Landscape patterns influence nutrient concentrations in aquatic systems: citizen science data from Brazil and Mexico

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Abstract: Studies of the effects of landscape configuration on nutrient concentrations in aquatic systems, apart from land cover percentages, remain limited. Understanding these influences is important to guide land use planning and avoid the undesirable consequences of artificial eutrophication. We investigated how land use and natural landscape attributes such as edge density, mean shape index, cohesion, and contagion were related to nitrate ($N-NO_3$) and phosphate ($P-PO_4$) concentrations in Brazilian streams and Mexican lakes. Data on nutrient concentrations were collected by citizen science volunteers from 2013 to 2016, and we calculated land use classes and landscape metrics for each watershed. We developed models to predict nutrient concentrations based on landscape metrics, watershed slope, and season after excluding autocorrelated predictors. We used the Generalized Additive Model for Location, Shape and Scale framework and found the distribution (gamma or lognormal) that provided the best fit to the data based on the Akaike Information Criterion. The best predictors were selected following a stepwise strategy. We found relatively high $N-NO_3$ (5–10 mg/L) and $P-PO_4$ (0.5–1.0 mg/L) concentrations in the watersheds in both countries. Landscape composition (percentages of urban and agricultural areas) and configuration (mean shape indexes for urban and agricultural land use) metrics were the key predictors in the model for $P-PO_4$ in Brazilian streams. In Mexican lakes, the predictors of nutrient concentrations were configuration metrics such as contagion and edge density of natural areas for $P-PO_4$, and cohesion of urban areas for $N-NO_3$. Our findings can be used as a starting point for land use planning, as well as for helping managers predict nutrient enrichment in watersheds within existing urban and agricultural areas. Our study highlights the importance of community-based monitoring that supplements regular monitoring initiatives because we were able to use data collected by citizen scientists to assess potential drivers of nutrient pollution and differences between countries.
Key words: Community-based monitoring, landscape patterns, nitrate, phosphate, streams, lakes

Nitrogen (N) and phosphorus (P) enrichment of water bodies that leads to artificial eutrophication is one of the most significant consequences of human activities in watersheds (e.g., Vollenweider 1968). Land use has global consequences for freshwater systems through a myriad of direct and indirect pathways (Foley et al. 2005). Both agriculture and urbanization can alter water N and P concentrations. Fertilizer use, livestock density, atmospheric deposition, and sewage inputs are the main drivers of nutrient pollution for lakes (Gildow et al. 2016, Templar et al. 2016) and streams (Poor

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and McDonnell 2007, Martí et al. 2010, Martin-Queller et al. 2010, Rattan et al. 2017, Taniwaki et al. 2017). Agricultural and farming activities associated with both cattle access to stream channels and fertilizer runoff can increase sediment delivery to streams and cause nutrient enrichment (Goss et al. 2014, Conroy et al. 2016). Urbanization can also be an important driver of in-stream nutrient concentrations (Haase 2009, Gessner et al. 2014). Indeed, in low-income countries, urbanization can sometimes be more influential on freshwater systems than agriculture (Gücker et al. 2016, Tromboni and Dodds 2017). Thus, there is heightened concern for water quality in cities in developing nations, where the greatest increase in human populations is expected (Grimm et al. 2008). From a freshwater management point of view, nutrient conditions and their drivers in protected and altered sites provide valuable information that managers can use to define pollution abatement and water quality goals, regulate water withdrawals for different uses, and control wastewater discharge into receiving water bodies.

The magnitude of the human influence on aquatic systems depends on their natural characteristics. Streams and lakes with relatively small watersheds (i.e., drainage areas from 10–100 km^2) can exhibit more pronounced and clear spatial differences in relation to water physical and chemical variables because of the interaction between the attributes of the watershed and the directional processing of materials (Kling et al. 2000). Additionally, nutrient dynamics differ among lotic and lentic ecosystems because of their hydrodynamic characteristics, such as water residence time (Essington and Carpenter 2000), morphometric characteristics such as circular or elongated shape (Bohn et al. 2011), light availability, and other features. These differences can be especially pronounced for ecosystems that are located in different biomes. Therefore, improving water quality in streams and lakes will probably require different management practices such as lowering nutrient concentrations for trophic state abatement or protecting areas for biodiversity (Davies et al. 2008).

Nutrient concentrations and water quality in a catchment depend on land use and the location (position) of various types of land cover within the catchment. This effect has been described in both lotic (Hunsaker and Levine 1995) and lentic ecosystems (Liu et al. 2012). The influences of land use and landscape configuration on water quality can be distinguished by studies that consider landscape patterns and natural watershed biophysical attributes as additional drivers of water quality (see Griffith 2002, Griffith et al. 2002, King et al. 2005, and Clément et al. 2017). However, compared with conventional land cover approaches, few water management studies have incorporated landscape configuration, and even fewer have focused on small aquatic ecosystems (Ding et al. 2016). The association between landscape patterns and water quality might be useful for management purposes because watershed management plans could, for example, incorporate vegetation buffers (Xiao et al. 2016) or promote connections between remnant forest fragments (Lee et al. 2009). Further, management plans could ensure the control and regulation of urban expansion, creation of new settlements, and agricultural conversion.

Headwater streams are numerous and can significantly influence the downstream water quality of the main stem of a stream or river (Alexander et al. 2000, Peterson et al. 2001, Dodds and Oakes 2008). Small lakes, ponds, and impoundments (surface area <1 km^2) are more common globally than their larger counterparts (Downing et al. 2006), so understanding the main factors that influence their water quality is especially important. The landscape patterns, i.e., the composition and configuration of land use types in a landscape, that surround small aquatic systems may be more influential than landscape patterns that surround larger aquatic systems. This is because drainage into small systems is greater relative to their volume and the influence of the catchment can be more important (e.g., Thornhill et al. 2017a).

Curiously, small lentic (e.g., Downing et al. 2006), and small lotic ecosystems (Allan 1995) are often overlooked in regulatory monitoring programs (Loiselle et al. 2016). In addition, there is little information on how landscape patterns differ between small streams and lakes. This lack of information probably occurs because of the high costs involved in traditional water quality monitoring schemes (Cunha et al. 2017a). Environmental data collected through citizen science initiatives therefore represent an interesting opportunity for monitoring under-studied systems (Newman et al. 2011, Thornhill et al. 2017b), and may allow the acquisition of high-resolution information and larger amounts of data (see Cunha et al. 2017b). Thus, data collected by citizen scientists could supplement existing regulatory monitoring by agencies (Hadj-Hammou et al. 2017).

We aimed to assess the influence of landscape patterns (at the watershed level) on bioavailable inorganic forms of N and P in Brazilian streams and Mexican lakes. We used nutrient data from a citizen science project collected between 2013 and 2016 to assess whether N and P concentrations were correlated with landscape metrics. We compared Brazilian streams with Mexican lakes because we had similar data collected by citizen scientists from these places (see Castilla et al. 2015 for more details). Streams and lakes have fundamental differences in their hydrodynamics, interactions with their watersheds, and light regimes, which leads to potential differences in their trophic state and nutrient dynamics. Thus, we hypothesized that the potential drivers of nutrient pollution in Brazilian streams and Mexican lakes would be different.

METHODS

Study sites and data collection

We selected 7 Brazilian streams and 5 Mexican lakes for this study (Fig. S1 [Figs S1–S7 are all in Appendix S1]). The study sites had small watershed areas that ranged from 10.5 to 212.9 km^2 in Brazil and 6.4 to 291.0 km^2 in Mexico. The median slopes (i.e., elevation change divided by hydrologic length) ranged from 4.2 to 5.4% in Brazil and 8.4 to 25.3% in Mexico (Table 1).

Brazilian streams We studied streams in Curitiba, Paraná, Southern Brazil and its surroundings. These streams primarily flow through agricultural areas, although some flow through urbanized areas. Curitiba has ~1.9 million inhabitants, and the average demographic density is 4027 inhabitants/km^2 (IBGE 2016). Curitiba receives ~1500 mm of precipitation annually, and its mean monthly air temperatures range from 12.9 to 20.6°C. There are 5 soil types in the Brazilian study watersheds, and oxisols are the predominant soil type (51–90%) (SoilGrids 2018, USDA).

Mexican lakes We studied lakes in the Mexico City Metropolitan Area (MCMA), which includes the 16 boroughs of Mexico City and 38 other municipalities (INEGI 2014). The population of MCMA is ~20 million inhabitants, and the average population density is 2600 inhabitants/km^2. MCMA receives ~800 mm of precipitation annually, and its air temperatures range from 8.4 to 18.7°C (INEGI 2014). The MCMA is among the areas with the fastest population growth in Mexico (Tortejada 2006). There are 8 soil types in the Mexican watersheds, and alfisols are most common (37–100%) (SoilGrids 2018).

Citizen science sampling methods

The aquatic systems in each country were monitored by volunteers from the FreshWater Watch (FWW) citizen science project (see Castilla et al. 2015, Loiselle et al. 2017). Volunteers worked in groups of ≥2 people and sampled local water bodies from February 2013 to October 2016. Each stream and lake was sampled at 1 representative site at least 10 times (see Table 1). Sites were selected to ensure a homogeneous and representative reach or portion of the stream and lake was sampled, and volunteers avoided sampling at confluences of tributaries or close to water inlets or withdrawals. Volunteers gathered a total of 176 observations

Table 1. Site names, geographic coordinates, watershed areas, and median slopes of the streams and lakes examined in this study. The number of observations (n) is shown as total number (number for dry/number for rainy period) for each site.

Dataset	Site name	N total (dry/wet)	Geographic coordinates (latitude, longitude; decimal degrees)	Watershed area (km^2)	Median slope (%)
Brazilian Streams	Palmital	19 (11/8)	−25.393239, −49.173877	67.7	5.4
	Itaqui	15 (7/8)	−25.525462, −49.091585	19.9	4.5
	Timbu	35 (15/20)	−25.371754, −49.086292	23.4	4.2
	Pequeno	13 (7/6)	−25.519528, −49.145998	86.0	4.9
	Barigui	44 (19/25)	−25.514849, −49.338483	212.9	5.0
	Atuba	20 (10/10)	−25.443130, −49.200466	108.5	4.9
	Canguiri	30 (11/19)	−25.378084, −49.120195	10.5	5.2
Mexican Lakes	Chapultepec	69 (24/45)	19.424117, −99.184851	6.4	8.4
	Tezozomoc	29 (19/10)	19.500592, −99.210167	249.5	21.9
	Canotaje	132 (71/61)	19.274832, −99.104392	160.2	11.8
	Guadalupe	152 (51/101)	19.623616, −99.298035	291.0	18.5
	Madín	146 (56/90)	19.526677, −99.266395	96.7	25.3

in Brazilian streams and 528 observations in Mexican lakes (Table 1).

Volunteers measured nitrate ($N\text{-}NO_3$) and phosphate ($P\text{-}PO_4$) concentrations of unfiltered water samples in situ with colorimetric methods. Volunteers measured $N\text{-}NO_3$ with the N-(1-napthyl)-ethylenediamine reaction (Strickland and Parsons 1968, Ellis et al. 2011) and reported the results in specific ranges (<0.2, 0.2–0.5, 0.5–1, 1–2, 2–5, 5–10, and >10 mg/L). Volunteers measured $P\text{-}PO_4$ with inosine enzymatic reactions (Berti et al. 1988) and also reported these results in specific ranges (<0.02, 0.02–0.05, 0.05–0.1, 0.1–0.2, 0.2–0.5, 0.5–1, and >1 mg/L). More information on volunteer training, health and safety procedures, quality control, feedback to participants, and other FWW specifications can be found in Thornhill et al. (2016) and Cunha et al. (2017a).

Watershed delineation and land use characterization

We used the coordinates for the sampling sites provided by the volunteer groups to locate the water quality sampling sites in ArcMap (ArcGIS 10.5, Redlands, California; Table 1). We delineated the contributing watershed above each sampling site with the Hydrology tool in ArcGIS 10.5, and used the raster input files with a 15-s flow direction and flow accumulation from the mapping product HydroSHEDS – Shuttle Elevation Derivatives at multiple scales (Lehner et al. 2006). These raster files were derived from the digital elevation model generated by the Synthetic Aperture Radar (SAR) during the Shuttle Radar Topography Mission in the year 2000 (Farr et al. 2001).

We used land use and land cover (LULC) data for 2013 in Brazil (MapBiomas Project 2018) and 2010 in Mexico (CEC 2017) to characterize land use in the study watersheds. Both datasets had a spatial resolution of 30 m, and the Brazilian dataset had 27 LULC classes and the Mexican dataset had 19 LULC classes. We clumped the classes in each LULC dataset into 5 broad categories: natural, agriculture, urban, open water, and others (Table 2). We used only the categories natural, agriculture, and urban for the landscape pattern analysis.

Landscape pattern analysis

Our landscape analyses followed 2 main steps. First, relevant composition and configuration metrics were preselected based on a literature review (e.g., Uuemaa et al. 2005, Moreno-Mateos et al. 2008, Lee et al. 2009, Bu et al. 2014, Wang et al. 2014, Qiu and Turner 2015, Shen et al. 2015, Huang et al. 2016). These pre-selected metrics were calculated for all the study watersheds with Fragstats 4.2.1 (McGarigal et al. 2012). We used the 8-neighbor rule, which is an analysis parameter that considers the 8 cells adjacent to a focal cell, (the 4 orthogonal and 4 diagonal neighbors), to aid in patch delineation (McGarigal 2015). Second, we calculated Pearson correlation coefficients to evaluate the linear correlation among all metrics for natural, agricultural, and urban categories. We excluded 1 variable from every pair of highly correlated metrics ($\rho \geq |0.8|$) to avoid collinearity (Zuur et al. 2010, Dormann et al. 2012). However, we also wanted to keep a relevant subset of predictors that addressed different aspects of landscape patterns, so we preferentially retained metrics that were the only representative of a particular attribute (e.g., related to area, shape, and aggregation). The final set of metrics we used to assess relationships between landscape pattern and $N\text{-}NO_3$ and $P\text{-}PO_4$ concentrations was: PLAND_urb, PD_nat, PD_agri, SHAPE_MN_nat, SHAPE_MN_agri, SHAPE_MN_urb, COHESION_nat, and CONTAG for the Brazilian watersheds; and PLAND_agri, PLAND_urb, ED_nat, ED_urb, COHESION_urb, and CONTAG for the Mexican watersheds (nat = natural, agri = agricultural, urb = urban) (Table 3). For further information, such as calculations to obtain these metrics from LULC datasets, see McGarigal (2015).

In addition to landscape metrics, we used watershed slope information as a predictive variable for the concentrations of $N\text{-}NO_3$ and $P\text{-}PO_4$, because watershed slope can strongly influence water quality (Clément et al. 2017). Median slopes for Brazilian and Mexican watersheds were calculated with the R package *raster* (Hijmans 2017). Slope raster files were obtained with the ArcGIS 10 software. For this purpose, we used elevation data (resolution of 1 arc-seconds, ~30 m) that was generated by the SRTM (Shuttle Radar Topography Mission) in the year 2000 (Farr et al.

Table 2. Land use and land cover (LULC) reclassification used in this study and original LULC classes in the study watersheds in Brazil and Mexico.

Original LULC in the study watersheds		LULC reclassification into broad categories
Brazil (MapBiomas Project 2018)	Mexico (CEC 2017)	
Natural forests and non-forest natural formations	Needleleaf, evergreen, and deciduous forests; mixed forests; shrublands; grasslands	Natural
Pasture, agriculture, and forest plantation	Cropland	Agriculture
Urban infrastructure	Urban and built-up	Urban
Water bodies	Water	Open water
	Barren lands	Others

Table 3. Definition and interpretation of class and landscape metrics calculated for Brazilian and Mexican watersheds.

Class metrics	Definition and interpretation
Percentage of Landscape (PLAND, %)	A measure of landscape composition that is widely used in ecological studies. It indicates the proportion of each LULC class in the landscape and permits the comparison of landscapes of different sizes.
Patch Density (PD, number/100 ha)	This metric measures the number of patches of a LULC class per area. It informs about the subdivision of a patch type but does not inform about the size and spatial distribution of patches. Like PLAND, it allows comparisons between landscapes of different sizes.
Edge Density (ED, m/ha)	This metric indicates the perimeter of a LULC class per area. It allows comparison between landscapes of different sizes.
Mean Shape Index (SHAPE_MN, dimensionless)	This metric measures the complexity of patches. Values close to 1 indicate that patch shapes are similar to a square, whereas greater values indicate that patch shapes are more irregular.
Cohesion Index (COHESION, dimensionless)	This index measures the connectivity of a class. Values range from 0 < COHESION < 100. Lower values indicate that a focal class has a low proportion of landscape and is more subdivided and less connected. Greater values indicate that the focal class has more proportion of the landscape and patches are more aggregated.
Landscape metrics	
Contagion Index (CONTAG, %)	This metric considers all classes to measure the clumpiness of landscapes. It considers interspersion and dispersion of patches, evaluating adjacencies between pixels of patch types. It ranges from 0 < CONTAG ≤ 100. Lower values indicate that LULC classes are maximally disaggregated and interspersed, whereas the maximum value indicates that LULC classes are maximally aggregated.

Source: adapted from McGarigal (2015)

2001). The elevation data were downloaded from the USGS database through the Earth Explorer platform.

We also included season as a metric in our models by including October to March as the wet period in Brazil and May to October as the wet period in Mexico. We coded seasonality as a dummy variable, with values 0 for the dry season and 1 for the wet season.

Statistical analyses

To understand the relationship between $N\text{-}NO_3$ and $P\text{-}PO_4$ concentrations and landscape metrics, watershed slope, and season in both Brazilian streams and Mexican lakes, we adopted an approach based on statistical regression. First, we used the Generalized Additive Model for Location, Shape and Scale (GAMLSS) framework for 2 specific reasons: 1) GAMLSS allows explanatory variables to be used for more than 1 parameter instead of only 1 parameter like most other models, and 2) GAMLSS allows the response variable to be an interval-censored variable, which is most realistic for our scenario. Second, we attempted to find the distribution of nutrient values that best described the data. Our candidate distributions were censored versions of both gamma and lognormal distributions, and we compared fits to these distributions with the Akaike Information Criterion (AIC), which can be used to compare non-nested GAMLSS. Third, we used a stepwise model selection strategy based on the AIC criterion to determine the predictors that best explained the data for each nutrient in each country. Finally, we estimated model coefficients. More details about the procedure and the model assumptions are provided in the Supplementary Materials.

Distribution selection We tested whether a censored version of the gamma or lognormal distributions provided the best fit to our data for each nutrient in each country (Figs S2–S5). Both distributions are positively skewed and defined over positive real numbers and therefore appropriate for modeling nutrient concentrations. Despite these similarities, they may have different shapes and behaviors, especially in their tails.

We compared the null model (i.e., the model with no explanatory variables) of each distribution with the Akaike Information Criterion (AIC) (Akaike 1974). We found that the Gamma distribution best described the Brazilian stream data. In this case, the parameterization followed Eq. 1,

$$f(y|\mu,\sigma) = \frac{y^{1/\sigma^2-1}\cdot\exp(-y/(\sigma^2\mu))}{(\sigma^2\mu)^{1/\sigma^2}\cdot\Gamma(1/\sigma^2)}, \qquad \text{(Eq. 1)}$$

where the expected value for nutrient concentrations is $E(y) = \mu$, Γ is the gamma function, the variance is $Var(y) = \sigma^2\mu^2$, and y, μ, and σ are all > 0 (for further information see Supplementary Materials).

The lognormal distribution (Eq. 2) fit the data for the Mexican lakes best based on AIC. For Mexican lakes, we parameterized the models following Eq. 2,

$$f(y|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \frac{1}{y} \cdot \exp\left(\frac{-[\log(y) - \mu]^2}{2\sigma^2}\right), \quad \text{(Eq. 2)}$$

where the expected value for nutrient concentrations is $E(y) = \exp(\mu + \sigma^2/2)$, the variance is $Var(y) = \exp(2\mu + \sigma^2) \cdot [\exp(\sigma^2) - 1]$, and $y > 0$, $-\infty < \mu < \infty$ and $\sigma > 0$.

Random effects The sampling design included repeated observations of the same watersheds across seasons and years, so we tested for the existence of correlated observations by specifying a normally distributed random effect parameter in each model. This parameter is a coefficient that varies for each observational unit, thereby allowing the construction of a proper model for clustered data (Gelman and Hill 2007). The random effect was not defined to be obligatory in the final models but was considered as another candidate for the model selection procedure (see Stasinopoulos et al. 2016).

Stepwise model selection We used a forward stepwise selection strategy to identify the metrics that best predicted nutrient concentrations in each country. This process started with a null model, and we then did a forward search to find the metrics that best defined both μ and σ. Next, we did a backward search for μ. In each step, we selected the model with the lowest AIC score, because this indicates the best fit to the data (Akaike 1974, Stasinopoulos et al. 2016). This selection procedure relies on the fact that the AIC criterion can be obtained from the global deviance, with a penalty term for the effective number of parameters.

Parameter estimation We estimated the model parameters of the best-fitting models within the GAMLSS framework (Stasinopoulos and Rigby 2007). The data collected by the volunteers in both countries were interval-censored (i.e., the results in mg/L were expressed in ranges, and not in their exact values), so we fitted the model with the R package *gamlss.cens* (Stasinopoulos et al. 2016), which generates and fits censored versions of distributions.

RESULTS

Nutrient concentrations

Both N-NO_3 and P-PO_4 concentrations varied greatly between the 2 types of aquatic systems. N-NO_3 concentrations varied across Brazilian streams (from <0.2 to 5–10 mg/L), with the highest concentrations in Atuba, Barigui, and Palmital (most frequent N-NO_3 ranges for these sites: 2–5 mg/L or 5–10 mg/L; Fig. S6). For P-PO_4 in Brazilian streams, concentrations were most frequently <0.02 mg/L (Fig. S6). The highest N-NO_3 concentrations in Mexican lakes occurred in Chapultepec lake (most frequent range: 5–10 mg/L), whereas the highest P-PO_4 concentrations occurred in Guadalupe and Chapultepec lakes (most frequent range: 0.5–1.0 mg/L; Fig. S7).

Landscape metric calculations

The watersheds of the streams and lakes had a variety of land use compositions (Table 4). Urban areas covered between 7.7 to 54.8% and 3.9 to 86.1% of the Brazilian stream and Mexican lake watersheds, respectively. Agriculture was the predominant land use in most of the Brazilian watersheds (4 out of 7, maximum of 47.5%). In Mexican watersheds, the primary land use was natural (2 out of 5, maximum of 67.3%), followed by agriculture (2 out of 5, maximum of 56.2%), and urban (1 out of 5, maximum of 86.1%). However, the 'natural' category in the Mexican watersheds included needleleaf forests, evergreen forests, deciduous forests, mixed forests, shrublands, and grasslands (Table 2), which can have anthropogenic influences of different magnitudes.

The Brazilian stream watersheds had relatively similar configuration metrics. The Canguiri watershed had the highest values for PD_nat (4.97/100 ha) and PD_agri (4.68/100 ha), but it had the lowest values for COHESION_nat (95.63%) and CONTAG (38.96%). Thus, compared with the other sites, this watershed had the highest concentration of natural and agricultural patches per area, its natural vegetation was more fragmented and less connected, and its LULC classes were disaggregated and interspersed throughout the watershed. These measures indicate that the LULC categories in this watershed were more fragmented than the other Brazilian sites.

The configuration metrics for the Mexican watersheds were more variable. For example, ED_nat and ED_urb ranged from 9.72 to 36.83 and 13.98 to 29.14 m/ha, respectively. CONTAG had lower values in Brazilian watersheds (38.96–49.83%) than in Mexican watersheds (48.54–74.40%). These results indicate that land uses in the Brazilian study areas were more disaggregated and interspersed than land uses in the Mexican study areas.

Model results

The models that best predicted P-PO_4 and N-NO_3 concentrations highlighted different potential drivers of nutrient enrichment in each country. In Brazilian streams, PLAND_urb was positively associated with P-PO_4 concentrations (coefficient of the best model: +0.03, see Table 5), whereas SHAPE_MN_agri (coefficient = −3.18) and SHAPE_MN_urb (coefficient = −11.13) were negatively associated with P-PO_4 concentrations (Table 5). The factor season was also associated with P-PO_4 concentrations, and the negative

Table 4. Landscape metrics calculated for watersheds of Brazilian streams and Mexican lakes. PLAND: Percentage of Landscape (%), PD: Patch Density (number/100ha), SHAPE_MN: Mean Shape Index, COHESION: Cohesion Index, CONTAG: Contagion Index (%), ED: Edge Density (m/ha), nat = natural, agri = agricultural, urb = urban.

	Brazilian streams								Mexican lakes				
Metric	Palmital	Itaqui	Timbu	Pequeno	Barigui	Atuba	Canguiri	Metric	Guadalupe	Madín	Tezozomoc	Canotaje	Chapultepec
PLAND_nat	34.4	41.9	31.8	44.6	24.8	18.9	33.6	PLAND_nat	53.1	67.3	30.8	31.1	2.7
PLAND_agri	34.4	40.8	35.3	47.5	36.9	26.2	44.0	PLAND_agri	36.3	28.3	36.2	56.2	9.4
PLAND_urb	31.0	16.6	32.8	7.7	38.1	54.8	22.3	PLAND_urb	9.3	3.9	32.9	12.6	86.1
PD_nat	2.94	3.78	3.16	2.84	2.61	2.41	4.97	ED_nat	35.70	36.83	31.64	14.54	9.72
PD_agri	3.94	2.92	3.98	1.58	3.94	4.53	4.68	ED_urb	24.24	13.98	29.14	15.14	26.58
SHAPE_MN_nat	1.62	1.64	1.63	1.73	1.69	1.64	1.64	COHESION_urb	98.47	95.61	99.62	98.78	99.89
SHAPE_MN_agri	1.83	1.84	1.84	1.74	1.57	1.66	1.81	CONTAG	52.99	67.18	48.54	64.27	74.40
SHAPE_MN_urb	1.23	1.26	1.29	1.28	1.30	1.27	1.28						
COHESION_nat	98.98	97.97	97.81	98.53	97.44	97.56	95.63						
CONTAG	40.90	42.90	40.40	49.83	41.51	47.43	38.96						

Table 5. Fitted models for nitrate (N-NO_3) and phosphate (P-PO_4) in Brazilian streams and Mexican lakes for both seasons. PLAND: Percentage of Landscape (%), $SLOPE_{med}$: median slope, SHAPE_MN: Mean Shape Index, CONTAG: Contagion Index (%), ED: Edge Density (m/ha), COHESION: Cohesion Index, season: dry (0) or wet (1).

Response variable	Best model
Phosphate in Brazilian streams	Distribution: gamma
	$\mu = exp(16.08 + 0.03 \cdot PLAND_{urb} - 1.01 \cdot season - 3.18 \cdot SHAPE\_MN_{agri} - 11.13 \cdot SHAPE\_MN_{urb})$
	$\sigma = exp\ (-0.30)$
Nitrate in Brazilian streams	Distribution: gamma
	$\mu = exp\ (0.12 + \gamma_1)$
	$\sigma = exp\ (1.32 - 0.04 \cdot CONTAG)$
	$\gamma_1 \sim N(0, 1.13)$
Phosphate in Mexican lakes	Distribution: lognormal
	$\mu = -2.07 + \gamma_1$
	$\sigma = exp(2.26 - 0.03 \cdot CONTAG - 0.07 \cdot SLOPE_{med} + 0.03 \cdot ED_{nat})$
	$\gamma_1 \sim N(0, 0.56)$
Nitrate in Mexican lakes	Distribution: lognormal
	$\mu = -1.22 + \gamma_1$
	$\sigma = exp(-20.43 + 0.20 \cdot COHESION_{urb} + 0.02 \cdot PLAND_{agri})$

coefficient (-1.01) suggests that P-PO_4 concentrations were higher in the dry season. The best-fitting model for N-NO_3 concentrations in Brazil, included only the random effect, which indicates that the land use and landscape predictors did not help to explain N-NO_3 concentrations. However, the variance of N-NO_3 (see σ, Table 5) was negatively related to CONTAG, suggesting that the variance was smaller when the LULC patches were more continuous and aggregated.

In Mexican lakes, CONTAG (coefficient $= -0.03$, see Table 5), SLOPE_med (coefficient $= -0.07$), and ED_nat (coefficient $= +0.03$) were significant predictors for P-PO_4 concentrations. COHESION_urb ($+0.20$) and PLAND_agri ($+0.02$) were both positively associated with N-NO_3 concentrations in the lakes.

All of the models, except the model of P-PO_4 concentrations in Brazilian streams, included the random effect (γ) (see Table 5 and more details in the Supplementary Material).

DISCUSSION

In this study we used a nutrient dataset obtained by citizen science volunteers to investigate the relationship between landscape patterns and bioavailable nutrient concentrations in lentic and lotic aquatic systems. The citizen science volunteers focused on different types of water bodies depending on local environmental priorities (streams in Brazil and lakes in Mexico). These comparisons were useful in assessing the factors that led to nutrient enrichment in water bodies with fundamental differences (i.e., lotic vs lentic regime). We think the dataset provided by volunteers is of sufficient quality to allow for a comparison of the potential influences of landscape patterns on nutrient concentrations in streams and lakes, which can differ markedly in their trophic state and nutrient dynamics (Dodds et al. 1998).

Nutrient concentrations in these streams surpassed reference baselines proposed for tropical rivers and streams (e.g., Cunha et al. 2011, Fonseca et al. 2014). In some Brazilian streams, we found P-PO_4 concentrations >0.1 mg/L, which are above the upper limits established by the water quality guidelines in Brazil (CONAMA 2005). The maximum N-NO_3 concentrations in these streams ranged from 5 to 10 mg/L.

Nutrient reference conditions for some of the Mexican watersheds are as low as 0.03 mg/L for N-NO_3 and 0.19 mg/L for P-PO_4 (Carmona-Jiménez and Caro-Borrero 2017). P-PO_4 concentrations were much higher than the baseline in Mexican lakes, with concentrations frequently between 0.5 to 1.0 mg/L. Thus, most Mexican lakes included in this study are eutrophic based on trophic state criteria (e.g., Carlson 1977). This finding is consistent with both a previous study that found eutrophic conditions in the Madín Lake through GIS-assisted spectral analysis (Aguirre 2014) and a study that reported the presence of cyanobacteria and eutrophic/hypertrophic conditions in the Chapultepec and Canotaje Lakes (Arzate-Cárdenas et al. 2010). N-NO_3 concentrations were also higher than the respective baselines, especially in Tezozomoc and Chapultepec lakes.

Urbanization was one of the most important factors related to nutrient enrichment conditions (see Table 5) because factors associated with urbanization, including PLAND_urb, SHAPE_MN_urb, and COHESION_urb were important predictors in most of the best-fitting models. Our results suggest that the percentage of land covered by urban areas was associated with higher $P\text{-}PO_4$ concentrations in Brazilian streams. Similar results have been observed in Estonia (Uuemaa et al. 2007) and China (Bu et al. 2014, Zhao et al. 2015, Ding et al. 2016). $N\text{-}NO_3$ in Mexican lakes was also positively associated with COHESION_urb, indicating that both greater proportions of urban land and more connection among urban patches lead to higher $N\text{-}NO_3$. Similarly, Liu et al. (2012) suggested that large and clustered urban patches can have a more significant impact on lake water quality than small and scattered patches in a Chinese watershed.

Poor sanitary infrastructure that leads to low levels of sewage collection and treatment is an important driver of nutrient enrichment conditions in urban water bodies (Capps et al. 2016). At the national level, wastewater treatment levels are still low in both Brazil where only 45% of wastewater is treated (SNIS 2016), and Mexico where only 57% of wastewater is treated (Conagua/SGAPDS/Gerencia de Potabilización y Tratamiento 2016). According to Barajas (2010) and Aguirre (2014), one of the main nutrient sources in the highly nutrient-enriched Madín and Guadalupe Lakes is untreated domestic wastewater that is delivered directly to these lakes. Thus, our results are consistent with the findings of other studies that highlight the importance of land use in highly urbanized regions of the world, especially in developing countries (Urban et al. 2006, Tromboni and Dodds 2017).

More regular patches of both urban and agricultural areas, demonstrated by lower SHAPE_MN_urb and SHAPE_MN_agri, were associated with greater $P\text{-}PO_4$ concentrations in the Brazilian stream sites (Table 5). Regular patches of urban areas and agricultural crops may be associated with more consolidated settlements and intensive agricultural activities, which probably contribute to higher in-stream $P\text{-}PO_4$ enrichment. The lower $P\text{-}PO_4$ concentrations in the rainy season in Brazil were probably a consequence of a dilution effect from increased discharge in the rainy period.

The presence of forest at the watershed level and near-stream riparian vegetation usually result in lower turbidity and organic C (Cunha et al. 2016) as well as lower nutrient concentrations (Souza et al. 2013), which therefore have a beneficial effect on in-stream water quality. We did not assess riparian zone characteristics in this study, but in Brazilian streams the urban influences seemed to swamp the effects of natural areas (Table 5), which can often attenuate nutrient loads (Abildtrup et al. 2013, Cunha et al. 2016). Additionally, although we did not take distance from urban areas into account, the presence of urban settlements close to the study streams (see Fig. S1) probably influenced the results.

Previous studies have reported that the Aggregation Index for natural areas (forests) at the riparian scale is negatively associated with $N\text{-}NO_3$ concentrations (Ding et al. 2016). However, our model of $N\text{-}NO_3$ concentrations in Brazilian streams included only a random effect, suggesting that other factors were more important than any landscape predictors. Thus, our results contrast with previous studies that have reported a significant influence of agricultural land use, configuration of agricultural patches, or both on $N\text{-}NO_3$ availability in streams (Jones et al. 2001, Wu et al. 2012). However, in our study, the Contagion Index was negatively associated with $N\text{-}NO_3$ variance [$\sigma = \exp(1.3230 - 0.0372 \cdot \text{CONTAG})$, Table 5]. This result suggests that $N\text{-}NO_3$ concentrations in Brazilian streams were less variable in watersheds that had highly aggregated LULC classes (see Table 3).

Nava-López et al. (2016) reported that almost ½ of water quality variation within the 50-m riparian zone of a lake in Mexico City was explained by land use and topography. Our model of lakes in Mexico highlighted the positive influence of edge density of natural areas (ED_nat) on $P\text{-}PO_4$ concentrations in Mexican lakes. Also, ED_nat was highly correlated with PLAND_nat ($p = 0.86$, data not shown), which indicates that the proportion of natural vegetation may be driving the $P\text{-}PO_4$ concentrations in Mexican lakes. Mori et al. (2015) found similar effects in agricultural landscapes in Brazil, where watersheds with more forest cover had higher $N\text{-}NO_3$ concentrations. Thus, agricultural areas may override the ability of natural vegetation to retain nutrients since the latter would be degraded and fragmented (Mori et al. 2015). In Mexican watersheds, natural grasslands were included in the natural areas category (percentages ranges from 17–100% of the 'natural' class, Table 2), and these natural grasslands can be used for some grazing (CEC 2017). Natural grasslands may therefore retain nutrient inputs less efficiently than forests, which could lead to higher $P\text{-}PO_4$ concentrations in Mexican lakes.

Our results showed that $P\text{-}PO_4$ in Mexican lakes was influenced by watershed slope, but $N\text{-}NO_3$ was not. Median watershed slope was a significant predictor for $P\text{-}PO_4$, and steeper areas were associated with lower $P\text{-}PO_4$. These results suggest that surface runoff, which is probably influenced by slope, was negatively associated with in-lake $P\text{-}PO_4$ concentrations. Therefore, P inputs to the Mexican lakes were probably primarily from point-sources of pollution such as sewage. Slope and runoff can also influence $N\text{-}NO_3$ concentrations in water bodies in tropical watersheds (e.g., see Castillo 2010). In our study, however, PLAND_agri and COHESION_urb were important $N\text{-}NO_3$ predictors, which have also been found in other studies (e.g., Hundey et al. 2016).

Seasonality was not important in the $P\text{-}PO_4$ and $N\text{-}NO_3$ concentration models in Mexican lakes. This result suggests that in-lake processes can be more important for controlling N and P dynamics in tropical lakes. Fraterrigo and Downing (2008) found that in-lake processes and land use in the immediate surroundings (i.e., nearshore) usually have a dominant influence on water quality in watersheds with low transport capacity, relative to land use characteristics of the whole catchment. However, Chapultepec, Tezozómoc, and Canotaje Lakes receive treated effluents from wastewater treatment plants. Water quality in these lakes is therefore also highly dependent on the water treatment processes, because different technologies produce treated effluents with different characteristics of organic matter, nutrients, and solids (Metcalf and Eddy 2016).

To fully understand the watershed influences on N and P concentrations in our study streams and lakes, we will need to consider other factors we did not include in our study, such as stream and lake size, hydrologic connectivity with groundwater and streams, and presence of artificial drainages (Riera et al. 2000, Martin and Soranno 2006). Further, we did not measure primary production in the water bodies, but different processes occur in lakes (phytoplankton activity) vs streams (activity of biofilm communities, e.g., periphyton) that affect nutrient cycling (Battin et al. 2003, Cunha and Calijuri 2011, Ribot et al. 2012). These factors can alter bioavailable N and P concentrations and therefore influence the net effects of landscape patterns on nutrient enrichment in the water bodies.

We also recognize the limitations of comparing different countries and different types of aquatic systems, especially because the land use data was available from different years in Brazil and Mexico. However, even with these data availability constraints, we were able to explore potential factors related to nutrient pollution for both study systems.

The impact of urban and agricultural areas on water quality is well documented worldwide (e.g., Nakano et al. 2008, Howell et al. 2012, Mori et al. 2015). However, addressing spatial configuration at multiple scales, in addition to the traditional approach of land use percentages (Gergel 2005, Qiu and Turner 2015), seems fundamental for any water quality study. The best statistical models for Brazilian streams and Mexican lakes included landscape composition metrics related to urbanization and agriculture, and they also showed that landscape configuration was important. Thus, landscape configuration should be taken into account by managers as they plan land use and predict water quality conditions in existing urban and agricultural areas.

Conclusions

In this study, we evaluated the influence of landscape patterns on bioavailable nutrient concentrations in streams and lakes from 2 different countries. N-NO_3 and P-PO_4 concentrations were successfully gathered by volunteers, highlighting the opportunity of citizen science for environmental monitoring, especially for developing countries like Brazil and Mexico. The dataset provided by volunteers was of sufficient data quality to allow for an assessment of the effects of landscape patterns on nutrient concentrations in the local water bodies.

The statistical models that best predicted P-PO_4 and N-NO_3 concentrations in Brazil and Mexico identified different potential drivers of nutrient enrichment in each case. Our data suggests that land use configuration, in addition to the percentages of urban and agricultural areas, is important. In Brazil, the mean shape index of both urban and agriculture categories was negatively related to P-PO_4 concentrations (more regular patches associated with greater concentrations). Concentrations of P-PO_4 in Mexico were positively associated with edge density of natural areas, suggesting that natural grasslands retain nutrient inputs less effectively than forests and may be a source of nutrients. The N-NO_3 model did not explain the concentrations in Brazilian streams well, but the variance in concentrations was negatively related to contagion, indicating that concentrations were more stable when LULC classes were maximally aggregated. Finally, for N-NO_3 in Mexican lakes, higher connectivity among urban patches (i.e., more cohesion) was associated with higher N-NO_3.

Altogether, these results reinforce the need for different strategies regarding nutrient abatement in streams and lakes because they are influenced differently by watershed landscape patterns. One of the most important outcomes of our research is that the models showed that land use configuration was relevant to water quality and therefore that land use composition alone does not provide enough information about nutrient enrichment in different types of water bodies. Our models could be tested and validated and then used to predict water quality conditions (P-PO_4 and N-NO_3) in catchments with existing urban and agricultural areas, because expected nutrient concentrations can be calculated from relatively simple landscape metrics and characteristics. Moreover, our findings can be used as a starting point for watershed management and for prioritizing the protection of more vulnerable areas or the occupation of more suitable areas for urban or agricultural expansion in Brazil and Mexico.

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