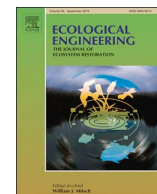




Contents lists available at ScienceDirect

Ecological Engineering

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# Associations between county-level land cover classes and cyanobacteria blooms in the United States

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## ARTICLE INFO

### Keywords:

Harmful algal bloom  
Cyanobacteria  
Phycocyanin  
Wetland  
Crop coverage  
Nutrient loading  
Satellite remote sensing  
Open water  
Land cover

## ABSTRACT

Cyanobacteria blooms can cause public health concerns related to drinking water quality and water recreation. The rapidly changing global climate is anticipated to bring about an increased frequency of extreme weather events (e.g. stronger storms, more extensive droughts), which are expected to promote more frequent cyanobacteria blooms that persist for longer durations in freshwater. **Land use planning, landscape management, and ecological engineering may present mitigation opportunities for decreasing the occurrence and intensity of current and future cyanobacteria blooms through improved nutrient management strategies thereby reducing eutrophication of watersheds.** To examine the potential impacts of various land cover classes (and their relative density) on cyanobacteria bloom coverage, county-level data were obtained or generated from the National Land Cover Database and the national nutrient inputs to the land surface database. These data were paired with **county-level estimates of cyanobacteria bloom area obtained by satellite-based MERIS (Medium Resolution Imaging Spectrometer).** **Multivariable zero-inflated beta regression models were constructed for the U.S. and five U.S. regions for assessing the relationships between the proportion of county area experiencing a cyanobacteria bloom, county land cover types, and nutrient loading.** The land cover type associated with the greatest decreases in bloom area in the national model was deciduous forest ( $p < 0.001$ ). Open water extent ( $p = 0.001$ ) and **nitrogen loading from manure ( $p = 0.002$ ) and fertilizer ( $p < 0.001$ )** were positively associated with the proportion of water characterized as experiencing a cyanobacteria bloom. A significant interaction ( $p < 0.001$ ) was observed between cultivated crop coverage and open water extent. **Overall, increasing cultivated crop coverage was associated with increasing proportions of cyanobacteria blooms.** Low intensity, medium intensity, and high intensity development land uses were not associated with bloom coverage in the national model, although development land uses were positively associated in several regional models. Ultimately, there is evidence that county-level land cover and nutrient loading, notably N in the national model, can impact county-level cyanobacteria bloom coverage. **Given regional model differences, additional remote sensing-based studies that examine watershed-based effects on cyanobacteria coverage are needed to establish watershed-specific associations.** Studies that transcend county boundaries may provide greater utility than this correlational study for better characterizing land uses and mitigation measures that impact or could impact cyanobacteria bloom coverage in U.S. surface waters.

## 1. Introduction

### 1.1. Societal impacts of harmful cyanobacteria blooms

Natural and anthropogenic land uses influence nitrogen (N) and phosphorus (P) loading in aquatic ecosystems (Foley et al., 2005). The

combined effect of N and P in aquatic systems influences the likelihood for cyanobacteria (blue-green algae) populations to bloom (Paerl et al., 2016a,b). During blooms, public health and aquatic ecosystems may be imperiled due to the formation of health-relevant cyanotoxins (Carmichael, 1997; Carmichael and Boyer, 2016; Brooks et al., 2016), carcinogenic disinfection byproducts (Delpa et al., 2009), and

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<http://dx.doi.org/10.1016/j.ecoleng.2017.07.032>

Received 24 April 2017; Received in revised form 26 July 2017; Accepted 27 July 2017  
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dissolved oxygen depletion (Scavia et al., 2014). Bloom events have downstream effects to local economies through harm to fisheries, livestock, land values, recreation/tourism, and drinking water treatment costs (Carmichael, 2008; Cunha et al., 2016). Changes in the global climate enhance the likelihood of more cyanobacteria blooms (Paerl and Huisman, 2009). Accordingly, efforts to mitigate and minimize cyanobacteria bloom development in aquatic ecosystems are timely.

## 1.2. Cyanobacteria blooms and public health

Cyanobacteria present significant public health concerns when densities of toxin-producing genera are elevated and producing toxins in waters used as a source for drinking water and recreation. Cyanotoxins produced during harmful bloom events may act as potent hepatotoxins, neurotoxins, cytotoxins, irritants, and/or gastrointestinal toxins (Carmichael, 1997). Several cyanotoxins are produced by cyanobacteria (e.g. anatoxin, saxitoxin, cylindrospermopsin, microcystin, etc.), however, guidelines are typically based upon microcystin. Elevated levels of microcystin, have been linked to liver cancer (Yu, 1995) and in an extreme case, the death of 76 dialysis patients in Brazil (Carmichael et al., 2001). Cyanobacteria bloom intensity as measured via remotely sensed phycocyanin pigment concentrations has been positively associated with liver disease in the U.S. (Zhang et al., 2015). Mouse and pig toxicity studies have demonstrated harmful effects (Fawell et al., 1994; Falconer et al., 1994) and these animal studies informed the World Health Organization (WHO) in setting provisional drinking water and moderate recreational water risk guidelines of 1.0 µg-microcystin/L and 20 µg-microcystin/L, respectively (WHO, 2003). WHO recommends advisory signage for water recreators at 20,000 cyanobacteria cells/mL (WHO, 2003), which approximates to 4 µg/L of microcystin.

## 1.3. U.S. geographic distribution of microcystins

Cyanobacteria are ubiquitous and their production of cyanotoxins suggests elevated densities of cyanobacteria compared to areas where toxins are not detected. Overall, microcystins (a group of commonly measured cyanotoxins) were readily detected in inland waters in the most recent 2012 National Lake Assessment for the U.S. (U.S. EPA, 2016). Microcystins, which typically become more common as cyanobacteria densities increase (Marion et al., 2012), were observed in 39% of all U.S. lakes and reservoirs. In the most agriculturally-dense ecoregions, microcystins were more frequently observed. Specifically, 76% of Northern Plains lakes, 79% of Southern Plains lakes, and 66% of Temperate Plains lakes had detectable microcystins. Additionally, 6% of Northern Plains lakes had microcystin levels > 20 ppb; compared to 1.6% and 0.2% for Temperate Plains and Southern Plains lakes, respectively. Furthermore, the Northern Plains lakes also led the nation in the frequency of water quality impairment related to N and P (U.S. EPA, 2016). Human population densities and urban development are low in this region. Agricultural impacts are major drivers for elevated N, P, and cyanobacteria in the U.S. and for inland and coastal waters worldwide (Bennett et al., 2001). The 2012 National Lake Assessment findings in regards to regions with elevated N, P, and cyanotoxins were similar to 2007 National Lake Assessment. In both cases, land use practices, N, and P, are linked to cyanotoxins in lakes (Beaver et al., 2014).

## 1.4. Nutrient reduction strategies and land use impacts on cyanobacteria

In the midst of a changing global climate anticipated to enhance the frequency and duration of cyanobacteria blooms, mitigation measures for controlling terrestrial releases of N and P are recommended before they enter receiving waters (Hamilton et al., 2016). In cases where N and P enter aquatic systems, nutrient reduction strategies have been proposed or utilized through the promotion of aquatic macrophyte

growth including wetland development (Paerl et al., 2016a,b; Paerl, 2014; Dunne et al., 2015). Assessments of whether or not wetlands remove nutrients have indicated that the majority do reduce nutrient loads (Fisher and Acreman, 2004); however, such assessments have not been widely performed on their ability to reduce cyanobacteria bloom frequency.

Recent attempts to assess large-scale landscape factors for predicting microcystin concentrations determined that local influences were most influential in predicting elevated toxin levels (Taranu et al., 2017). The land use adjacent to lakeshores, distances from nature preserves, and within-watershed land uses have all been implicated as major drivers of cyanobacteria bloom frequency (Doubek et al., 2015; Marmen et al., 2016; Katsiapi et al., 2012).

## 1.5. Remote sensing for cyanobacteria bloom and land use determination

For broad scale monitoring of cyanobacteria blooms when field measurements are not possible or not existent, remote sensing offers an opportunity for estimating blooms and bloom intensity. Since the phycocyanin pigment is unique to cyanobacteria and is positively associated with elevated levels of microcystins in inland waters (Marion et al., 2012), phycocyanin may serve as an indicator of bloom conditions. Estimates of phycocyanin concentrations in water have been determined remotely with satellite imagery and these results have been positively correlated with *in-situ* measurements of phycocyanin and genetic markers indicative of cyanobacteria and cyanotoxin-producing genes in near shore environments (Lee et al., 2015). Recent application has also occurred for estimating cyanobacteria blooms within the state of Ohio's inland lakes, ponds, quarries, and rivers that are 300 m or greater in width (Gorham et al., 2017).

Remote sensing for determining different land uses at different spatial and geographical levels has been occurring for over a half century, and remotely sensed land cover data have been classified using a common classification system since 1976 (Anderson et al., 1976). Modern studies on land use categories and water quality are common; however, U.S. studies on cyanobacteria occurrence as it relates to remotely sensed land cover are not as common (Doubek et al., 2015). At the time of Doubek et al. (2015) and since that time, no other study has examined the geospatial relationships between phytoplankton (including cyanobacteria) and land uses on such a broad national scale. In Doubek et al., the land use determinations were made using 200 m wide perimeters around 236 natural U.S. lakes from the 2007 National Lake Assessment (U.S. EPA, 2009). The land uses were quantified from the 2006 National Land Cover Dataset (Fry et al., 2011). Collectively, land uses (notably agricultural and human development) coupled with nutrients and temperature influenced cyanobacteria density and N-fixing cyanobacteria dominance (Doubek et al., 2015).

## 1.6. Study objectives

General estimations are needed regarding the role and importance of various land uses in regulating cyanobacteria bloom occurrence in U.S. waters and abroad. Furthermore, county-level estimates may provide understanding as to whether or not and to what extent local (county-level) land uses impact cyanobacteria bloom potential in their own surface water supplies. The research questions investigated were (1) which land uses and (2) which type of nutrient (N or P) contributes the most to cyanobacteria bloom risks? To accomplish study objectives, remotely sensed cyanobacteria bloom coverage was determined for counties in the conterminous United States and then paired with data sources for county-level land cover and nutrient loading.

## 2. Methods

### 2.1. County-level cyanobacteria bloom coverage determination

County-level cyanobacteria bloom coverage data were derived from L1B full resolution images made available through the Medium Resolution Imaging Spectrometer (MERIS) onboard the European Space Agency ENVironmental SATellite (ENVISAT). Phycocyanin pigment concentration estimates were derived from MERIS L1B full resolution images by using the programmable visible-near infrared spectral band near 620 nm as described in Zhang et al. (2015). The spatial resolution for these satellite images was  $260\text{ m} \times 290\text{ m}$ .

In brief, the L1B images were obtained online from the National Aeronautics and Space Administration's (NASA) Goddard Space Flight Center via OceanColor (NASA, 2015). The images were retrieved for all days in August and September 2005. These two months were selected to generate a single large combined image for the period of time associated with late summer U.S. blooms. Late summer blooms have been speculated to be increasing due to changes in climate (Joechnk et al., 2008; Paerl and Huismann, 2008). Additionally, late summer has been linked to N:P ratios favorable for bloom development in major freshwater lakes frequently impacted by blooms, specifically Lake Erie in the U.S. and Lake Taihu in China (Michalak et al., 2013; Yang et al., 2017). Late summer has consistently generated the most significant blooms for Lake Erie nearly every year since 2002 (Wynne and Stumpf, 2015; Michalak et al., 2013; Rinta-Kanto et al., 2005).

The late summer NASA L1B image-based data obtained were refined for the conterminous U.S. as described in Zhang et al. (2015) to enable the estimation of phycocyanin levels using the protocol of Simis et al. (2005), which was developed specifically for estimating phycocyanin levels in turbid inland waters. Ultimately, all the refined images were combined into a single large image in which each pixel location was then assigned a maximum estimated phycocyanin concentration via maximum value composite determination in ArcGIS 10.0.

Pixel locations deemed in the bloom status had maximum phycocyanin concentration estimates  $\geq 4\text{ }\mu\text{g/L}$ . The  $4\text{ }\mu\text{g/L}$  threshold was set through an approximation of the phycocyanin concentration equivalent to  $\sim 20,000$  cyanobacteria cells/mL as described in Zhang et al. (2015) using the mathematically described relationship between phycocyanin and cyanobacteria cells/mL in Ahn et al. (2007). The cell density of 20,000 cyanobacteria cells/mL represents the microcystin-based threshold for water recreators as set by the World Health Organization (2003) and is treated by WHO as equivalent to  $10\text{ }\mu\text{g-chlorophyll } a/\text{L}$  when cyanobacteria dominate. Exposure to these waters or waters with higher cell densities would be expected to cause water users mild to severe irritation and/or possibly allergenic responses.

The proportion of county area experiencing a cyanobacteria bloom was determined using county boundary polygon data retrieved from the TIGER database of the U.S. Census Bureau. The county polygons were added to the rasterized MERIS image as an overlay in ArcGIS 10.0. The proportion of the county area pixels experiencing a bloom (maximum value composite  $\geq 4\text{ }\mu\text{g/L}$ ) was then determined using zonal statistics for each U.S. county by ArcGIS 10.0. Estimated proportions (and percentages) of the total area experiencing a bloom within each county were then available in tabular format and organized by the unique FIPS (Federal Information Procedures System) code.

### 2.2. Characterizing county-level land cover

The proportion of the landscape surface area for each land cover class was estimated in GRASS GIS (GRASS Development Team, 2015) for all counties in the conterminous U.S. states using rasterized land cover data from the 2011 National Land Cover Database (NLCD-2011) (Homer et al., 2015; U.S. Geological Survey, 2016). The resolution for the NLCD-2011 dataset is 30 m and for each 30 m grid cell, NLCD-2011 assigns a land cover classification. In total, there are 16 possible classes

including the following: open water, ice/snow, developed open space, low intensity development, medium intensity development, high intensity development, barren land, deciduous forest, evergreen forest, mixed forest, shrub/shrub forest, grassland, pasture, cultivated cropland, woody wetlands (swamps), and herbaceous wetlands (marshes). A county boundary layer was then projected with the land cover class data. Next, using the GRASS GIS report process, the proportions of each land cover class was generated for each county and processed as text output. FIPS codes were available for all the data in NLCD-2011, which enabled the merging of this dataset with the county-level cyanobacteria bloom data.

### 2.3. County-level nutrient input data

Nutrient input data from 2001 were obtained from the U.S. Geological Survey (Ruddy et al., 2006) for inclusion in the model development process for estimating the proportion of county area characterized as having a bloom for U.S. counties in the conterminous United States. These USGS data recently informed the National Water Quality Assessment (U.S. Geological Survey, 2017) and continue to be used in water quality management research as an indirect indicator of nutrient loading (Kalcic et al., 2016). The data (from 2001) were obtained in Microsoft Excel format (Ruddy et al., 2006) providing county-level estimates of total N and total P application to the surface. The estimates for fertilizer were derived from state-level reporting of county-level annual fertilizer sales. The fertilizer sales data were converted by Ruddy et al. (2006) from product tons to estimated tons of N and P. The manure-related nutrient inputs were estimated in tons of N and P using county-level estimates of livestock abundance from the Census of Agriculture. The estimates account for nutrient inputs (N and P) to the surface from manure due to the application, storage, and handling of manure. The estimates and variability in N and P account for differences attributable to the variability in manure from various livestock types among several other factors (Ruddy et al., 2006). These nitrogen loading data were used in model development as the following terms: nitrogen from fertilizer, nitrogen from livestock manure, and total farm-related nitrogen (manure + fertilizer). Similar inputs were considered in model development for phosphorus. Nutrient loading values for each county were expressed as  $\log_{10}\text{ kg/km}^2$  for 2001. An N:P ratio was developed using the total farm-related N and P values for each county and considered for inclusion in statistical models. All loading data were organized with FIPS codes for merging with the other data sets.

### 2.4. Modeling proportion of county area experiencing bloom

The county-level cyanobacteria bloom data from MERIS estimated the proportion of the area in every U.S. county experiencing a cyanobacteria bloom. The relationships between county-level land cover classes and county bloom area were assessed with multivariable zero-or-one inflated beta regression models. This statistical model approach enables the multivariable analysis of proportional dependent variables (values between 0 and 1) when either 0 and 1 is a frequent observation (Ospina and Ferrari, 2012). Recent environmental application of this approach occurred for predicting the proportion of pine forest area impacted by beetle infestation using several coarse explanatory variables such as slope, microclimate, etc. (Kaufeld et al., 2014). These quasi-maximum likelihood models are superior to ordinary least squares (OLS) regression approaches because as sample sizes increase, asymptotic distributions (S-curve) exist as dependent variables approach 0 and 1. Due to the high frequency of zero values in the outcome variable (bloom proportion), zero-inflated beta regression models were constructed and evaluated in Stata 14 (StataCorp, College Station, TX) for significance of predictive terms. The models were constructed using stepwise backwards selection procedures among all terms entered into a saturated model. Terms were entered into the saturated model if the

**Table 1**

Descriptive statistics for various cover area classifications expressed as proportions and for nitrogen loading for U.S. counties based upon national land use coverages and nutrient loading. Only parameters used in the final model are presented.

Parameter	Mean	Range	Percentile			
			25th	50th	75th	90th
Proportion of Surface in Bloom	0.02	0–0.69	0.00	0.00	0.01	0.04
Open Water Proportion	0.02	0–0.61	0.00	0.01	0.03	0.06
Cultivated Crops Proportion	0.21	0–0.91	0.01	0.09	0.37	0.65
Swamp Proportion	0.05	0–0.67	0.00	0.01	0.06	0.17
Marsh Proportion	0.01	0–0.59	0.00	0.00	0.01	0.03
Barren Land Proportion	0.00	0–0.39	0.00	0.00	0.00	0.01
Deciduous Forest Proportion	0.19	0–0.90	0.01	0.10	0.31	0.52
Fertilizer-N ( $\log_{10}$ [kg/km <sup>2</sup> ])	2.89	0–4.10	2.47	3.01	3.44	3.71
Manure-N ( $\log_{10}$ [kg/km <sup>2</sup> ])	1.14	0–4.72	0.67	0.98	1.48	1.85

crude association was significantly associated with the dependent variable ( $p < 0.05$ ). In the multivariable model, non-significant terms were removed sequentially based upon the highest p-value until all model terms were significant. Interaction effects were assessed among model terms and deemed significant if  $p < 0.05$ . Graphical plots related to this model were created using the marginsplot function in Stata 14.

### 2.5. Regional models

Using a similar approach for developing a national model, five regional models were constructed (Northeast [NE], Southeast [SE], Midwest [MW], Southwest [SW], and West [W]). The representative states for each region are provided in Table S1.

## 3. Results

Detectable cyanobacteria blooms as obtained from MERIS represented on average 1.56% of the entire county surface area among all U.S. counties (Table 1). The distribution was skewed, and the median amount of total surface area covered by cyanobacteria blooms was determined to be 0.05% across all U.S. counties. Among geographic regions, the 90th percentile values ranged from 3% to 6% across counties (Supplementary information, Table S2). Such estimations from MERIS were inclusive of all the surface area in the county, including all aquatic and terrestrial areas. The four U.S. counties with the highest percentage of total surface area covered by blooms ranged from 57% to 69% area coverage, all of which were coastal counties with a significant proportion of water in their total county area.

Among the cover types (land classes) used in the final model for predicting the proportion of surface area with a bloom for all U.S. counties, the most common terrestrial land classes were cultivated crop production ( $\bar{x} = 21\%$ ) and deciduous forests ( $\bar{x} = 19\%$ ). Swamps and marshes represented on average 5% and 1% of the average land cover across U.S. counties, respectively (Table 1). Open water represents on average 1% of the average county area and barren land use is less common ( $< 1\%$ ). For manure-related nitrogen inputs, the median loading was  $10^{0.98}$  kg/km<sup>2</sup> (9.55 kg-N/km<sup>2</sup>). Average county applications of fertilizer-N were much higher at  $10^{2.89}$  kg/km<sup>2</sup> (776 kg/km<sup>2</sup>).

Bloom coverage was predicted for all U.S. counties, and Table 2 demonstrates that open water, swamps, and marshes were positively associated with bloom coverage as evidenced by the significant positive coefficients. As aquatic areas in counties increased, as to be expected, so did bloom coverage. The largest coefficient in the model relates to the interaction term of cultivated crop coverage and open water (Table 2). Although representative of a small portion of the overall land cover for the U.S., barren land cover was positively associated with bloom coverage. Both fertilizer-N and manure-N were also positively associated

**Table 2**

Multivariable zero-inflated beta regression model for predicting the proportion of county surface area experiencing late summer cyanobacteria blooms among 2900 U.S. counties with complete data ( $P < 0.0001$ ).

Covariate <sup>a</sup>	$\beta$	$\beta$ SE	Z	p
Open Water	4.651	0.395	11.8	$< 0.001$
Cultivated Crops	−0.679	0.144	−4.70	$< 0.001$
Open Water $\times$ Cultivated Crops	27.04	2.014	13.4	$< 0.001$
Swamp	0.8320	0.293	3.90	$< 0.001$
Marsh	3.674	0.293	12.5	$< 0.001$
Barren Land	5.348	0.981	5.45	$< 0.001$
Deciduous Forest	−0.408	0.147	−2.79	0.005
Fertilizer-N ( $\log_{10}$ [kg/km <sup>2</sup> ])	0.2394	0.045	5.36	$< 0.001$
Manure-N ( $\log_{10}$ [kg/km <sup>2</sup> ])	0.1108	0.036	3.10	0.002
Constant	−5.001			

<sup>a</sup> Covariates represent proportion of county surface area unless otherwise noted.

with bloom coverage. The deciduous forest covariate was the only term that overall reduced bloom coverage indicated by the negative coefficient (Table 2).

The significant interaction effect ( $p < 0.001$ ) between open water and cultivated crops complicates the interpretation of the model coefficients. Figures depicting the relationships involving interactions were generated to ease interpretation. Fig. 1 illustrates that as the proportion of open water in a county increases, so does the proportion of area with a bloom. In Fig. 1, the four categories of cropland represent the 25th, 50th, 75th, and 90th percentiles for the U.S. For all levels of cropland coverage, as both cropland and water area increase, so does the likelihood of a bloom being observed. When the open water area exceeds approximately 10% of county area and cropland coverage exceeds the 75th percentile of 37%, the likelihood of a bloom increases exponentially.

Both the barren land cover class and the amount of nitrogen loading related to manure and fertilizer are predicted to increase the county area impacted by blooms in the national model. Despite a relatively large coefficient, the overall impact of barren land cover on bloom occurrence is minimized by the low prevalence of this land cover type across U.S. counties. The median proportion of county area in the barren class is 0.15% ( $\bar{x} = 0.51\%$ ; 90th percentile = 0.94%).

The impact of both manure-related and fertilizer nitrogen loading from within each county is associated with an increase in bloom coverage (Table 2). Despite considerable differences in the amount of within-county nutrient loading across the U.S., large increases in both manure-related and fertilizer nitrogen create relatively small changes in the predicted proportion of water covered by cyanobacteria blooms compared to the various land uses in the models. For example, the proportion of area predicted to experience a bloom increases

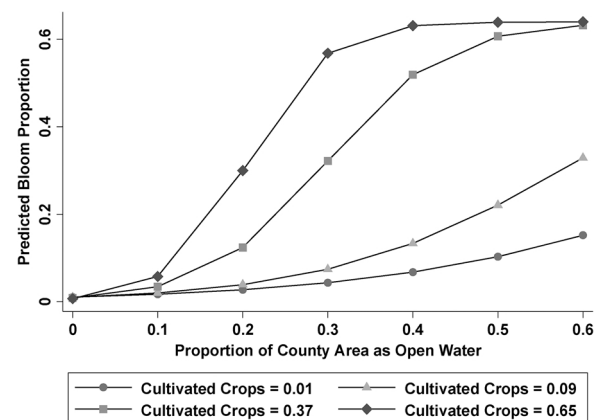


Fig. 1. Adjusted model predictions for the proportion of county area expected to be covered by late summer cyanobacteria blooms as a function of the proportion of open water and four specific levels of cultivated crop coverage for 2900 U.S. counties.



approximately 4% when comparing the 25th percentile and 90th percentile counties for fertilizer-N application (Supplementary information, Fig. S1). When comparing these percentiles (25th versus 90th) for manure-N, the change is ~1–2% (Supplementary information, Fig. S2). Phosphorus terms for manure and fertilizer were not included in the final national model as they were removed during the backward elimination approach ( $p > 0.05$ ) with marginal p-values ( $p = 0.056$  and  $p = 0.059$ , respectively). The N:P ratio of loading that was developed for each county was considered during model development; however, it was not significant when added to the final model ( $p = 0.143$ ).

In addition to the terms in the final national model, no other land cover classifications significantly improved the overall model. Other land uses speculated to be related to blooms were not associated with bloom coverage during model development or as additional terms to the final national model in Table 2. For example, low-, medium-, and high-intensity development as proportions of county land area were not associated with the outcome as individually added terms to the final national model ( $p = 0.576$ ,  $p = 0.905$ ,  $p = 0.737$ , respectively). Furthermore, total developed area (so it reads "Furthermore, total developed...": total developed area ( $p = 0.688$ ) and total developed open space ( $p = 0.958$ ) were not associated with %bloom when given consideration as individual terms in the final national model.

In regional models, open water coverage was positively associated with bloom coverage in all regions (Table 3). Furthermore, other aquatic land uses (marshes and swamps) were positively associated with blooms in two of five regions. In the three regions with the most counties (Northeast, Midwest, Southeast), the strongest predictor after open water area was either the cultivated crops interaction term or the cultivated crops term alone when using the Bayesian Information Criterion. None of the final regional models used all the same terms as the national model and every model was unique in regards to terms (Table 3). Full models are available as Supplementary information (Supplementary information, Tables S3–S7).

## 4. Discussion

### 4.1. Agricultural influences on cyanobacteria blooms

Cultivated cropland and open water coverage were the most significant predictors of late summer cyanobacteria blooms in the national county-based model and three of five regional models. The influence of agricultural land use effects on cyanobacteria occurrence has been previously described (Beaver et al., 2014; Katsiapi et al., 2012). Furthermore, based upon recent (2006 and 2012) direct measures of U.S.

**Table 3**

Significant positive and negative coefficients for one national and five regional models that estimate the proportion of county area expected to experience late summer cyanobacteria blooms.

Covariate <sup>a</sup>	U.S.	NE	SE	MW	SW	W
Barren Land	+					+
Cultivated Crops	+ <sup>b</sup>	+	+ <sup>b</sup>	+ <sup>b</sup>		
Deciduous Forest	–					
Evergreen Forest					–	
High-Intensity Development						+
Low-Intensity Development				+	+	
Marsh	+	+		+		
Mixed Forest						– <sup>b</sup>
Open Space		+		–		
Open Water	+	+	+	+	+	+
Shrub/Scrub Forest					–	
Swamp	+	+	+			
Fertilizer-N (kg/km <sup>2</sup> )	+			+		
Fertilizer-P (kg/km <sup>2</sup> )						+
Manure-N (kg/km <sup>2</sup> )	+			+		–

<sup>a</sup> Covariates represent proportion of county surface area unless otherwise noted.

<sup>b</sup> Significant interaction with open water term.

lakes and reservoirs, the majority of these water bodies with detectable microcystin toxins were in the watersheds and ecoregions with the greatest agricultural influences (Beaver et al., 2014; U.S. EPA, 2009, 2016). The results confirm this assessment, as the proportion of land area for cultivated crop agriculture was the most important parameter for predicting elevated cyanobacteria densities as determined remotely with MERIS. Notably, the effects of development were not significant drivers of elevated phycocyanin levels (%bloom) in the national model; however, development impacts were significant in models pertaining to the Midwest, Southwest, and West (Table 3). Development has been linked to water quality problems and blooms particularly when wastewater treatment is inadequate or non-existent (Foley et al., 2005). In more densely populated regions of the U.S. with more development than the agricultural regions of the Midwest and Plains, microcystins were not readily detected in the National Lake Assessments in 2007 or 2012 (U.S. EPA, 2009, 2016) suggesting that established urban landscapes and developed areas are not as influential for producing detectable levels of microcystins. Based upon data from the U.K. (Naden et al., 2016), it is plausible that advances in U.S. wastewater treatment (more tertiary treatment and phosphorus stripping) coupled with dramatic decreases in P due to regulations on household detergents have decreased bloom formation potential. In areas with agricultural and urban influences, greater reductions of P in receiving waters, coupled with higher concentrations of incoming N from agricultural runoff, non-N-fixing cyanobacteria, like *Microcystis*, may have a competitive advantage over N-fixing cyanobacteria (Huisman and Hulot, 2005). Such would be more likely in areas with more agriculturally impacted waters where N-loading is proportionally higher. The results presented here do not account for existing internal loads in the aquatic systems.

### 4.2. Open water and cyanobacteria blooms

The proportion of county area described as open water from the NLCD data was a strong predictor of the proportion of water in the county that blooms. As open water area increases, hydrologic flushing likely requires more water and more time. Longer water residence times in open water enable greater thermal stratification (less mixing) to occur, especially in the summer. The region with proportionally the most blooms in the US is the Great Plains. Climate scientists have described the region as a semiarid landscape prone to severe droughts (Livneh and Hoerling, 2016). Such conditions, coupled with high nutrient inputs from agriculture, increase the likelihood for cyanobacteria blooms in the region's open water. In temperate glacial lakes such scenarios favor cyanobacteria over eukaryotic green algae (Paerl, 2014) and the impact of these scenarios is most apparent during drought periods with warm water temperatures (Reichwaldt and Ghadouani, 2012; Lehman et al., 2017).

### 4.3. Nitrogen loading and cyanobacteria blooms

In a recent analysis of National Lake Assessment data, Zhang (2014) found that cyanobacterial bloom occurrence was significantly correlated with measured levels of both N (total) and P (total); however, N showed a two time stronger relationship (Zhang, 2014). Overall, more effort is still needed to better understand bloom dynamics and toxin production and the current study does not account for internal nutrient concentrations. Among nutrients in the national model (Table 2), N-loading from manure and fertilizers were the strongest nutrient predictors of late summer blooms and ultimately retained in the model. None of the P terms were significant ( $p > 0.05$ ). The use of the late summer data from MERIS may have biased the study towards assessing *Microcystis* blooms rather than blooms from all cyanobacteria bloom-forming taxa. Early influxes of N during periods of snow melt and/or rain runoff during the spring may enable late spring blooms by non-N-fixing cyanobacteria if water clarity is achieved; however, during a portion of the summer season, if N becomes limited, N<sub>2</sub> fixation can

occur by N-fixing cyanobacteria (e.g. *Aphanizomenon*, *Anabaena*, etc.) if sufficient P exists. With abundant incoming N from agricultural runoff and from sufficient N-fixation, *Microcystis* dominance can occur all year; however, in P-limited waters, such dominance may not occur until late summer with co-dominance by N-fixing cyanobacteria (Beversdorf et al., 2013). Ultimately, a singular focus on non-N-fixing cyanobacteria (e.g. *Microcystis*) and their toxins, may skew research and attention from potentially less common, but health-relevant harmful bloom formers such as N-fixing *Anabaena* and *Aphanizomenon* as well as their interactions with non-N-fixers.

In the model for the Western U.S., manure-N was associated with a decrease in bloom area while fertilizer-P was positively associated (Supplementary information, Table S7). Such results demonstrate the weakness of a national model for making national assumptions while also producing research questions about blooms in the West being P-limited.

#### 4.4. Cyanobacteria bloom attenuation by land cover types

As the proportion of county area increased for deciduous forests in the national model, the proportion of land area in the cyanobacteria bloom condition decreased. Forests provide valuable ecosystem services related to cyanobacteria bloom prevention including denitrification (Martin et al., 1999). In terrestrial forests, anaerobic microbial processes influence denitrification rates and such rates can vary temporarily and spatially (Kulkarni et al., 2015; Enanga et al., 2016). Significant cyanobacteria reduction effects were not observed for shrub/scrub forests or evergreen forest land types in national models, but these forest types were significant associated with decreased blooms in the West.

Forests currently represent on average 19% of the landscape of U.S. counties (Table 1). Forest coverage exceeding 47% of the landscape has been estimated to prevent eutrophication of Canadian streams (Clément et al., 2017). Future models and research may consider the potential benefits of swamp forests for reducing cyanobacteria bloom formation potential. Swamp forests and marshes are both often co-located near open water and are therefore more likely to be associated with blooms. Future studies examining bloom formation in counties with relatively high proportions of swamp forests and marshes are recommended. The increased usage of wetlands for nutrient attenuation to prevent future climate change-induced cyanobacteria blooms has been proposed as a mitigation strategy for circumstances whereby nutrient reductions are not feasible (Paerl et al., 2016a,b). Wetlands (swamps and marshes) have a long record of being intentionally used for decreasing nutrient concentrations in outflows and (Mitsch and Gosselink, 2007; Land et al., 2016). If wetlands are designed with the intent of performing nutrient storage and metabolism, appreciable reductions may not be readily achieved until an optimal or at least functioning microbial community structure is established and sufficient carbon inputs maximize productivity. Such efforts may take over ten to fifteen years (Song et al., 2014; Land et al., 2016).

#### 4.5. Study limitations

There are limitations to this study including the following: 1) the focus of the study was at the county-level rather than watershed level; 2) the data used in the study were not all collected at the same point in time; 3) the nutrient-removing or nutrient-releasing capacity of landscapes may vary substantially even from within the same land cover classifications; 4) the presence or detection of elevated phycocyanin levels from remotely sensed MERIS data does not guarantee that the cyanobacteria blooms detected are harmful; 5) the resolution from MERIS is more coarse than the NLCD data making determinations of associations more prone to error; 6) the coarse MERIS resolution does not enable assessment of lakes or ponds with a width below 300 m; 7) NLCD may incorrectly classify some locations (Wickham et al., 2017;

Smucker et al., 2016); 8) MERIS may not record images in cloudy regions or may be more error prone at the water-land interface due to adjacency effects (Beltrán-Abaunza et al., 2017, Gorham et al., in press); 9) cyanobacteria bloom dynamics are complicated and associations may hold true at the national level, but may not be true for certain ecoregions, watersheds, or open water areas. Future studies providing predictive models for cyanotoxin production using different remote sensing approaches, direct monitoring, or combinations thereof are recommended, particularly for inland U.S. waters (Brooks et al., 2017). Such approaches may require the use of additional remotely sensed data coupled with direct assessments of water with respect to cyanobacteria densities and a variety of other toxins beyond microcystin to validate models. Current models (including the one presented in this study) oversimplify the complex relationships between N:P ratios and cyanobacteria bloom development (Downing and McCauley, 1992; Paerl et al., 2016a,b), and therefore, future research is needed to enhance understanding of cyanobacteria bloom dynamics.

## 5. Conclusions

The results of this study reveal that the proportion of a county landscape existing as cultivated crop agriculture and as open water is linked to an increased likelihood for late summer cyanobacteria blooms within the same county for most U.S. counties. The models generated suggest that forests are linked to decreases in cyanobacteria bloom coverage at the national model and in several regional models. Developed landscapes were not significantly associated with late summer cyanobacteria blooms in the national model, but had impacts in some regional models. Future studies using phycocyanin estimates from MERIS coupled with data from NLCD may further elucidate relationships between land cover and cyanobacteria during different seasons and at different phycocyanin concentrations. Lastly, county-level land uses appear to have a direct effect on the likelihood for late summer cyanobacteria blooms to occur within the same county.

## Acknowledgements

The manuscript was made possible through the communications and presentations at EcoSummit 2016 in Montpellier, France. We are thankful for EcoSummit Delegate Pamela Maxine Cottrell from the Center for Contaminant Hydrology at Colorado State University for assisting in communicating research needs with collaborators. Lastly, the lead and last authors are truly grateful to Dr. William Mitsch, Dr. Li Zhang, and Florida Gulf Coast University for obtaining international travel assistance from the National Science Foundation for early career U.S. scientists to attend EcoSummit 2016. The travel assistance and manuscript were possible from funding by National Science Foundation Award no. 1619948 through the NSF Environmental Sustainability Program.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecoleng.2017.07.032>.

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