Spatial and temporal predictions of mosquito potential breeding sites and densities: integration of satellite imagery, *in-situ* data, and process-based modeling

Claire Teillet [1], Rodolphe Devillers [1], Annelise Tran [2], Renaud Marti [2], Marie Demarchi [3], Thibault Catry [1], Joseph Rwagitinywa [4], Johana Restrepo [4], Nadine Dessay [1], Emmanuel Roux [1,5]

[1] ESPACE-DEV (IRD, U. Montpellier, U. Guyane, U. La Reunion, U. Antilles, U. Perpignan, U. Nouvelle Calédonie), Montpellier, France – claire.teillet@ird.fr
[2] TETIS (U. Montpellier, AgroParisTech, CIRAD, CNRS, INRAE), Montpellier, France
[3] DEMARCHI Marie, Montpellier, France
[4] Collectivité Territoriale de Guyane (CTG), Direction de la Démoustication, Cayenne, France
[5] International Joint Laboratory Sentinela (IRD, Oswaldo Cruz Foundation (Fiocruz), U. Brasília (UnB)), Montpellier, France

Keywords: *Aedes*, machine learning, remote sensing, vector control, population dynamics model.

Abstract:

Dengue fever, primarily transmitted worldwide by the mosquito *Aedes aegypti*, poses significant public health challenges in tropical and subtropical regions. While effective vector control is crucial in the absence of reliable dengue vaccines, traditional control methods face obstacles like mosquito resistance to insecticides and a very high cost. By combining geospatial data, including satellite imagery, as descriptors, and entomological surveys as target variables in a Random Forest model, we predicted the number of potential mosquito breeding sites, derived the associated environmental carrying capacity for larvae, and used the Arbocarto process-based model to predict *Ae.aegypti* population densities in an urban region of French Guiana, South America. Our findings highlight that remote sensing data may help predict the number of potential breeding sites over urban areas. Our simulations indicate higher mosquito densities in urban residential areas and a strong spatial and temporal heterogeneity. These densities fluctuate according to intra-annual variations in temperature and precipitation, with higher densities associated with intermediate housing. A comparison with the conventional estimation of environmental carrying capacity for larvae in the current Arbocarto procedure highlights the advantages of our approach. Our study demonstrates the utility of integrating remote sensing with predictive modeling to enhance vector surveillance and control strategies, and provides a replicable approach for monitoring a dengue vector mosquito population in dynamic urban landscapes.

1. Introduction

Dengue virus is a mosquito-transmitted pathogen causing dengue fever, a major public health issue in tropical and subtropical regions. One of its main vectors, *Aedes aegypti*, thrives in urban environments (Kolimenakis et al., 2021). In the absence of effective vaccines for dengue, effective vector surveillance and control strategies are key to prevent outbreaks. However, current control methods which mainly rely on insecticide spreading and mechanical elimination of breeding sites can lead to mosquito resistance to insecticides, environmental pollution, and are very costly in terms of time, human, and financial resources (Weeratunga et al., 2017; Epelboin et al., 2018). Modeling the spatial and temporal distribution of mosquito abundance can help identify and prioritize areas to improve vector control and guide policies. Process-based (or mechanistic) models have been applied in different geographical contexts to study *Aedes* mosquito population dynamics in time and space (Erguler et al., 2016; Dickens et al., 2018; Tran et al., 2020; Bonnin et al., 2022). French Guiana, a French overseas department located in South America, faced multiple dengue outbreaks in the recent decades (e.g., 2006, 2009-2010, 2013, 2020-2021) and an ongoing outbreak that began in 2023. The sole vector of dengue in French Guiana is *Ae. aegypti*. The potential risk of *Ae. Albopictus* introduction in French Guiana further compounds the challenge of vector-borne diseases, as highlighted by these recent outbreaks (Epelboin et al., 2018). These events have encouraged local vector control authorities to explore the potential of *Ae. aegypti* population dynamics models to identify hotspots before and during epidemics, at fine temporal and spatial scales. Remote sensing can provide cost-effective and reproducible methods to help characterize urban environments, for example, associated with breeding sites (Machault et al., 2014; Bailly et al., 2021; Teillet et al., 2024), or to estimate climatic variables associated with the mosquito life cycle, mainly driven by temperature and rainfall (Moreno-Madriñán et al., 2014; Richman et al., 2018; Lorenz et al., 2020). This study proposes a new approach based on remote sensing to predict mosquito population dynamics on Cayenne Island, French Guiana, through the prediction of the number of potential *Ae. aegypti* breeding sites and process-based modeling. This research is the first attempt to use remote sensing and process-based modeling to predict mosquito populations across cities of French Guiana.

2. Materials and Method

2.1 Study site

The study was conducted on Cayenne Island, French Guiana (South America), a peninsula comprising the municipalities of Cayenne, Matoury, and Remire-Montjoly (Figure 1).

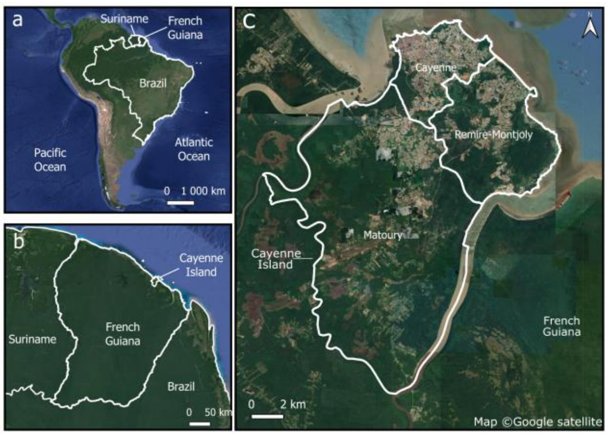

Figure 1: Study Site: (a) French Guiana located in South America; (b) French Guiana neighboring countries and Cayenne Island; (c) Municipalities of Cayenne, Rémire Montjoly, and Matoury

2.2 Data

Information on mosquitoes' potential breeding sites (i.e., objects such as flower pots, tires, or other containers with or without water - those with water being either positive or negative to larvae) was obtained from the '*Collectivité Territoriale de Guyane*' (regional administration – CTG) for 2022. The number of potential breeding sites, normalized by the number of prospected locations, was computed onto a 200m resolution square grid (Figure 2). Pléiades satellite image with a 0.5m resolution panchromatic band and four 2m resolution spectral bands (R, V, B, PIR) were acquired on July 20, 2022. A map of buildings was provided by the '*Institut national de l'information géographique et forestière*' (French national geographic institute - IGN - BD TOPO® 2022) and a 1m resolution digital elevation model (DEM) derived from a 2015 LiDAR acquisition was provided by CTG. Mean daily temperatures and rainfalls (2021-2024) at two weather stations within Cayenne Island were obtained from Météo France. A cartographic atlas of urban types produced in 2019 by the '*Agence d'Urbanisme et de Développement de la Guyane*' (urban planning agency in French Guiana – AUDeG) provided an expert-based classification of the urban landscapes of the study area (AUDeG, 2019).

2.3 Method

The 'Arbocarto' process-based model was used for modeling mosquito populations (Tran et al., 2020; Marti et al., 2022). The model is based on ordinary differential equations (ODE) that formalize the respective aquatic and adult stages of the mosquito life cycle. Transition functions from one stage to the next and mortality rates are driven by daily rainfall and temperature. 'Arbocarto' was developed using the Ocelet language, dedicated to the modeling of spatial dynamics and distributed under the free license CECILL C (available at https://www.arbocarto.fr/). In this study, Arbocarto was applied to a spatial division of the study area defined by vector control services, to plan and implement control actions. Corresponding spatial units are referred to hereafter as operational spatial units (OSU). One of the key elements of the model that allows its spatialization is the environmental carrying capacity for larvae, which represents the maximum number of larvae in a given spatial unit (*Kl*). *Kl* is estimated for each operational zone along with the daily cumulative rainfall and mean temperature. As output, the model predicts *Ae. aegypti* abundance per life cycle stage at a chosen frequency and for each operational zone. In this study, *Kl* was directly derived from the number of potential breeding sites, which was predicted using remote sensing data and machine learning.

Pléaides images were used to derive the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI), and texture indices computed using the FOTOTEX algorithm using Python's package "*fototex 1.5.9*" (Teillet et al., 2021). Urban vegetation was identified by thresholding the NDVI (NDVI > 0.2) and vegetation height was extracted by combining the resulting vegetation layer with the DEM. Averages of these variables were computed over the 200m grid cells. The building class area and the number of buildings were also calculated over the grid cells. Calculations were performed using QGIS software (v. 3.16). The landscape patch index for vegetation was computed, using the R Stats software (v. 4.2.1) and R "*landscapemetrics*" package (Hesselbarth et al., 2019).

A random forest (RF) model was built to predict the number of potential breeding sites across all grid cells of the study area, using the normalized number of potential breeding sites (target variable) and geospatial variables (descriptive features) (Figure 2). The RF model was computed using the R '*randomForest*' package (Segal, 2004). Gridded RF predictions of the normalized number of potential breeding sites were then multiplied by the number of buildings in order to obtain a total number of potential breeding sites per grid cell. Then, each grid cell was cumulated across OSU, proportionally to their surface area, and multiplied by 10 (the average estimate of the maximum number of larvae for each breeding site) to derive the environmental carrying capacity (*Kl*) per OSU. 'Arbocarto' was then applied, with meteorological variables (the daily maximal and minimal temperature and the daily cumulative rainfall) as complementary input and at a daily time step.

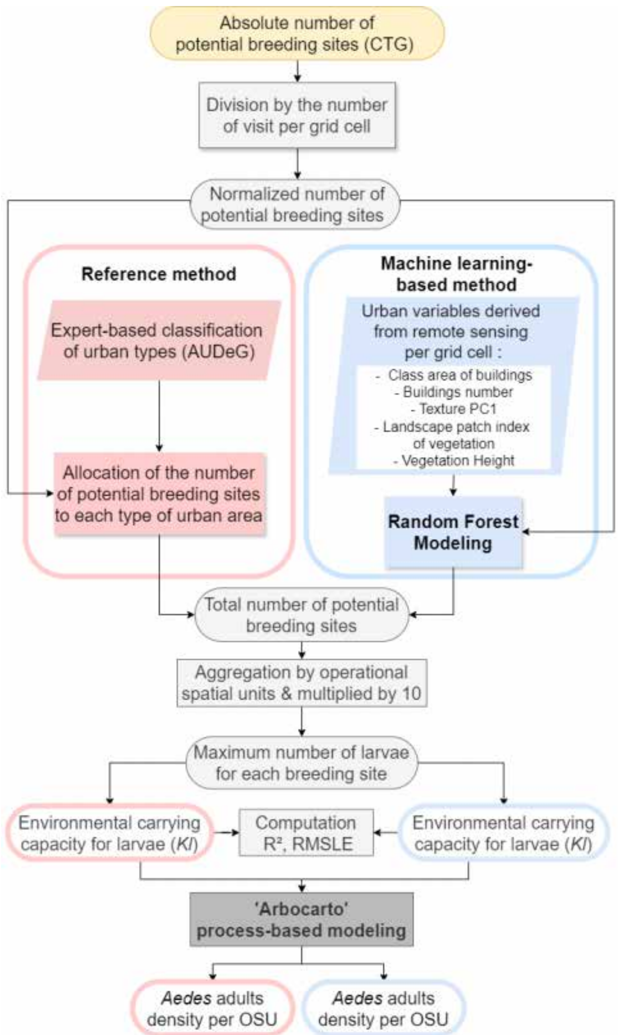

Figure 2: Methods for calculating environmental carrying capacity (*Kl*) and *Ae. aegypti* population densities.

Due to the lack of exploitable *Ae.aegypti* abundance data for results validation, our results were compared to those provided by the classical method for 'Arbocarto' implementation (considered as the "reference method"). Those are based on an expert-based classification of urban landscape and the empirical (based on observed potential breeding site data) estimation of the environmental carrying capacity by class (Figure 2). We used urban types delivered by AUDeG and assigned a value of environmental larval carrying capacity for each type of urban type based on the number of potential breeding sites and in accordance with the expertise of French Guiana vector control (Figure 3). The coefficient of determination (R^2) and root mean squared log error (RMSLE) were used to evaluate the predictions of environmental carrying capacity between the reference method and the machine learning-based method.

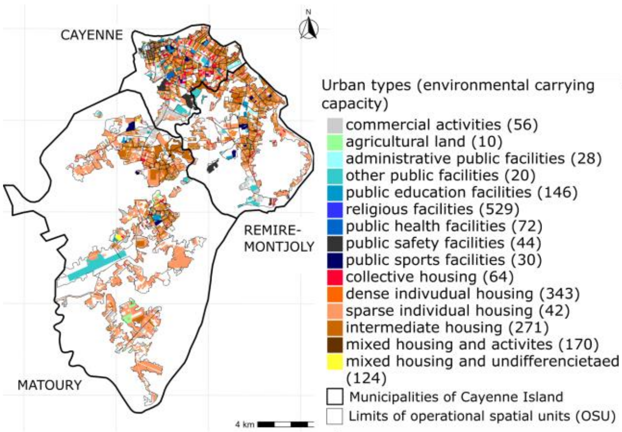

Figure 3: Urban types (AUDeG, 2019) and associated values of environmental carrying capacity (*Kl*) from "reference method"

3. Results

3.1 Potential breeding site predictions

The RF model showed a good fit between predicted and observed potential breeding site values (R^2=0.90). Residential areas with high building density had the highest predicted number of potential breeding sites (>93 per grid cell), while commercial areas had lower ones (<35). The majority of peri-urban areas with isolated houses showed values between 0 and 62 (Figure 4a).

3.2 Environmental carrying capacity (*Kl*)

The environmental carrying capacity (*Kl*), when aggregated by OSU, showed lower values in peri-urban and forest border areas, especially in Matoury and Remire-Montjoly (Figure 4b). OSUs in the center of Cayenne and within Matoury and Remire-Montjoly municipalities showed higher carrying capacities, ranging from 127 to 287 larvae per hectare. Hotspots (red values higher than 287 larvae per hectare) can be identified in the center of Cayenne and north of Matoury. A significant relationship was observed between machine learning-based predictions and reference method predictions over spatial units (R^2= 0.82, p-value < 0.001), showing a good agreement between the environmental carrying capacity as estimated by the reference method and by the machine learning-based approach (Figure 5a). We observe a similar distribution of the environmental carrying capacity for both methods (Figure 5b). However, despite similar trends, *Kl* values obtained with the machine learning-based method tend to be globally higher than those obtained using the reference values, as shown by Figures 5b and 5c. The significance of this observation was confirmed by a Wilcoxon test, which indicates a significant difference between machine learning-based predictions and reference method predictions (p-value < 0.001)

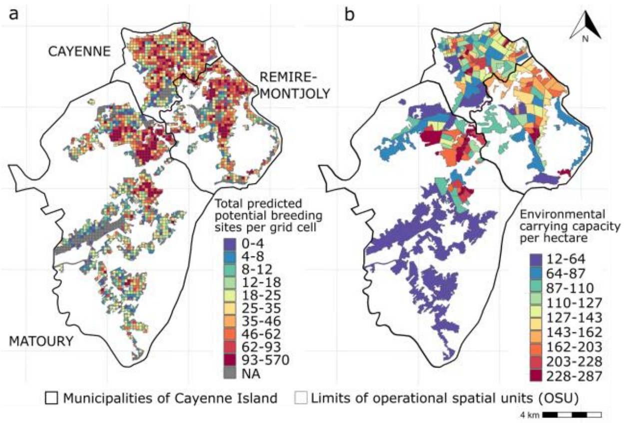

Figure 4: (a) Total number of potential breeding sites predicted by the RF model; (b) Derived environmental carrying capacity (*Kl*) based on the total number of potential breeding sites per grid cell, cumulated across operational spatial units (OSU)

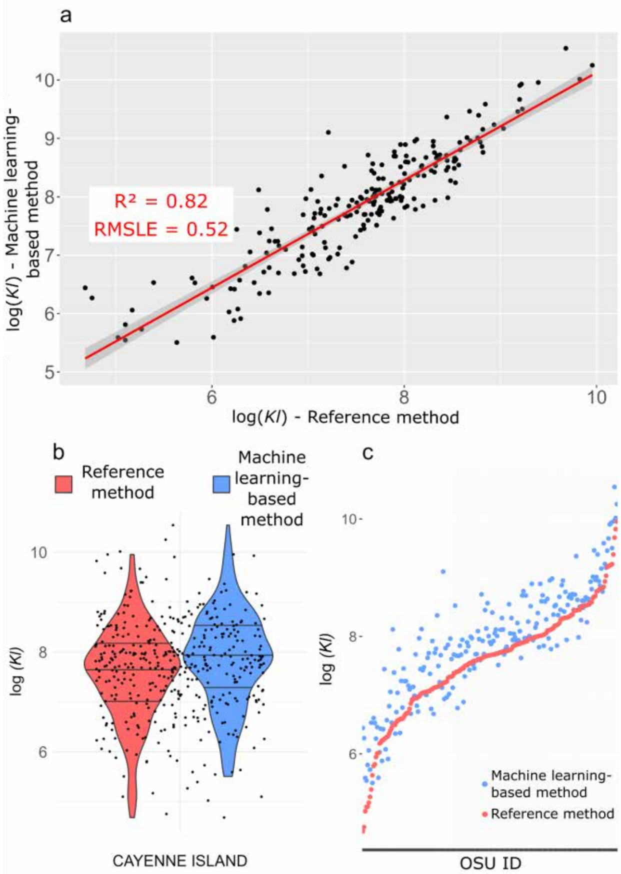

Figure 5: (a) Linear regression between the *Kl* predictions of the machine learning-based method and those of the reference method*;* (b) Distributions of *Kl* values as a function of the estimation method*;* (c) *Kl* values per OSU predicted by the reference method (red dots) ordered from the smallest to the largest value, and *Kl* values predicted by RF (blue dots).

3.3 Spatial and temporal mosquito densities

Maps of predicted mosquito densities highlight a spatial and temporal heterogeneity of *Ae. aegypti* populations on the study site in 2023. The highest mosquito densities (Figure 6c) are located in Cayenne and in residential areas north of Matoury. Outside of these hotspots, we observe a variability along the year across the rest of the territory, with densities ranging between 100 and 1500 (Figure 6). On the Cayenne Island, relatively high values of mosquito densities (750 to 1000) can be observed until mid-March, followed by an increase between April and May, and a decrease in values from June and during the dry season. The variations correspond to the season transitions, which are also observed to a lesser extent in the results of the reference method (Figure 6c).

In Cayenne, the range of the number of adult mosquitoes per hectare fluctuated between 183 and 4145, with an average of 1229. In Remire-Montjoly, the values varied between 132 to 4688, with an average of 1381. Finally, the mosquito estimated densities ranged from 68 to 6822 per hectare in Matoury, with an average of 1507. Our results tend to report higher average mosquito densities for Cayenne, Remire-Montjoly, and Matoury compared to the reference method.

By analyzing the composition of OSUs in terms of urban types, Figure 7 shows that OSUs with the highest *Ae. aegypti* densities per hectare (>1500) are predominantly composed of intermediate housing, dense individual housing, and sparse individual housing. For the lowest values (<250), OSUs are mainly composed of other public facilities (e.g., the airport area) or characterized by very high forest cover (e.g., two OSUs in Remire-Montjoly). For intermediate density classes, the urban composition is more diverse within OSUs (Figure 7).

4. Discussion

4.1 Potential breeding sites and derived environmental carrying capacity

Our results revealed a very heterogeneous spatial distribution of the observed potential breeding sites, with higher densities in built-up surfaces and densely populated residential areas than in commercial or peri-urban areas. This result is consistent with other studies that explored the spatial distribution of *Aedes* mosquitoes using remote sensing data in cities in Costa Rica (Fuller et al., 2010) and Brazil (Arduino et al., 2020). Although the RF model showed a high goodness of fit (R^2=0.90) when using the entire dataset, such a value suggests overfitting of the model and a limited ability of the model to be transferred to other contexts, as frequently shown for RF models (Kuhn and Johnson, 2013). However, our results could also be affected by a sampling bias, since the entomological dataset used was not collected specifically for the needs of this study but for immediate operational purposes, resulting in over- or under-representation of specific geographical areas (repeated visits to the same areas) or particular environmental contexts. However, normalization by the number of visits per grid cell helped reduce this bias in our study. New approaches such as the 'Uniform Sampling of Sampling Effort' (USSE) could help improve the sampling effort to minimize the effects of bias and gaps (Oliveira et al., 2024). Sampling strategies could also be improved by using remote sensing to determine optimal spatial repartition of sampling, such as in Rodriguez Gonzalez et al. (2023). As required by the process-based model used to estimate population densities, we multiplied the total number of potential breeding sites by 10 to obtain a maximum number of larvae. If this value was adapted from previous work (Tran et al., 2013), the productivity of larvae is known to vary according to seasons, types, and size of containers (David et al., 2009; Qureshi et al., 2023). While challenging, integrating these specific aspects could help improve the models.

4.2 Methods for calculating environmental carrying capacity

The similarity between our results and the reference method can be explained by the fact that both methods are based on the same dataset of observed potential breeding sites, as experts also based their opinions on these data. The values predicted by the machine learning-based method, which is globally higher, can be explained by the fact that the expert-based classification used by the reference method was created in 2019. Our method was carried out using the 2022 Pléiades image which could be more representative of the urban areas and conditions when the entomological data were collected (January to December 2022). The rapid development of urban areas in Cayenne Island could explain some differences in urban cover and therefore in predictions. The year of creation of the classification can therefore be a factor in underestimating the *Kl* values of the reference method. In addition, the expert-based classification of urban types is heavily influenced by the way the urban environment is perceived. By reducing the urban landscapes to urban types, the local landscapes' diversity could be reduced. However, such an approach is simple to implement and the *Kl* values per urban type can be easily adjusted by entomological experts to incorporate specific places with a high *Kl* value. Our machine learning-based approach directly exploits images, which improves the reproducibility of the method to estimate environmental carrying capacity, even when potential breeding sites data or fine scale urban types classification data are limited in a given area. The main methodological innovation of the study lies in the direct derivation of *Kl* from the number of potential breeding sites using remote sensing data and machine learning. Our method provides up-to-date environmental data at a fine-scale resolution, which makes it possible to update forecasts for different seasons or years. This makes our approach more adaptable to changing urban landscapes and environmental conditions, further justifying its potential for effective surveillance and vector control strategy design.

4.3 Dynamics of *Ae. aegypti* population

This paper provides the first estimation of *Ae. aegypti* mosquito densities at a fine spatial scale on Cayenne Island. Here, OSU's were defined based on human population distribution and to facilitate routine entomological surveys. They therefore vary widely in size, which could impact the results of our study. The effects of scale and zoning are well documented and can have a strong influence on effective analyses (Marceau, 1999; Bowman et al., 2014). Other methods could be explored by considering urban elements such as buildings and roads to divide urban space into small and coherent units of analysis according to urban landscapes where *Ae. aegypti* thrives (Schmidt et al., 2023; Cebeillac, personal communication, 2024). The predictions show that the inter-annual variability of mosquito densities is driven by seasonal changes (Figure 6), which is explained by the process-based model that is itself driven by temperature and precipitation. This finding coincides with previous studies (Tran et al., 2013; Bonnin et al., 2022). To our knowledge, no previous study has described the spatial and temporal heterogeneities in *Ae. aegypti* density at such a fine scale in French Guiana. Identifying variations in mosquito densities throughout the year within OSUs can provide a better understanding of dynamic patterns during both epidemic and inter-epidemic periods. This can also help prioritize vector control interventions in a context where such control is challenging due to the significant time and human resources required.

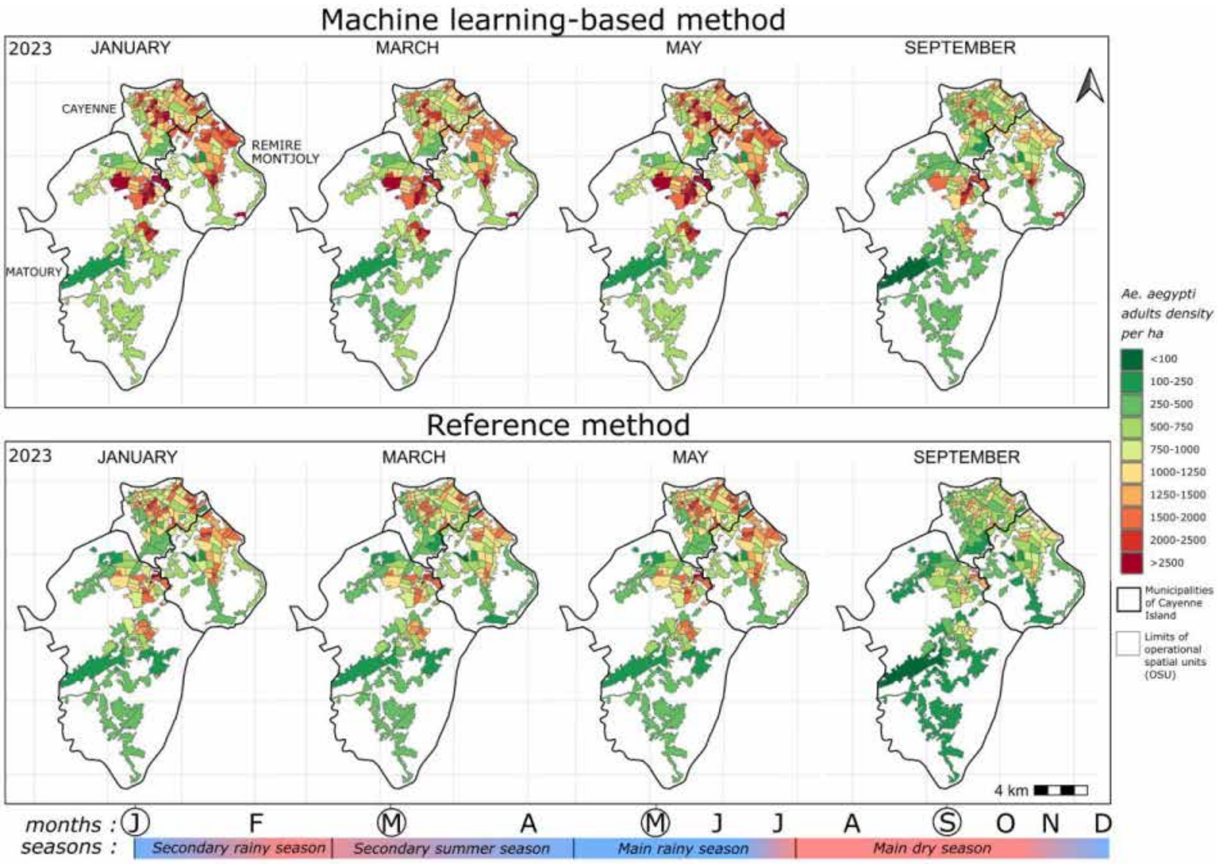

Figure 6: Maps of predicted *Ae. aegypti* abundances using the 'Arbocarto' process-based model with *Kl* predictions and *Kl* from the reference method for January (secondary rainy season), March (secondary summer season), May (main rainy season) and September (main dry season) 2023 over Cayenne Island.

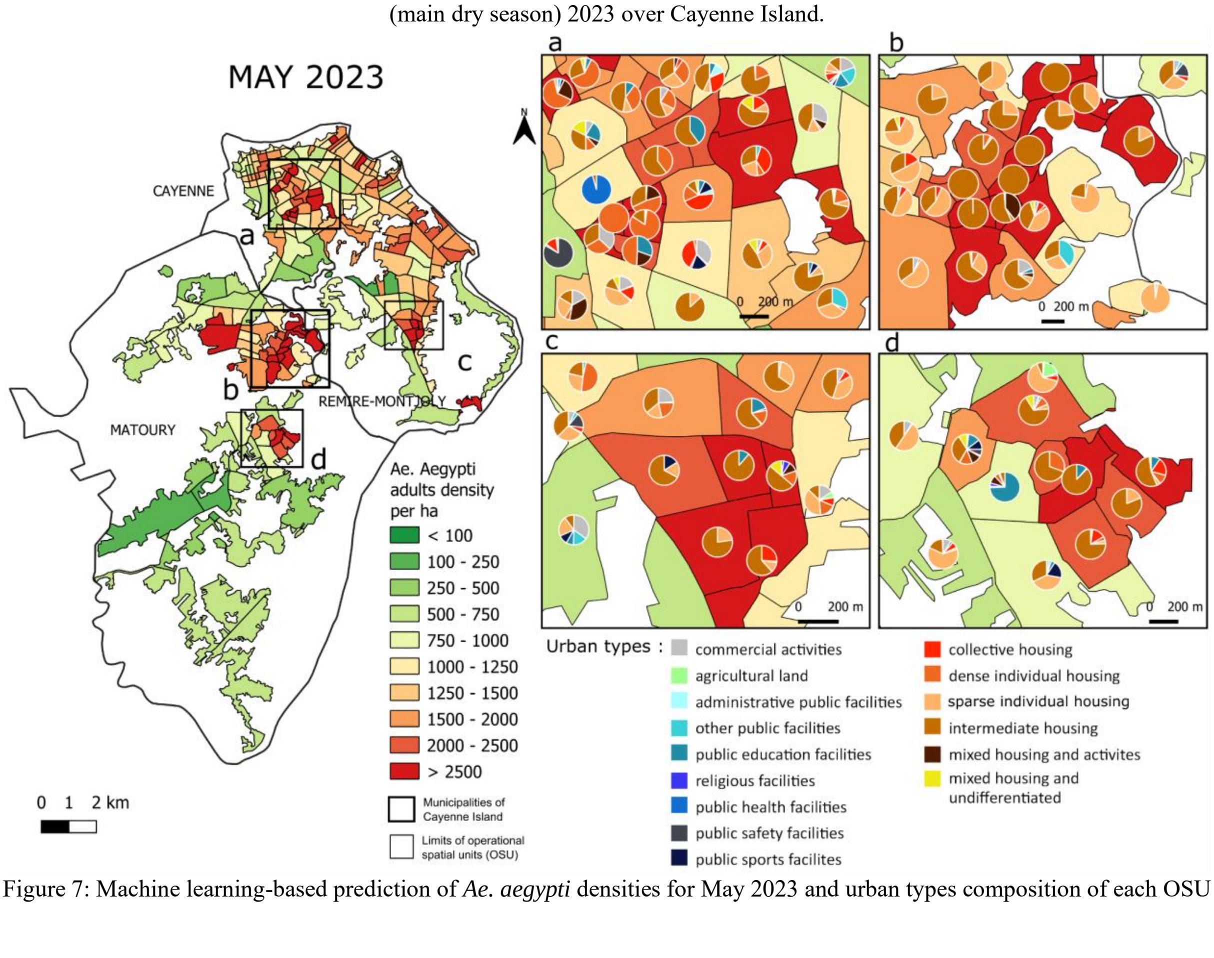

Figure 7: Machine learning-based prediction of *Ae. aegypti* densities for May 2023 and urban types composition of each OSU

The highest values of *Ae. aegypti* densities are in the most urbanized OSUs, as also demonstrated in several studies in other geographical contexts (Wimberly et al., 2020; Wilke et al., 2021). While analyzing urban types that composed the urban areas, we observe that OSUs with the highest mosquito densities are mostly composed of 'intermediate housing'. This urban type is characterized by a moderate population density with moderate-sized parcels, which may be regular or spontaneous, but is mainly composed of houses with gardens of various sizes (AUDeG, 2019). This type of peri-urban housing offers favorable conditions to the presence of *Ae. aegypti* due to the presence of houses with gardens and vegetation, as well as a sufficient population density that provides ample blood hosts for the mosquitoes.

5. Conclusions

Monitoring and controlling mosquito-borne diseases is critical in tropical areas. In French Guiana, a recent dengue outbreak in 2023 highlighted the need for operational mapping tools to optimize the actions of vector control services. This study demonstrates that a modeling approach based on the combination of *in-situ* data on potential breeding sites, very-high resolution remote sensing, machine learning, and process-based mosquito population models can be effective at estimating vector population over space and time. Such an approach helped provide an overview of the 2023 situation and is replicable to both epidemic and inter-epidemic periods. Although sampling biases may have influenced the results, our results offer promising prospects for improving the monitoring of vector populations and optimizing control strategies. The use of remote sensing images allows for continuous updates and better adaptability to changing urban landscapes and environmental conditions, thus enhancing the effectiveness of surveillance and vector control strategies. This paper also raises questions about the choice of spatial units to use for analyses, and highlights the need to use methods and sampling protocols based on both demographical, geographical, and environmental criteria. Insights to take these factors into account have been highlighted and would make it possible to enhance the effectiveness of vector control strategies in order to mitigate the impact of arbovirus diseases.

Acknowledgments

We thank the "Collectivité Territoriale de Guyane" (CTG) for providing the breeding site dataset. We also thank all the participants of the 'Arbocarto' training in French Guiana in November 2023 for fruitful exchanges (Patrice Azor, Timothée Bonifay, Virginie Cebrian, Loreinzia Clarke, Medie Collet, Leo Destison, Jean Bernard Duchemin, Loïc Epelboin, Amandine Guidez, Francky Mubenga, Johana Restrepo, Joseph Rwagitinywa, Stanislas Talaga). We also thank Juliette Guirado from AUDeG for useful discussions related to this study. Pléiades images were provided by DINAMIS ("Dispositif Institutionnel National d'Accès Mutualisé en Imagerie Satellitaire"). Pléiades © CNES 2022 Distribution AIRBUS DS. This work has been funded thanks to the French space agency CNES and the French Occitanie Region. It also received the support of the European PROGYSAT Interreg project.

References

Arduino, M. de B., Mucci, L.F., Santos, L.M. dos, Soares, M.F. de S., 2020. Importance of microenvironment to arbovirus vector distribution in an urban area, São Paulo, Brazil. Rev. Soc. Bras. Med. Trop. 53. https://doi.org/10.1590/0037-8682-0504-2019

AUDeG, 2019. Panorama n°4 de l'observatoire du foncier - Atlas des tissus urbains : Identification et description. Observatoire du foncier.

Bailly, S., Rousset, D., Fritzell, C., Hozé, N., Ben Achour, S., Berthelot, L., Enfissi, A., Vanhomwegen, J., Salje, H., Fernandes-Pellerin, S., Saout, M., Lavergne, A., Manuguerra, J.-C., Carod, J.-F., Djossou, F., Cauchemez, S., Flamand, C., 2021. Spatial Distribution and Burden of Emerging Arboviruses in French Guiana. Viruses 13, 1299. https://doi.org/10.3390/v13071299

Bonnin, L., Tran, A., Herbreteau, V., Marcombe, S., Boyer, S., Mangeas, M., Menkes, C., 2022. Predicting the Effects of Climate Change on Dengue Vector Densities in Southeast Asia through Process-Based Modeling. Environ. Health Perspect. 130, 127002. https://doi.org/10.1289/EHP11068

Bowman, L.R., Runge-Ranzinger, S., McCall, P.J., 2014. Assessing the relationship between vector indices and dengue transmission: a systematic review of the evidence. PLoS Negl. Trop. Dis. 8, e2848. https://doi.org/10.1371/journal.pntd.0002848

David, M.R., Lourenço-de-Oliveira, R., Freitas, R.M. de, 2009. Container productivity, daily survival rates and dispersal of *Aedes aegypti* mosquitoes in a high income dengue epidemic neighbourhood of Rio de Janeiro: presumed influence of differential urban structure on mosquito biology. Mem. Inst. Oswaldo Cruz 104, 927–932. https://doi.org/10.1590/S0074-02762009000600019

Dickens, B.L., Sun, H., Jit, M., Cook, A.R., Carrasco, L.R., 2018. Determining environmental and anthropogenic factors which explain the global distribution of *Aedes aegypti* and *Ae. albopictus*. BMJ Glob. Health 3, e000801. https://doi.org/10.1136/bmjgh-2018-000801

Epelboin, Y., Chaney, S.C., Guidez, A., Habchi-Hanriot, N., Talaga, S., Wang, L., Dusfour, I., 2018. Successes and failures of sixty years of vector control in French Guiana: what is the next step? Mem. Inst. Oswaldo Cruz 113, e170398. https://doi.org/10.1590/0074-02760170398

Erguler, K., Smith-Unna, S.E., Waldock, J., Proestos, Y., Christophides, G.K., Lelieveld, J., Parham, P.E., 2016. Large-Scale Modelling of the Environmentally-Driven Population Dynamics of Temperate *Aedes albopictus* (Skuse). PLOS ONE 11, e0149282. https://doi.org/10.1371/journal.pone.0149282

Fuller, D.O., Troyo, A., Calderón-Arguedas, O., Beier, J.C., 2010. Dengue vector (*Aedes aegypti*) larval habitats in an urban environment of Costa Rica analysed with ASTER and QuickBird imagery. Int. J. Remote Sens. 31, 3–11. https://doi.org/10.1080/01431160902865756

Hesselbarth, M.H.K., Sciaini, M., With, K.A., Wiegand, K., Nowosad, J., 2019. landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography 42, 1648–1657. https://doi.org/10.1111/ecog.04617

Kolimenakis, A., Heinz, S., Wilson, M.L., Winkler, V., Yakob, L., Michaelakis, A., Papachristos, D., Richardson, C., Horstick, O., 2021. The role of urbanisation in the spread of *Aedes* mosquitoes and the diseases they transmit—A systematic review. PLoS Negl. Trop. Dis. 15, e0009631. https://doi.org/10.1371/journal.pntd.0009631

Kuhn, M., Johnson, K., 2013. Measuring Performance in Regression Models, in: Kuhn, M., Johnson, K. (Eds.), Applied Predictive Modeling. Springer, New York, NY, pp. 95–100. https://doi.org/10.1007/978-1-4614-6849-3_5

Lorenz, C., Castro, M.C., Trindade, P.M.P., Nogueira, M.L., de Oliveira Lage, M., Quintanilha, J.A., Parra, M.C., Dibo, M.R., Fávaro, E.A., Guirado, M.M., Chiaravalloti-Neto, F., 2020. Predicting *Aedes aegypti* infestation using landscape and thermal features. Sci. Rep. 10, 21688. https://doi.org/10.1038/s41598-020-78755-8

Machault, V., Yébakima, A., Etienne, M., Vignolles, C., Palany, P., Tourre, Y., Guérécheau, M., Lacaux, J.-P., 2014. Mapping Entomological Dengue Risk Levels in Martinique Using High-Resolution Remote-Sensing Environmental Data. ISPRS Int. J. Geo-Inf. 3, 1352. https://doi.org/10.3390/ijgi3041352

Marceau, D.J., 1999. The Scale Issue in the Social and Natural Sciences. Can. J. Remote Sens. 25, 347–356. https://doi.org/10.1080/07038992.1999.10874734

Marti, R., Castets, M., Demarchi, M., Catry, T., Besnard, G., Chouin, S., Clément, C., Esteve-Moussion, I., Etienne, M., Foussadier, R., Habchi-Hanriot, N., Jouanthoua, F., L'Ambert, G., Godal, A., Tran, A., 2022. ARBOCARTO: An operational spatial modeling tool to predict *Aedes albopictus* dynamics and the impact of vector control interventions [WWW Document]. URL https://publications.cirad.fr/une_notice.php?dk=601276 (accessed 4.3.24).

Moreno-Madriñán, M.J., Crosson, W.L., Eisen, L., Estes, S.M., Estes Jr., M.G., Hayden, M., Hemmings, S.N., Irwin, D.E., Lozano-Fuentes, S., Monaghan, A.J., Quattrochi, D., Welsh-Rodriguez, C.M., Zielinski-Gutierrez, E., 2014. Correlating Remote Sensing Data with the Abundance of Pupae of the Dengue Virus Mosquito Vector, *Aedes aegypti*, in Central Mexico. ISPRS Int. J. Geo-Inf. 3, 732–749. https://doi.org/10.3390/ijgi3020732

Oliveira, U., Soares-Filho, B., Nunes, F., 2024. Controlling the effects of sampling bias in biodiversity models. J. Biogeogr. n/a. https://doi.org/10.1111/jbi.14851

Qureshi, A., Keen, E., Brown, G., Cator, L., 2023. The size of larval rearing container modulates the effects of diet amount and larval density on larval development in *Aedes aegypti*. PLOS ONE 18, e0280736. https://doi.org/10.1371/journal.pone.0280736

Richman, R., Diallo, D., Diallo, M., Sall, A.A., Faye, O., Diagne, C.T., Dia, I., Weaver, S.C., Hanley, K.A., Buenemann, M., 2018. Ecological niche modeling of *Aedes* mosquito vectors of chikungunya virus in southeastern Senegal. Parasit. Vectors 11, 255. https://doi.org/10.1186/s13071-018-2832-6

Rodriguez Gonzalez, C., Guzman, C., Andreo, V., 2023. Using VHR satellite imagery, OBIA and landscape metrics to improve mosquito surveillance in urban areas. Ecol. Inform. 77, 102221. https://doi.org/10.1016/j.ecoinf.2023.102221

Schmidt, T.L., Elfekih, S., Cao, L.-J., Wei, S.-J., Al-Fageeh, M.B., Nassar, M., Al-Malik, A., Hoffmann, A.A., 2023. Close Kin Dyads Indicate Intergenerational Dispersal and Barriers. Am. Nat. 201, 65–77. https://doi.org/10.1086/722175

Segal, M.R., 2004. Machine Learning Benchmarks and Random Forest Regression.

Teillet, C., Devillers, R., Tran, A., Catry, T., Marti, R., Dessay, N., Rwagitinywa, J., Restrepo, J., Roux, E., 2024. Exploring fine-scale urban landscapes using satellite data to predict the distribution of *Aedes* mosquito breeding sites. Int. J. Health Geogr. 23, 18. https://doi.org/10.1186/s12942-024-00378-3

Teillet, C., Pillot, B., Catry, T., Demagistri, L., Lyszczarz, D., Lang, M., Couteron, P., Barbier, N., Adou Kouassi, A., Gunther, Q., Dessay, N., 2021. Fast Unsupervised Multi-Scale Characterization of Urban Landscapes Based on Earth Observation Data. Remote Sens. 13, 2398. https://doi.org/10.3390/rs13122398

Tran, A., L'Ambert, G., Lacour, G., Benoît, R., Demarchi, M., Cros, M., Cailly, P., Aubry-Kientz, M., Balenghien, T., Ezanno, P., 2013. A Rainfall- and Temperature-Driven Abundance Model for *Aedes* albopictus Populations. Int. J. Environ. Res. Public. Health 10, 1698–1719. https://doi.org/10.3390/ijerph10051698

Tran, A., Mangeas, M., Demarchi, M., Roux, E., Degenne, P., Haramboure, M., Goff, G.L., Damiens, D., Gouagna, L.-C., Herbreteau, V., Dehecq, J.-S., 2020. Complementarity of empirical and process-based approaches to modelling mosquito population dynamics with *Aedes albopictus* as an example—Application to the development of an operational mapping tool of vector populations. PLOS ONE 15, e0227407. https://doi.org/10.1371/journal.pone.0227407

Weeratunga, P., Rodrigo, C., Fernando, S.D., Rajapakse, S., 2017. Control methods for *Aedes albopictus* and *Aedes aegypti*. Cochrane Database Syst. Rev. 2017, CD012759. https://doi.org/10.1002/14651858.CD012759

Wilke, A.B.B., Vasquez, C., Carvajal, A., Moreno, M., Fuller, D.O., Cardenas, G., Petrie, W.D., Beier, J.C., 2021. Urbanization favors the proliferation of *Aedes aegypti* and Culex quinquefasciatus in urban areas of Miami-Dade County, Florida. Sci. Rep. 11, 22989. https://doi.org/10.1038/s41598-021-02061-0

Wimberly, M.C., Davis, J.K., Evans, M.V., Hess, A., Newberry, P.M., Solano-Asamoah, N., Murdock, C.C., 2020. Land cover affects microclimate and temperature suitability for arbovirus transmission in an urban landscape. PLoS Negl. Trop. Dis. 14, e0008614. https://doi.org/10.1371/journal.pntd.0008614