-lake GPP estimates that span large geographic extents and across trophic states in order to identify a robust 'global' algorithm, I hypothesize that there is a positive relationship between satellite-derived surface temperature and in-lake metabolism estimates, and that a global algorithm can be identified with the incorporation of weather anomaly corrections. Because lakes are influenced by their surrounding watersheds, I also examine MODIS land cover data and in lake modeled GPP to examine the influence of land cover types on productivity. Finally, I explore whether the combination of watershed land cover and in-lake temperature results in stronger predictions of in-lake GPP.

METHODS

Study system and site description

GLEON dataset

The study system for this project includes ten globally distributed lakes that are a subset of the twenty-five lakes used by Solomon et al. (2013) that examined in-lake metabolism through modeling gross primary productivity and respiration. These lakes are part of the Global Lake Ecological Observatory Network (GLEON; www.gleon.org), whose mission it is to understand lake ecosystem function in a changing environment. Many GLEON lakes are equipped with high frequency and high-resolution sensors that collect dissolved oxygen (DO), water temperature, and light data along with meteorological variables. Several recent papers (e.g., Solomon et al. 2013) have utilized these data to model in-lake daily metabolism (GPP and respiration). In this study, I include Lake Balaton (Hungary), Kentucky Lake (Kentucky USA), Lake Mendota (Wisconsin, 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 (Wisconsin, USA) (Table 1) all of which have modeled GPP data for 2008.

Table 1. List of Lakes and Identifying Information. Lakes utilized in this study span a variety of trophic states, sizes, and geographic locations. Latitude is in degrees North of the prime meridian and longitude is in degrees West of PM.

Lake Name	Country	Latitude	Longitude	Area (km^2)	Average GPP (mg O2/L/d)	Trophic State	Start Date	End Date
Balaton	Hungary	46.717	17.245	38	2.57	Oligotrophic	6/13/08	10/11/08
Kentucky	USA	36.739	-88.109	970	2.19	Mesotrophic	1/1/08	12/30/08
Pontchartrain	USA	30.316	-90.283	1603	1.76	Olio-mesotrophic	3/21/08	12/31/08
Rotorua	New Zealand	-38.066	176.266	79.8	0.73	Eutrophic	7/13/07	7/12/08
Sunapee	USA	43.383	-72.033	16.7	0.052	Oligotrophic	5/1/08	10/30/08
Taihu	China	31.287	120.202	2338	2.69	Eutrophic	10/9/07	10/30/08
Müggelsee	Germany	52.438	13.648	7.46	2.33	Eutrophic	3/11/08	12/7/08
Mendota	USA	43.099	-89.652	39.4	2.32	Oligotrophic	7/10/08	11/3/08
Rotoiti	New Zealand	-38.039	176.428	34.6	0.57	Eutrophic	7/25/08	7/23/09
Trout	USA	46.029	-89.665	16.1	0.076	Oligotrophic	5/30/08	11/10/08

To create a model predicting in-lake GPP from lake surface temperature, I used in-lake gross primary production estimates (mg O_2/L/d) for GLEON lakes (Solomon et al. 2013) as the dependent variable in my model. These GPP estimates were derived by analyzing changes in dissolved oxygen as measured by the in-lake buoys using maximum likelihood fit methods.

Remote sensing dataset

The remote sensor used in this study is MODIS (Moderate Resolution Imaging Spectroradiometer), a sensor aboard NASA's AQUA satellite that completes a rotation around the Earth every one to two days at varying spatial resolution depending on the information gathered. The MODIS lake surface temperature data used in this study are stored on a 1 km sinusoidal grid as average values of clear-sky surface temperature in the 8-day period.This temporal frequency of this MODIS data is critical to estimate the daily lake GPP data, and preferred to that of other sensors such as LANDSAT which only completes an Earth rotation once every 16 days and therefore provides fewer data points. MODIS has 36 spectral channels or bands that provide information about conditions in the water, land, and atmosphere (Table 2). 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 NASA's Land Processes Distributed Active Archive Center website (LPDAAC), but region-specific algorithms may need to be applied to these data to acquire desired measurements. Using the MODIS sensor to study changes in ecosystem processes and patterns over time is preferred given its increased temporal granularity compared to other sensors.

Table 2: MODIS spectral bands and their primary uses. MODIS sensor has 36 available spectral bands, and bands 1-3 are used to calculate the Land Surface Temperature product.

Band Number	Primary Use
1-3	Land/Cloud Aerosol Boundaries
4-7	Land/Cloud Aerosol Properties
8-16	Ocean Color/Phytoplankton/Biogeochemistry
17-23	Atmospheric Water Vapor
24-25	Atmospheric Temperature
26-28	Cirrus Cloud/Water Vapor
29	Cloud Properties
30	Ozone
31-32	Surface/Cloud Temperature
33-36	Cloud Top Altitude

The MODIS land cover data are also from the LPDAAC and are stored on a sinusoidal grid at a 500-meter resolution. Single images showing land cover are available for each one year time period (Table 3). I combined the 16 MODIS Land Cover classifications from Type 1 into five groups for easier analysis. Groups 1,2,3,4, and 5 comprised group 1, called 'Forest.' I classified groups 6 and 7 as shrublands. I combined groups 8,9, into a savanna/grassland classification. I identified groups 11,12, and 14 as croplands, and lastly groups 13 and 16 as urban/bare. I excluded snow, ice and water because of the focus on terrestrial land cover in the watershed.

Table 3: MODIS MCD12Q1 Land cover types description (Classes 1-4) The MODIS land cover product has distinctly classified land cover types, including forests, savannas, and croplands.(Source: LPDAAC)

Class	IGBP (Type 1)	UMD (Type 2)	LAI/fPAR (Type 3)	NPP (Type 4)
0	Water	Water	Water	Water
1	Evergreen needleleaf forest	Evergreen needleleaf forest	Grasses/Cereal crops	Evergreen needleleaf vegetation
2	Evergreen broadleaf forest	Evergreen broadleaf forest	Shrubs	Evergreen broadleaf vegetation
3	Deciduous needleleaf forest	Deciduous needleleaf forest	Broadleaf crops	Deciduous needleleaf vegetation
4	Deciduous broadleaf forest	Deciduous broadleaf forest	Savanna	Deciduous broadleaf vegetation
5	Mixed forest	Mixed forest	Evergreen broadleaf forest	Annual Broadleaf vegetation
6	Closed shrublands	Closed shrublands	Deciduous broadleaf forest	Annual Grass vegetation
7	Open shrublands	Open shrublands	Evergreen needleleaf forest	Non-vegetated land
8	Woody savannas	Woody savannas	Deciduous needleleaf forest	Urban
9	Savannas	Savannas	Non-vegetation	
10	Grasslands	Grasslands	Urban	
11	Permanent wetlands			
12	Croplands	Croplands		
13	Urban and built-up	urban and built-up		
14	Cropland/Natural veg mosaic			
15	Snow and ice			
16	Barren or sparsely vegetation			
254	Unclassified			

GPP and lake surface temperature model

To determine potential relationships between these MODIS products and the in-lake modeled GPP estimates, I initially explored four MODIS data products. These products were: Surface Temperature and Emissivity, (MYD11A2), Vegetation Indices (MYD13A2), Surface Reflectance (MYD09A1), and Terrestrial Gross Primary Production (MYD17A2). Initial tests revealed strong relationships only between in-lake modeled GPP and the surface temperature observations (measured in Kelvin); I therefore selected the MYD11A2 product as the main focus for this investigation.

I obtained surface temperature observations from NASA's Reverb metadata discovery tool (NASA LPDAAC 1). I also downloaded MODIS Aqua surface temperature product (MYD11A2) data for each lake for the time periods (Table 1) 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 complied from daily 1 km resolution photos. 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. I processed the retrieved hdf files in MATLAB (r2016a) by running scripts to extract daytime LST data. Pixel indexing ensured that the point of MODIS observation was in the center of each lake body. I compiled daily in-lake GPP estimate values into 8-day average values in order to be comparable to the 8-day average LST values. To ensure that temperature outputs were from the lake instead of nearby land, I used Google Maps to cross-referenced the coordinates of the lake data points used in this study.

To determine the relationship between lake surface temperature (LST)(independent variable x) and in-lake GPP (dependent variable y) for each of the 10 lakes, I used linear regression to create best fit curves a general, combined model, heretofore referred to as the 'Global' model (GM). I also examined relationships for individual lakes. First, I screened for invalid outputs and removed temperature values of 0. I plotted eight-day averaged GPP values against eight-day averaged LST values. I then used linear regression to create a model for each lake, fitting the data to a univariate quadratic equation.

GPP and lake surface temperature global model validation

As a preliminary test of my global model's effectiveness for predicting, over a broad geographic region, in-lake GPP, I used LST data from a lake in the GLEON metabolism study (Lake Acton) as a test case. Lake Acton was the only lake used for validation because it was not included in the creation of the GM and it was the only remaining lake Solomon et al. (2013) with identically calculated GPP values and large enough in area to be captured by the 1-km MODIS sensor. To test the strength of the GM, I used the resulting quadratic equation from the global model to predict the GPP of my test case Lake Acton (dependent variable) from the LST (independent variable). Next, I correlated the new, MODIS-derived estimated GPP values with Solomon et al.'s (2013) previously in-lake modeled GPP values and fit a linear line to the plotted points.

Land cover and GPP model

Because land cover can influence the amount and type of nutrients that enter a lake system and thus affect a lake's productivity, it was important to also consider the effect of land cover on lake GPP. To analyze the relationship between watershed land cover type and lake GPP, I first I downloaded the MODIS land cover product MCD12Q1 (NASA LPDAAC 2). For each lake, I downloaded a single hdf file from the LPDAAC for the corresponding one year time period and read it into ArcMap (version 10.4.1).

To conduct the watershed delineation, I obtained preprocessed GeoTIFF files from Cary Institute GIS specialist from the Weathers' Lab, B. Steele to create Digital Elevation Models (DEMs). Then, I calculated watershed boundaries using the pour point method (Jenson and Domingue 1988) in ArcMap (ESRI). I layered the land cover raster over the newly created watershed boundary layers. Using the zonal statistics tool in the Spatial Analyst extension, I calculated the number of pixels within the watershed boundary containing each land cover type to obtain percentage land cover types.

To test if there was a relationship between lake GPP and land cover, I ran a correlation test for the number of pixels in each land cover type and lake GPP. There are 16 distinct land cover types as identified by the MCD12Q1 product, but I compressed them into five groups for ease of analysis (Table 4).

Table 4. Land Cover groupings. Five compressed land cover groups derived from the original 16 MODIS land cover classifications land cover types 0 and 15 were discarded, which are water, snow and ice.

Land Cover Group	Label	MODIS Pixel Labels	
1	Forest	1-5	Evergreen needleleaf, evergreen broadleaf, deciduous needleleaf, deciduous broadleaf, mixed
2	Shrublands	6-7	closed and open shrublands
3	Grasslands	8-10	wood savannas, savannas, grasslands
4	Wetlands and Croplands	11,12,14	permanent wetland, croplands, natural vegetation mosaic
5	Urban and Barren	13,16	urban and built up, barren or sparsely vegetated

Multivariable Model

If there is a positive relationship between number of pixels in each land cover type and lake GPP, this indicates that land cover type affects GPP in some way, and land cover will become a variable in a now multi-variable model, since temperature no longer suffices as the only input. To determine the relative importance of in-lake temperature and surrounding watershed land cover on in-lake GPP, I performed a correlation test between the two variables. Since the land cover data are temporally static unlike the temperature data, I used a single, average GPP point for each lake as well as the percent land to then create a multivariate model using GLM or generalized linear modeling in R.

RESULTS

GPP and lake surface temperature model

MODIS LST data correlated positively with in-lake modeled GPP in linear regression. The relationships was significant at the $p \leq 0.001$ level. The best fit model for all combined lake data, or global model GM, is the positive univariate quadratic equation $GPP=0.0046(LST)^2$ –

0.038(LST) + 0.23 (Figure 1 and 2). The R-squared value is 0.279 and the p-value is 3.23 E -19. In addition, nine of the ten individual lake models had higher R^2 fits than that of the GM (Table 5). The two best fit individual lake models were Kentucky and Rotorua, with R-squared values of 0.59 and 0.71, respectively. Both lakes are in temperate zones, with Kentucky in the Northern Hemisphere and Rotorua in the Southern Hemisphere (Figure 3). The lines for the individual lake models show the optimum temperature ranges for best fit to be between 15 and 20 degrees Celsius (Figure 4). Lakes with poor individual fits such as Balaton have temperatures outside this optimum range. In addition, all or most of the data points lakes with stronger individual fits (like Rotorua) do not have outliers far beyond this range. It is also interesting to note that most of the individual model lines curve upward with the exception of Rotoiti, which, while more flat, inflects downwards. Lastly, lakes with poorer individual fits tend to be more oligotrophic (Balaton, Mendota, Trout), while stronger fit lakes are more mesotrophic and eutrophic (Kentucky, Rotorua, Rotoiti).

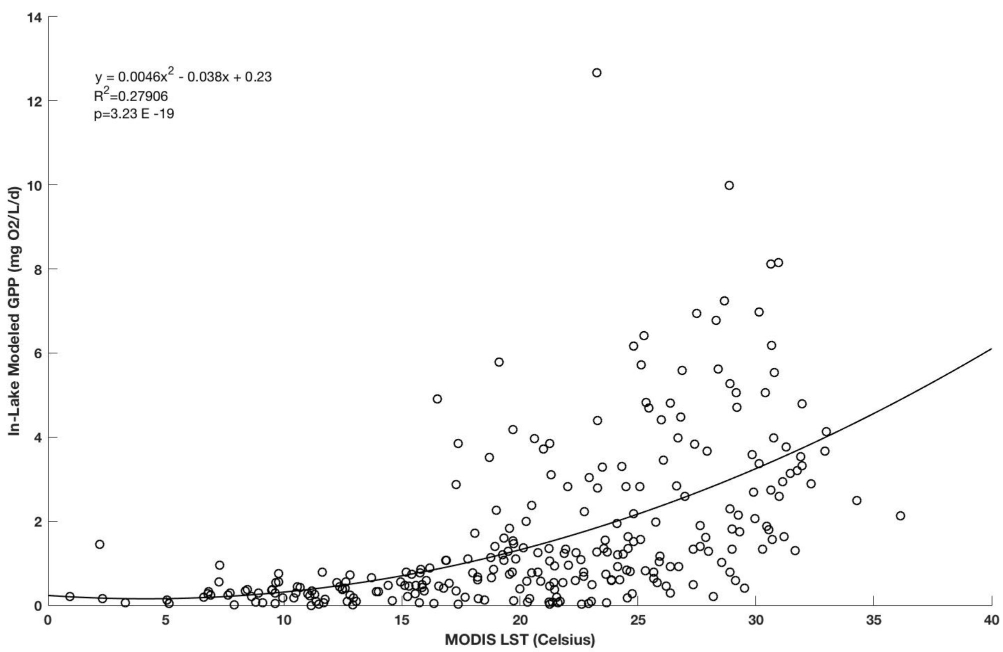


Figure 1. **General Model (GM) for relationship between MODIS LST and In-Lake Modeled GPP.** Quadratic model fit for all 10 lakes' GPP predicted from MODIS temperature output. (n=263, R^2= 0.27906, p=3.23 E -19).

Table 5. **Regression Analysis.** Results of regression analysis of MODIS LST output versus in-lake modeled GPP. Shows the coefficient of determination, significance level, and number of data points (N) for each individual lake general regression model.

Lake Name	Country	R^2	P-value	N
Balaton	Hungary	0.31	0.097	10
Kentucky	USA	0.59	< 0.001	45
Mendota	USA	0.55	0.005	13
Müggelsee	Germany	0.33	0.001	31
Pontchartain	USA	0.35	< 0.001	32
Rotoiti	New Zealand	0.58	< 0.001	45
Rotorua	New Zealand	0.71	< 0.001	44
Sunapee	USA	0.57	< 0.001	23
Taihu	China	0.52	< 0.001	43
Trout	USA	0.05	0.966	19

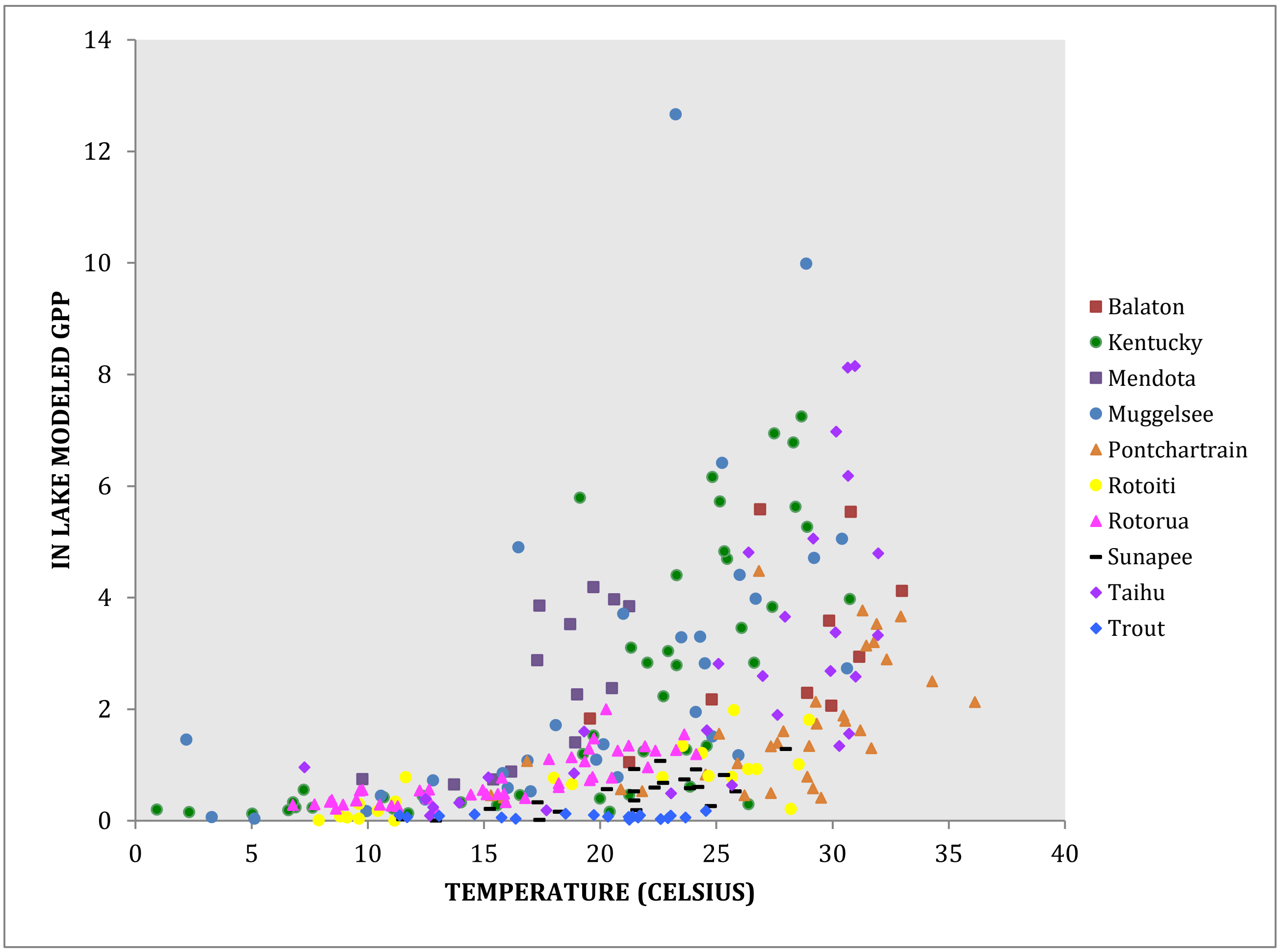
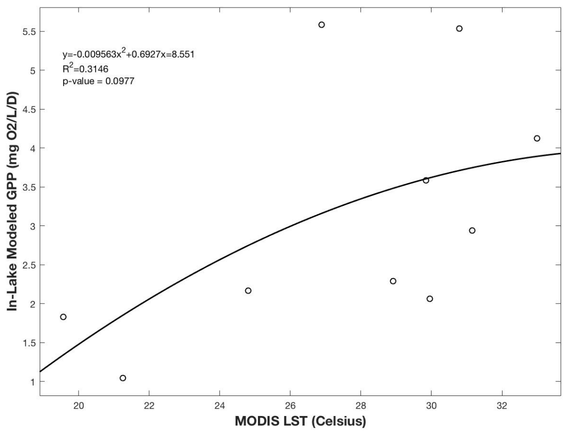
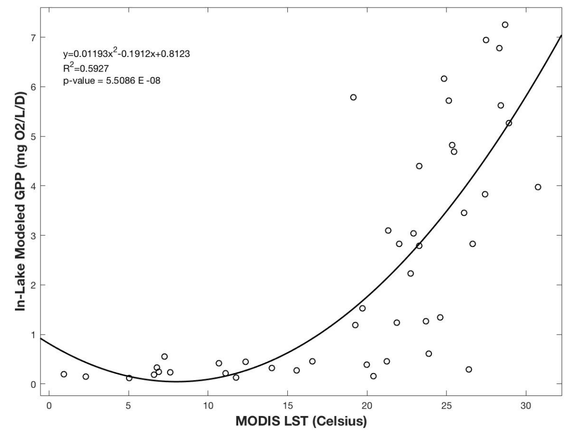


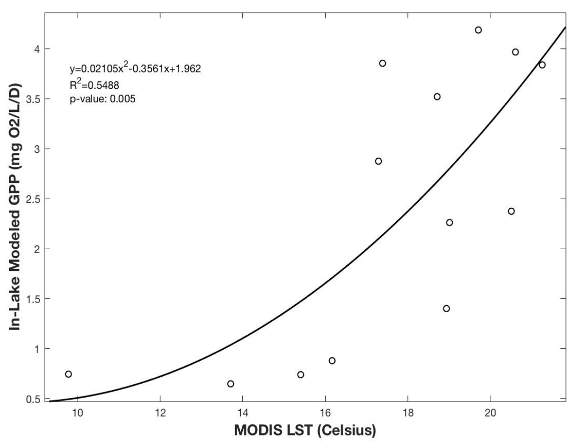
Figure 2. All-lakes separated by color . The lake with the most outliers is Müggelsee, as it has 3 points outside the range of points. All of the data points for Trout are very close to zero.



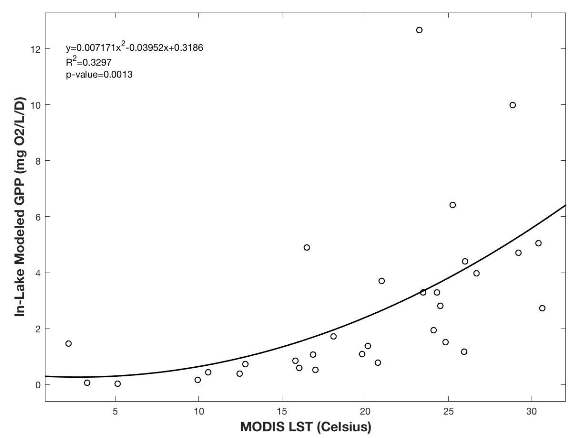
A) Balaton



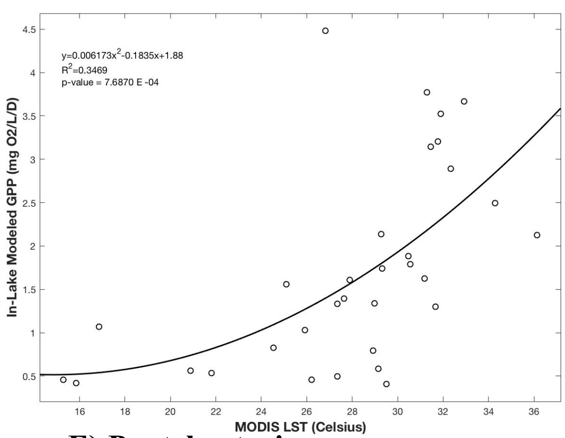
B) Kentucky



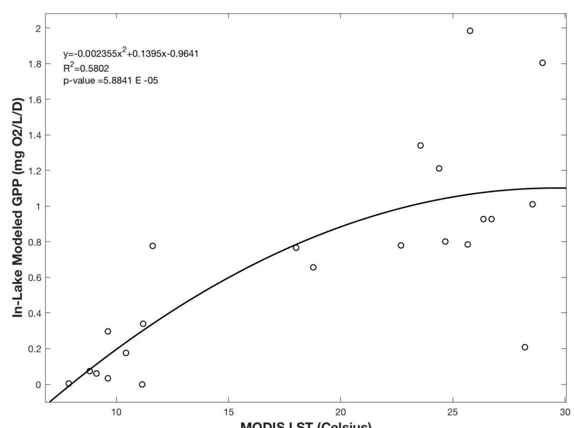
C) Mendota



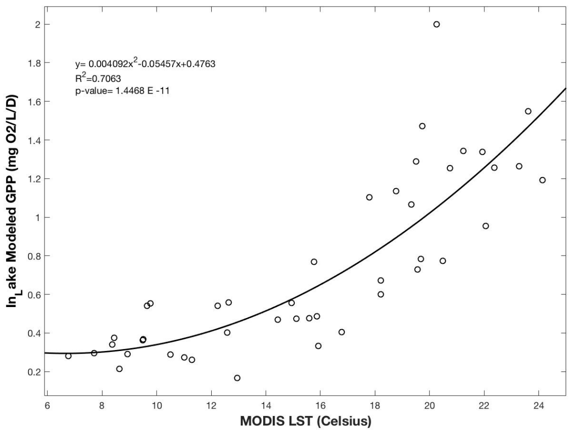
D) Müggelsee



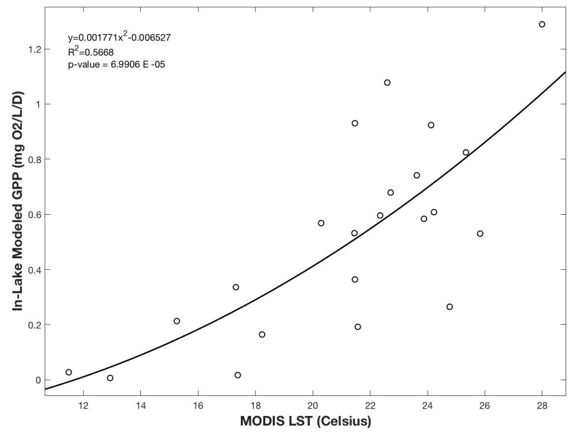
E) Pontchartrain



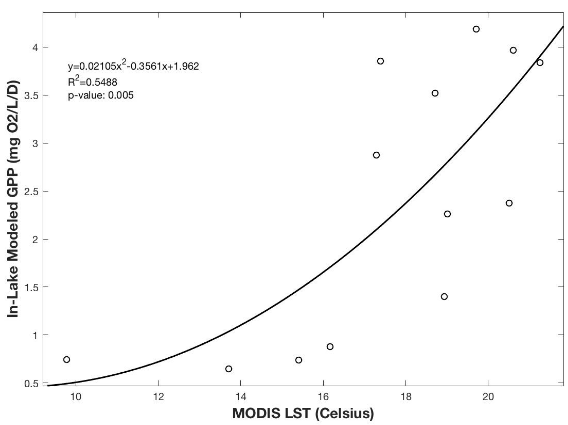
F) Rotoiti



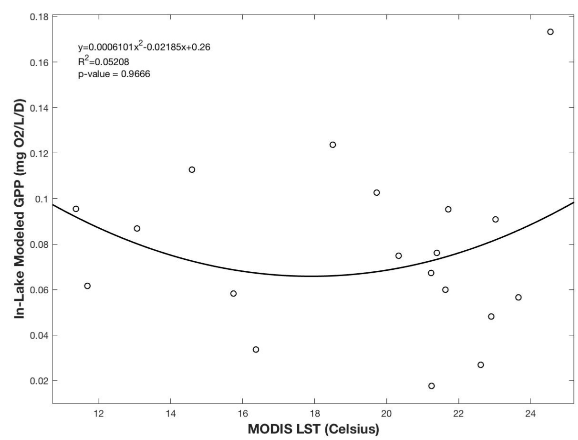
G) Rotorua



H) Sunapee



I) Taihu



J) Trout

Figure 3. **Individual relationships between MODIS LST and In-Lake Modeled GPP for 10 study lakes.** Lakes with the strongest fit include Kentucky and Rotorua. All lakes except Trout have a R^2 fit that is higher than the global model. Trout has a model fit equation of $y = 24.405x^2 - 71.03x + 51.75$ that is not statistically significant. Other lakes with R^2 fit above 0.5 include Rotoiti (0.58), Mendota (0.55), and Taihu (0.52). The remaining lakes had R^2 fits between 0.31 and 0.44.

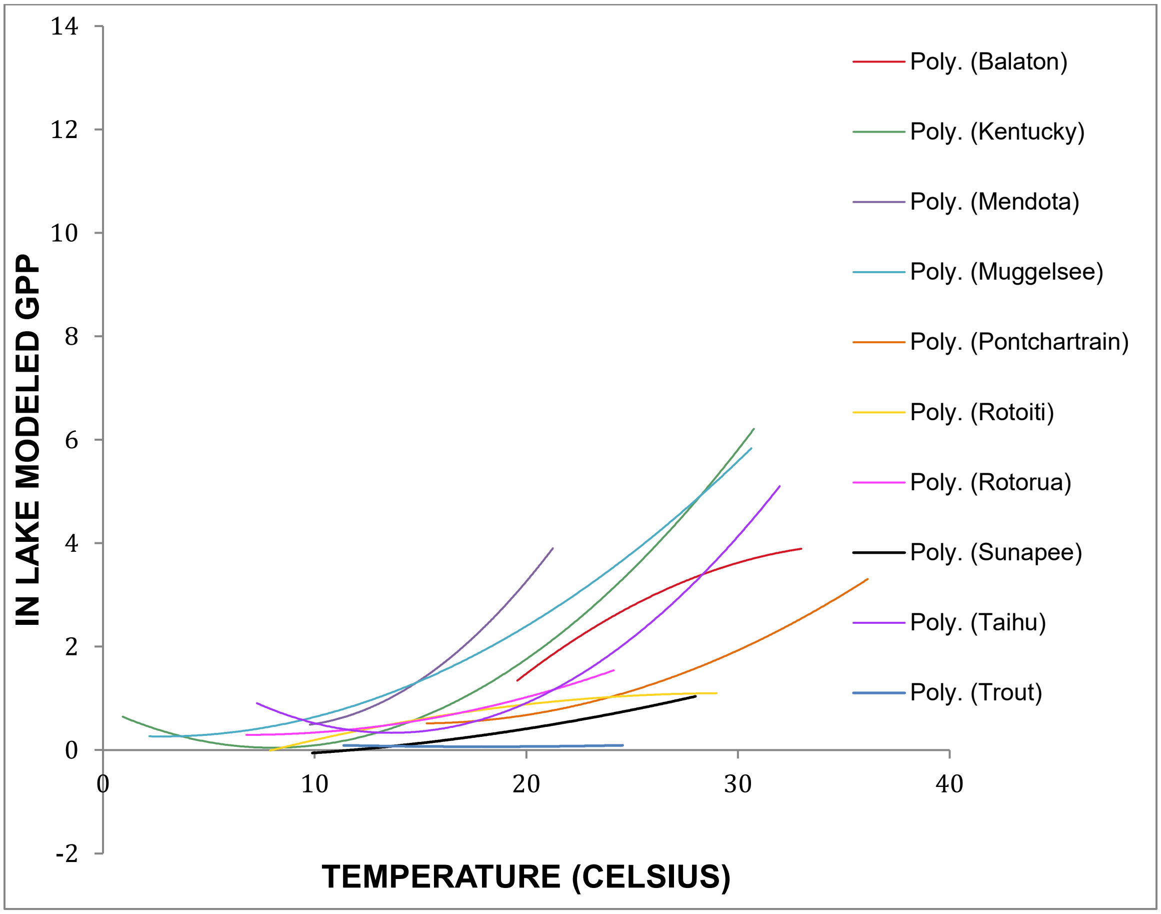


Figure 4. All lake model fit curves separated by color. Most GPP values fit are between 0 and 6 mg O_2/L/D, but individual lakes with temperatures in between 15 and 20 degrees Celsius have the best-fit models. Trout has extremely low GPP values such that it is almost a flat line and consequently has a poor model fit.

GPP and lake surface temperature model validation

Validation of the general model with Lake Acton data determined a positive correlation between the MODIS-derived estimated GPP values of lake Acton obtained from the global model and the previously modeled in-lake GPP values (Figure 5). MODIS-derived GPP estimates correlate with the in-lake GPP estimates with a correlation coefficient value of 0.8719 and a p-value of 0.0002. It is important to note that there are only 12 available data points for this model validation. Three of these 12 points lie above the 45-degree, one-to-one line fitted to the graph, and nine lie below, suggesting a potential under-estimation of the model.

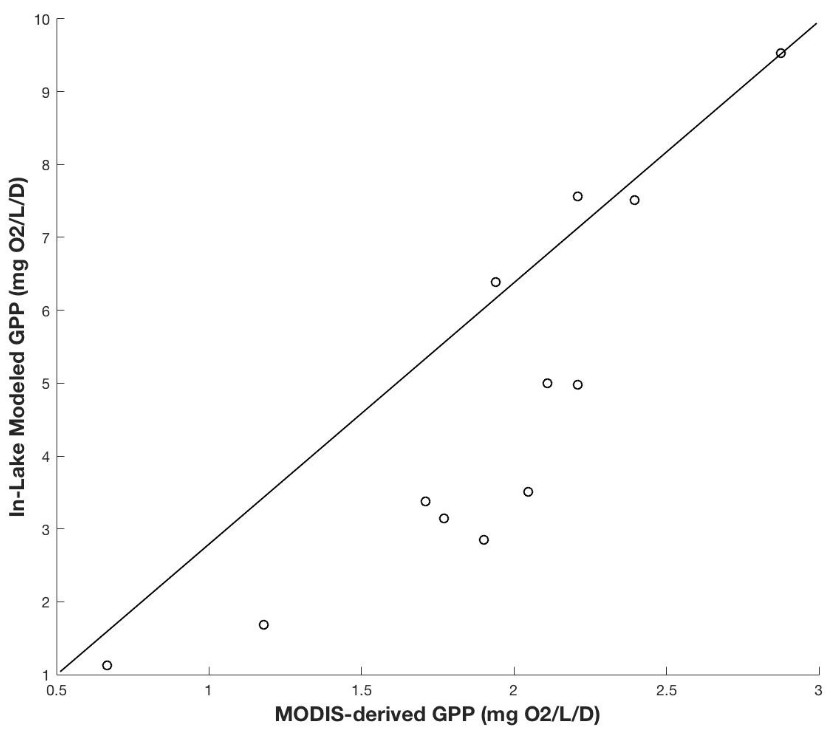


Figure 5. **General Model Validation.** Correlation for Lake Acton GPP predicted from MODIS-derived GPP 'Global Model'. (N=12, R=. 8719 3 p=. 00021784).

Land cover and GPP model

I found a positive correlation (r= 0.67) between the percent cover of forested land cover types (Group 2) and and the in-lake estimated GPP values for the 10 lakes (Figure 6). Two of the lakes, Kentucky and Sunapee, had greater than 50% forest cover in the watershed (Figure 7). Several of the lakes' watersheds had a high percentage of wetland and cropland cover, or Group 4 (Figure 8). None of the remaining four land cover types had a significant correlation with GPP lake values and were consequently not included in the models.

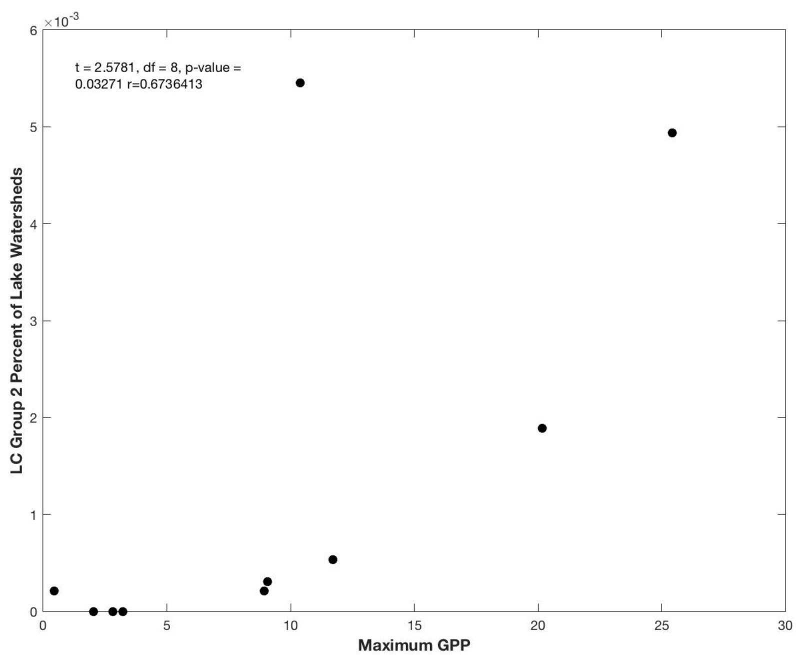


Figure 6. Correlation between forested land cover and GPP. Land cover types 2 (combination of forest types) are positively correlated with in-lake modeled GPP for all ten lakes (R=0.67, p= 0.03271).

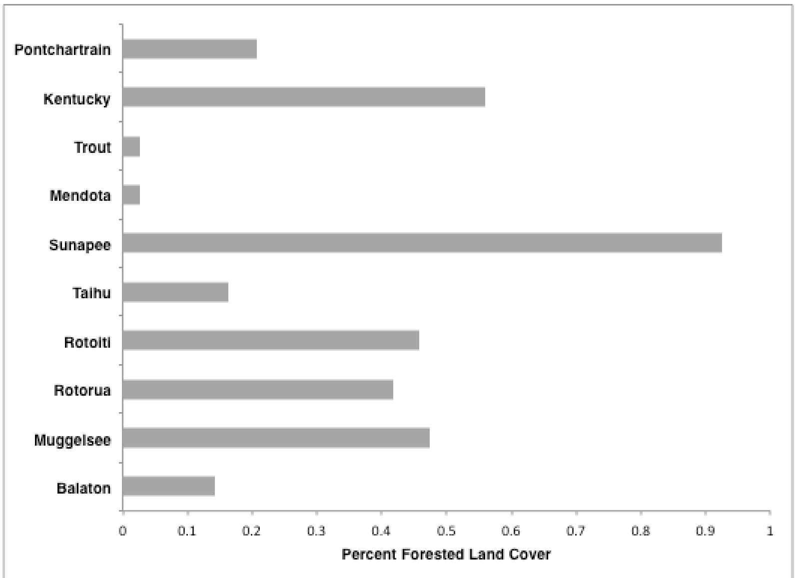


Figure 7. Percent forested land cover within watershed for all lakes. Sunapee's watershed is 93% forested, Kentucky is 56% forested, and Müggelsee is 47% forested. Both Mendota and Trout have the values, with only 3% of the watershed covered in forest.

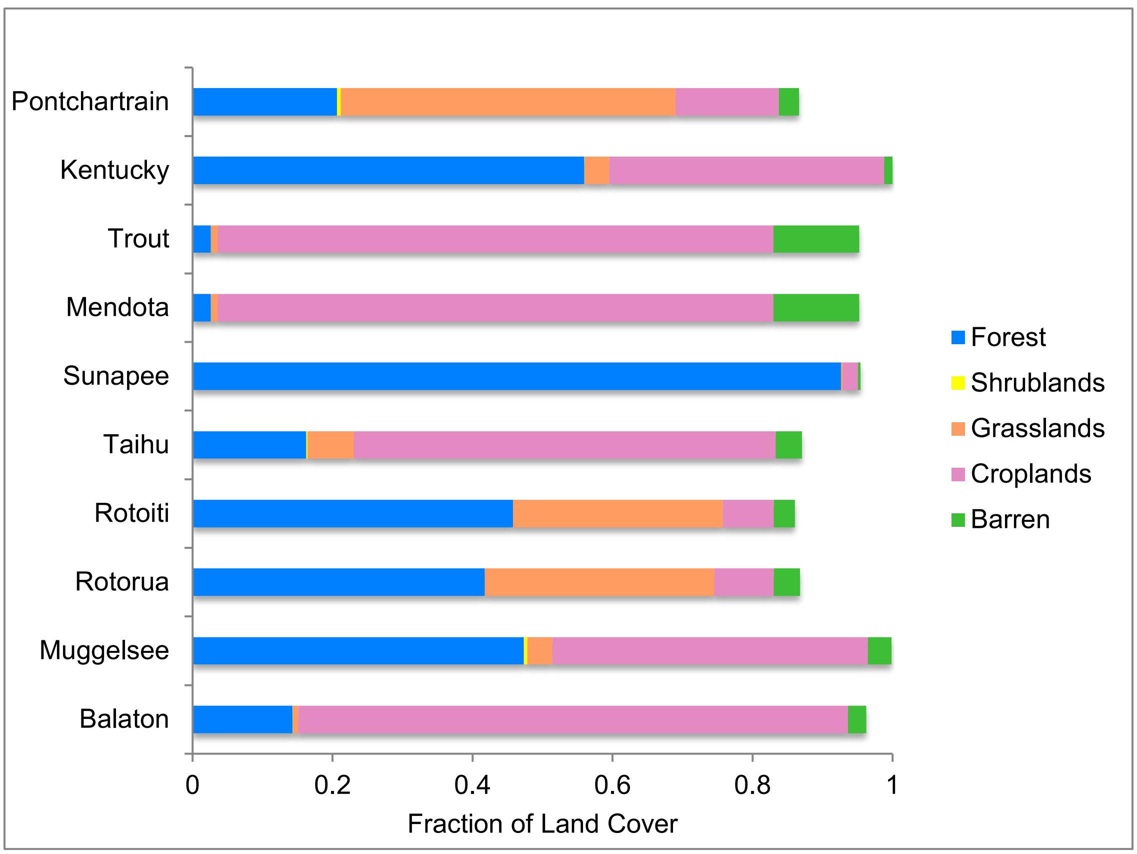


Figure 8: Relative land covers of lake watersheds. The two largest contributing land cover groups to the study lakes are forest and cropland or groups 1 and 2. Almost no lake watersheds contain land shrublands.

Multivariable Model

The variables of land cover type and temperature as predictors of in-lake GPP are best explained by the multivariable general linear model y=_0.0949x^2 + 2478.7678z + 3.3221 where y is the maximum GPP, x is the temperature, and z is the percent land cover type. (R^2= 0.455, p-value = 0.1191). Unlike the GM, which used only 8-day average temperature values as the predictor variable, temperature values used in this model are the maximum values within the yearlong study period. Although these results are not statistically significant? ($p < .15$) and are from generalized linear modeling techniques, the multivariate model has a higher R^2 than the original model describing the relationship between MODIS in-lake temperature and GPP.

DISCUSSION

Estimating lake gross primary productivity using remote sensing data has many potential uses. First, GPP is a fundamental ecosystem function. As such, it can be used in mass balance models (Wilkinson et al. 2013) and as an index of environmental change. Second, there is a worldwide concern about the increase of toxic algal blooms (Gilbert and Burford 2017). To the extent that these blooms are a primary contributor to lake GPP, the use of RS tools and products in monitoring and, ultimately managing lakes shows great promise.

In this study, where I modeled in-lake gross primary productivity using MODIS land surface temperature data for 10 globally distributed lakes, I found that the general model predicted GPP from remotely sensed temperature observations and accounted for 27% of data variability. That approximately 1/3 of the variance was explained in the model may be a result of several complex biological and ecological phenomena. On a cellular level, metabolic rates of organisms are influenced by temperature. In addition, lake GPP is affected by landscape scale characteristics such as watershed conditions. Despite the variability in the data stemming from various biological mechanisms, the results of this study are promising for global application given its large spatial scale and variety of lake systems.

Physical and biological lake properties relating to lake temperature

The global model explains only 27% of variability in the data, and the rest may be explained by physical and biological properties of lakes contributing to both GPP and temperature. This model fit of 27% is similar to other limnology studies that use MODIS for individual lakes, and predictive capacities generally hover of around 30% (Gitelson et al. 2008, Wu et al. 2009). For studies of more easily detectable physical lake parameters such as suspended materials, models for coastal waters such as the Gulf of Mexico explained up to 89% of data variability (Miller and McKee 2004). Thus, the contributions of physical lake parameters to GPP could also affect data variability.

In addition, while the GM model in this study considers the easily (remotely) detectable parameter of temperature, it does not capture necessarily more indirect lake characteristics including nutrient dynamics. For example, the difference in the productivity-limiting nutrient phosphorus may lead to data variability, since lakes such as Rotorua, Rotoiti, and Rotorua have 30, 30.3, and 32.7 µg/L phosphorus, indicative of meso-eutrophic lakes, while Lake Sunapee only has 5.3 µg/L. Data variability could also be attributed to differences in nutrient dynamics between lakes.

Temperature and GPP are also affected by nutrient dynamics. The individual models with strongest R^2 fits were Rotorua (0.71), Rotoiti (0.58), and Kentucky (0.59), which are recorded as eutrophic and mesotrophic. These lakes' temperatures did not exceed 30 degrees Celsius. Moreover, temperature is the best predictor of chlorophyll biomass (Staehr and Jensens 2007), and chlorophyll biomass is essentially gross primary production. Analysis of ice cores from the Vostok Lake give evidence 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).

The models for individual lakes had stronger R^2 than the GM, which suggests that lakes can vary considerably over global scales. Differences in within lake and external lake properties may be responsible for the varying strengths of individual models. For example, GPP is 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). Lake Mendota algal-macrophyte interactions are controlled by lake morphometry and temperature (Carpenter 2005), and the algae and macrophytes contribute to lake GPP. In addition, nutrient inputs and algal productivity are influenced by lake properties such as depth (Staehr and Jensen 2007). In addition, Rotoiti and Rotorua are fed by relatively smaller watersheds, 520 km^2 and 124 km^2, while Kentucky is a reservoir with an extremely large watershed of 104,117 km^2 and also is a reservoir.

Lake size and depth also contribute to GPP. Interestingly, one of the weaker models, Balaton, has a maximum depth of only 4 meters and a larger watershed of 2750 km^2. Rotoiti has a maximum depth of 125 m while Rotorua has a maximum depth of only 24 m yet both lakes have strong individual model fits. Large, shallow lakes have well-mixed water columns (Chen et al. 2003) and these lakes tended to have higher productivity and better model fits. Lake size also plays an important role in in-lake productivity and its heterogeneity. For example, Lake Taihu is known to have different concentrations of chlorophyll α 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 such large lakes that would be time consuming to obtain in situ.

Finally, Trout Lake had GPP values ranging from only 9.79×10^{-13} mg O_2/L/d to 0.43 mg O_2/L/d, while other lakes' GPP values generally ranged in between 1 and 10 mg O_2/L/d, with several values reaching 25 mg O_2/L/d. Trout was the only lake for which no real relationship existed between GPP measurements and MODIS temperature output. It was also the second smallest lake with an area of 16.7 km^2. The lack of a relationship between GPP and LST could be because these GPP values were far too small and there a threshold of GPP measurements below which relationships between the two variables cannot be determined. The potential threshold 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, as seen with studies measuring chlorophyll fluorescence (Frankenberg et al. 2014). These differences in lake depth, size, watershed size, and productivity levels point to potential contributors of variability, but it is difficult to pinpoint their specific impacts.

Impact of in-lake processes

Storms and microstratification may affect the spread in the individual lake models. Some modeled GPP values were slightly lower than expected, especially in lakes with fewer data points such as Balaton and Trout. Microstratification occurring in lakes correlates with lower values of GPP and respiration (Coloso et al. 2011). Given that microstratification was not measured or considered in any of the individual lakes, I do not know if it occurred, or if disruptions to microstratification are responsible for data outliers. Storm-induced destratification and subsequent changes in algal communities have been documented in Lake Balaton, Hungary (Padisák et al. 1990). Destratification leads to loss of algal species, thereby decreasing GPP rates and serves to mitigate algal blooms (Visser et al. 2016).

Daily changes in GPP that potentially caused by storms were not captured in this study because the GPP values were averages of 8-day time periods. Lack of reliable climate and storm data for lakes outside of the US restrict the focus of this to well-studied lakes within the US that experienced storms. For example, precipitation data from NOAA showed that Lake Sunapee experienced considerable amounts of precipitation during the study period. On Lake Sunapee (Richardson et al. 2017) storms decoupled GPP and respiration, and caused short-term decreases in GPP. Richardson et al. (2017) classified the storm threshold as 19.5 mm of rain, and during my study period in 2008, Sunapee experienced several storm days with up to 81.53 mm of rain in a single event (NOAA 2008). It is possible that these storms did affect GPP and introduced variability. If MODIS could provide daily LST observations, these could identify individual storm events, to reveal GPP outliers.

Temperature dependence of respiration

Another contributor to the variability in model strength is the temperature dependence of ecosystem respiration. Solomon et al. 2013 also calculated lake respiration, which, when subtracted from the GPP values yields NPP or Net Primary Production. Solomon's methods suggest that 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. In fact, some of the lakes with the best-fit individual models including Kentucky and Rotoiti had negative net primary production values, meaning that they were losing more mg O_2/L/day than they were creating, indicating that respiration may also play a role in the relationship between GPP and temperature. However, it is hard to remotely detect respiration since it is measured in situ with light and dark bottle methods, wherein water samples at different irradiance levels are captured in chambers and respiration is measured using elemental tracers (Staehr et al 2010). Next steps in this project could include comparing Solomon et al.'s (2013) respiration rates with the MODIS temperature output to help to determine other drivers of the relationship and improve model strength.

Watershed land cover type impact

The relationship between forested land cover in the lake watershed and lake productivity suggests that land cover types affect GPP. Increased forested land cover type correlated to higher GPP values. Percent land cover determines sediment flux to and influences and water quality in lakes, which can in turn affect productivity (Crosbie and Fraser 1999).

DOC or Dissolved Organic Carbon, from trees/vegetation and soils in watersheds can flow into lakes.. DOC can alter nutrient availability such as phosphorus and carbon, and changes in these nutrient levels can affect primary productivity (Williamson et al. 1991). High concentrations of DOC lead to reduced primary productivity since productivity can be light limited and high DOC lakes are dark (Carpenter et al. 2001). This suggests that perhaps the positive relationship between GPP and forested land cover may be controlled by other factors as well. For example, if forested types have nitrogen-fixing trees such as alder, the nitrogen from forests can drain into the lake and support blue green algae (Goldman 1961). In uplands where forests cover up to 90% of the watershed, terrestrial systems are responsible for most of the nitrogen loading to lakes (Canham et al. 2012). Because lake Rotoiti, Trout, Kentucky, and Müggelsee have high amounts of forest cover (estimated via Google Earth), it is possible the GPP- forest cover relationship may be from forest nitrogen-loading. A survey of the types of trees within the watersheds and the presence and absence of nitrogen-fixing trees is a good first step in answering this question.

Although forested land cover types did correlate with GPP values, other types did not. These land cover types include grasslands and savannas, wetlands, croplands, and urban (Figure 8). Looking at permanent wetlands within the watersheds could reveal a relationship between wetlands and GPP, as net biomass produced in wetlands turns is exported to other freshwater systems and can increase productivity (Canham et al. 2012).In addition, land use impacts on low productivity lakes differ from those for high-productivity lakes (Hoffman and Dodson 2005), and isolating my land cover type results by lake trophic state may confirm this. Although forested land cover types were the only ones to correlate with GPP, this may be an artifact of sampling, as only two of the ten study lakes, since only Kentucky and Sunapee had greater than 50% forested land cover within their watersheds. Other lakes had a combination of urban, farmland, and grasslands within their watersheds. For example, both Trout and Mendota had 26% croplands within their watersheds (Figure 8). Land cover impacts on productivity are just one part of complex mechanisms that affect lake metabolism, many of which provide challenges in creating remotely sensed models of productivity.

Remote sensing accuracy in predicting GPP

The 0.27 R^2 for the global model and even higher values for individual lakes suggest that remote sensing can predict GPP on a global scale, but that it is more accurate on smaller scales. This estimate is in agreement with a number of previous lake remote sensing studies that reveal that their algorithms are better suited for regional prediction of lake indices in that more variables can be considered and finer scale differences can be noticed (Dörnhöfer and Oppelt 2016, Woelmer et al. 2016). In addition, it is possible that a temporal resolution finer than 8 days is needed for more accurate GPP prediction. Furthermore, for each of the lakes, there are several days throughout their corresponding one-year time period (which encompass all seasons) 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. The global model was validated with only Acton Lake because there was only one available lake from the Solomon et al. (2013) study that was not included in our general model but still large 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. To explain more of the data variability, future models could consider a larger suite of lakes with a range of sizes, areas, and land cover types within their watersheds. The scope and the time constraints of this study allow for opportunities in future model improvement.

Challenges and opportunities

Although the lake models produce some promising results with predictive capabilities on par with those of similar studies, this is only a first step toward building a global GPP product for freshwater lakes One primary challenge for this model is the limited spatio-temporal inference of remote sensing, which is particularly relevant to algal blooms since some can appear suddenly overnight (Matsunaga 1999) 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 using only surface temperatures might affect the certainty of the model. 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 produce daily LST outputs. Daily surface temperatures are available at coarser resolution and downscaling techniques may resolve this issue. Correlating daily GPP values with 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. (2013) attribute uncertainty in their model to ecological variation along with statistical uncertainty from the bootstrapping method. A major source of uncertainty cited is the process error that occurs when the DO concentration (used in making the GPP estimates) changes because of some process not explicitly mentioned in the model (Solomon et al. 2013). This same ecological variation could be contributing to the spread in the data points when being fit to the model. Ultimately, model uncertainty is partially a result of difficulty in quantifying impacts of indirect influencers of GPP (Knoll et al. 2003).

Future Directions and Product Development

Despite uncertainty resulting from ecological variation among lakes and logistical difficulties with the state of technology of remote sensing, there remains potential to apply remote sensing technologies to ecosystem-scale lake metrics of lake function. Despite the global model only explaining 27% of the data variability, this result is still promising since the lakes are globally distributed and have a range of ecological and physical properties. Although the current

GPP model is more accurate on a finer scale, improvements such as including a wider suite of lakes and analyzing watersheds along a gradient of forest cover could result in a good global predictor. Currently, there is no freshwater GPP MODIS product, and the creation of a more robust algorithm that considers other ecological parameters could lead to a global data 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 (MODIS product user guide, Wen 2006), which is mechanistically different from the photosynthetic rates that were used to obtain GPP values from Solomon et al. (2013). Because net ecosystem productivity and organic carbon accumulation are not always equivalent in aquatic systems (Lovett et al. 2006), future aquatic GPP products or algorithms must produce estimates of GPP 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. Ultimately, this preliminary study suggests that remote sensing can be used for global-scale understanding of lake metabolism and ecosystem processes.

Broader Implications

This project can ultimately lead to the creation of a publically available freshwater GPP data product that allows further study of lake metabolism and its role in the global carbon cycle. The nature of this study allows for prediction of GPP levels during all non-ice seasons, which over long-term analysis can reveal broad patterns about GPP fluctuations. The relationship between GPP and temperature confirmed by this study is important because 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.

This model may be applicable to other large freshwater systems such as rivers, and can help in furthering understanding of the global carbon cycle. In addition, a model with temporally frequent data over large landscape areas can reveal trends that not visible over current scales (Palmer et al. 2015, Dörnhöfer and Oppelt 2016). Beyond being useful to limnologists and ecosystem scientists, local lake protection associations, NGOs and government agencies can access the data product to make management decisions especially regarding harmful algal blooms (Kutser et al. 2006). In conclusion, the findings in this project suggest that freshwater GPP can be predicted using temporally frequent remotely sensed temperature data, and that a global algorithm can be identified. Ultimately, this model can help people across the globe better understand mechanisms and patterns of lake metabolism and use them to respond to the threats that lake ecosystems face.

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