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Article

Mapping Urban Landscapes Prone to Hosting Breeding Containers for Dengue-Vector Mosquitoes: A Case Study in Bangkok

Eric Daudé ^{1,*} , Alexandre Cebeillac ², Kanchana Nakhapakorn ³ and Rick Paul ^{4,5} 

¹ Centre National de la Recherche Scientifique (CNRS), Research Institute on Contemporary Southeast Asia (IRASEC), Bangkok 10330, Thailand

² Centre National de la Recherche Scientifique (CNRS), UMR 6266 IDEES, Normandie University, 76000 Rouen, France; alexandre.cebeillac1@univ-rouen.fr

³ Faculty of Environment and Resource Studies, Mahidol University, Nakhon Pathom 73170, Thailand; kanchana.nak@mahidol.ac.th

⁴ Centre National de la Recherche Scientifique (CNRS), UMR 2000, Institut Pasteur, Université Paris-Cité, 75015 Paris, France; richard.paul@pasteur.fr

⁵ Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environnement (INRAE), USC 1510, 75007 Paris, France

* Correspondence: eric.daude@cnrs.fr

Abstract: Dengue fever is an urban, tropical, and semi-tropical disease transmitted by *Aedes aegypti* and *Aedes albopictus* mosquitoes. One significant challenge lies in identifying reliable intra-urban indicators of their densities. Following standardized sampling protocols that adequately take into account the spatial heterogeneity of the geographical contexts which may influence mosquito habitats is therefore fundamental to compare studies and follow such relevant indicators. We develop a method for subdividing urban territory based on environmental factors which are susceptible to influence the density of potential mosquito-breeding containers. Indeed, the presence of these containers, most of which are produced by humans, is essential for the renewal of mosquito populations. Land-uses variables and their local variations are determinant in this analysis. Starting from each building and its immediate neighborhood described in terms of vegetation and open area, we computed the local landscape metrics of a million buildings in Bangkok. We then used segmentation and clustering techniques to generate homogeneous zones based on these components and physiognomy. Subsequently, a classification process was conducted to characterize these zones according to land-use and composition indicators. We applied this automatic clustering method within Bangkok's urban area. This classification built from hypotheses on the existence of links between the types of urban landscape and the presence of outdoor containers must be evaluated and will serve as a foundation for the spatial sampling of field studies for vector surveillance in Bangkok. The choice of sampling zones, even if it must be based on an administrative division due to the decentralization of health agencies in Bangkok, can then be enriched by this new, more functional division. This method, due to the genericity of the factors used, could be tested in other cities prone to dengue vectors.

Keywords: clustering; satellite images; urban landscape; breeding container; dengue



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1. Introduction

Dengue is endemic in tropical and subtropical regions and there is now a risk of endemisation in certain temperate regions, due to global warming and the invasion of mosquito vectors [1]. Dengue virus is primarily transmitted by *Aedes aegypti* mosquitoes, and secondarily by *Ae. albopictus*. Dengue fever is particularly a burden in urban settings, because its main mosquito vector, *Ae. aegypti*, is well-adapted to anthropized and urban environments. This species colonizes cities, where it finds all the resources it needs to thrive [2]: high population densities, numerous egg-laying containers and vegetation

providing pockets of coolness [3]. Growing urbanization, environmental degradation and large-scale migration are particularly impacting the burden of dengue [4,5]. Estimates put the number of dengue virus infections at over 390 million every year, of which 100 million cause clinical symptoms [6].

Monitoring the colonization and reproduction of mosquito populations in urban areas is a major challenge for limiting the risk of dengue, chikungunya or zika epidemics in low and high-income countries [7]. Mosquitoes use all kinds of containers to lay their eggs, as long as they are likely to be exposed to water: jars, tires, flower pots, cisterns, solid waste, etc. The diversity of urban landscapes in terms of buildings, vegetated areas, open spaces and land use all have an impact on the number of these potential mosquito-breeding containers. Vector control measures focusing on eliminating breeding containers (environmental hygiene) are laborious and require substantial fieldwork to identify all potential containers, making them unfeasible on the scale of a city. For example, in Bangkok, which covers an area approaching 1570 km², vector surveillance can only be performed piecemeal. Furthermore, in challenging economic contexts for mitigating complex tropical health issues, it is crucial to efficiently utilize financial and human resources [8]. Therefore, the aim is to develop a methodology to enable a more targeted strategy by selecting areas based on breeding-container-centered criteria. These containers are mainly produced by humans to meet their needs (storage of water for drinking), for amenities (flower pots) or as byproducts of their activities (waste, storage of materials). We therefore hypothesize that land use and spatial organization could be proxies for the presence of these containers, and potentially for mosquito abundance [9]. To go further than simply describing the types of containers used by mosquitoes to lay their eggs, our aim is then to describe the characteristics of the places where these containers are produced. The challenge is then to use this classification to estimate local densities of potential mosquito-breeding containers. This relationship would then enable spatially targeted integrated vector management, such as biological control, community-based interventions and environmental management [10].

Risk studies focusing on vectorial indices or mosquito-breeding containers and which incorporate geography for sites selection follow different approaches. They may use a targeted approach, focusing on specific types of places like cemeteries or parks [11], or follow a geographical transect method based on population densities, selecting areas from the city center to the periphery [12]. Alternatively, they may take a random approach [13], treating territory as if it were not a discriminating risk factor, or base their selection on indirect data, such as dengue cases or socio-ecological parameters [14]. When these studies aggregate container or entomological data [15], they typically do so at an administrative level, which limits the analysis of environmental factors on these indicators due to the diverse landscapes within these levels [16].

Geographical information systems combined with remote sensing analysis are widely used to identify and characterize these complex biological and environmental interactions [17–19]. Associations between satellite-derived environmental factors such as humidity, temperature and land-cover type with vector density are used to characterize vector habitats [20]. For dengue studies only, Marti et al. [21] selected 78 papers that study the relationship between landscape variables, dengue cases and vector indices in urban areas. Most of these papers take dengue cases or vector indices as their starting point, and construct environmental variables a posteriori to describe the geographical context [22,23]. What these studies reveal is that there is little evidence of quantifiable associations between vector indices and dengue transmission, limiting their use for epidemic prediction [24–26]. This may be linked to the aggregation scales chosen for the spatial sampling units, ranging from premises [27,28], neighborhoods [29,30], district [31,32] to city scale [12,33], failing to capture the factors that come into play in these complex human–mosquito interactions. This is confirmed by meta-analyses which highlight the need for standardized sampling protocols that adequately take into account the spatial heterogeneity of the geographical contexts of diseases [16]. Statistical relationships between environmental contexts and vector indices are, on the other hand, much stronger. However, most of these studies are based either on data randomly

sampled in urban areas, on data collected in particular types of land use such as cemeteries, markets or parks [34–37] or mostly focusing on socio-economic factors [38,39], which do not permit generalization to the scale of an entire city. To the best of our knowledge, few studies have attempted to characterize, at high spatial resolution, the composition and organization of a large urban area in order to estimate the local densities of potential mosquito-breeding containers, and by extension the carrying capacity of a vector mosquito. Based on the finding according to which types of urban housing influence indoor mosquito breeding and dengue cases, and close to our perspective, Seidahmed et al. [40] show significant relations between the densities of water drains and buildings according to different height classes with the dengue incidence and the vector densities in Singapore. However, Singapore is a unique case in terms of collecting and exploiting geolocated data enabling such data-driven knowledge [41]. Close to our perspective centered on mosquitoes and their habitat, the use of artificial intelligence was used to detect containers on street view images in Bangkok [15]. However, these data were then systematically aggregated at the district level to be able to characterize them in terms of densities per inhabitants and per square kilometer. Administrative scales and census data too often constitute the basis of aggregation to the detriment of environmental factors.

The aim of this paper is to present a method for partitioning the urban area of Bangkok, Thailand, into zones that are homogeneous in terms of criteria affecting the suitability for mosquito-breeding containers. We first present the method used to divide up the urban space using satellite images and data collected online. Based on criteria specific to the constraints encountered by mosquitoes during their development, this division enables us to construct a classification of Bangkok. This map could be used for a sampling protocol and aggregation base for potential breeding containers throughout Bangkok. These results are then discussed before drawing conclusions.

2. Materials and Methods

Developed within the framework of conservation biology, the Resource-Based Habitat Concept (RBHC) [42,43] consists of using an organism's primary needs to deduce its functional habitat or potential ecological niche. We follow this approach based on the primary needs of mosquitoes to select environmental factors which could explain the uneven distribution of their presence in urban space [44]. Here, we focus on the starting point of the mosquito life, the container from which they emerge. The presence of breeding containers is particularly interesting because it is directly associated with the standard empirical vector indices (House-Index, Container Index and Breteau index), and its differentiated presence may be a marker of territorial heterogeneity of vector densities. *Ae. aegypti* prefers to lay eggs in artificial containers produced by human activities and "containers" that come directly from vegetation, such as tree holes or conical foliage [5]. Based on these observations, there is a need to systematically study the effects of environmental context (land use and urban planning) on the local densities of outdoor containers. In doing so, the choice of spatial resolution to define the different spatial contexts is fundamental in order to avoid the fairly common modifiable area unit problem [45,46]. Indeed, when building ecological niche models, common mistakes often arise from aggregating environmental variables at a resolution higher than the species records [47]. This frequently occurs when administrative boundaries are used as aggregative entities. The proposed method should result in a spatial division that aligns with both the landscape profiles of outdoor containers and the resulting vector risks.

2.1. Data Collection

2.1.1. City as a Patchwork of Independent Blocks

Ae. aegypti, the primary vector of the dengue virus in urban areas, lives in or near buildings and requires humans and vegetation for feeding and shade for resting [48]. It has a limited flight range, only a few hundred meters [49], as it finds most of its resources around its place of emergence and as landscape features can act as barriers or corridors

to its dispersal [50]. In dengue endemic cities, the spatial distribution of mosquito populations can be then viewed as an optimal localization system, with current mosquitoes benefiting from the efforts of previous generations that had gradually explored the city's neighborhoods, settling and developing in those with the highest survival rates. As a result, the majority of a mosquito cohort born in a neighborhood lives and dies in that same neighborhood [51], as do the subsequent generations [52]. However, this limited travel distance is also influenced by urban constraints, with major traffic arteries and high building densities probably limiting the mosquito's ability to disperse [53,54]. From the mosquito's perspective, the city is less a vast territory that can be easily colonized than a heterogeneous, independent collection of neighborhoods that are more or less favorable to its establishment.

Using Bangkok as our study case, the first objective is then to partition the municipal area into a set of autonomous blocks sized to accommodate the maximum vector dispersal capacity. Given the total surface area of approximately 1570 km² and a land use characterized by a significant presence of cultivated areas on the outskirts, we have reduced the study area to the central part of Bangkok (Figure 1), which represents 21% of the territory's total surface area but is home to 53% of the population (based on the 2010 census).

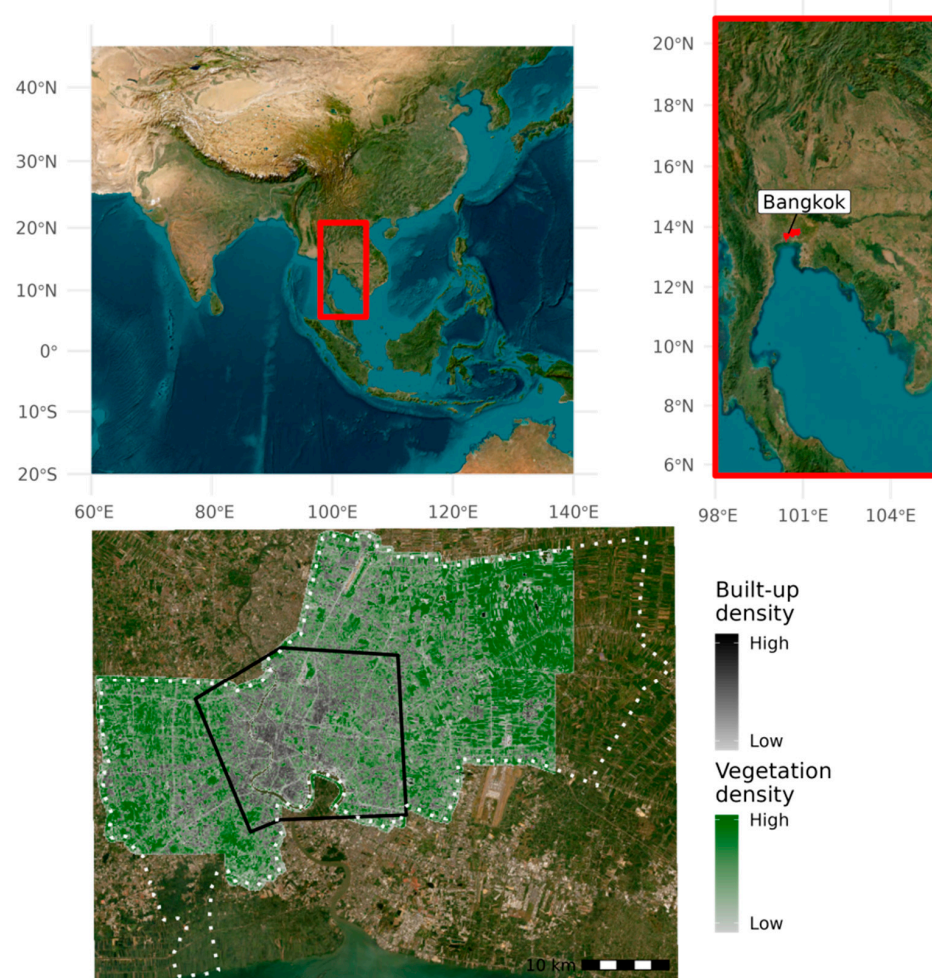


Figure 1. Location of Bangkok (red outline) in the Gulf of Thailand (top map) and spatial extent of the Bangkok Metropolitan Administration (bottom map, outline in white dots) with its built-up (shaded gray) and vegetation density (shaded green)—obtained, respectively, by summing the area of buildings provided by Bing Map and the vegetation from Pléiades (CNES) images (NDVI > 0.22) in a 125 m grid. The study area (black outline) is centered on the highly urbanized area.

We use data from OpenStreetMap (OSM) and Bing Map (BM) to divide the study area into blocks. Little is known in the literature about the width of roads or rivers and their effect on mosquito crossing capacity. *Ae. aegypti* mosquitoes prefer crossing smaller and quieter roads over larger and busy roads [13,55]. The study by [54] is based on a 24-metre-wide road, which we take as our initial reference: we applied the criterion that roads and canals wider than 20 m are distances that mosquitoes cannot cross, equivalent to a minimum of twice two lanes for roads. Road and canal sections were obtained via OSM and overpass API (https://wiki.openstreetmap.org/wiki/Overpass_API, accessed on 1 March 2023). While the metadata provide information on lane type, speed limit and traffic direction, there are no systematic details on the number or width of lanes in the study area. To address this limitation, we used Bing Map as a second dataset. BM provides a free vector layer of buildings covering a large part of the globe (<https://blogs.bing.com/maps/2023-06/Bing-Maps-Global-Building-Footprints-released>, accessed on 1 March 2023). These were delineated by processing satellite images and applying segmentation and neural network techniques (<https://github.com/microsoft/GlobalMLBuildingFootprints>, accessed on 1 March 2023): 1.1 million buildings have been retrieved for Bangkok, including just under 400,000 in our study area. Although there are some discrepancies with reality on the ground (such as missing or grouped buildings, and inaccurate spatial coverage), these data are more representative than those provided by OSM, which only contains 120,000 buildings for Bangkok (OSM consulted in 1 March 2023). In the absence of more precise cadastral data, this is the database we used for the following analysis (Figure 2).

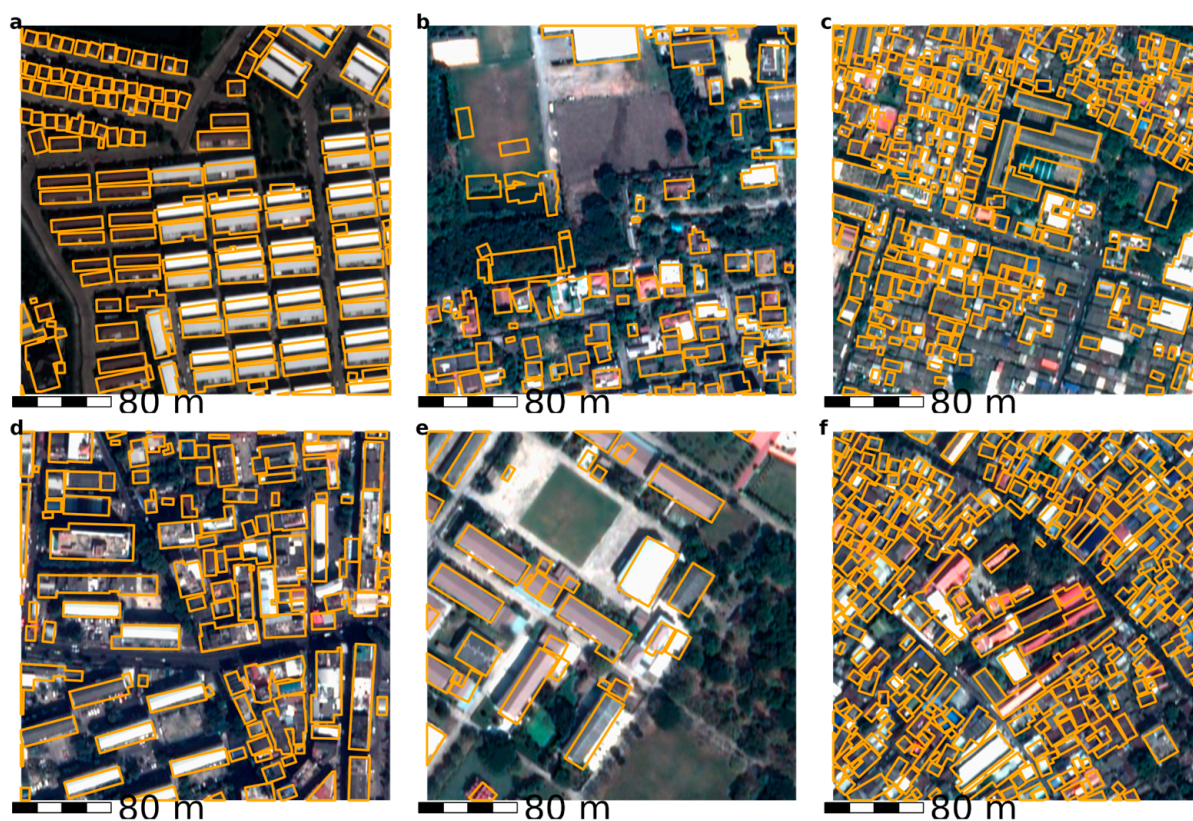


Figure 2. Example of polygons representing buildings (orange color) provided by Bing Map, with Pléiades satellite image as base map.

To estimate the width of the road and waterway, we calculated the distance between all contiguous buildings and attributed these data to the road and waterway sections provided by OSM. We then retained the road segments that intersect at least 50 percent of the layer of buildings that are 20 m or more apart (Figure 3). This first step has allowed us to construct a preliminary territorial division of 287 blocks.

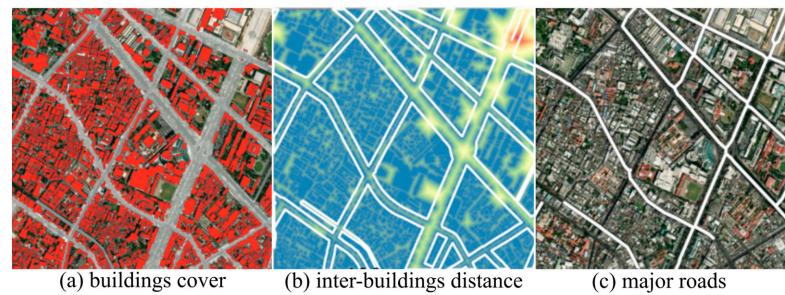


Figure 3. Starting from building polygons in red provided by Bing Map (a) to compute distance between buildings (from blue to red) associated with roads (b) in order to select roads provided by Open Street Map with a width superior to 20 m (in white, (c)).

The large surface area of the resulting blocks and the analysis of the road sections resulting from this first method revealed that many major roads were not taken into account. We therefore added a second criterion to identify these major sections: road traffic, to the extent that this factor also contributes to limiting the movement of the mosquito [13,55]. We then considered heavily travelled roads as a proxy for the width and importance of these roads in the transport network. The Tomtom service (<https://www.tomtom.com/traffic-index/bangkok-traffic/>, accessed on 1 September 2023) was used to collect this information hour by hour using web scrapping methods (https://analytics.huma-num.fr/UMR_IDEES/scrap_tomtom_md.html, accessed on 1 September 2023). Roads characterized by heavy traffic (Five traffic flow classes can be recorded per road segment—closed; no delay; minor delay; major delay (2 levels)-, we recorded the two last classes) during weekdays were then selected and used to divide the previous blocks. To avoid multiplying the number of blocks while maintaining the notion of mosquito mobility capacity, blocks representing an area smaller than a circle with a radius of 250 m (i.e., the maximum dispersion of *Aedes* from its place of emergence) were merged with their neighbors to obtain larger blocks. Additionally, we specifically distinguished large vegetated areas such as urban parks exceeding 3 ha [36] and cemeteries [34,37], which, due to their functions and environmental characteristics, are considered autonomous blocks. Based on these physical criteria (width of roads and rivers), the study area was divided into 654 blocks (Figure 4) with an average surface area of 55.37 ha (standard deviation: 58.2 ha, median: 37.7 ha).

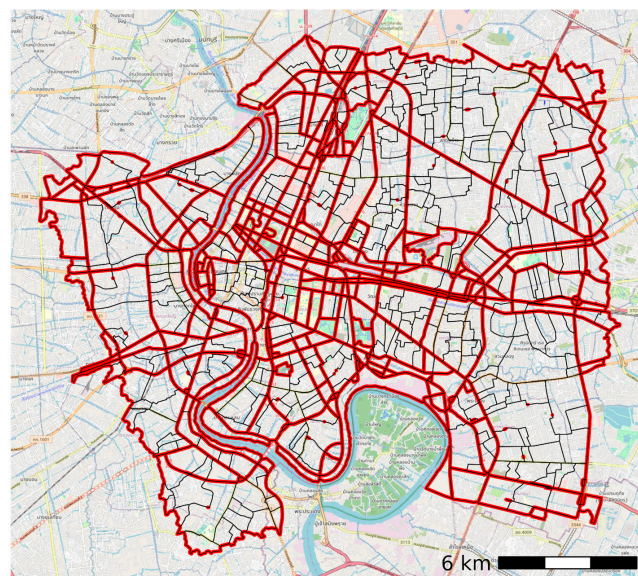


Figure 4. Construction of urban blocks. The red contours represent the main roads and river that are considered as major barriers to mosquito movement.

Given the radio-concentric organization of Bangkok’s transport system, this division results in major differences in surface area between blocks in the center, which are well “irrigated” by major traffic arteries, and those on the outskirts. Using this initial division into a set of autonomous blocks from the perspective of mosquito dispersal, we present in the next section the data used to describe the composition and configuration of these blocks in terms of buildings and vegetated areas.

2.1.2. Landscape Metrics of Urban Blocks

We characterize urban landscapes from a mosquito and breeding-container-centric perspective, focusing on physical variables of the built city [56]. This approach means we will not directly use socio-economic data or data on human population densities. This position follows studies showing that landscape factors alone yielded better predictability for mosquito abundance than socioeconomic factors [9]. However, these characteristics are indirectly reflected in the landscapes they help to shape. For example, affluent residential districts with gardens and large houses are distinguishable from poor districts with high building densities and little vegetated space. And we hypothesize that the types and densities of mosquito-breeding containers vary across these different neighborhoods. We describe the spatial heterogeneity of the urban landscape [57,58] by a compositional component (type and proportion of different elements) and a configurational component (spatial form and arrangement of these elements in the landscape).

2.1.3. A Diversified Presence of Urban Vegetation

Unlike most objects in urban areas (such as roads, water and buildings), vegetation emits radiation mainly in the near infrared and very little in the red. To capture this, we used Pléiades satellite images at a 50 cm spatial resolution (after pansharping, or spectral interpolation). These images consist of three spectral bands in the visible spectrum (red, blue, green) and one spectral band in the near infrared. These cloud-free images cover a large part of Bangkok in 2016 and 2021. From these images, we calculated the Normalized Difference Vegetation Index (NDVI), widely used in remote sensing as an indicator of vegetation activity, which was already associated with cases of dengue fever [23,59]. NDVI values range from -1 to 1 . Negative values generally indicate an absence of vegetation and a value close to 1 indicates a strong presence of vegetation. Values between 0.2 and 0.5 can correspond to shrubs and lawns, and tropical urban forests for NDVI values above 0.5 [60]. Applied to the different blocks, NDVI highlights the level of vegetation activity and allows for the identification of discrete areas of vegetation, including isolated trees, courtyard gardens or public parks (Figure 5).

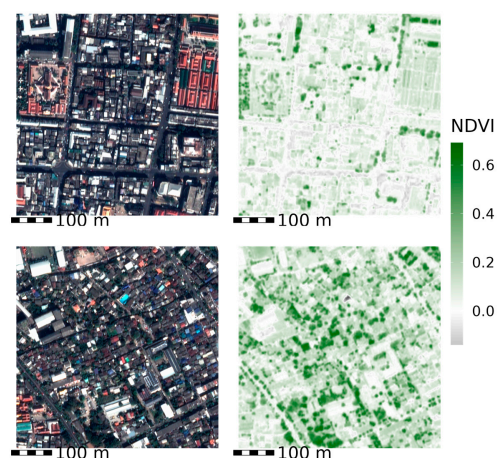


Figure 5. Vegetation extraction on the right (NDVI) from Pléiades images on the left. Large areas of vegetation can be distinguished, such as small urban gardens (bottom images), and distinct plant clusters, groves or isolated trees (top images).

The advantage of the NDVI is then to precisely qualify (flower grove, shrubs, trees, lawns, parks, urban forest) and quantify (number of patches) the vegetated areas, all of which are conducive to the presence of mosquitoes. It is then possible to analyze their distribution around built-up areas, which could contribute to providing mosquitoes with more or fewer breeding containers.

2.1.4. Estimating Building Heights

Various indicators can be used to qualify the built environment as a proxy for human presence and *Ae. aegypti* habitats [21]. In this context, buildings can be defined by their area, height, shape, roof type, density or distance from other nearby land uses (vegetation, water, roads, fields, etc.) [40,61,62]. We particularly emphasize building height, as this is an important proxy for human densities [63], and the organization of buildings in relation to each other (side-by-side or distant) and their densities.

Pléiades images are available in batches of three images taken at the same time from three different angles (tri-stereoscopy). This allows for the application of photogrammetry techniques to obtain a Digital Surface Model (DSM), providing an elevation value for each pixel in the area under consideration (Figure 6). The DSM calculation was carried out by the CNES Solid Earth Division (<https://en.poleterresolide.fr/dsm-opt-service/>, accessed on 1 September 2023, Digital Surface Models from OPTical stereoscopic very-high resolution imagery, is a DataTerra service operated by the ForM@Ter (Solid Earth) cluster, in collaboration with the Theia (Continental Surfaces) cluster and the DINAMIS system).

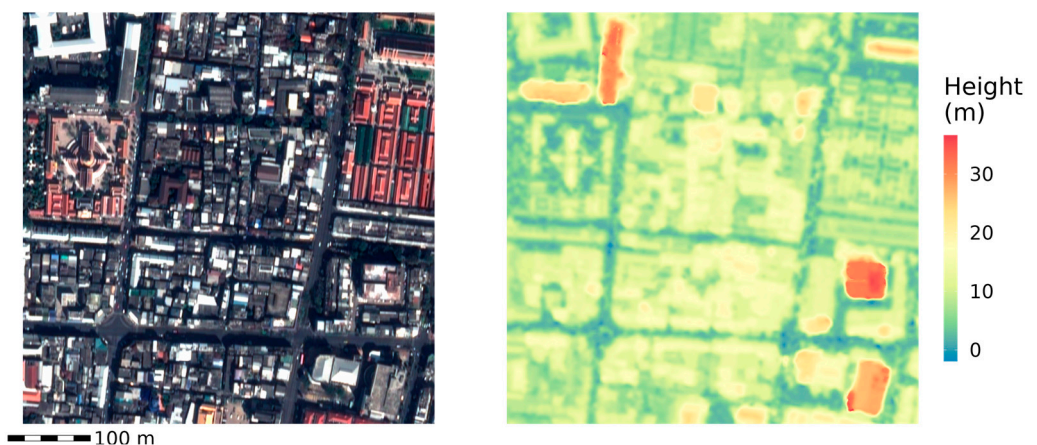


Figure 6. Estimation of building heights (right, in meters) from Pléiades tri-stereoscopic images (left, one of the three images).

Having extracted the vegetation zones (from isolated trees to parks), the buildings and their heights for all 654 blocks (Figure 4), the following section presents the method used to describe the shapes and organization of the buildings among themselves, their grouping within homogeneous neighborhoods and their description in landscape terms.

2.2. Methods

Potential egg-laying containers are mainly produced by humans, and are located close to where people are active, such as where they work, eat and live [5]. However, high population densities do not necessarily imply a high density of outdoor breeding containers, as these are mainly found in the open spaces between buildings [64]. Courtyards, gardens, terraces, sidewalks and gaps between buildings are all areas regularly identified as having a significant presence of egg-laying containers [22,65,66]. We therefore propose to use an approach centered on the building and its immediate surroundings to develop this description following a methodology in six steps (Figure 7).

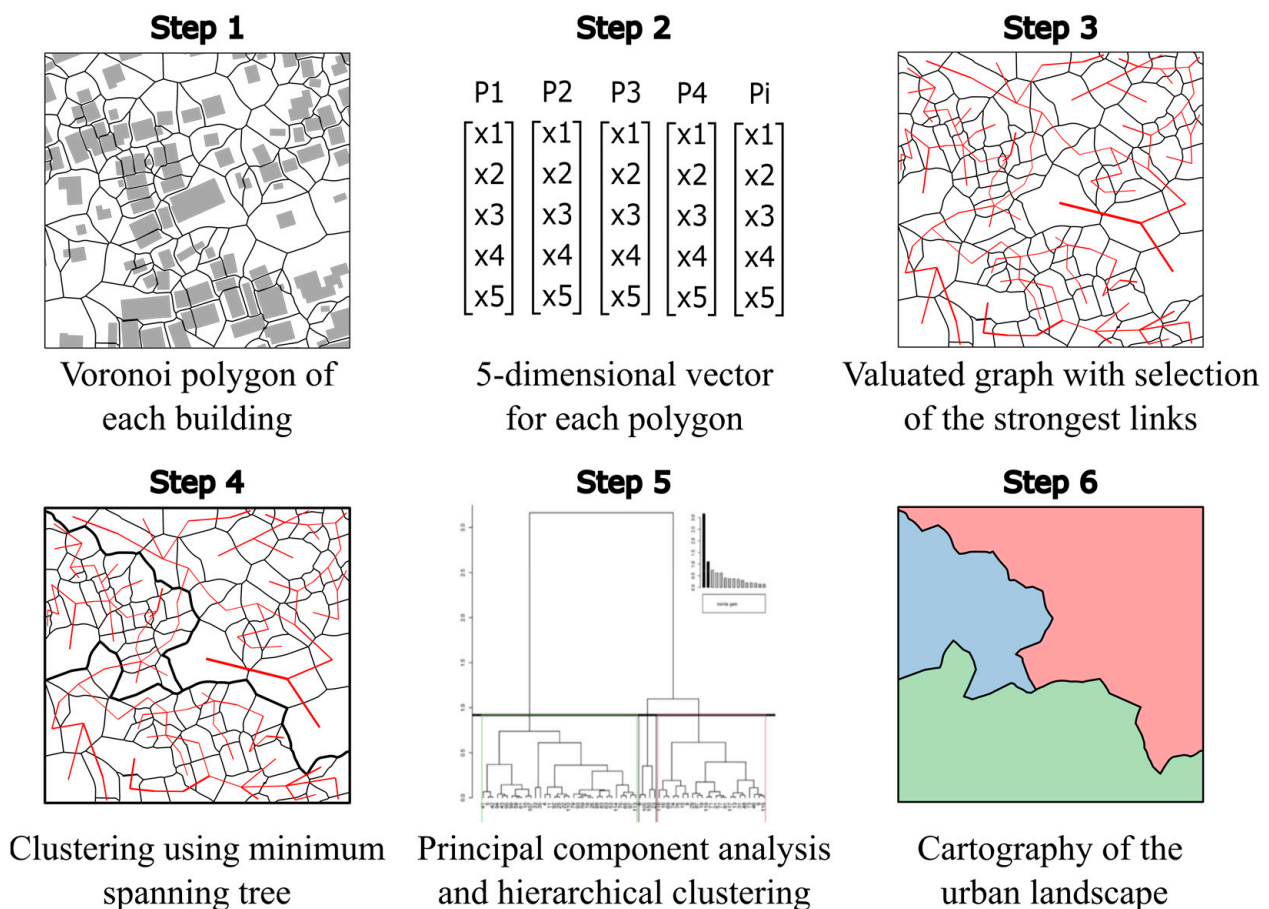


Figure 7. Methodology developed to describe the city on the basis of buildings, elementary entities of the urban territory.

- Step 1: The spatial footprint of building

First, we delimit the immediate environment of each building by constructing Voronoi polygons [67] over the entire building layer, i.e., 400,000 buildings. This involves creating a spatially continuous tiling of polygons associated with each building, so that any point within a polygon is closest to the corresponding building. This gives the hypothetical building's extension area on its surroundings (with a bias since we do not take into account the full road network or dividing walls), based on the spacing between buildings. This space can be a private area, such as a courtyard or parking lot surrounding the building, or a public space between buildings, such as a road or undeveloped area. We used the simple features SF 1.0-17 package for R for geometrical operations [68,69].

- Step 2: Local description of the building

Next, we assign each building its surface area (buildings are polygons coming from the BM data base) and its height from the DSM provided by the CNES Solid Earth Division. This allows us to define the level of proximity between buildings by dividing the building's surface area by the surface area of the Voronoi polygon. When this ratio is close to 1, it means that the buildings are locally close to each other and occupy a large proportion of the interstitial spaces. Conversely, a ratio close to zero characterizes buildings that have a large expanse of open space (in the sense of undeveloped space) in their vicinity.

To characterize the composition of these open spaces, we extract the area of vegetation surrounding the building. Based on the literature [60] and on visual interpretation of Pléiades images, we computed the number of pixels where NDVI > 0.24 and the number of isolated "green" patches. This last number serves as an indicator of the level of scattering of vegetation. For example, a large garden continuously surrounding a building will be

treated as one patch of vegetation if it covers 100% of the available space outside the building. However, if trees and flowerbeds are dispersed around the same building, it will be considered as multiple patches that do not cover the entire available space. All this information is recorded in the form of a vector of five parameters normalized between 0 and 1. This vector is then used to characterize the local environment of each building (Figure 8).

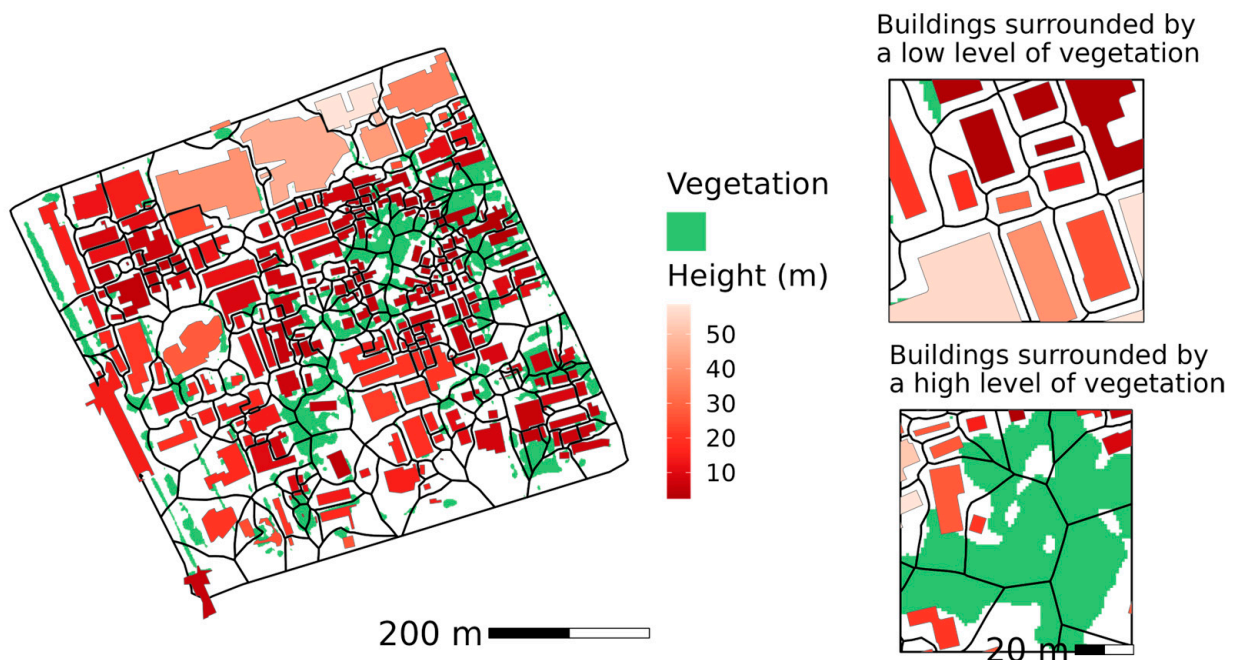


Figure 8. Example of the constructed area of influence (black contour, Voronoï polygon) of each building (red) with their height (red gradient), vegetated areas (green) and free spaces between and around buildings (white).

The next step is to group polygons based on criteria of similarity and geographical proximity. We assume here that the profile and density of mosquito-breeding containers in different zones could be interpolated with knowledge on buildings and their surrounding environments.

- Steps 3 and 4: Birds of a Feather

Voronoï polygons of the buildings are clustered using the SKATER (Spatial 'K'uster Analysis by Tree Edge Removal) clustering algorithm [70]. This algorithm works in two stages.

The first stage in the algorithm is to link together all adjacent polygons that share a common edge (i.e., all direct neighbors' polygons, as shown in Figure 9B). Each link between two polygons (x and y) is weighted by a distance between the two adjacent nodes (i.e., Voronoï polygons in our case), such as:

$$\text{dist}(\vec{v}_x; \vec{v}_y) = \sum_{j=1}^5 \left| \left(\vec{v}_{x,j} - \vec{v}_{y,j} \right) \right| \quad (1)$$

We use the five-dimensional vector constructed in the previous step to compute this Euclidean distance with no units: surface area of the building (from Bing Map), its height (from DSM Pléiades), the area of the Voronoï polygon previously computed, the density and number of vegetation patches present in the polygon (from the NDVI). These variables are normalized for the computation of a non-geographical distance [71]. The more similar their characteristics are, the lower this synthetic distance measure between two adjacent areas.

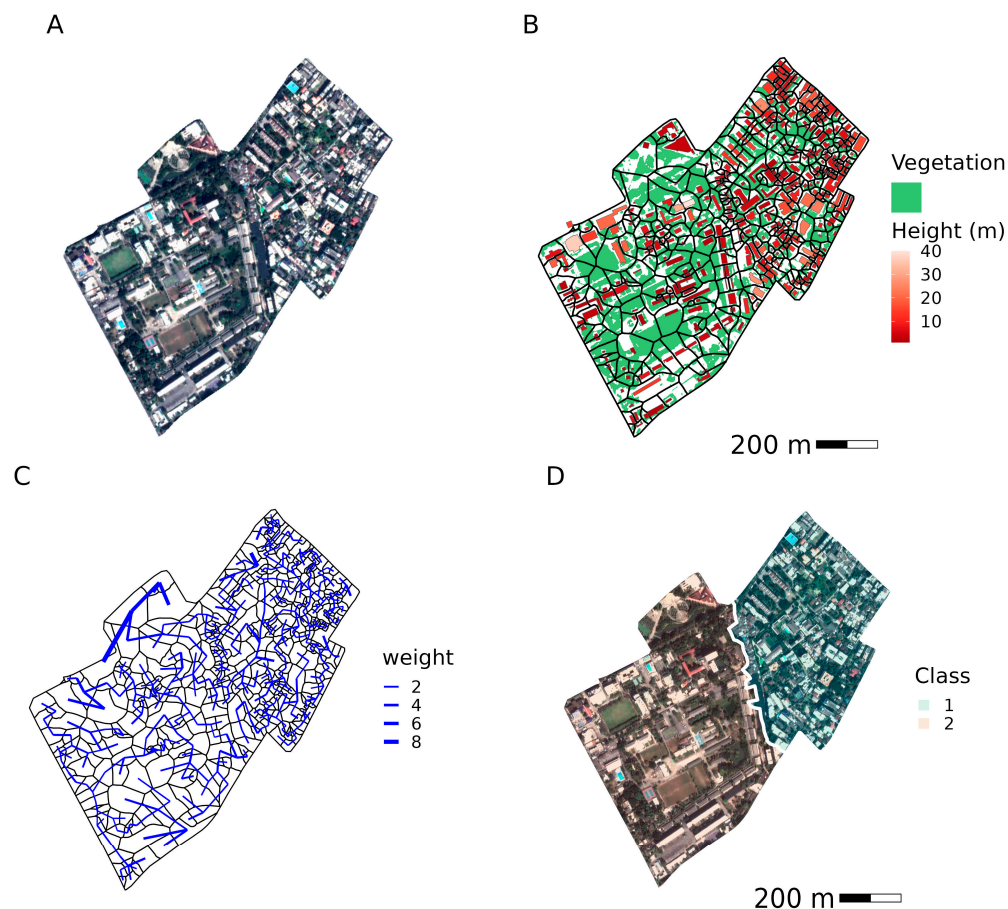


Figure 9. Example of buildings grouping into two zones by clustering. From built polygons from Bing Map (A), Voronoi polygons of each building (B), result of the minimum spanning tree based on the completed graph where each link is weighted (C) and clustering by proximity and similarity (D).

The second stage in the SKATER clustering algorithm is to calculate the minimum spanning tree based on Prim's algorithm [72]. It consists of searching for a tree passing through all the points of the network and which minimizes the total weight of the graph (Figure 9C). This process links each polygon to its most similar neighbor. The minimum spanning tree algorithm tends to choose the link between two adjacent polygons with the lower distance in order to minimize the global cost of the network (sum of the distances).

The Skater algorithm then cuts the graph into N predefined disjoint subsets of vertices using a tree edge removal approach (Figure 9D). Unlike other spatial clustering algorithms such as *clustgeo* [73], all associated Voronoi polygons within the same subset necessarily form a spatial continuum. A minimum aggregation criterion can be defined for each final subset, such as a class area or number of elements (e.g., at least N buildings or a vegetation rate of $X \text{ m}^2$). As an aggregation criterion, we set a minimum area in line with the maximum displacement of a mosquito from its place of emergence, which is the area of a circle with a radius of 250 m, equivalent to 19.6 hectares. The algorithm used here is implemented in R, in the *spdep* library [69].

- Steps 5 and 6: Description of these new homogeneous urban zones

In line with our objective, we consider these zones as the elementary spatial units with a high degree of similarity in terms of land use and organization. They will therefore potentially be the basic units for future sampling plans and aggregation of the data collected related to mosquito-breeding containers. The next two steps, therefore, focus on producing a typology of these zones, in order to provide a synthetic reading of the study area as a whole.

We use principal component analysis (PCA) and hierarchical clustering (HC) to characterize and map these zones. PCA is well suited to analyze highly correlated variables, which is the case of landscape metrics [74]. We use the correlation circle to analyze the contribution of each landscape metrics to the construction of the principal axes, so that it is possible to hierarchize the sources of landscape variability. These multivariate analyses then permit the extraction of the main multivariate patterns of the datasets and provide a typology of the zones.

3. Results

We used the 400,000 buildings located in the 654 blocks defined by the main traffic arteries and waterways of Bangkok (Figure 4). Each of these blocks constitutes an “isolated” geographical area from the point of view of mosquitoes, i.e., the probability that mosquitoes emerging in one of these blocks will travel autonomously to another is considered very low. We apply the processing chain (Figure 7) on the 400,000 buildings to compute the Voronoï polygons and to feed them with the five factors (surface area of the building, its height, surface area of the Voronoï polygon, density and number of vegetation patches in the polygon). The spatial cluster analysis then aggregates the 400,000 Voronoï polygons into 1472 zones in the constrain borders of the 654 blocks. We assume that all these 1472 zones are homogeneous in terms of land use and spatial organization (Figure 10).

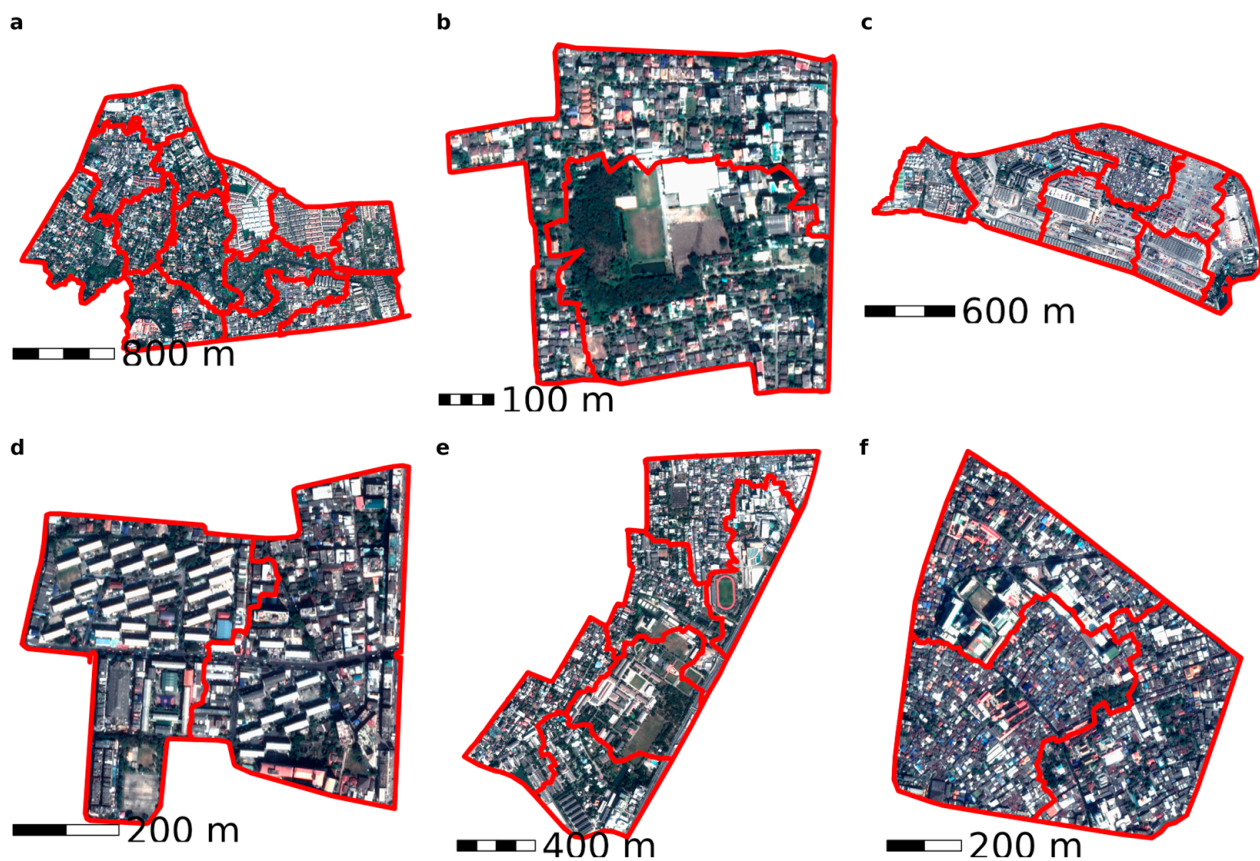


Figure 10. Examples of segmentation of different blocks into homogeneous zones in terms of composition and landscape configuration.

We then apply the last two steps of our method to qualify these 1472 zones. We computed the means of the five factors—vegetation density, patch-vegetation density, built-up density and open spaces between and around buildings—for each zone (Figure 11).

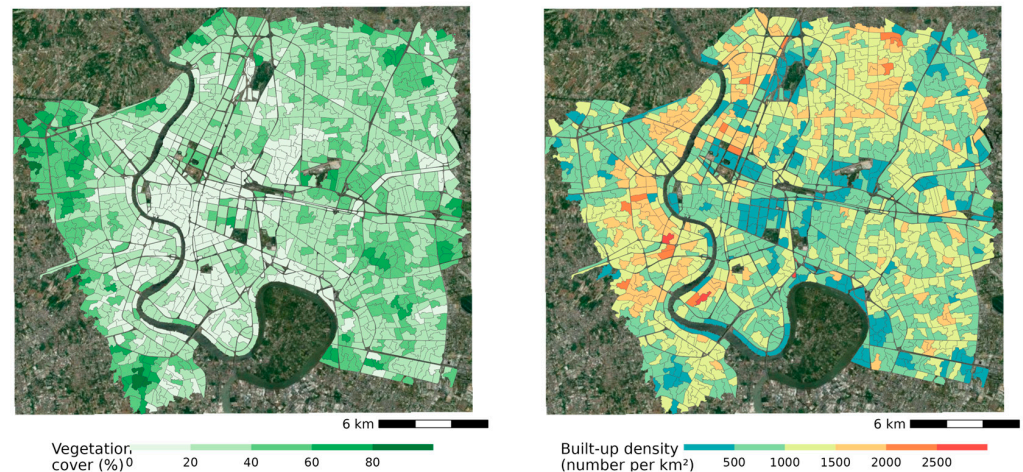


Figure 11. Importance of vegetation (left) and building densities (right) in Bangkok's zones.

We use principal component analysis (PCA) to characterize their composition regarding these variables. The first axis alone accounts for 47.9% of this information, followed by 25% for axis 2 and 20% for axis 3 (Figure 12).

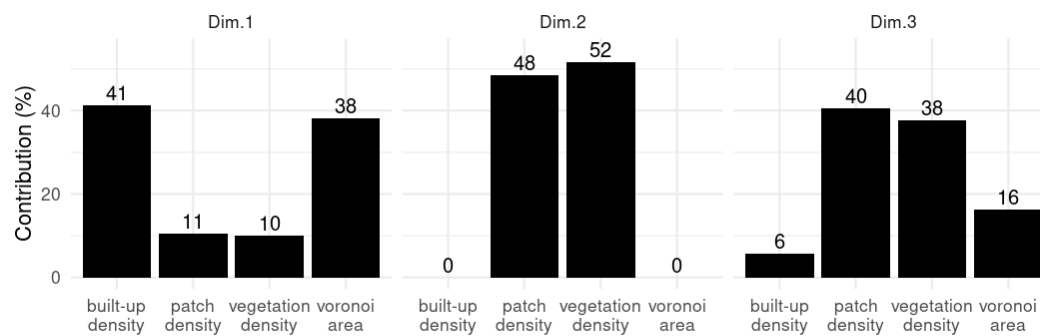


Figure 12. Inertia of the 3 factorial axes (respectively, 47.9%, 24.8% and 19.4%) and variable contributions to each axis.

The PCA distinguishes areas with high building density from others characterized by large inter-building distances (axis 1). The two building-related criteria (built-up density and Voronoi area) contribute to 80% of the axis' total inertia, while the vegetation-related criteria (density and number of patches) contribute to 20% of the axis' total inertia.

The second axis (dim. 2) represents the vegetation part of the composition of the urban landscape, distinguishing between highly vegetated neighborhoods with a cover approaching that of large urban parks, and neighborhoods with a dispersed semi-spatial pattern of vegetation patches, each small in area but sometimes consisting of isolated trees. The zones that come out of this axis are close to 100% vegetated.

Finally, the third axis represents areas with a somewhat intermediate configuration to the first two, with more or less dense built-up areas and where vegetation is either dispersed or united within a large, continuous plant cover (axis 3).

Given the role of the human habitat in the production of breeding containers, we then focus on axis 1 and axis 3 for the remainder of the analysis (Figure 13). Zones characterized by axis 2 will be identified as special points (large parks, cemeteries) which, by virtue of their functions and environmental characteristics, are considered autonomous zones and should be sampled as such for entomological surveillance [34]. In these examples, we clearly identify a distinct structuring of the zones based on their positions relative to the two factorial axes. Axis 1 contrasts areas with very dense, small buildings (on the right) against areas with larger, but less densely situated buildings (on the left). Axis 2

contrasts areas with significant plant cover, typical of gardens and small urban parks in private residences (bottom), against areas where vegetation is more sparse, mainly present as isolated trees between buildings or along secondary transport routes (top).

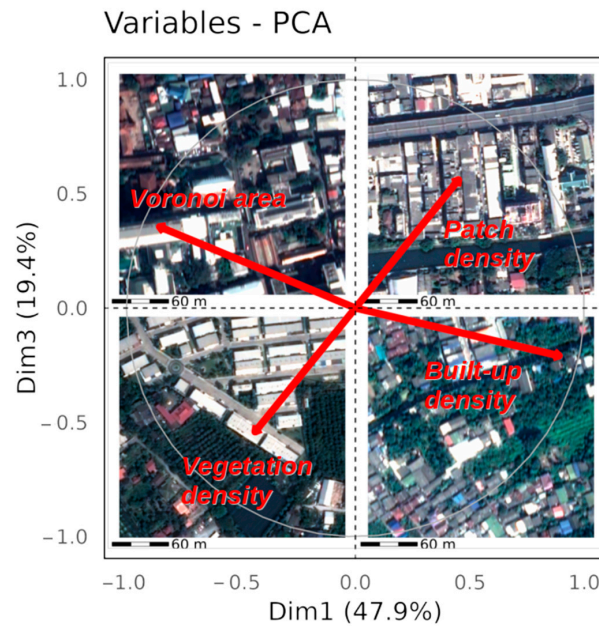


Figure 13. Examples of zones associated with Axis 1 and Axis 3 of the PCA.

We finally carried out a classification of all 1472 zones to map these different classes in our study area. The structure of the dendrogram and the composition of the resulting classes led us to choose a division into six classes (Figure 14).

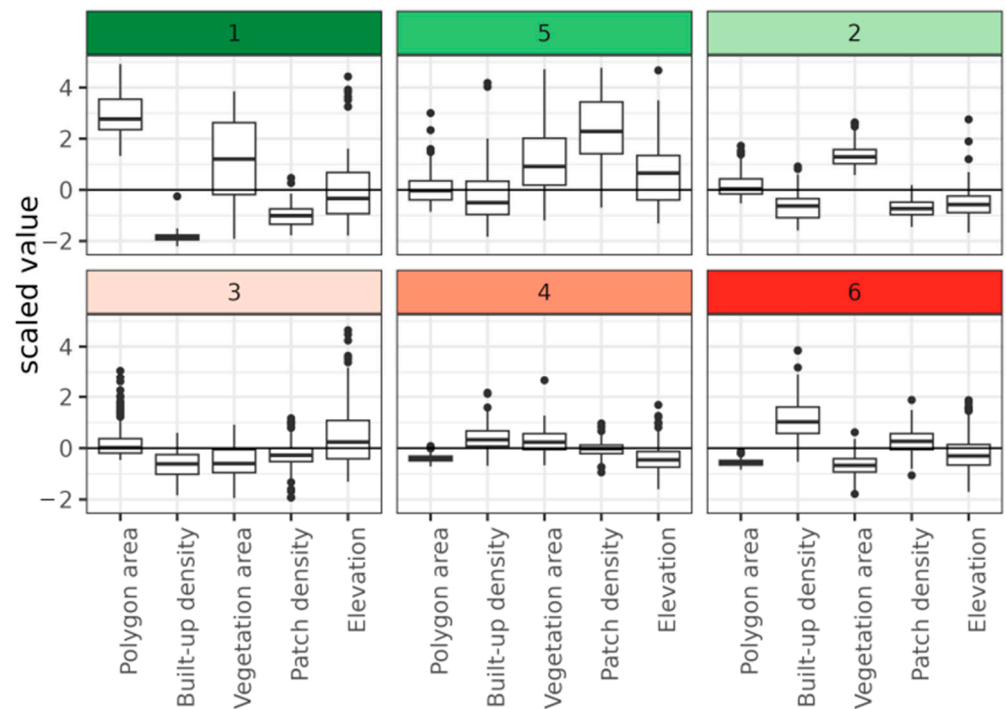


Figure 14. Contributions of the 4 descriptive variables (Elevation as a supplementary variable) to inter-zone landscape differentiation (6 classes) for all 1472 zones within our study area.

Class 1 is characterized by the large amount of open space around the buildings and the amount of vegetation. These areas are few and far between in the city center, characterized by large complexes with nearby parks, or along the Chao Phraya River with its large port areas. Class 2 represents zones with a high level of vegetation density, which can be found in the periphery of the area and some near the very large parks that have not been included in the analysis. The area is characterized by the presence of successive tall buildings typical of downtown Bangkok, which can be likened to the Class 5 zones located on the outskirts of these areas and which feature a configuration with large towers surrounded by significant green spaces. Class 3 represents Bangkok's urban center, with buildings of more than 20 stories stuck together and with little green space. Class 4 is a continuum of Class 3, with slightly lower buildings, less floor space and more vegetation. Finally, Class 6 represents areas of very high building density, found to the west of the river and to the north of the town center. These consist mainly of small houses or buildings with very little open space. The majority of Bangkok's poor neighborhoods fall into this category. The mapping of these six classes shows the spatial continuity of Bangkok's urban organization (Figure 15).

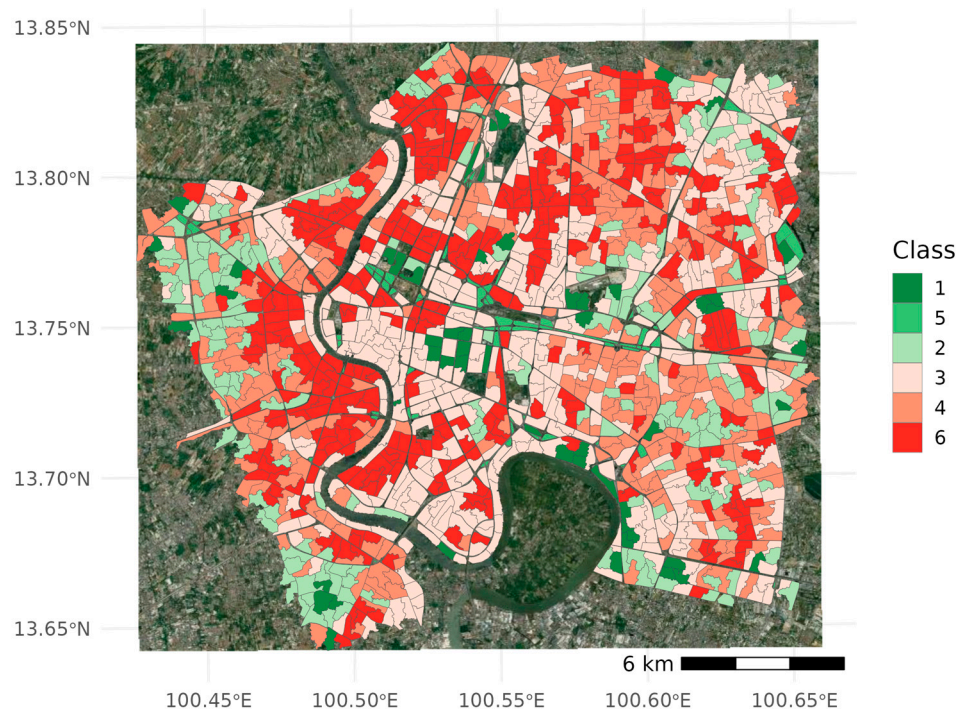


Figure 15. A typology for the center of Bangkok that takes into account the density and height of the buildings, the extent of vegetation cover and the configuration of open spaces between and around the buildings.

Although each zone was constructed on the sole basis of internal coherence (in terms of composition and configuration) and delimited on the basis of a maximum distance defined according to a characteristic of the mosquito vector (the maximum travel distance), this classification reveals a relatively harmonious urban layout, with a continuity in the organization between neighboring zones.

4. Discussion and Conclusions

Vector control targets individual households to eliminate indoor containers or adult mosquitoes during epidemics, but public spaces are frequently neglected [75]. Yet, there is strong evidence to conduct further research to investigate the impact of urban planning and urban housing on the presence of mosquitoes and risk of dengue in urban areas. Risk maps that provide information at a spatial precision that can be used for actions are also

needed. Indeed, *Aedes aegypti* mosquitoes breed in containers and are closely associated with humans at levels of proximity that cannot be captured on an administrative scale. Using this scale to aggregate data could even mask the complexity of urban landscapes where human and mosquitoes interact [47]. The aim of this paper was then to present an original method to produce a typology of Bangkok based on determining criteria for urban mosquitoes, and more particularly their outdoor habitats.

The choice to focus on outdoor breeding containers and habitats is their link with the risk for outside transmission of dengue, affecting both residential and visiting population. Moreover, there is evidence for vector adaptation to outdoor breeding containers and seasonal shifts between human-filled containers (for drinking water for example) and rain-fed during monsoon season [76]. Coming mainly from human activities, we hypothesized that the presence of outdoor containers could be deduced from the shape and height of buildings, by the presence of different types of vegetated areas and by the availability and the configurations of the available open spaces between and around the buildings to accommodate these egg-laying containers. We have therefore developed a six-step methodology to classify the Bangkok city-center into homogeneous micro zones according to these criteria.

Since administrative boundaries have a priori no logical connection with the presence or absence of mosquito egg-laying containers, we first divide Bangkok's urban space into an autonomous set of 654 blocks based on the role played by major transport infrastructure in constraining mosquito movements (Figure 4). The main traffic arteries and waterways therefore act as boundaries between the blocks. Within these blocks, we found private households, commercial or industrial buildings, public buildings like schools or hospitals and religious buildings with public spaces between them or around them. The public spaces can be public streets, car parks, green areas for leisure, abandoned areas and dumping grounds. These blocks also accommodate populations whose volume varies on a daily basis according to the nature of these activities. These populations and activities are the productive basis for mosquito egg-laying containers. Indeed, these containers are flower pots, tires stored in parking lots, objects abandoned in a backyard, construction equipment, rubbish in vacant lots or along lightly used and unmaintained roads. Our aim was therefore to describe these places using ubiquitous attributes that allow us to account for the homogeneity of landscape organization on a small scale, while highlighting the diversity of urban composition on the scale of Bangkok. By doing so, these spatial units, the zones, could serve as a foundation for sampling and spatial aggregation in vector index studies.

Clustering methods enabled us to construct 1472 zones within these 654 blocks. This division is much finer than the administrative divisions available, with, respectively, 35 khet (districts) and 126 Khwaeng (subdistricts) in our study area. The spatial organization of the vegetated zones displays a radial-concentric gradient, with the notable exception of the presence of large urban parks such as Lumpini or Benchakitti (Figure 11, left). Building densities, expressed as the number of buildings per square kilometer, offer unique information compared to the more conventional representation of built-up area densities (Figure 11, right). The map reveals the highest densities west of the Chao Phraya River and north of Bangkok, areas that are home to numerous residential neighborhoods with single-family homes, whose greater or lesser density points to an economic axis not explored here but nonetheless revealed. According to this indicator alone, the least dense areas appear in the hyper-center, which is home to many large residential and commercial complexes. Yet, these large complexes leave little room for the interstices and backyards that are traditionally home to containers.

Multifactor analysis then enabled us to classify these zones into six classes with different composition and configuration characteristics (Figure 15). The working hypothesis is that two zones with similar landcover and organization, albeit geographically distant, will have a closer number and type of potential containers than two different but neighboring areas. As previously noted, the classes are organized spatially. The central area predom-

inantly consists of Class 3 zones, characterized by tall buildings with a large footprint, minimal or no vegetation and limited space between buildings. Moving east, Class 4 zones are found, which correspond to built-up areas with vegetation, such as individual gardens or parks in gated communities. To the west and north, Class 6 areas are prevalent, featuring a high number of small individual or collective dwellings that are closely intertwined.

The choice of sampling zones, even if it must be based on an administrative level due to the decentralization of health agencies or the availability of data, could then be enriched by this descriptive and functional division. Indeed, the aggregation of data relating to mosquitoes and their habitats at the subdistrict level could make us miss the environmental determinants of this mosquito/urban environment relationship. Half of the 126 subdistricts in our study area are made up of three or four classes of different neighborhoods, and a quarter of the subdistricts presents a high degree of spatial heterogeneity, with the presence of five or six classes of environment types (Figure 16). Only eight subdistricts present a strong internal coherence in terms of urban landscape with the presence of a single class. These effects of smoothing environmental characteristics by spatial aggregation could then be all the more important as we move away from these homogeneous subdistricts, due to their small size, from the urban center.

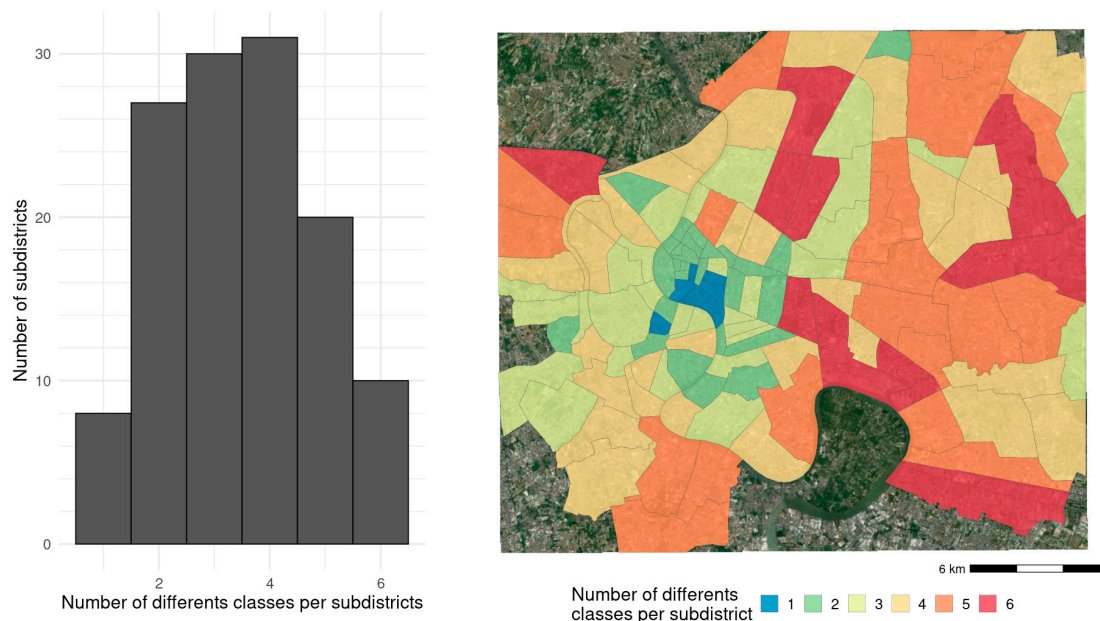


Figure 16. Subdistricts (Kwaengs) of Bangkok with varying degrees of internal spatial heterogeneity. Histogram of the number of subdistricts according to the number of classes (**left**) and spatial organization of these subdistricts (**right**).

Some limitations of this work need to be addressed. Given the importance of data in the construction of this segmentation and typology, we remind that, at the time of writing, the Bing map building database is incomplete. We cannot know the percentage of buildings not represented in this database, but it was the most complete public database available. The absence of buildings in the database has a direct impact on the construction of blocks, as distances between buildings are used to infer road widths, which are absent from OSM data. Finally, we used Bing map data to characterize the most important routes in terms of traffic. However, the link between traffic and road width has not been verified, and it is possible that a narrow secondary road, with a strategic role in local access, is of no consequence in terms of barrier to the passage of mosquito vectors.

Other limitations of this work will need to be explored. Firstly, the consistency of the segmentations produced by the clustering algorithms, in particular the minimum spanning tree, should be assessed. The divisions produced by clustering when projected onto satellite

images seem consistent with what we can see of the spatial compositions and configurations (Figure 10). In these examples, the borders constructed by the algorithm correspond to the breaks observed in the organization of space. To validate this approach, we should increase the number of comparisons between observed rupture and boundaries produced by the algorithm. We therefore plan to compare the divisions produced by geomaticians using visual inspection of the blocks with those resulting from our segmentation chain.

Another limitation to explore is the sensitivity of the fragmentation to the weighting of the vector variables. In this study, we assigned equal weight to the parameters, but one could argue that the differences in terms of heights of the buildings between two adjacent areas are more important than differences in terms of vegetation covers. This differential can only be assessed and possibly introduced into the analysis once the first container density datasets have been studied.

Finally, a thematic limitation is the consideration of only the physical dimensions of the urban landscape. Areas with similar built surface area and green space distribution can be characterized by important differences in socio-demographic terms, and impact the type and density of containers found there. Therefore, further studies should incorporate socio-economic factors into zone typologies when they are selected for field studies.

Beyond these perspectives, the next step will involve conducting field surveys to quantify the number of outdoor potential egg-laying containers, their types and their spatial distribution within selected areas from each of the classes identified in this study. The challenge will be to validate the thematic and methodological choices of this classification by demonstrating significant statistical relationships between the container data and the different landscape classes. Finally, another challenge will be to validate the spatial data processing chain set up during this study in Bangkok in other urban areas with comparable datasets.

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