## 1 Aedes aegypti and Aedes albopictus abundance, landscape coverage

# 2 and spectral indices effects in a subtropical city of Argentina.

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16 Running head: Landscape coverage associated with *Aedes aegypti* and *Aedes*17 albopictus.

#### 18 Abstract

The presence, abundance and distribution of Aedes (Stegomvia) aegypti (Linnaeus 19 20 1762) and Aedes (Stegomvia) albopictus (Skuse 1894) could be conditioned by different data obtained from satellite remote sensors. In this paper, we aim to estimate the effect 21 of landscape coverage and spectral indices on the abundance of Ae. aegypti and Ae. 22 23 albopictus from the use of satellite remote sensors in Eldorado, Misiones, Argentina. 24 Larvae of Aedes aegypti and Ae. albopictus were collected monthly from June 2016 to April 2018, in four outdoor environments: tire repair shops, cemeteries, family 25 26 dwellings, and an urban natural park. The proportion of each land cover class was determined by Sentinel-2 image classification. Furthermore spectral indices were 27 calculated. Generalized Linear Mixed Models were developed to analyze the possible 28 effects of landscape coverage and vegetation indices on the abundance of mosquitoes. 29 The model's results showed the abundance of Ae. aegypti was better modeled by the 30 minimum values of the NDVI index, the maximum values of the NDBI index and the 31 interaction between both variables. In contrast, the abundance of Ae. albopictus has to 32 be better explained by the model that includes the variables bare soil, low vegetation 33 34 and the interaction between both variables.

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urban environment; dengue; Eldorado city.

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#### 40 Introduction

In the world, the most important mosquito species in terms of disease transmission to 41 42 humans are: Aedes (Stegomyia) aegypti (Linnaeus 1762) and Aedes (Stegomyia) albopictus (Skuse 1894). The arboviruses transmitted by these mosquitoes cause some 43 of the most important diseases in the world (dengue, yellow fever, Zika, chikungunya 44 45 and others), representing one of the greatest concerns for public health due to the great global interconnection mainly due to human population migrations, tourism, the growth 46 of the transport of food and products, environmental changes related to urbanization, 47 deforestation and climate change, among others (Juliano & Lounibos, 2005; Rúa-Uribe 48 et al., 2012). These mosquito species are present in urban, suburban, and rural 49 settlements in tropical, subtropical and temperate regions due to their ability to inhabit 50 both natural (e.g., tree holes) and artificial (e.g., manholes, water storage containers, 51 flower pots, used tires) breeding sites (Hawley, 1998; Vezzani & Carbajo, 2008). In 52 53 particular, the distribution of Ae. aegypti include tropical, subtropical and temperate regions of the world, where it is considered an anthropophilic mosquito and is present 54 mainly inside homes in urban areas. Aedes albopictus is distributed in the tropics 55 56 worldwide, but also in temperate regions in the northern hemisphere, and is associated with the peri-domicile of suburban and rural environments (Lima-Camara et al., 2006, 57 Robert et al., 2020). 58

In Argentina, since the first record in the country during the first half of the 20th century, *Ae. aegypti* was present in several provinces of the country. Currently, it is present in 19 provinces: Buenos Aires, Catamarca, Chaco, Córdoba, Corrientes, Entre Ríos, Formosa, Jujuy, La Pampa, La Rioja, Mendoza, Misiones, Neuquén, Salta, San Juan, San Luis, Santa Fe, Santiago del Estero and Tucumán (Grech *et al.*, 2012; Rossi, 2015; Páez *et al.*, 2016). The first record of *Ae. albopictus* in Argentina dates from 1998

when it was found in the cities of San Antonio and Eldorado in Misiones province
(Rossi *et al.*, 1999; Schweigmann *et al.*, 2004). For 20 years, it had only been detected
in three other cities in Misiones (Puerto Iguazú, Comandante Andresito, and Colonia
Aurora) (Vezzani & Carbajo, 2008; Lizuain *et al.*, 2019). At present, it has been found
for the first time in Corrientes province in 2019, 200 km to the south from its previous
records, representing the southernmost distribution in South America (Goenaga *et al.*,
2020).

The presence, abundance and distribution of Ae. aegypti and Ae. albopictus could be 72 conditioned by the landscape coverage from the differences presented in the biology, 73 ecology and development of these vectors (Mudele & Gamba, 2019; Mudele et al., 74 2021). Changes in environmental conditions as a result of urbanization have been 75 related (directly or indirectly) to the availability of breeding sites, and the modification 76 in the abundance, richness, development and survival of adult mosquitoes (Baldacchino 77 et al., 2017; Benitez et al., 2020). Different data obtained from satellite remote sensors 78 79 have been used to indicate and identify favorable breeding sites for mosquitoes (Hassan et al., 2013). Some studies have linked mosquito populations to remotely detected land 80 cover features. Vanwambeke et al. (2007) found a high probability of finding larvae of 81 Ae. albopictus in the peri-urban. It has also been related to the presence of mixed areas 82 of urbanization and vegetation (Manica et al., 2016). While the abundance and 83 distribution of Ae. aegypti has been related to a greater extent, with variables related to 84 urbanization, such as the presence of buildings (Sallam et al., 2017; Benitez et al., 85 2019). 86

On the other hand, vegetation is one of the most important and frequently described environmental characteristics in the spatial analysis of these species, being repeatedly used in research based on the calculation of satellite spectral indices (Heinisch *et al.*,

2019). Numerous indices can be obtained from algorithms applied on the original 90 remote sensor bands, two of these are potentially indicative of the presence of mosquito 91 breeding sites due to the dependence of the immature stages on the aquatic habitat 92 (Vanwambeke et al., 2007). The Normalized Difference Vegetation Index (NDVI) is the 93 spectral vegetation index most used in spatial and temporal studies (Estallo *et al.*, 2018; 94 Benitez et al., 2019). Along with this, the Normalized Difference Water Index (NDWI) 95 have been widely used in mosquito studies for many years (Pope et al., 1994; Mudele & 96 Gamba, 2019), as well as applied in the study of vector-borne diseases (Estallo et al., 97 2012). 98

For Argentina, although the knowledge about the biology of Ae. aegypti is well 99 documented (Carbajo et al., 2006; Estallo et al., 2018; Benitez et al., 2019), there is 100 very little work on Ae. albopictus since its detection in 1998 (Schweigmann et al., 2004; 101 Lizuain et al., 2019; Faraone et al., 2021). In this context and due to the absence of 102 vaccines for most of the viruses transmitted by these two species, vector management 103 104 and control is the main current tool to prevent their spread. Therefore, the aim of this study was to estimate the effect of landscape coverage and spectral indices on the 105 abundance of Ae. aegypti and Ae. albopictus from the use of satellite remote sensors in 106 Eldorado, Misiones, Argentina. 107

## **108** Materials and Methods

#### 109 Study site

Eldorado city (Fig. 1) is located in the northwest of Misiones province, within the Neotropical region (26° 24′ S, 54° 38′ W). The phytogeographical region is Paraná province. The area characterized by the presence of three arboreal strata, with lianas, epiphytes and hemiepiphytes and an undergrowth of ferns and herbaceous and shrubby phanerophytes, including bamboos (Oyarzabal *et al.*, 2018). The climate is subtropical,
hot and humid, without a marked dry season. The mean annual temperature is 22 °C,
with a maximum temperature of 38.5 °C (January) and a minimum of 5.4 °C (July); the
mean annual rainfall is 2020 mm (Silva *et al.*, 2008).

Eldorado is the third-largest city in the province with a population of 100,000 inhabitants and a surface of 215 km<sup>2</sup> where 14% corresponds to rural areas, 30.6% to natural forests and 55.4% to other uses (Molinatti *et al.*, 2010). The city expands on both sides along the National Route N° 12. The main economic activities of the region are forestry (sawmills, pulp and paper industry) and agriculture, oriented to industrial crops production of (yerba mate, tea, tobacco and citrus).



Argentina

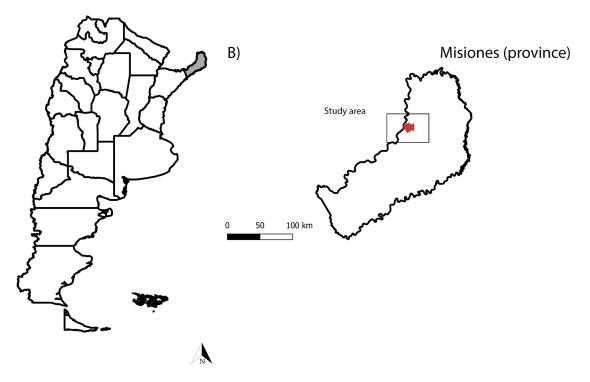




Fig. 1. (A and B) Geographic location of the study area in Misiones, Argentina.

#### 125 Entomological sampling

Larvae of Aedes aegypti and Ae. albopictus were collected monthly from June 2016 to 126 April 2018, in four outdoor environments: tire repair shops, cemeteries, family 127 dwellings, and an urban natural park (Parque Schwelm) (Fig. 2). Sampling sites with 128 larval presence of both species were georeferenced using the Global Position System 129 130 (GPS-Garmin eTREX 10). The number of monthly samples was N = 60, distributed as follows: 20 natural habitats; 20 artificial habitats of cemeteries, 10 of repair shops and 131 10 of houses. The homes were visited according to the provisions of the Environmental 132 Sanitation Direction of the Municipality of Eldorado, where each month different 133 neighborhoods were visited. The larvae were transferred to the laboratory of the 134 135 Institute of Regional Medicine for their breeding (larvae of instar I, II and III), conservation and determination. For morphological identification of the specimens 136 (fourth instar larvae), dichotomous keys (Darsie 1985; Consoli & de Oliveira 1994) 137 were used. 138

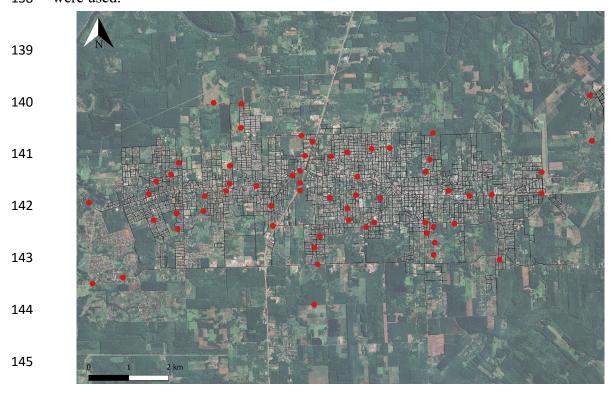
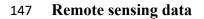




Fig. 2. Distribution of sampling sites in Eldorado, Misiones, Argentina.



In order to estimate the different landscape coverage in the city, images from the Sentinel-2 satellite were used. Five images from the satellite were used, which were downloaded from the Land Viewer website (https://eos.com/landviewer/). The satellite images correspond to the succession of stations from the three years of sampling and were selected according to the availability of images on the website and the absence of clouds over the area of interest.

154 Spectral indices

On each satellite image, spectral indices were calculated: Normalized Difference 155 Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and 156 Normalized Difference Built-up Index (NDBI). The NDVI reflects the contrast of 157 vegetation reflectivity between the spectral regions of Red (R) and Near Infrared (NIR) 158 reflectance (Eq.1). This index can be associated with the vegetation cover, in terms of 159 abundance and vigor, since it is strongly related to the photosynthetic activity of the 160 vegetation, allowing to identify the presence of vegetation on the surface and 161 characterize its spatial distribution. The values vary from -1 to +1, where high values 162 correspond to areas with vigorous vegetation, negative values are associated with covers 163 164 such as water and values close to zero correspond to bare soil (Chuvieco Salinero, 2008). On the other hand, the NDWI is an index that takes into account the water 165 content present in the mesophyll of the leaves and indirectly measures precipitation and 166 soil humidity (Estallo et al., 2012). It varies between -1 and +1, depending on the water 167 content of the leaves, but also on the type of vegetation and cover. It is based on the 168 contrast between the reflectances of Short-wave Infrared (SWIR) and NIR wavelengths 169 (Eq.2) (Gao 1996). The NDBI is an index that highlights urban areas, where there is 170 typically a higher reflectance in the SWIR region, compared to the NIR region (Zha et 171

172 al., 2003). Positive NDBI values indicate built-up areas and those close to 0 indicate

vegetation, while negative values represent bodies of water (Ranagalage *et al.*, 2017).

174 NDVI = (NIR-R) / (NIR+R) (Eq.1)
175 NDWI = (NIR-SWIR) / (NIR+SWIR) (Eq.2)

176 NDBI = (SWIR-NIR) / (SWIR+NIR) (Eq.3)

177 Land cover classification

To determine landscape coverage in Eldorado, supervised classification (Minimum 178 179 Distance to Mean) was performed using QGIS 3.4.15 software (https://www.qgis.org/). Five land cover classes were obtained: water (rivers, lakes, artificial bodies of water), 180 bare soil (soil without any vegetation cover, unpaved streets), urban areas (buildings, 181 paved streets and roads), low vegetation (herbs and grasses) and high vegetation (trees 182 and shrubs). The accuracy of the classification was measured by a confusion matrix and 183 the value of the Kappa's coefficient, where values close to 1 indicate greater accuracy of 184 the classification method. The areas for verification were determined from the 185 visualization of images published in Google Earth ©. A total of 100 control points were 186 defined by landscape coverage following the criteria recommended by Chuvieco 187 Salinero (2008). Regarding the classification of Sentinel-2 images, the global precision 188 of the classifications ranged from 91% to 99.6%, with Kappa's coefficients from 0.887 189 190 to 0.995. One of the final classified images can be seen in Figure 3.

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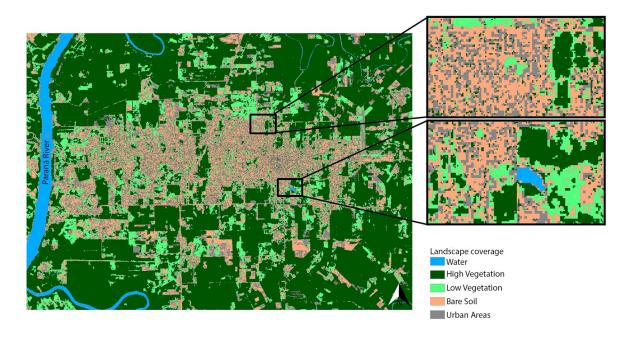


Fig. 3. Supervised classified image for Eldorado from November 12, 2016.

#### 196 Buffer areas

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Around each sampling site, circular influence areas of 100m were generated, avoiding the overlapping of the areas and taking into account the biology of the vector. Once these areas were constituted in each classified image, the proportions of each class of landscape coverage were extracted, as well as the mean, minimum and maximum values of NDVI, NDWI and NDBI.

#### 202 Data analysis

To analyze the possible effects of landscape coverage and vegetation indices on the abundance of larvae, generalized linear mixed models (GLMM) were constructed for each species separately with a Negative Binomial distribution. To control for overscattering, a logarithmic link function was used (Zuur *et al.*, 2009). In our analyzes, the response variable used was the number of larvae collected at each site per month. The sites were incorporated as a random effect to include spatial dependence. The

- 209 explanatory variables used are shown in Table 1. Water coverage was not incorporated
- 210 into the models because it was not found in any buffer area.
- 211 Table 1. Explanatory variables used to explain the variation in the abundances of Ae. aegypti and Ae.
- 212 *albopictus* in Eldorado, Misiones.

Variable	Description
highV	Proportion of high vegetation cover extracted from a 100m buffer around each sampling site
lowV	Proportion of low vegetation cover extracted from a 100m buffer around each sampling site
soil	Proportion of bare soil cover extracted from a 100m buffer around each sampling site
urban	Proportion of urban areas cover extracted from a 100m buffer around each sampling site
ndvi	Mean value of NDVI extracted from a 100m buffer around each sampling site
ndvimin	Minimum value of NDVI extracted from a 100m buffer around each sampling site
ndvimax	Maximum value of NDVI extracted from a 100m buffer around each sampling site
ndwi	Mean value of NDWI extracted from a 100m buffer around each sampling site
ndwimin	Minimum value of NDWI extracted from a 100m buffer around each sampling site
ndwimax	Maximum value of NDWI extracted from a 100m buffer around each sampling site
ndbi	Mean value of NDBI extracted from a 100m buffer around each sampling site
ndbimin	Minimum value of NDBI extracted from a 100m buffer around each sampling site
ndbimax	Maximum value of NDBI extracted from a 100m buffer around each sampling site

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First, data exploration was implemented following the protocol described in Zuur *et al.* (2010). The explanatory variables were standardized to balance their weight and also to avoid introducing errors in the model produced by the different measurement units of each variable. Then, a Spearman's test was performed to analyze the correlation of theexplanatory variables.

The models were built using a manual step-by-step forward procedure. We began by 219 220 evaluating the significance of each response variable from univariate GLMM. The variables that were significant for each species were in turn used as starting points in the 221 different branches of the modeling. Subsequent variables were added one at a time as 222 long as they did not have a correlation coefficient >0.7 with some variables already 223 included. Interactions between them were also tested. In each step, the significance of 224 each addition was evaluated with a significant reduction (2 points) in the Akaike 225 Information Criterion corrected for low sample sizes (AICc) (Zuur et al., 2009). The 226 GLMMs were classified according to the AICc and the model with the lowest value was 227 selected as the best model. The multicollinearity between variables was evaluated in the 228 final models using the Variance Inflation Factor, considering a threshold value equal to 229 5. Finally, the ggResidpanel package was used to verify the normality of the residual 230 distribution and evaluate the residual plot. 231

The free software R, version 4.0.3 (https://www.r-project.org/) and the packages lme4 (*glmer.nb* function), MuMin (*model.sel* function) and car (*vif* function) were used to perform the statistical analyzes.

#### 235 **Results**

A total of 23,658 mosquitoes of the species under study were collected during the entire sampling period. Of that total, *Ae. aegypti* presented a relative abundance of 86.70% (n = 20,511), while *Ae. albopictus* of 13.30% (n = 3147).

Based on the exploratory analysis of the variables and considering those with statisticalsignificance in the univariate GLMMs, 5 model branches were constructed for *Ae*.

*aegypti* and 1 branch for *Ae. albopictus*. For the first species, the univariate GLMMs of: highV, soil, ndvimin, ndbi and ndbimax were started, and after considering the correlations between the independent variables, 66 models were made that evaluated the addition of more variables and interactions. In contrast, for *Ae. albopictus* GLMMs were modeled from the variable: soil, making 14 models (see Tables A-G in Supporting Information). In Table 2, the selected models within each branch are displayed from the comparison of the goodness of fit indicators (AICc) for the species under study.

248 Table 2. GLMM selected for *Ae. aegypti* and *Ae. albopictus*.

Specie	Model	Variable	AICc
Ae. aegypti	Ma3	highV+ndvimin	7683.7
	Ms11	soil*ndvimin	7643.2
	Mv16	ndvimin*ndbimax	7633.7
	Mb5	ndbi*ndvimin	7648.1
	Mm16	ndbimax*ndvimin	7633.7
Ae. albopictus	Ms11	soil*lowV	3440.9

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The GLMM results showed that the larvae abundance of *Ae. aegypti* was better modeled by the minimum values of the NDVI index, the maximum values of the NDBI index and the interaction between both variables (Table 3). In contrast, the abundance of *Ae. albopictus* has to be better explained by the model that includes the variables soil, lowV and the interaction between both variables (Table 4). The other GLMM with the same AICc (soil\*ndbimax) was not selected for presenting a vif >5 in the interaction between the variables.

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Variable	Estimate	Std. Error	Z value	Pr(> z )
Intercept	5.18544	0.01475	351.6	<2e-16**
ndvimin	-14.48629	0.01481	-977.8	<2e-16**
ndbimax	-6.94077	0.01481	-468.6	<2e-16**
ndvimin*ndbimax	17.40568	0.01482	1174.7	<2e-16**

# 260 Table 3. Coefficients of the final GLMM selected for Ae. aegypti.

261 An asterisk means p < 0.05, two asterisks mean p < 0.01.

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#### 263 Table 4. Coefficients of the final GLMM selected for *Ae. albopictus*.

Variable	Estimate	Std. Error	Z value	Pr(> z )
Intercept	0.2294	0.5501	0.417	0.6766
soil	0.3630	1.1394	0.319	0.7500
lowV	-2.9152	1.3444	-2.168	0.0301*
soil*lowV	10.5393	4.4811	2.352	0.0187*

An asterisk means p < 0.05, two asterisks mean p < 0.01.

#### 265 **Discussion**

The present study allowed us to identify the effect of landscape covers and vegetation indices on the spatio-temporal larvae abundance of *Ae. aegypti* and *Ae. albopictus* from the use of Sentinel-2 images in a subtropical city of Misiones, Argentina.

The global distribution of ecological rivals, *Ae. aegypti* and *Ae. albopictus*, have changed in recent decades due to differences in their abilities to compete with each other (Bennett *et al.*, 2021). Generally, *Ae. aegypti* is highly adapted to the domestic environment, and therefore abundance is positively correlated with increasing urbanization (Higa, 2011). In this study, a negative association was found between the abundance of *Ae. aegypti* and NDVI minimun values and NDBI maximun values. In accordance with Bennett *et al.*, (2021) who found a negative association with lower
NDVI values for both species in Panamá.

Urban areas provide this mosquito with food, shelter, reproduction and oviposition sites 277 278 (Flaibani et al., 2020). Previous studies in the United States, Costa Rica, Puerto Rico, Brazil and Argentina, have related the abundance of the species with urban areas, 279 buildings and high housing density (Carbajo et al., 2006; Vezzani & Carbajo, 2008; 280 Fuller et al., 2010; Little et al., 2011; Montagner et al., 2018; Benitez et al., 2019, 281 Heinisch et al., 2019). In turn, Chaves et al., (2021) in Costa Rica found a negative 282 association between vegetation index (measured through the Enhanced Vegetation 283 Index-EVI-) and the abundance of Ae. aegypti, while Samson et al., (2015) found that 284 urban areas identified by Urban Index were found to be important in predicting 285 distribution of the species and that the results of their models show a high probability 286 for Ae. aegypti in and around urban areas. In accordance with our findings about the 287 negative association of Ae. aegypti with the maximum values of NDBI, a spatial study 288 carried out in Buenos Aires city, Argentina found that the proliferation of mosquitoes 289 Ae. aegypti was highest in medium urbanization levels (not densely built on the 290 suburban areas) (Carbajo et al., 2006). Due to the different population densities of both 291 cities, we expect that the maximum values of NDBI in Eldorado (57,323 inhabitants) 292 will be related to the mean values of NDBI in Buenos Aires (12,801,364 inhabitants). In 293 cities with a high degree of urbanization and high population density, the peripheral area 294 is the most conducive to the reproductive activity of the vector since urbanized areas of 295 the city offer few spaces with vegetation (for food and shelter), few breeding sites and 296 297 reduce the connectivity between patches of habitat that are more favorable (Carbajo et al., 2006, Benitez et al., 2019) 298

Our study found a positive association between the abundance of *Ae. aegypti* and the interaction between both indices in accordance with previous studies for Costa Rica (Troyo *et al.*, 2009) and temperate Argentina area (Benitez *et al.*, 2019) where moderately built-up residential areas with moderate tree cover likely contain a relatively high number of positive habitats for this species, therefore heterogeneity in urban areas can be linked to the distribution of this species.

On the other hand, the distribution of Ae. albopictus is associated with vegetation in 305 rural, suburban and urban areas and its abundance is negatively affected by 306 urbanization. This difference in distribution along the urban-rural gradient is associated 307 with behavior related to blood feeding, host preference, and preference for vegetation, 308 offering ideal conditions for resting and egg laying (Heinisch et al., 2019; Higa, 2011; 309 310 Manica *et al.*, 2016). We observed a negative association between the abundance of the species and low vegetation coverage, and a positive association between the interaction 311 of soil and low vegetation. In this work, the land cover class soil has been related 312 313 around the sampling sites with sandy streets (unpaved road) more characteristic of suburban areas (see Fig. A-C in Supporting Information). Our results are according to 314 Myer et al. (2019), who found an important relationship between the abundance of Ae. 315 *albopictus* and grass cover (negative) and the interaction between impervious and grass 316 317 cover (positive).

In agreement with Rey *et al.* (2006), Honorio *et al.* (2009) and Cianci *et al.* (2015) low vegetation coverage that includes grasses was negatively associated with the abundance of *Ae. albopictus* larvae, indicating that open areas are less attractive for this mosquito species. In Porto Alegre, Brazil, *Ae. albopictus* was dominant in urban areas with vegetation, relating its adaptation to transition zones between urban and non-urban/natural habitats (Montagner *et al.*, 2018). According to Forattini (2002), the adaptation of the species to transition zones results from being able to use larval habitats or breeding sites and sources of blood food from both environments. Likewise, in Florida, United States, Rey *et al.* (2006) found a positive relationship between the abundance of immature *Ae. albopictus* and land covers: ground vegetation, unpaved road and bare ground.

This is the first work carried out in the country to relate the abundance of Ae. albopictus 329 with products derived from remote sensors, and the results obtained provide important 330 knowledge about the biology of this species in Argentina. The Pan American Health 331 Organization (PAHO, 2016) has recommended the following in areas of recent 332 infestation by Ae. albopictus the immediate responsibility to contain and control it if 333 possible, to prevent further spread. For this, knowledge is required on numerous aspects 334 of the ecology of the species, areas of distribution, periods of greater activity, among 335 others that generate baselines to understand the dynamics of pathogen transmission and 336 therefore implement effective programs of control. 337

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### 347 Author Contributions

Mia E. Martin: Formal analysis, Writing - original draft, Writing - review & editing.
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Writing - review & editing. Marina Stein: Conceptualization, Funding acquisition,
Methodology, Investigation, Resources, Supervision, Writing - original draft, Writing review & editing. Elizabet L. Estallo: Formal analysis, Methodology, Writing - original
draft, Writing - review & editing.

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