



## Spatial structure of phytoplankton metacommunities and their functional groups in a neotropical floodplain

Leonardo Beserra da Silva<sup>1\*</sup> , Ludgero Cardoso Galli Vieira<sup>1</sup> , Thallia Santana Silva<sup>1</sup> ,

Leonardo Fernandes Gomes<sup>1</sup> , Ana Caroline de Alcantara Missias<sup>1</sup>,

Flávio Roque Bernardes Camelo<sup>2</sup> & Regina Célia Gonçalves<sup>2</sup>

<sup>1</sup>Universidade de Brasília, Faculdade de Planaltina, Núcleo de Estudos e Pesquisas Ambientais e Limnológicas, Vila Nossa Senhora de Fátima, 73340-710, Brasília, DF, Brasil.

<sup>2</sup>Universidade de Brasília, Instituto de Ciências Biológicas, Departamento de Ecologia, 70910-900, Brasília, DF, Brasil.

\*Corresponding author: [leobeserra08@gmail.com](mailto:leobeserra08@gmail.com)

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**Abstract:** The spatial and temporal patterns and dynamics of biological community structure can be better understood through the lens of metacommunity theory, in which the effect of local (deterministic processes, ecological niche theory) and regional (stochastic processes, neutral theory) processes are evaluated as the main predictors of phytoplankton. The objective of this paper was to evaluate the effect of local environmental characteristics, spatial, and landscape predictors on the phytoplankton community in lakes of the Araguaia River floodplain. We evaluated the following questions: (i) What is the specific importance of physical and chemical water characteristics (local environmental predictors), dispersive processes (spatial predictors), and land use and occupancy (landscape predictors) in the phytoplankton metacommunity structure, both for taxonomic and functional groups? (ii) Does the buffer size used in land use and land cover measurement around the sampling units show differences in phytoplankton community prediction? All the predictors could explain the phytoplankton structure but the spatial were the most important. The buffers showed different predictive abilities, with taxonomic classification being related to larger sizes of buffers and functional groups the opposite. The great influence of spatial predictors can be explained by source-sink dynamics, where dispersal is so strong that it can diminish the effects of local predictors and guarantee a large flux of organisms to sink communities. In conclusion, dispersive processes have been shown to strongly influence the spatial structuring of the phytoplankton metacommunity and we highlight the need to consider buffers' size when assessing the landscape's effect on phytoplankton communities.

**Keywords:** *Land use and occupation; Araguaia River; MBFG; dispersion.*

## Estrutura espacial de metacomunidades fitoplanctônicas e seus grupos funcionais em uma planície de inundação neotropical

**Resumo:** Os padrões espaciais e temporais e a dinâmica da estrutura da comunidade biológica podem ser compreendidos por meio das lentes da teoria de metacomunidades, no qual o efeito dos processos locais (processos determinísticos, teoria do nicho ecológico) e regionais (processos estocásticos, teoria neutra) são destacados como os principais preditores do fitoplâncton. O objetivo deste trabalho foi avaliar o efeito de preditores ambientais locais, espaciais e de paisagem sobre a comunidade fitoplanctônica em lagos da planície de inundação do Rio Araguaia. Avaliamos as seguintes questões: (i) Qual é a importância específica das características físicas e químicas da água (preditores ambientais locais), dos processos dispersivos (preditores espaciais) e do uso e ocupação do solo (preditores de paisagem) na estrutura da metacomunidade fitoplanctônica, tanto para grupos taxonômicos quanto funcionais? (ii) O tamanho do buffer usado na medição do uso e da ocupação do solo ao redor das unidades de amostragem mostra diferenças na previsão da comunidade fitoplanctônica? Todos os preditores explicaram a estrutura do fitoplâncton, mas os espaciais foram os mais importantes. Os buffers mostraram diferentes habilidades preditivas, com a classificação taxonômica sendo relacionada a tamanhos maiores de buffers e grupos funcionais, o oposto. A grande influência dos preditores espaciais pode ser explicada pela dinâmica fonte-sumidouro, em que a dispersão é tão forte que pode diminuir os efeitos dos preditores locais e garantir um grande fluxo de organismos

para as comunidades de sumidouros. Em conclusão, foi demonstrado que os processos dispersivos influenciam fortemente a estruturação espacial da metacomunidade de fitoplâncton e destacamos a necessidade de considerar o tamanho dos *buffers* ao avaliar o efeito da paisagem sobre as comunidades de fitoplâncton.

**Palavras-chave:** *Uso e ocupação da terra; rio Araguaia; MBFG; Dispersão.*

## Introduction

The distribution of species and their abundances in aquatic environments are determined mainly by deterministic effects and niche filters (Huszar et al. 2015, Moresco et al. 2017). On the other hand, dispersive effects cannot be disregarded, as these can influence the structure of biological communities in a metacommunity context (Hill et al. 2017, Oliveira et al. 2020). This combination of deterministic (niche importance) and neutral (dispersal processes) effects can act in a complementary way in structuring metacommunities (Leibold et al. 2004). Leibold et al. (2004) formulated four models/paradigms within metacommunity theory (species sorting, mass effects, patch dynamics, and neutral), and these vary according to the relative importance of local (deterministic) and regional (neutral) processes in structuring metacommunities. Furthermore, metacommunity structuring can be associated with more than one of these paradigms (Brown et al. 2017).

In addition to local abiotic variables, measures related to land use also influence the distribution of aquatic species and have come to be incorporated in several metacommunity studies (Machado et al. 2016, Costa et al. 2020, Rocha et al. 2020). Indeed, human activities can result in the deterioration of water quality, change in flow, and other impacts on aquatic ecosystems (Smith 2003), which influences species richness and composition. However, the impacts and magnitudes depend on the spatial scale (Zhang et al. 2018). Thus, larger scales comprising agricultural and urban landscapes may result in nutrient concentrations in aquatic environments, while smaller scales may result in local impacts, such as altered streamflow (Xiao et al. 2016, Petlusova et al. 2019).

Numerous studies conducted in aquatic environments have demonstrated the importance of local predictors such as nutrients, environmental conditions, competition, and predation (Wojciechowski et al. 2017a, b, Cunha & Juen 2020) on the structure of phytoplankton communities. Furthermore, spatial predictors such as distance between habitat patches, size of habitat patches, and connectivity in the geographic distribution of phytoplankton have been highlighted as important predictors of phytoplankton (Hill et al. 2017, Moresco et al. 2017, Oliveira et al. 2020). Finally, in recent years studies have used different land use and land cover types as predictors of phytoplankton. However, there is no standard in the size and type of spatial scale used in these studies, and there are studies that use buffers of 30 meters (Machado et al. 2016), 50 meters (Meier et al. 2015), 50, 100, 250, and 500 meters (Costa et al. 2020).

Among the aquatic communities, phytoplankton present a good model for metacommunity assessment because they respond rapidly to diverse environmental and biotic variations in these ecosystems, besides presenting very short life cycles (i.e., several generations within a single seasonal season) (Amengual-Morro et al. 2012, Litchman et al. 2012). Furthermore, studies with phytoplankton functional approaches facilitate the evaluation of biological responses as a function of

environmental predictors (Machado et al. 2016), as well as being a complementary analysis for understanding ecosystem processes and stability, since several species present redundancy in their ecological functions, and by these redundancies promote ecosystem stability (Walker 1992, Thébault & Loreau 2005).

There are several classifications of the phytoplankton community into functional groups: functional groups - FG (Reynolds 2002, Padisák et al. 2009), Morphofunctional Groups - MFG (Salmaso & Padisák 2007) and Morphology-Based Functional Groups - MBFG (Kruk et al. 2010). The MBFG divided species into seven groups, considering morphofunctional characteristics and their relationships with physiological needs. In the study by Lobo et al. (2018), all the cited classifications were tested in shallow floodplain lakes, and the MBFG classification best represented phytoplankton community dynamics. Furthermore, MBFG classification provides an objective and simple approach to classifying phytoplankton organisms (Kruk et al. 2010).

Therefore, this study assessed the following questions: (i) What is the specific importance of physical and chemical water characteristics (local predictors), dispersive processes (spatial predictors), and land use and land cover (landscape predictors) in structuring the phytoplankton metacommunity, both for taxonomic data and functional groups? ; (ii) Does the buffer size used in land use and land cover measurement around the sampling units (in this study, floodplain lakes) show differences in phytoplankton community prediction? Thus, as the study area comprises lakes of a floodplain and the analyzed period occurred in the high-water season (greater connectivity and environmental homogeneity; (Thomaz et al. 2007), we expect that local predictors have less influence on phytoplankton and the spatial predictor is the main structurer of the metacommunity. Furthermore, different buffer sizes will result in varying types of land use and land occupancy, as smaller buffers will primarily consist of native vegetation, because of riparian areas, while larger buffers may primarily comprise agricultural landscapes, as agriculture is the primary land use in the Araguaia River watershed. In this way, larger buffer sizes may capture a wider range of environmental characteristics that influence phytoplankton, such as nutrient concentration, temperature, exposure to sunlight, and additionally, water bodies scattered throughout the landscape may serve as quality habitat patches for phytoplankton, thus facilitating dispersion along the watershed by promoting connectivity between lakes.

## Material and Methods

### 1. Study area

The Araguaia River has its source in the Serra Kayapó, near Emas National Park, in the State of Goiás, Brazil. It has a length of 2,110 km and can be divided into three parts: upper, middle, and lower Araguaia. It has an area of approximately 377,000 km<sup>2</sup> and is one

of the main watersheds draining the Brazilian cerrado (Latrubesse & Stevaux 2002). The middle Araguaia is composed of an alluvial floodplain with ferruginous coarse sand deposition (Latrubesse & Stevaux 2002, Aquino et al. 2008) that extends for 1,160 km. The entry of large tributaries such as the Vermelho River, Peixe River, Crixás River, Cristalino River, Mortes River, among others, notably increases the drainage area of the Araguaia (Latrubesse & Stevaux 2002). The climate is classified as tropical with dry winter and has a strong seasonal variation with two periods: rainy, between October and April, and dry, from May to September (Alvares et al. 2013). In the last 40 years, the Araguaia River has suffered impacts from human activities due to increased deforestation, mining, and aquaculture (Latrubesse & Stevaux 2006, Pelicice et al. 2021). Because it is one of the only large water systems that does not have dams, it is the target of projects to create hydroelectric reservoirs, especially in the upper Araguaia region (Latrubesse et al. 2019).

We sampled 15 lakes located in 5 tributaries (three lakes per tributary) of the Araguaia River (Vermelho River, Peixe River, Crixás River, Cristalino River, and Mortes River) and 35 lakes connected to the main river channel, all located in the middle Araguaia (Fig 1). We performed the sampling in January 2019, during the rainy season. We obtained samples of the phytoplankton community and physical and chemical variables of the water in the pelagic region of each lake.

## 2. Biological variables

We collected phytoplankton samples from the subsurface (ca. 50 cm) and stored them in 100 mL dark, amber flasks. Subsequently, they were fixed with a lugol solution. The phytoplankton density was estimated by the method of Utermöhl (1958) using a Zeiss inverted microscope with 400× magnification. We identified the organisms down to the lowest possible taxonomic level, and the density was expressed as individuals per milliliter (ind/mL) (Komarek & Fott 1983, Komarek & Anagnostidis 1983, Bicudo & Menezes 2006). After taxonomic identification, organisms were classified according to the morphology-based functional groups (MBFG) proposed by Kruk et al. (2010).

## 3. Physical and chemical variables

The following physical and chemical variables were determined in situ using a Horiba multiparameter probe (Model U-50): water temperature (°C), turbidity (NTU), pH, dissolved oxygen (DO mg/L), electrical conductivity (mS/cm) and total dissolved solids (STD g/L).

For the determination of cations and anions (nitrate, phosphate, ammonia, magnesium, potassium, and calcium), water samples were collected at an average depth of 20 cm from the water sheet (Baird et al. 2017), filtered (cellulose filters with porosity of 0.45 µm), frozen and subsequently analyzed in a chromatograph (APHA 2015).

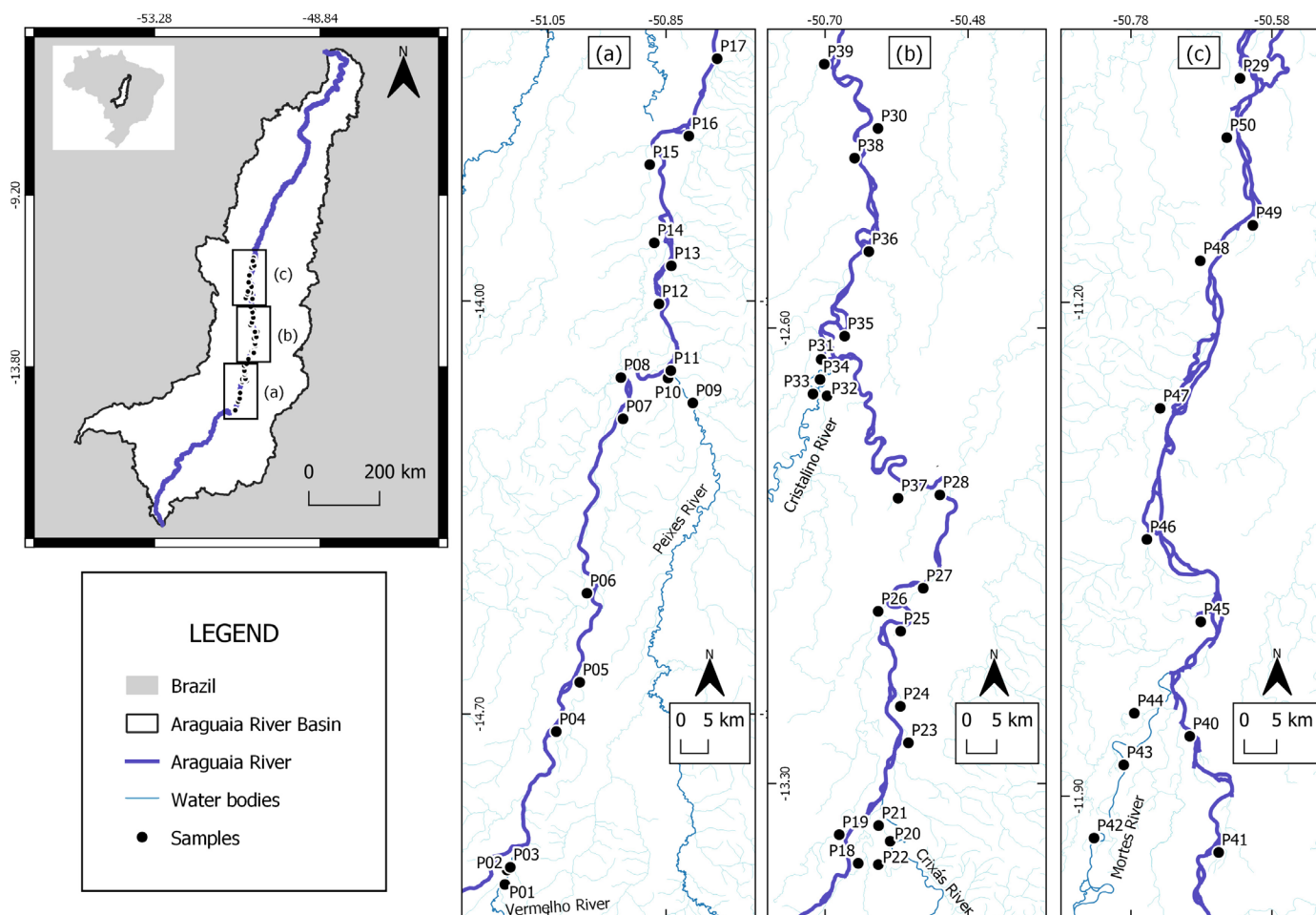


Figure 1. Sampling units located in the Araguaia River Basin.

#### 4. Spatial variables

Spatial variables were obtained by converting the geographic latitude and longitude coordinates to the Cartesian plane using the geoXY function from the SoDA package (Chambers 2014). Subsequently, a distance-based Moran eigenvector map (dbMEM) (Legendre & Legendre 2012) was constructed to model the spatial structure using variables obtained from the Cartesian plane. Eigenvectors with positive spatial correlation and eigenvalues larger than Moran's I expectation were retained for analysis. Finally, we determined which axes to use through forward selection, using two selection criteria:  $R^2$  and the significance value  $p$ . MEMs closer to 1 indicate larger spatial scale, while those further away indicate smaller spatial scale.

We opted to use the dbMEM (directional dispersal) analysis in our study, despite the recognized importance of directional processes, such as water flow, in floodplain lakes (Naselli-Flores & Padišák 2016). However, the phytoplankton community in these environments is also influenced by non-directional dispersal processes, such as wind action and animal movement (Incagnone et al. 2015). Therefore, the dbMEM analysis is suitable because it can capture both directional and non-directional processes, providing a more comprehensive view of phytoplankton dispersal.

#### 5. Landscape variables

To evaluate land use and occupation in the surroundings of the sampling points, we used the land cover map of the Araguaia River basin made available by MapBiomas (Souza et al., 2020 base year 2019), in matrix format. Using the ArcGis 10.8 program, the land cover data were projected to the UTM SIRGAS 2000 22S coordinate system.

The MapBiomas data presented twelve land use classes, so it was necessary to reclassify and group some of these classes, as shown in Table 1.

Subsequently, the reclassified file was converted to a vector file, where the sampling points were inserted. Buffers of different sizes (50, 500, 1500, and 10000 meters) were delimited around each sampling

point in the lakes by calculating the distance map, intersecting the land use with the delimited buffers. These results were converted into percentages and used in the analyses performed. Finally, we performed Redundancy Analysis (RDA) to select the spatial scales that best explained the variation in the phytoplankton community and its MBFG groups.

#### 6. Statistical analyses

Aiming to achieve greater parsimony with the selection of local and spatial predictor variables, the collinearity between them was measured, and a selection of variables was made. This linear dependence was analyzed using variance inflation factors (VIF), and values above 10 were removed (Borcard et al. 2018). After this, the forward selection analysis was performed, using two selection-stopping criteria (Borcard et al. 2018): the first was significance (associated variables with  $p$ -values  $< 0.05$ ), and the second was the adjusted  $R^2$  of the global model (variables that had the adjusted  $R^2$  greater than the global model) (Blanchet et al. 2008). This analysis was performed by the adespatial package (Dray et al. 2022). In addition, we added variables that were left out of the model, but whose effect on the phytoplankton community is well described in the scientific literature. We added variables that were left out of the model, but whose effect on the phytoplankton community is well described in the scientific literature.

To assess the influence of each predictor matrix (environmental, spatial, and landscape) on the phytoplankton community (biological matrix), an RDA was performed (Borcard et al. 2018). Subsequently, for each predictor that significantly explained the variance in the biological matrix, variance partitioning was performed with partial Redundancy Analysis (PDR) to find out how much the biological matrix is explained by a) only the environmental matrix, b) only the spatial matrix, c) only the landscape matrix, and d) the junction of all (Legendre & Legendre 1998). These analyses were performed by the vegan package (Oksanen et al. 2022). To avoid the influence extreme density values, we standardized the data by Hellinger's method from the standardize function of the vegan package.

## Results

We identified 287 species along the middle Araguaia River, where the classes Zygnematophyceae (84 species) and Chlorophyceae (57 species) had the highest species richness. Lakes 47 (Araguaia River, 74 species), 09 (Peixe River, 57 species), and 21 (Crixás River, 57 species) had the highest species richness. The density of organisms was highest in lakes 40 (Araguaia River, 2,161 individuals per mL), 21 (Crixás River, 1,832 individuals per mL), and 37 (Araguaia River, 1,734 individuals per mL), respectively. Only lake 21 is in a tributary, and in lake 40, *Chroomonas coerulea* exhibited a dominance, contributing to 49% of the phytoplankton density in that lake, surpassing other species. The lakes showed low nutrient concentration values, where all lakes were classified as ultraoligotrophic and with high mean temperatures (Table 2). We detected that different land use and land cover types dominated the different sizes of buffers. The 50-meter buffers were mainly composed of water bodies and riparian vegetation, while the 10000-meter buffers had large proportions of forests and cerrado stricto sensu, but also large areas of agriculture (Fig 2).

**Table 1.** Comparison between the land uses obtained in MapBiomas and after reclassification.

Land use (MapBiomas)	Reclassification
Pasture	
Sugarcane	Agriculture
Soy	
Crop mosaic	
Planted forest	Silviculture
Grassland	Grassland
Savanna	Cerrado stricto sensu
Water bodies	Water bodies
Forest	Forest
Exposed soil	Exposed soil
Mining	
Urban	Urban

**Table 2.** Summaries of the physical and chemical characteristics of the lakes. Min = minimum values, Max = maximum values, Std. Dev. = standard deviation, DO = dissolved oxygen, Temp = temperature, TDS = total dissolved solids, Transp = transparency, TSI = trophic state index.

	Min	Median	Mean	Max	Std. Dev.
DO (mg/L)	0.0	6.1	5.6	8.8	2.1
pH	4.9	6.3	6.3	7.1	0.5
Temp (°C)	26.4	30.4	30.6	33.8	1.7
TDS (g/L)	0.004	0.025	0.023	0.041	0.009
Depth (m)	1.9	3.6	4.2	10.5	1.9
Transp (cm)	44.0	100.0	106.6	228.0	39.6
Nitrate (mg/L)	0.1	0.6	1.2	6.4	1.5
Ammonia (mg/L)	1.1	1.9	2.2	4.5	1.0
Potassium (mg/L)	2.2	4.9	5.0	9.0	1.6
Magnesium (mg/L)	0.003	0.011	0.017	0.083	0.017
Calcium (mg/L)	1.1	2.3	2.4	4.4	0.7
Phosphate (mg/L)	0.002	0.019	0.030	0.183	0.032

### 1. Variable selection

Based on the variable selection procedures, eight local predictors and seven spatial predictors were chosen concerning phytoplankton taxonomic classification. Regarding MBFG groups, eight local predictors and one spatial predictor were selected (Table 3).

Several buffer sizes were important in explaining both the taxonomic classification and the MBFG groups. Taxonomic classification was best explained by the 10,000-meter scale and was selected for variance partitioning, while for the MBFG groups, the 50-meter and 500-meter scales were significant, but the 50-meter scale obtained the greatest explanation and was selected for RDAP (Table 4).

The variance partitioning performed between taxonomic data and local, spatial, and landscape predictors had a residual of 0.795, and the spatial and landscape predictors were significant in explaining the variation in phytoplankton taxonomic composition. The spatial predictors explained 7.2%, and the landscape predictors explained 0.5% (Table 5). The shared variance among all compartments was the third largest (5.0%), which may reveal a joint structuring of the predictors evaluated. Regarding the MBFG groups, since the RDA with local predictors were not significant ( $p = 0.1$ ) we only performed with the spatial and landscape predictors, the variance partitioning had a residual of 0.783, and only the spatial (6.8%) and landscape (11.0%) predictors were explained.

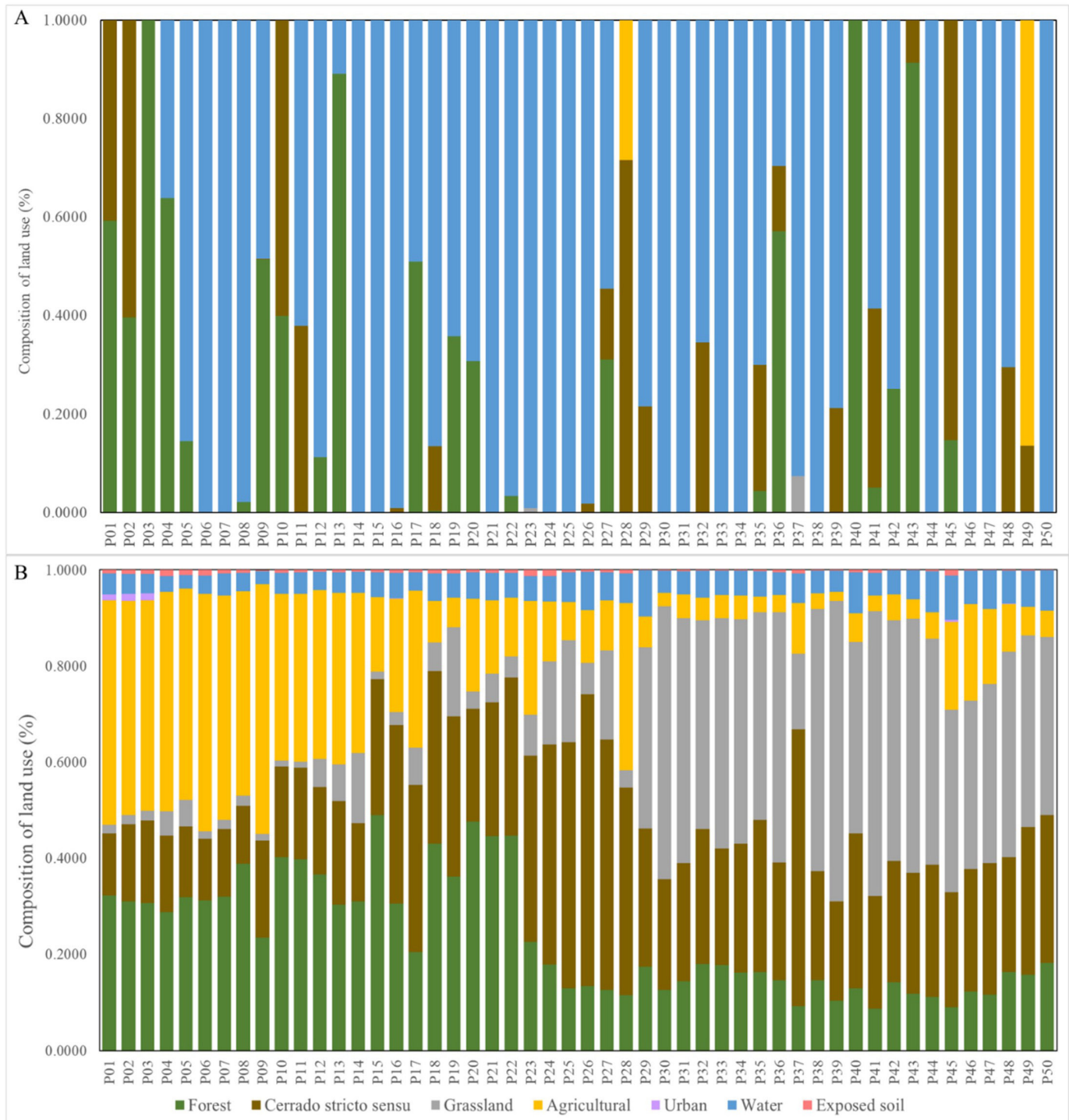
## Discussion

The results show the importance of spatial and landscape predictors for structuring the phytoplankton metacommunity of floodplain lakes. Local predictors had no influence on taxonomic data or functional groups, which may have been caused by important variables that were not evaluated. Furthermore, the significant results for spatial and landscape predictors were very low, indicating that there are additional processes structuring this community that have not been assessed. These results corroborate our first hypothesis that space would be the main predictor of the phytoplankton community, and local predictors would be less influential

in the rainy season. This may have been caused by the homogenization of abiotic conditions occasioned by the flood pulse, which may decrease the strength that the environmental filter has on communities, but also by the permanence of the spatial filter still strong even during the rainy season (Junk et al. 1989, Carvalho et al. 2001, Thomaz et al. 2007). Furthermore, the large spatial scale assessed (reflected by the MEMs selected by forward selection) in this study may have captured better the influence of spatial predictors (dispersal processes) in the phytoplankton metacommunity since increasing the spatial scale may increase dispersal limitation in passively dispersing organisms (De Bie et al. 2012).

Other studies in the same floodplain found the influence of local predictors as structuring the phytoplankton community (Machado et al. 2016) or the influence of no predictors (Nabouf et al. 2009, Moresco et al. 2017), and only Machado et al. (2016) assessed the effect of land use and land cover on the phytoplankton community. In this study, a buffer size of 30 meters was used, which was not significant in explaining the phytoplankton structure. The results of our study differ somewhat from others due to the greater influence of spatial and landscape predictors on phytoplankton, this may have been caused by the spatial scale we sampled (approximately 600 km of straight-line river course) and also by the size of the buffers we analysed, which may have better captured the influences of spatial predictor and landscape on phytoplankton. As a result, this metacommunity showed a dynamic more similar to mass effects paradigm due to the source-sink dynamics where the spatial predictor is strong enough that species occur in habitats that have even sub-optimal conditions (Leibold & Miller 2004). The species-sorting effect is generally stronger in autotrophic organisms. However, increasing spatial scale can decrease its effect and increase dispersal limitation, which may explain this result from our study (Soininen 2014).

As expected, different buffer sizes exhibited varying predictive abilities concerning taxonomic classification and MBFG groups. Regarding the variance partitioning, the landscape predictor explained only the taxonomic classification. Furthermore, taxonomic classification may be more associated with agricultural, given the predominance of these landscape types in larger buffers. In comparison, smaller buffers are predominantly occupied by riparian zone vegetation, at least within



**Figure 2.** Types of land use and land cover found around each sample unit in the 50 m (A) and 10000 m (B) buffers. The water classification encompasses water bodies not part of the lake but within the buffer.

this study area. The vegetation around the lake influences the chemical and physical properties of the water, either in the case of pollutant removal and decreasing allochthonous nutrient loading in the case of natural vegetation (Zhang et al. 2020) or even increasing nutrient loads coming from surface runoff when the land use is composed of agriculture (Broetto et al. 2017). Thus, we can expect MBFG groups to be associated with these 50-meter buffers, mainly because functional

groups directly reflect the niche preferences of each species (Stendera & Johnson 2006, Kruk et al. 2010). On the other hand, the association of taxonomic data with 10000-meter buffers may reflect regional processes such as emigration and immigration, mainly due to the heterogeneity of habitats and landscape connectivity (Peres-Neto et al. 2012, Meier et al. 2015). Thus, the different buffer sizes may reflect distinct processes in the phytoplankton community.

**Table 3.** Variables selected to compose the matrices of local and spatial predictors for each response matrix used in the study. DO = dissolved oxygen, TDS = total dissolved solids, MEM = Moran's eigenvector map.

	Taxonomy	MBFG
Local predictors	DO, TDS, Magnesium, Transparency, Nitrate, Ammonia, Phosphate	DO, TDO, Magnesium, Transparency, Nitrate, Ammonia, Phosphate
Spatial predictors	MEM 1, MEM 2, MEM 3, MEM 5, MEM 6, MEM 8, MEM 9	MEM 3

**Table 4.** Results of RDAs between landscape predictors and taxonomic and MBFG group classification. Values in bold were significant ( $p < 0.05$ ).

Buffer size	Taxonomy		MBFG	
	R <sup>2</sup> adjusted	p	R <sup>2</sup> adjusted	p
50 meters	0.021	0.096	0.149	<b>0.001</b>
500 meters	0.069	<b>0.001</b>	0.082	<b>0.027</b>
1500 meters	0.047	<b>0.002</b>	0.034	0.183
10000 meters	0.109	<b>0.001</b>	0.046	0.114

**Table 5.** Partition of variance of local, spatial, and landscape predictors and their intersections. Values in bold showed significance ( $p < 0.005$ ). not test. = compartments that cannot be tested.

Predictor	Taxonomy		MBFG	
	R <sup>2</sup> Adjusted	p	R <sup>2</sup> Adjusted	p
Local	0.031	0.18	not test.	not test.
Spatial	0.072	<b>0.001</b>	0.0680	<b>0.001</b>
Landscape	0.005	<b>0.010</b>	0.110	<b>0.002</b>
Local* Landscape	0.008	not test.	not test.	not test.
Local*Spatial	-0.0072	not test.	not test.	not test.
Spatial* Landscape	0.047	not test.	0.0390	not test.
Local* Spatial* Landscape	0.050	not test.	not test.	not test.
Residual	0.795	not test.	0.783	not test.

The 10000-meter buffer referring to land use and land cover (landscape variables) was expected to reflect changes mainly in lake nutrient concentrations (Zhou et al. 2012) since land use changes to agricultural and/or urban areas increase nutrient fluxes to aquatic ecosystems (Silva et al. 2011, Su et al. 2013). Doubek et al., (2015) demonstrated the dominance relationship of nitrogen-fixing

cyanobacteria in lakes surrounded by agricultural landscapes, with nutrient input and changes in water temperature brought by runoff being important factors in explaining this relationship. Other studies have also demonstrated the relationship between cyanobacteria and agricultural and urban landscapes (Paul et al. 2012). In turn, Dinophyceae, Crysophyceae, and diatoms have shown a relationship with forested areas (Katsiapi et al. 2012), which may reflect the preference of these organisms for oligotrophic environments (Reynolds 2002).

### Conclusion

Our study reveals how space and landscape were important in structuring the phytoplankton community, serving as a basis for future environmental alterations in the Araguaia River, especially regarding dam construction and reduction in water levels that may decrease connectivity among lakes. Based on our analysis of different buffer sizes related to land use and occupancy in the phytoplankton community, we conclude that there is a differentiated impact on phytoplankton according to the buffer size. Our results demonstrate that larger buffers predominantly affect the overall composition and abundance of phytoplankton, whereas smaller buffers exert greater influence on functional groups. This distinction underscores the importance of considering not only the spatial extent of the buffer but also its qualitative characteristics when planning future studies in floodplains, particularly because floodplains may exhibit various types of land use and occupancy.

### Associate Editor

Marcelo Marinho

### Author Contributions

Leonardo Beserra da Silva: Conceptualization, methodology, writing; original draft and writing; review & editing.

Ludgero Cardoso Galli Vieira: Resources, conceptualization and writing; review & editing.

Thallia Santana Silva: Methodology and writing; review & editing.

Leonardo Fernandes Gomes: Methodology and writing; review & editing.

Ana Caroline de Alcantara Missias: Methodology and writing; review & editing.

Flávio Roque Bernardes Camelo: Methodology and writing; review & editing.

Regina Célia Gonçalves: Methodology and writing; review & editing.

### Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Ethics

This study did not involve human beings and/or clinical trials that should be approved by one Institutional Committee.

## Data Availability

Supporting data are available at <<https://data.scielo.org/dataset.xhtml?persistentId=doi:10.48331/scielodata.Y98EJI>>.

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