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Review

A Mapping Review on Urban Landscape Factors of Dengue Retrieved from Earth Observation Data, GIS Techniques, and Survey Questionnaires

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Received: 13 December 2019; Accepted: 20 February 2020; Published: 13 March 2020

Abstract: To date, there is no effective treatment to cure dengue fever, a mosquito-borne disease which has a major impact on human populations in tropical and sub-tropical regions. Although the characteristics of dengue infection are well known, factors associated with landscape are highly scale dependent in time and space, and therefore difficult to monitor. We propose here a mapping review based on 78 articles that study the relationships between landscape factors and urban dengue cases considering household, neighborhood and administrative levels. Landscape factors were retrieved from survey questionnaires, Geographic Information Systems (GIS), and remote sensing (RS) techniques. We structured these into groups composed of land cover, land use, and housing type and characteristics, as well as subgroups referring to construction material, urban typology, and infrastructure level. We mapped the co-occurrence networks associated with these factors, and analyzed their relevance according to a three-valued interpretation (positive, negative, non significant). From a methodological perspective, coupling RS and GIS techniques with field surveys including entomological observations should be systematically considered, as none digital land use or land cover variables appears to be an univocal determinant of dengue occurrences. Remote sensing urban mapping is however of interest to provide a geographical frame to distribute human population and movement in relation to their activities in the city, and as spatialized input variables for epidemiological and entomological models.

Keywords: Dengue; Urban landscape; environment; remote sensing; interdisciplinary

1. Introduction

Around half of the global population is exposed to the risk of dengue virus transmission [1]. This risk exists in nearly a hundred countries, with an estimated 390 million cases per year worldwide [2]. Urban areas are particularly at risk because of (i) the larval habitats of the *Aedes* mosquitoes [3–5] (ii) the high density of human populations, and (iii) the multiplicity of migration and commuting patterns, that could be catalysts for the rapid spread of infectious diseases [6].

Worldwide, *Aedes aegypti* is the primary vector of the virus that causes dengue, while *Aedes albopictus*, a homologous species with a lesser vector competency, is responsible for large dengue epidemics in southeast Asia [7]. The authors of Reference [8] have shown that *Aedes* distributions are currently the widest ever recorded, and are now extensive in all continents, including North America and Europe. Both species have become increasingly capable of exploiting man-made container habitats and human blood meal hosts [9,10], demonstrating their high-level of ecological plasticity and remarkable adaptation to urban settings [11]. The abundance and distribution of *Aedes* mosquitoes are influenced by climatic, topographic, land use and land cover (LULC) factors [10]. The relationship between entomological indicators of *Aedes aegypti* abundance and dengue virus infection is not straightforward [12], and it is difficult to identify a minimal entomological threshold for dengue transmission [13]. This is probably due to (i) the remarkable capacity of *Aedes aegypti* to survive and efficiently transmit the dengue virus even over low population densities [14] (ii) the irregularity of dengue epidemic patterns influenced by serotype dynamics and herd immunity at various level scales [15,16], and (iii) the competence of *Aedes aegypti* to transmit the dengue virus which is highly variable and depends on exogenous factors [12]. Urbanization has substantially increased the density, larval development rate, and adult survival time of *Aedes albopictus*, which in turn has potentially increased the vector capacity [4,17]. Many of the *Aedes* control strategies in development will have time-lagged impacts on adult populations ([18], e.g., Wolbachia and transgenics).

The complex association between the dengue virus (DENV), humans, and *Aedes* populations leads to the question of an appropriate geographic scale to measure the importance of the risk factors, as parameters and processes at a given scale are frequently not important or not predictive at another scale [13]. In the case of vectorial diseases, space may be seen as (i) an actor through the numerous spatially-dependent determinants (environmental, socio-economic, climatic) that influence the spread of the pathogen, and (ii) a medium where humans, reservoirs and vector populations interact and allow the circulation of the pathogen [19]. Although most dengue risk factors are likely to exhibit spatial dependence [13,20], few articles have applied spatial analysis methods in dengue studies [21]. Of the 263 articles on dengue outbreaks reviewed in the literature by Guo et al. [22] over the 1990–2015 period, around twenty deal with spatialized and environmental risk factors. The lack of information on the explicit spatial relationships between human and vector encounters and virus exposure have become a complicated challenge to prevention programs due to the lack of specific targets for vector control. Transportation networks, human mobility and socially structured human movements might shape dengue transmission [23]. The heterogeneity of a urban landscape could influence the biologically-relevant parameters that define vectorial capacity, through habitat suitability, socio-ecological processes and local temperature variations such as urban heat islands (UHI) [24]. However, the impacts of landscape structure on epidemiological processes have been largely neglected in the past [25], and there is still a need for a spatialized integrated approach at various spatial scales [20,24], to combine methods from epidemiology, ecology, statistics and geographic information sciences [25–27].

Over the last twenty-five years, advancement in spatial epidemiology has been largely driven by the use of Geographical Information Systems (GIS) and georeferencing data systems [28,29]. In the case of vector-borne diseases, it may also include remote sensing techniques, which present a high-potential in disease risk mapping and environmental contextualizing [30–33], but probably still remains underutilised [34,35]. Remote sensing uses the notion of a proxy, that is a measurable variable which represents an indirect measure of an impractical physical variable that cannot be measured directly [35]. In the case of vector-borne diseases, entomological data surveys are often costly, labor-intensive and remain scarce [13,36]. Therefore, authors often use the proxies of mosquito breeding or resting sites based on the vector-knowledge reviewed in the literature [17,37]. Despite a more systematic use of GIS and the implementation of spatial statistical methods, the availability of health data and appropriate exposure data often remain limiting factors [38]. National passive notification systems present high variability in the standard of data and metadata storage, which highlights the importance of local knowledge through seroprevalence survey and questionnaire-based responses that can help to add clarity in uncertain regions [39].

We propose here a mapping review to create an inventory and identify the most relevant landscape factors potentially involved in dengue transmission in urban contexts from different data sources. Mapping reviews enable the contextualization of in-depth systematic literature reviews within broader literature and identification of gaps in the evidence base [40]. Mapping reviews share common purposes with scoping reviews, such as examining how research is conducted and structured on a certain topic, the identification of available evidence and the investigation of knowledge gaps [41,42], but provide a systematic map representation to categorize the included articles. Taking an interdisciplinary view, we propose a systematic search of articles into the literature to:

(i) identify the landscape factors according to various sources and geographical units of production;
(ii) map co-occurrence networks associated with the landscape factors, in order to identify the potential underlying structure of fields;
(iii) evaluate qualitatively the respective importance of the above for the mapping of the dengue risk.

2. Material and Methods

2.1. Systematic Search of Articles

This systematic review used the guidelines presented in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [43]. The methodology is summarized in Figure 1 and the detailed steps are presented hereafter. Data at the identification and the screening process steps were extracted by two independent researchers (RM and ZL), and discrepancies were resolved concordantly. The searches were performed in four on-line bibliographic databases, from inception to 31 December 2019:

1. **Science Direct**: e.g., *Annals of Epidemiology, of Global Health, of Tropical Biomedicine, International Journal for Parasitology, Acta Tropica, Infectious Disease Clinics of North America, etc.*;
2. **Web of Science**: e.g., *International Journal of Environmental Research and Public Health, Asian Pacific Journal of Tropical Medicine, Environment Development and Sustainability, International Journal of Environmental Research and Public Health, Journal of Medical Entomology*, etc.;
3. **PubMed**: e.g., *International Journal of Health Geographics, PLOS Neglected Tropical Diseases, The Brazilian Journal of Infectious Diseases, etc.*;

4. **Scopus**: e.g., *e.g., Asia Pacific Journal of Public Health, BMC Infectious Diseases, Epidemiology and Infection, Geocarto International, etc.*;

and considered either "all fields" (including bibliography references) or only "title-keywords-abstract" according to the database query form, and limited to the type "journal article". The logical structure of the queries was based on the following formula:

(i) dengue AND (urba* OR cit*) AND ("land use" OR "land cover" OR landscape OR dwelling OR habitation)

The character * being the classical symbol for regular expressions, corresponding to any character or group of characters, for example, urba* refers to the words urban, urbanization, and so forth. No constraints on the study period and language were imposed in the search queries. All search records from the four on-line databases were then combined together [n = 2342], using the free and open-source reference management software Zotero (https://www.zotero.org/). In addition, a search in Google Scholar® was done to avoid the omission of relevant articles [n = 272]. Duplicates [n = 311] were automatically removed from the [n = 2614] combined records leading to [n = 2303] at the end of the identification stage.

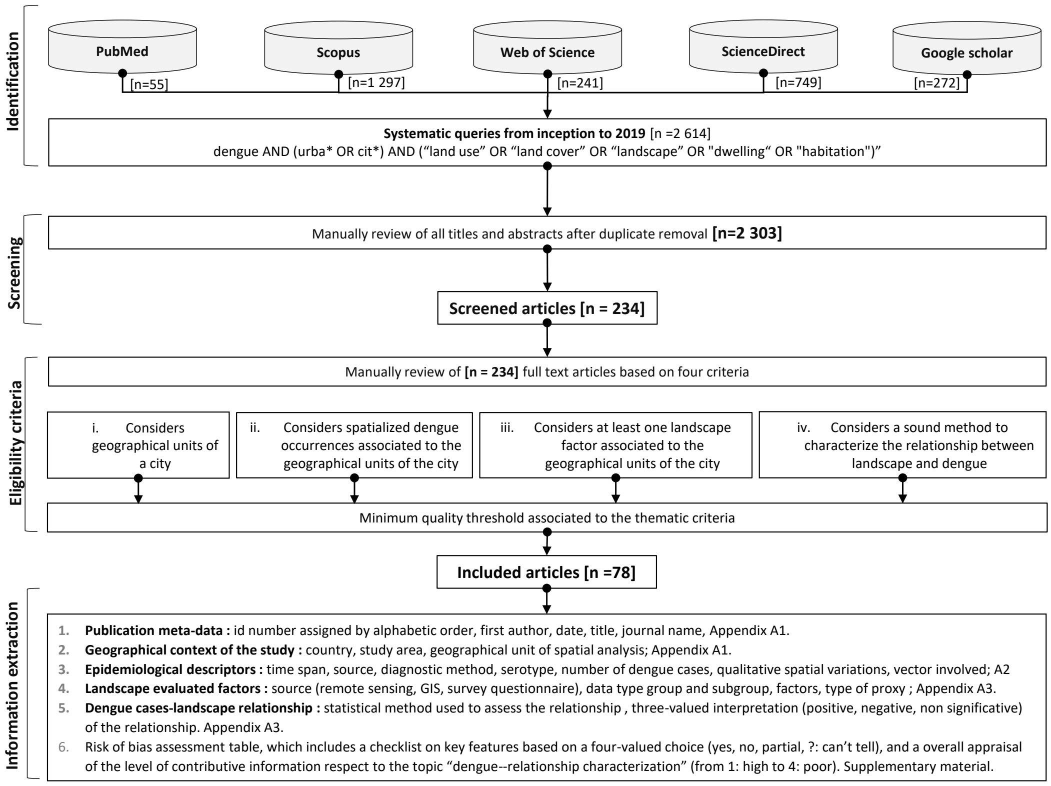

Figure 1. Stages of systematic search to retrieve included article to our four criteria, following the PRISMA statement [43].

2.2. Screening, Selection Criteria, Risk of Bias, and Contribution of the Articles

A systematic checking of the titles and abstracts was conducted in order to select only the peer-reviewed original research articles dealing with the relationships between landscape factors and dengue cases, leading to [n = 234] at the end of the screening step, excluding those deemed irrelevant to the topic. Based on a full text reading, screened studies at the previous step were included if:

(i) they consider geographical units within a city;

(ii) they included spatialized dengue cases, collected by passive notification systems or by serological surveys;
(iii) they identified and characterized the influence of landscape factors on dengue occurrences in an urban context;
(iv) they described the explicit relationships between landscape classes and dengue data.

In contrast, studies that:

(i) consider rural areas, or include large part uncovered by urban areas;
(ii) do not consider dengue occurrences, but solely *Aedes* mosquitoes as proxy of dengue presence;
(iii) do not include any explicit landscape feature, for example, solely consider meteorological variables (temperature, wind speed etc.) or socio-economic variables (income, status etc.);
(iv) do not bring any evidence or information on the used models to perform the relationship between dengue occurrences and landscape features;

were excluded, which finally resulted in [n = 78] articles included in the review, at the end of the eligibility step. A total of 156 articles were discarded at the end the screening stage based on criteria 1 (does not consider an urban geographical unit of a city, [n = 36]), criteria 2 (does not consider spatialized dengue cases [n = 26]), criteria 3 (does not consider at least one landscape factor, [n = 31]), criteria 4 (does not perform a relationship between dengue and landscape, [n = 49]), or based on an insufficiently described methodology ([n = 13]).

We considered landscape factors in a "broad" definition, centering around a virus perspective: vectors and humans are hosts, and their respective trajectories lead to a complex interaction, which facilitate or hamper the virus circulation. Therefore, we considered entomological variables and human densities or movements as dynamic features of the landscape. On the other hand, we limited our definition of landscape factors to physical variables, and discarded direct references to socio-economic data, as level of income, *per capita* gross domestic product (GDP), or unsatisfied basic needs. We have in the first place considered a "Built City", i.e. a city as a physical entity, or the area devoted to primarily urban uses [44]. Such definition is in line with the global urban mapping approaches, and automatic extraction of built-up area [45–47]. As a proxy of human presence and *Aedes* habitats, urban areas within a city reflect a "certain density" of buildings, which threshold varies according to the geographical context and authors definition, out of the scope of this paper. We did not have either considered the question of city size, an issue of considerable significance in urban and regional analysis.

Various methods exist to appraise the quality of studies included in a review, and assess the corresponding risk of bias. These methods differ greatly in applicability across study designs, and approaches: e.g., scale vs checklist, presence/absence of summary score etc. [48]. During the screening stage, we performed a first "minimum quality threshold associated to the thematic criteria" (Figure 1) in order to discard articles were the data set or the methodological descriptions remain unclear. At the eligible stage, we included a checklist on key features of the 78 included articles based on a four-valued choice ("yes", "no", "partial", "can't tell") to characterize (i) the completeness of the epidemiological and the entomological dataset (ii) the degree of maturity of the methods to produce the landscape factors (iii) the characterization of the dengue–Landscape relationship. We also provide an overall appraisal of the level of contributive information respect to the topic "dengue–relationship characterization" (from 1: high to 4: poor). These information are available in a table format as Supplementary Materials.

Our entire bibliographic database, structured according to the PRISMA steps, may be consulted at the following web address: https://www.zotero.org/groups/2159925/article-review_dengue_landscape/items/collectionKey/. By browsing the Zotero folders, readers could see the different results obtained through the systematic requests on the one-line databases, and by picking one particular article in the "non eligible" folder, readers could visualize the reason associated to the inclusion/exclusion decision in the note section (right window in the online application).

2.3. Structuring of the Information Extracted from the Included Articles

We referenced the included articles by an identification (id) number assigned alphabetically from 1 to 78, which corresponded to reference numbers [135] (Ali et al., 2003) to [212] (Zellweger et al., 2017) in the bibliography section (please refer to the appendix for a full description). We manually extracted the information concerning the data, the methods, and the main results to build three analysis tables, according to the following categories (please refer to the appendix section for exhaustive tables):

(i) the geographical context: country, study area (city), geographical unit of spatial analysis (Table 1 and Appendix A);

(ii) the epidemiological descriptors: start and end years of an outbreak or survey, dengue data type (incidence, prevalence, case number), medical analysis to confirm the diagnosis (clinical signs, laboratory analysis), number of dengue cases (and incidence rate when available), spatial variation and pattern(s) observed, vector species involved (Table 2 and Appendix A);

(iii) the landscape factors: data source according to three subcategories: remote sensing images (sensor name), Geographic Information System (GIS) layers, and survey questionnaires. We also extrapolated the type of proxy associated (i.e., the element of the transmission cycle represented, for example, "exposure to *Aedes* bite"), and the type of data (e.g., land use or housing type and characteristics) according to a two-level classification, called data group and sub-group, respectively (Table 3 and Appendix A);

(iv) the search of a relationship between urban determinants and dengue cases: type of statistical and spatial methods used to quantify the relationship between dengue cases and environmental determinants, interpretation of the relationship through a three-valued index: positive (+), negative (−), or non-significant (NS) (Table 3 and Appendix A).

Table 1. Structuring of the data extracted from the articles on the publication meta-data and the geographical context. First line (id: 3) is given as an example. Please refer to the annex-table 1 for the whole dataset ([n = 78] articles).

ID	Publication Meta-Data				Geographical Context		
	Author	**Date**	**Title**	**Journal**	**Country**	**City**	**Geographical Unit of Spatial Analysis**
3	Araujo	2015	Sao Paulo urban heat islands have a higher incidence of dengue than other urban areas	The Brazilian Journal of Infectious Diseases	Brazil	Sao Paulo	Districts

Table 2. Structuring of the data extracted from the articles on the epidemiological context. First line (id: 3) is given as an example. Please refer to the annex-table 2 for the whole dataset ([n = 78] articles). In last column, we indicate if vectors are only mentioned (M) or observed (O) in the study.

ID	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
3	2010–2011	Passive notification (COVISA)	IgG (ELISA)	NA	N = 7415	Heterogeneous	*Aedes aegypti (M)*

Table 3. Structuring of the data extracted from the articles on the landscape factor production and the dengue-landscape relationship. First line (id: 3) is given as an example. Please refer to the annex-table 3 for the whole dataset ([n = 78] articles).

ID	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
3	Landsat 5 TM image	Land cover	Surface Temperature	Urban heat islands	+	Vectors resting sites and virus replication (at large-admin level)	Multiple cluster analysis

2.4. Analysis and Representation of the Information

2.4.1. Cartographic Representation

Based on the information extracted from the geographical context and the epidemiological information, we mapped the cities corresponding to the 78 study sites (QGIS LTR 3.4). We distinguished the types of epidemiological data according to their sources: passive surveillance system, or serological studies (incidence or prevalence). We also mapped the techniques employed to produce the information related to landscape factors: survey questionnaire, GIS data, and remote sensing imagery.

2.4.2. Co-Word Analysis through Self-Defined Tags Co-Occurrences

To understand how landscapes factors are produced and those that could be critical in urban dengue transmission, we adapted a method derived from bibliometric visualization techniques (Figure 2). Such approaches are based on the mapping of a network, which represents the degree of keyword co-occurrence of predefined article descriptors, like co-authors, or tags. Co-word networks may help to identify the conceptual structure, that uncovers links between concepts through term co-occurrence. Promising implementations of such literature analysis tool have been recently developed ([49,50], NAILS, bibliometrix). To perform this network mapping, here we used VOSviewer software (V1.6.11), a tool for constructing and visualizing bibliometric networks [51], and already used to perform review analysis ([33], e.g., Remote Sensing in Human Health). To map the structure associated with the landscape factor production, we exported the bibliographic references according to three categories: remote sensing images, GIS data, and survey questionnaire. From the bibliometric manager (Zotero 5.0.73), we chose a standardized tag format developed by Research Information Systems (RIS), compatible with VOSviewer and the module *create map based on bibliographic data*. To map the networks, we chose *Co-occurrences* with *Keywords* as units of analysis, associated with the *full counting method*. Here, keywords refer to self-defined tags, identified by the authors of this review, and associated with landscape factors, structuring terms, and a three-valued interpretation associated with the dengue-landscape relationship (positive, negative, or non-significant) (Figure 2). We defined the minimum number of occurrences as 1, in order to map the entire landscape factor network. Here, a node is associated with a tag (or keyword), with an edge representing a link of co-occurrence between two tags. To map the networks associated with the nature of the relationships between the landscape factors and the observed dengue cases, we adopted the same approach for each of the four defined spatial units: household, neighborhood, small-administrative, large-administrative (including city-level (Figure 2). As VOSviewer is mainly designed to visualize large maps containing thousands of items, it could have been challenging to read the full-network, so we added a post-treatment step, in order to make some items more readable by modifying the character font (Inkscape, version 0.92.4).

Survey questionnaires and census data originate from socio-geographical approaches, while entomological observations are part of medical entomology. As these were mainly collected during household investigation, they were associated it with survey questionnaires in the data structure representation, as part of socio-ecological surveys.

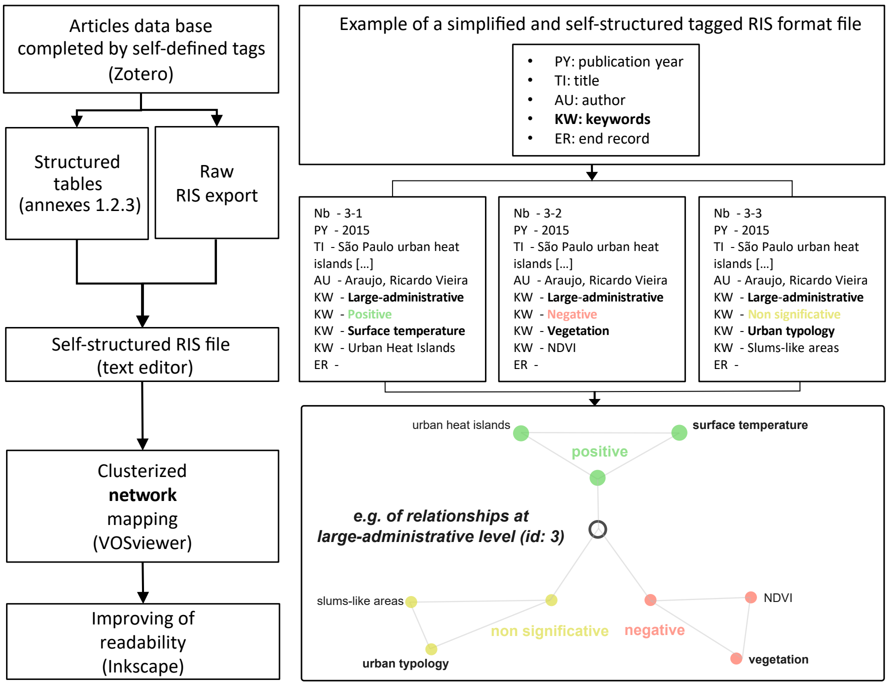

Figure 2. Method used to map the co-occurrence relationship between the self-defined tags, here keywords, for each of the articles. Keywords are specific self-defined tags, which may here refer to: landscape factors (e.g., "Urban Heat Island"), structuring terms (in bold, e.g., "Urban typology" or "large administrative-level"), or nature of the relationship (in color, e.g., "positive"). We added a tag, called Nb (number), which helps to identify the id number of the included article (here 3 of [n = 78]).

3. Results from Information Extraction

3.1. Geographical and Epidemiological Contexts

Temporality and location of the included articles (Figure 3):

- The oldest article was published in 1986, and refers to a dengue transmission episode observed in two Puerto Rican communities which occurred in 1982 (id: 73). Four articles were published in the 1990s, and refer to putative determinants and predictors of infection in Mexico (id: 34), risk factors observed in Puerto Rico (id: 55), determinants of dengue-2 infection in Australia (id: 43), and relationship between Breteau, House index (HI), and occurrences of dengue in Malaysia (id: 60);
- Twenty articles were published between 2000 and 2009, mainly in Brazil (ids: 18, 27, 28, 46, 61, 62), Central America (ids: 7, 9, 12, 21, 25, 52, 69), South America (id: 56), South and East Asia, Bangladesh (id: 1), and Thailand (ids: 65, 70, 71). Two articles were published in West and Central Pacific, Palau (id: 4), and Hawaii (id: 26);
- From 2010 and before 2015, we identified 16 articles, which were concerned principally with Central and South America: Costa Rica (id: 44), Colombia (id: 45), Ecuador (id: 59), and Brazil (ids: 5, 6, 8, 48), East Asia: in China (ids: 15, 36, 74), in Malaysia (id: 19, 75), in Thailand (ids: 35, 57), and in the Philippines (id: 23). One of the two articles published in the Middle East (Saudi Arabia) was from 2011 (id: 32);
- Since 2015, the majority of the thirty-seven study sites were located in South Asia, mainly in China (ids: 10, 13, 14, 16, 29, 37, 39, 50, 51, 53, 66, 76), India (id: 41, 63) and Pakistan (id: 40), and South East Asia: Vietnam (ids: 33, 68), Singapore (ids: 24, 58, 77), Malaysia (id: 67), and Indonesia (ids: 31, 49, 54, 72). Five articles since 2105 related to Central and South America: Mexico (id: 22),

Brazil (ids: 3, 47), Argentina (id: 11), Colombia (ids: 17, 42), and Ecuador (ids: 30, 38). We found only one article concerning Africa (Kenya), published in 2016 (id: 20), and the second article of the Middle East (Saudi Arabia) which was from 2019 (id: 2);

- Various articles concern urban areas located in an insular context: Palau in the western Pacific (id: 4), Puerto Rico (id: 55), Hawaii (id: 26), Singapore (ids: 24, 77), Taiwan (Province of China) (ids: 15, 16, 74), Trinidad (id: 12) and New Caledonia (ids: 64, 78). Two studies make a cross-border comparison, between USA and Mexico border-cities (ids: 9, 52);
- Most study sites are limited to a unique city, excepted in some cases, which consider various urban areas (id: 2, multi-stage stratified cluster sampling in four cities of Saudi Arabia), (id: 34, serosurvey in 70 localities of Mexico), (id: 44, correlational epidemiological study conducted in the country's 81 cantons of Costa Rica), (id: 45, 30 selected municipalities of Colombia's Córdoba Department), (id:50, seven cities of the Guangdong province, located at the Pearl River estuary) (id: 67, various degrees of urbanization between cities in Malaysia), (id: 64, different elevation levels in New Caledonia);
- Ten articles focused on the city of Guangzhou, located in the south-central part of Guangdong Province in China (ids: 10, 13, 14, 36, 37, 39, 51, 53, 66, 76). Guangzhou is considered as "the center of transportation, finance, industry and trade in southern China and has frequent economic and cultural communication with the nations of Southeast Asia and Africa" (id: 14). If historically, dengue fever has re-emerged in China in 1978 from its first appearance in Foshan city (Guangdong province), Guangzhou, with its 14.49 millions resident population, has "always been the hardest hit area of [dengue fever] DF in Guangdong Province and China", with epidemic episodes that have "gradually intensified" (ids: 14, 39);
- Collectively, these review articles propose a broad spatial sampling of the inter-tropical belt, traditionally associated with dengue occurrences [2], and consider dengue cases observed over a thirty seven year time–span, between 1982 and 2019 (Figure 3).

Epidemiological characteristics of the included articles:

- The dengue virus can cause a large range of symptoms, ranging from an asymptomatic form, which includes the vast majority of infections, and may be associated with various degrees of infection: dengue fever (DF), dengue hemorrhagic fever (DHF) to the potentially fatal dengue shock syndrome (DSS) [52]. Generally, most articles refer to dengue cases that include a broad interpretation of the disease expression, especially fever (DF). Twelve studies in the method section refer explicitly to DHF cases (ids: 7, 12, 17, 25, 31, 38, 49, 59, 60, 65, 75, 68), and two to DSS (id: 31, 65). In Indonesia for example, only DHF cases are mandatorily reported (id: 49);
- We identified 23 articles based on serological surveys performed by the authors (ids: 2, 7, 8, 9, 20, 22, 26, 28, 30, 34, 35, 43, 48, 49, 52, 55, 61, 67, 70, 71, 73, 75, and 77). In such approaches, based on fieldwork, household location is used to spatially identify the dengue cases. Fifty-five other articles were based on passive notification of cases collected by local and national health agencies. Such databases may collect the patient address or refer to an administrative division to locate the cases, without further information on a potential place of transmission (ids: 15, 16, 19, 23, 32, 35, 57, 64, 66, 78). A geocoding step is necessary where patients home addresses are available to associate (X, Y) coordinates in a GIS;
- Geocoding was performed manually (ids: 3, 54, 65, 67, 69) or probably manually (ids: 11, 18, 17, 31), and in 5 cases by an automatic method (id: 42 R script-ArcGIS server, ids: 37 and 53 http://www.gpsspg.com/xGeocoding/) or probably automatic method (id: 46 MapInfo, id: 76 not described method). The authors may decide to spatially aggregate the dengue cases at a coarser resolution to perform the association with other data sources (id: 10, "Gross Domestic Product" at township/street level; id 38, census block);
- Considering the temporal aspect, 26 articles use datasets, which cover at most three years. The longest time series of dengue cases was an uninterrupted 22 years dataset in the city of Guangzhou,

China, from 1978 to 2014 (id: 66). Most publications aggregated dengue data and calculated the yearly average incidence rate;

- Almost all of the 78 publications included articles which confirmed a highly non-uniform spatial distribution in the urban context, regardless of the spatial scale of analysis. Global or focal cluster detection are commonly based on global/local Moran's index to detect the presence of overdispersion based on autocorrelation analysis [53], and is based on either a sliding circular window (cylinder, if the time dimension is considered), or consider each spatial unit towards contiguous neighbor units (ids: 10, 16, 17, 18, 38, 46, 54, 58, 65, 78). Its value comprises between [-1,+1], and reflects the assumptions about the spatial phenomenon in question to detect negative or positive spatial auto-correlation. In the articles of this review, a local Moran's index often highlights the presence of a spatial correlation at fine scale. Various articles identify clusters (ids: 1, 3, 10, 16, 17, 18, 24, 31, 36, 37, 38, 39, 46, 51, 53, 58, 63, 65, 70, 71, 74, 78), hotspots (ids: 10, 19, 50, 56, 59) and coldspots (id: 10, 50). In one study (id: 42), the authors tested several structures of spatially explicit Bayesian models in order to estimate the relative risk (RR) of dengue.

Entomological consideration in the included articles:

- The majority of the articles only mention the implication of the *Aedes* vector in the introduction and/or the discussion sections, and exclude entomological consideration in the method or in the data acquisition. Nineteen articles performed entomological observations of: *Aedes aegypti* (ids: 1, 4, 5, 6, 9, 24, 26, 28, 34, 52, 55, 58, 60, 61, 73), *Ae. albopictus* (ids: 1, 4, 9, 26, 58, 60, 66), or of *Ae. (Stegomya) genus* (ids: 12, 25, 65) without distinction between both species;
- Thirty-six articles mentioned *Aedes aegypti* as the main or exclusive vector, six mentioned *Ae. albopictus* as the main or exclusive vector (ids: 10, 13, 39, 50, 51, 53), and ten mention both or just the *Ae. (Stegomya) genus* as responsible for the dengue transmission process (ids: 14, 16, 36, 41, 49, 54, 57, 67, 74, 75). Only one study dispensed with an entomological database prior to the survey, made available by the infectious disease surveillance system (id: 66, Notifiable Infectious Disease Report System (NIDRS), Guangzhou);
- The potential heterogeneous nature of the spatial dispersion of mosquito density has been analysed in some studies (in relation withe dengue occurrences), through, notably (i) the intensity of larvae-positive breeding sites by properties inspected in each block, unsing the kernel estimator method (id: 5), parameterized with a flight distance of 280 m which is associated with the *Aedes aegypti* female [54], (ii) the extrapolation by ordinary kriging of entomological indicators associated with the four life stages of *Ae. aegypti*: (absolute) number of *A. aegypti* eggs in the block, and number of positive buildings for *Ae. aegypti* larvae-pupae and adults in the block, divided by the number of buildings surveyed in the block (id: 6).

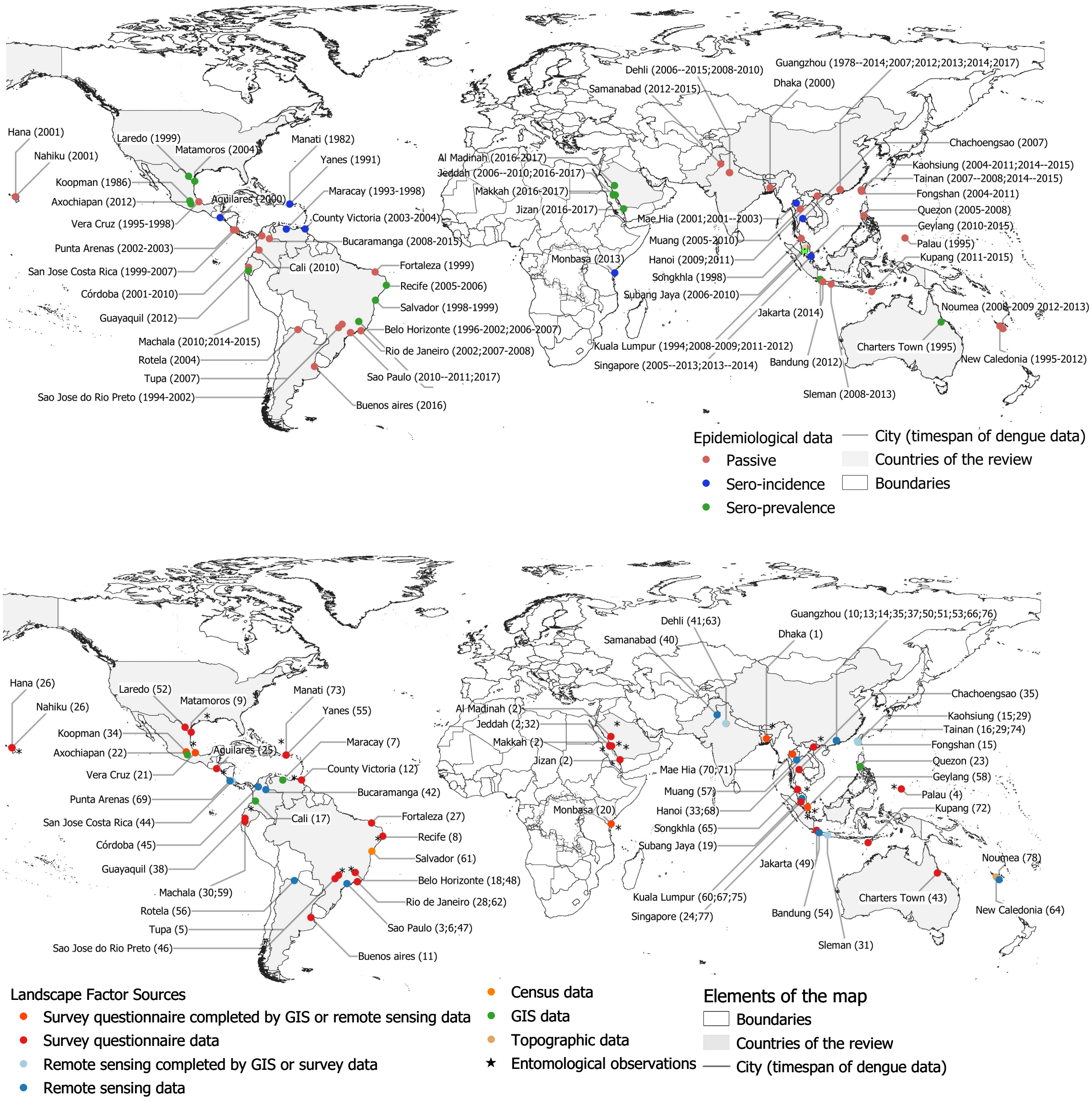

Figure 3. Top: localization and characteristics of the epidemiological data sets of the 78 articles of the review. We indicate the type of sources (serological surveys or passive notification system) and the temporal range associated with the dengue data. Bottom: localization and characteristics of the landscape data sets of the 78 articles of the review. We indicate the type of sources: questionnaire surveys, GIS, Remote sensing data, and the availability of entomological data (*).

3.2. Production of the Landscape Factors Associated to Dengue Cases

Type of approaches: We identified five approaches that led to the production of landscape characteristics (Figures 3 and 4):

(i) Survey questionnaire, including census data;
(ii) *in situ* entomological observation;
(iii) Geographical Information system (GIS) data;
(iv) Topographical measurements;
(v) Remote sensing data (RS data), originated from satellite images.

Data sources network considering all approaches: The graphical representation of the data sources network, considering all type of data, highlights the strong polarization between "survey questionnaire" and "remote sensing images" (Figure 4):

- "RS images" are strongly connected to the "land cover" properties of the environment, while "survey questionnaire" is strongly connected to "housing characteristics", "housing type", "construction material" and "entomological observation". "GIS data" sources are both connected to "remote sensing images" and "survey questionnaire", highlighting its interface position as a bridge between human geography approaches and digital geography (e.g., [55]);
- "GIS data" connect well to the "land use" characteristics of the environment, the "infrastructure level" and the "typology" of the urban area. It is noteworthy that the node "*Aedes aegypti* mention" is at the centre of the network, which shows that entomologist information relative to the 78 included studies, centred on observed dengue cases, are coming from a knowledge base of the mosquitoes rather than direct observations. Entomological observations concerning *Aedes aegypti* and *albopictus*, considered together or separately, belong to the "survey questionnaire" cluster, while *Aedes aegypti* and *Ae. albopictus* mentions belong to "remote sensing image" or "GIS data" clusters (Figure 4);
- Considering the publication year associated with the data source (Figure 4), it is noteworthy that "survey questionnaire" and "entomological observations" are associated with the oldest publications, and "remote sensing" and "GIS data" with the most recent. However, the "remote sensing images" cluster is associated with the 2000–2015 period satellite missions (Landsat 5–7, MODIS, IKONOS, ALOS), and not to the most recent ones (e.g., Sentinel missions, except for id: 41). Satellite imagery and GIS data have been used to complete and contextualize some survey questionnaires in multi-sources studies, e.g., Google Earth images used for photo-interpretation (ids: 20, 57), normalized difference vegetation index (NDVI) index and urban characteristics (id: 50), or GIS data used to localize entomological observations (ids: 24, 58) or altitude associated with the mosquitoes' environment (ids: 21, 34, 44, 64);
- By jointly using remote sensing and GIS data sources, some authors were able to describe both land use and land cover properties of the study area, e.g., vegetation index and urbanization level (id: 10), road network density and aging infrastructure (id: 14), bare soil detection and building type (id: 19), urban typology ("Urban Park") and vegetation cover through NDVI index (id: 29), "urban village" and NDVI index (id: 51).

Data sources network considering remote sensing images: By mapping the structure of data from the "remote sensing images" source (Figure 5), we observe a strong structuring around the "land cover" properties of the landscape, mainly retrieved by the MODIS (500 m), ASTER (30 m), and Landsat 5 TM, 7 (30 m) moderate and high resolution sensors:

- "Land cover" is characterized by:
  - surface temperature (ids: 3, 42, 47, 76);
  - detection of buildings through the brightness index (id: 56);

- vegetation cover through NDVI and VFC (ids: 3, 10, 29, 36, 42, 44, 45, 47, 51, 56, 69, 76, 78);
- water areas (ids: 14, 36, 41, 47, 56, 66, 67), and cropland (id: 36).

- "Building" is characterized by roof shape (id: 54), density (ids: 31, 41, 57, 69, 70), and surroundings based on density and distance from other land cover/use classes, e.g., vegetation (ids: 31, 56, 57, 67, 69, 70, 71), bare soil (ids: 19, 71), water-areas (ids: 56, 67, 71), cropland (ids: 36, 70), or road density (id: 36);
- "Land use" characterization is associated with high resolution sensors like Landsat 8 (30 m XS, id: 10) and ALOS (10 m XS, id: 57), and overall with very high resolution sensors like Ikonos (4 m XS, id: 19), Quickbird (2.4 mm XS, id: 10, 31, 69), WorldView 2 (0.46 m PAN, id: 54), Google Earth (Digital globe imagery, id: 20, 40) images, and Spot 5 (2.5 m PAN, id: 14, 32);
- "Land use" is thematically associated with "urban typology" and refers to the buildings function, e.g., residential, commercial, religious, industrial, or temporary construction (ids: 10, 19, 20, 57). Some authors define a local spatial index associated with the degree of urbanization and infrastructure of the area, e.g. the "percentage of urban villages" (ids: 10, 53), the percentage of "village area with vegetation" (id: 71), or the "quality of neighborhood" (id: 32).

Data sources network considering GIS: "GIS data" sources are initially collected from various sources such as digitised maps, geocoded census data, or in situ observations. The network shows a strong connection with the "land use" properties of the environment (Figure 5). Urban landscape is characterized through:

- "urban typology" associated with (i) urban morphology with construction height, e.g. "high or low-rise housing" (id: 58), (ii) building function, e.g., "tire repair shops" (id: 18) (ii) area functions, e.g., "residential/commercial/recreation" areas (ids: 19, 23, 57), "informal settlement" areas (id: 23, 51), "Park" (id: 29) "cemeteries" (id: 18);
- "infrastructure level", e.g., proximity to the hospitals (id: 1), water network connection (ids: 15, 18, 23), canal and ditches (id: 15), "road density" or "parks area"(ids: 10, 18, 37, 50, 51);
- "housing type", e.g., connections between houses. Some authors also considered topographic data, like shade or altitude, which influence the *Aedes* presence;
- GIS Land cover data indicates the presence of water areas and wetland (id: 16), and cropland (id: 16, 29);
- "Human presence" is characterized by geocoded density (id: 7);

Data sources network considering survey questionnaires: In the context of this mapping review, "survey questionnaires" associated with census data constitute the largest data sources for landscape characterization associated with dengue cases (Figure 6), and inform at household-level according to:

- housing type, with distinction between apartment, house, empty house, poor-condition house, old flat, sheds, shanty, villa with or without garden (ids: 2, 8, 13, 30, 38, 44, 48, 65, 74, 77), the number of storeys (ids: 26, 35, 46, 75, 77), and the construction material used to build the house: wood, stone, concrete, brick-wood, bamboo, or mixed material (ids: 4, 35, 55, 70, 71, 72, 73, 77);
- housing characteristics, by observing the presence/absence of : screens on the windows (ids: 4, 13, 26, 30, 35, 43, 65, 70, 73), shade in the patio (id: 30) house windows (id: 35), bednets (id: 71) air conditioning system (id: 9, 43), gutter rain water (id: 27), the connection to the water network or the presence of water containers (id: 8, 30, 43), the connection to a sewage system (ids: 8, 18, 68) or the collection of garbage and waste (ids: 8, 27, 30).

At an aggregate-level, for example, neighborhood or small-administrative level, survey questionnaires provide information about:

- land use through the characterization of (i) the urban typology, e.g., slum-like areas (ids: 3, 28, 65, 73), distinction between commercial, residential, landmarks (ids: 17, 35, 65, 74), neighbor proximity (id: 26) (ii) the infrastructure level, often derived from "census data", e.g., street drainage (ids: 9, 21, 65), water network (ids: 17, 59, 62), garbage collection (ids: 17, 65), public services availability (ids: 21, 61, 62, 63), and access to paved road (id: 38);

- some scarce information about the land cover in the surroundings: (i) the presence and characteristics of the vegetation, e.g., distance to "vegetation", "tree height", or "forested areas" (ids: 26, 63, 71, 73, 75) (ii) the presence of "bare soil" or cropland (id: 4);
- the topography of the urban site with the observation of the shade (ids: 26, 73), or the orientation of the street relative to the prevailing wind (id: 27);
- human density (ids: 17, 44, 61, 62, 74, 77), in some cases associated to some socio-economic characteristics (id: 63), human mobility (ids: 11, 77), or commuting patterns (ids: 28, 74).

Entomological observations are divided between:

1. direct mosquito observation at the different stages, through classical entomological (Breteau/house/container) index or self-defined index such as "number of females *Aedes aegypti* per person" (ids: 1, 4, 5, 6, 12, 24, 26, 28, 33, 34, 58, 59, 60, 68, 73);
2. breeding and resting sites, e.g., discarded container, uncovered water container, standing water in various recipients (ids: 9, 20, 25, 30, 34), or premises index (id: 61).

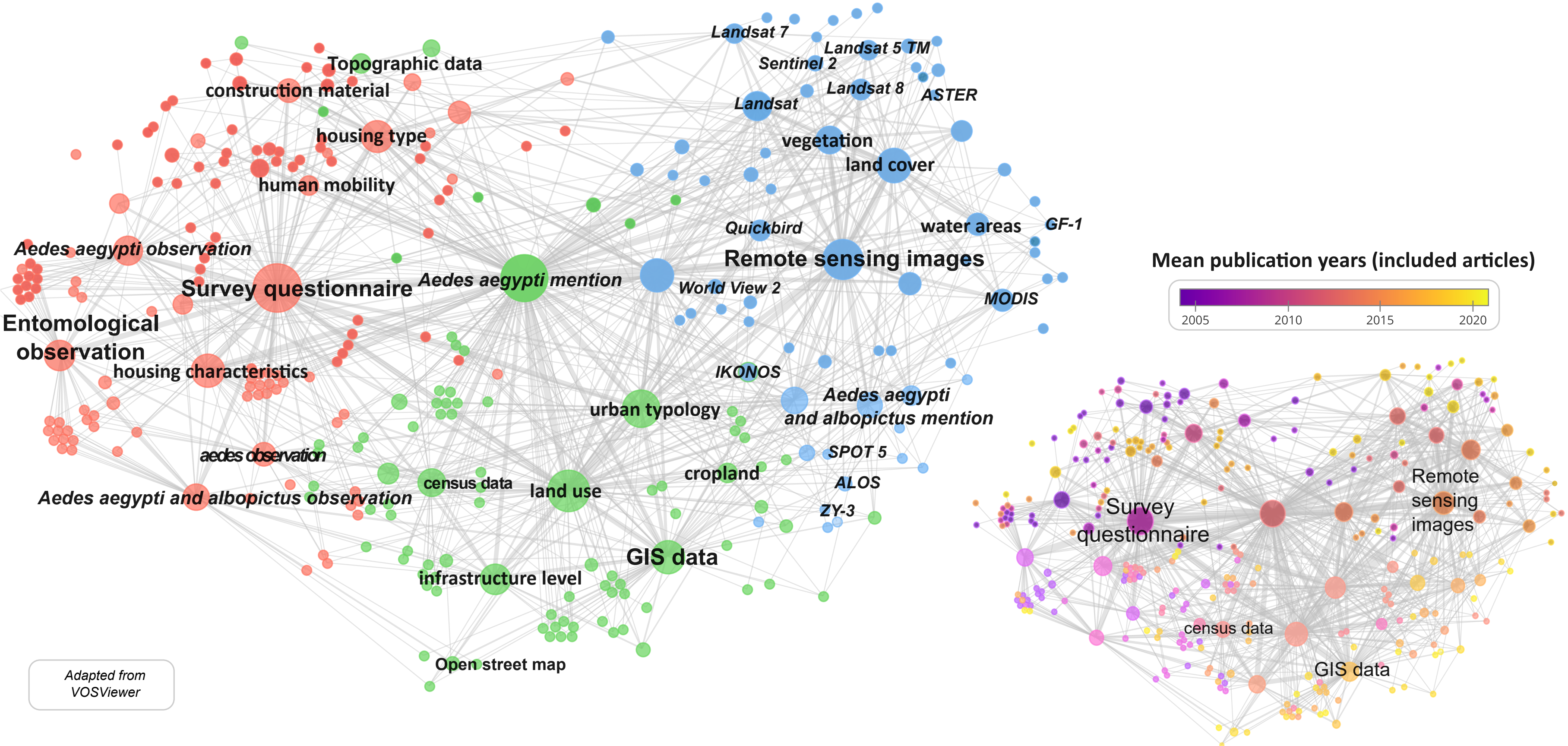

Figure 4. Keywords co-occurrences network associated to the 78 included articles, clustered by data sources (**left**), and year of publication (**right**). Nodes without labeling refer to landscape factors, which are detailed in the following network and sections. Nodes in italics refer to the type of the data acquisition sources

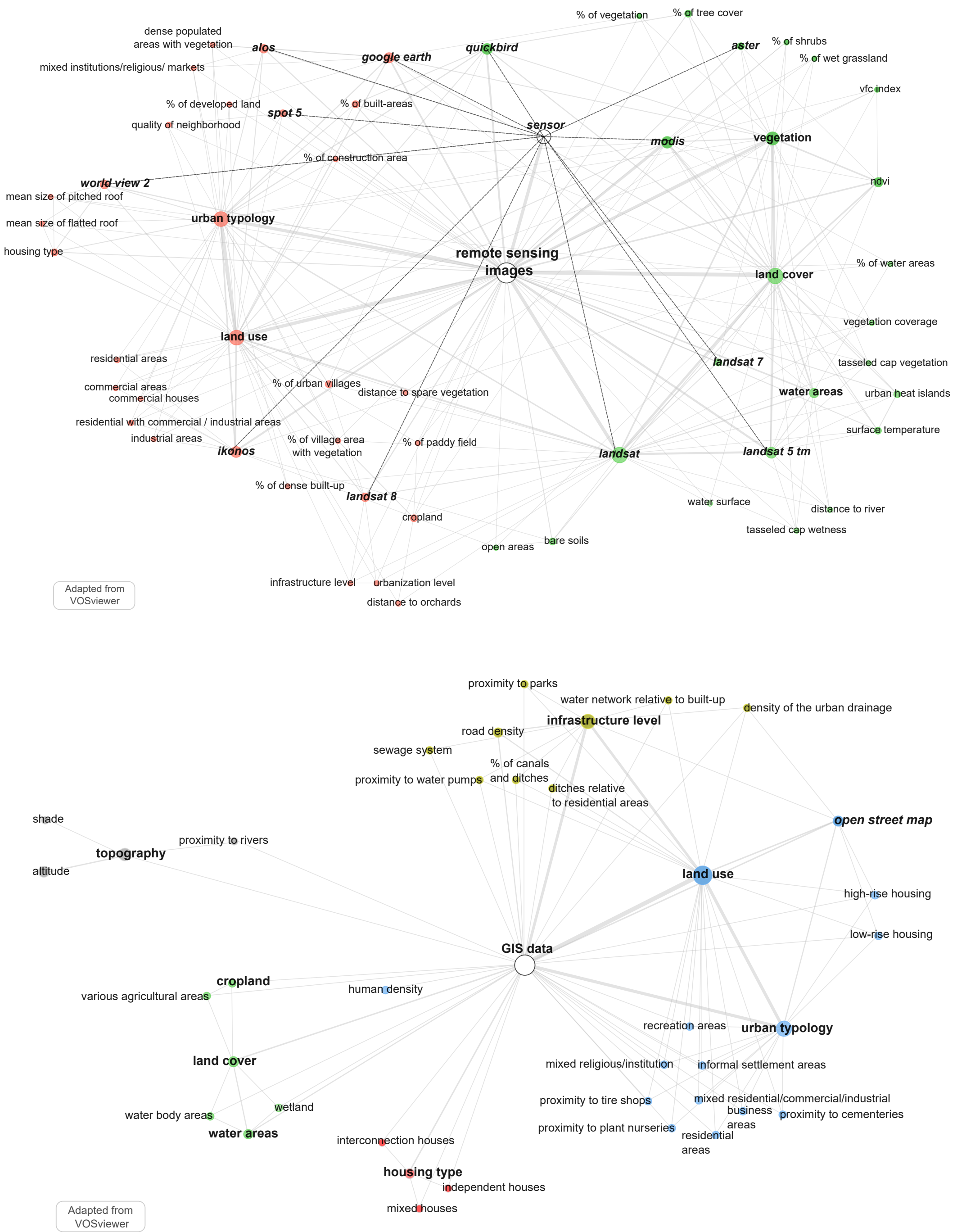

Figure 5. Co-occurrences network mapping of the self-defined keywords related to the articles using remote sensing images (**top**) and Geographic Information System (GIS) (**bottom**) to produce the landscape factors.

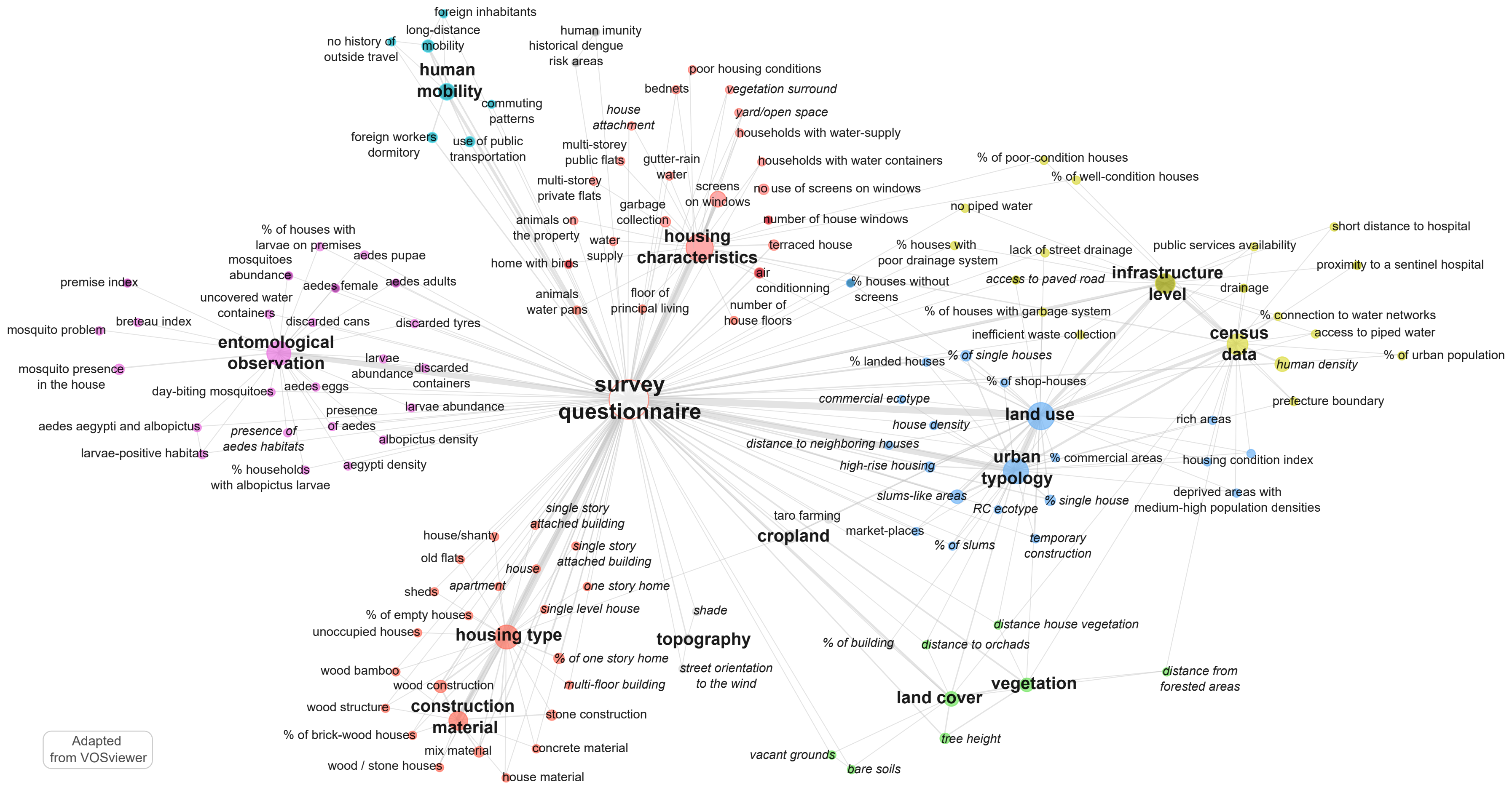

Figure 6. Co-occurrence network mapping of the self-defined keywords related to the article using survey questionnaires to produce the landscape factors. We indicate in orange those factors that could also be produced through remote sensing techniques.

4. Dengue–Landscape Relationship Modeling

4.1. Proxies According to the Geographical Units of Spatial Analysis

Of the articles in this review, all the relationships between dengue occurrence and landscape features were based on aggregated data at a given geographic level. Relationships were not identified for individual dengue cases, except in id 22 (human mobility patterns of recently DENV-infected subjects). Since we considered data from survey questionnaires, a large number of relationships were identified at fine scale household-level, where the authors mainly considered the influence of house type and characteristics in the dengue transmission process, and exposure to *Aedes* bites by including entomological observations (ids: 1, 4, 8, 12, 13, 20, 25, 26, 34, 35, 48, 52, 55, 60, 68, 75, 77). Urban administrative divisions were often considered because (i) they represented the legal unit of dengue cases reports (ii) other datasets, such as demographic or socio-economic data, were aggregated and available at the same levels. Generally, the authors considered the smallest local administrative level, but we noticed a large diversity in the 78 articles in the names of organizations and the denomination of national administrative units: "Districts" (ids: 3, 32, 33, 36, 65), "Li" (id: 15), "BSA" (id: 16), Locality (id: 19), "Barrangay" (id: 23), "Cantones" (id: 44), "Municipios" (id: 62), "Colonies" (id: 63), "Villages" (id: 74), "health sectors" (ids: 27, 69) and "national census tracts" (ids: 11, 17, 38, 46). Five authors proposed a study considering the whole city (ids: 21, 41, 50, 64, 66) or very populated areas (id: 60). Various authors aggregated the data at the neighborhood level, considering dengue diffusion at fine scale linked with *Aedes* flight, or human density and proximity to *Aedes* presence (ids: 5, 6, 7, 9, 14, 18, 24, 28, 49, 54, 56, 57, 58, 59, 61, 67, 70, 71, 73, 78). According to individual authors justifications, we interpreted the choice of a landscape factor, considered at a given geographical unit of analysis, by its link to one or several mechanisms involved in the dengue transmission process (Table 4):

1. ecological factors favorable to *Aedes* presence and development through direct entomological observations, or elements of the landscape favoring the presence of breeding-resting sites;
2. probabilities of human exposure to *Aedes* bites at household-level through small-scale proxies associated to the housing type or its characteristics;
3. probabilities of human-vector encounter considered at neighborhood, small and large administrative levels;
4. virus conservation and diffusion through human mobility.

Table 4. Landscape factors interpreted as proxies of different processes involved in dengue transmission according to the geographical level of data aggregation.

Landscape Factors	Proxies of	Geographic Level
Housing characteristics: Animal water pans, Households with water supply, regular water supply, water containers, sewage system, garbage collection **Entomological observation:** Larvae-positive habitats, Breeding, discarded , infested discarded plastic containers, Discarded tire casings, Infested discarded cans, uncovered water containers **Urban tyopology:** Slum-housing **Land cover and use:** tree height **Topography:** shade	*Aedes* breeding or resting site	Household level
Housing characteristics: Screens on windows, absence of air conditioning, Home with birds, house floors, Floor of principal living, Number of house windows, screens for house windows, yard/open space, shanty, Animals on the property, Living near open sewers, Bednets **Housing type:** Apartment, house, old flats, sheds, one storey homes **Entomological observation:** Presence of adult *Aedes albopictus* and *Ae. aegypti*, *Aedes aegypti* and *Ae. albopictus* population density, % of houses with larva on the premises, Number of female *Aedes aegypti* per person, Mosquito presence in the house , Breteau and house indexes **Construction material:** Wood, concrete, stone and concrete construction **Urban typology:** Temporary construction, % of village area with vegetation Distance of house to vegetation, to river, Distance to waterbodies, % of bare soil in 200 m-buffer zone **Land cover land use:** Distance house to vegetation, to river, Distance to waterbodies, % of bare soil in 200 m-buffer	Exposure to *Aedes* bite	
Human Long-distance mobility	Human-virus mobility	
Entomological observation: Larvae abundance, Breteau Index, Premise index, Mosquito abundance, *Aedes* Adults indicators **Housing type:** Mean size of pitched and flatted roof. **Urban typology:** Slum housing **Infrastructure level:** Density of the urban drainage network, Access to piped water **Land cover land use:** Taro farming, Tasseled cap vegetation, wetness, brightness, vegetation coverage	*Aedes* presence, breeding or resting site	Neighborhood level
Housing type: Multi-floor building, Single story attached and detached building **Construction material:** Brick-made, wood houses **Urban typology:** Dense populated areas surrounded by vegetation, Ratios on residential, industrial, commercial areas, slums-unplanned areas, Distances to neighboring houses % of developed land, distance to roads **Land cover land use:** Distance from forested areas, % of vegetation, % of water areas, % of bare soil in 200 m-buffer	Human-*Aedes* encounter	

Table 4. *Cont.*

Landscape Factors	Proxies of	Geographic Level
Infrastructure level: Short distance from hospital. Human household density, Commercial activity with human movements	Human-virus mobility	Neighborhood level
Housing characteristics: Gutter rain **Infrastructure level:** % of households with no piped water, without systematic or inefficient garbage collection **Topography:** Street orientation to the wind **Land cover:** NDVI, VFC, Water-body areas, Agriculture, Wetland, Urban heat islands, % of tree cover	*Aedes* presence, breeding or resting site	Small administrative level
Housing characteristics: Poor housing condition, houses without windows screens **Housing type:** Independent, mixed, unoccupied houses **Urban typology:** % of urban villages, of single and empty houses, of building, of slums. Ratios on residential, industrial, commercial areas, Informal, deprived or wealthy areas, house density, Markets place, Landmarks, Urbanisation level **Land cover:** Open areas, Vacant ground	Human-*Aedes* encounter	Small administrative level
Infrastructure level: Human density, Road density, Use of public transportation	Human-virus mobility	Small administrative level
Infrastructure level: Drainage **Land cover:** Urban heat islands, NDVI, % of shrubs, wet grassland, water area, paddy field	Human-*Aedes* encounter	Large administrative level
Urban typology: Quality of neighborhood, % of construction area **Infrastructure level:** Public services availability	*Aedes* presence, breeding or resting site	Large administrative level

4.2. Statistical Models

To quantify the relationships between urban landscape factors and dengue cases, the authors adopted methodologies based on statistical and spatial analysis fields, classically employed in spatial epidemiology or disease risks geography [38]. Correlation is commonly used to quantify the direction and strength of the relationship, through Pearson and Spearman (ranking) correlation coefficients (ids: 1, 24, 29, 31, 33, 42, 44, 53, 56, 60, 61, 62, 64, 65, 67, 69, 76). The odds ratio, which quantifies the strength of the association between two events is also often used (ids: 13, 20, 25, 26, 27, 34, 48, 68). Ecological regression analysis was used to estimate a relationship equation between "dengue cases" and one or more independent "landscape-based predictors" at a given area-level, underlying several assumptions on the data distribution and its associated errors, such as independence between observed cases. Assuming a Gaussian conditional distribution of the dependent variable in respect to the predictors, several studies considered simple, multiple, or generalized linear models (ids: 17, 45, 47, 62, 66). Based on a Bernoulli conditional distribution of the categorical outcome variable in respect to its predictors, most of the authors used logistic and multivariate logistic regression models to estimate the probabilities of a dengue infection (ids: 2, 9, 13, 18, 22, 26, 39, 41, 43, 49, 70, 71, 75, 77). To introduce non-linearity terms due to the spatial dependence of the predictors, some authors considered the generalized additive model (GAM) (ids: 6, 10, 28, 50, 51). To adapt the model to local contexts, some authors used the geographically weighted regression method (GWR), which takes non-stationary variables into consideration and models the local relationships between predictors and dengue cases (ids: 14, 17, 32, 53, 54). Two studies considered a generalized linear mixed model (GLMM, id: 8, 29), a model that, in addition to the fixed effect, includes a random effect for which the hypothesis of independence of observations is no longer assumed [36].

5. Qualitative Relationships between Landscape Factors and Dengue Cases

5.1. Mapping of Relationships at Household-Level

Except for the use of air conditioning, which could appear as a protective factor (ids: 52, 55), the housing characteristics considered in the included articles generally presented non–significant relationships with dengue cases (Figure 7): e.g., the number of windows in a house, the distinction between "public" or "private" multi-storey flats, floor of principal entry, the use of water containers, or the housing size. Screens on windows might appear to be a protective factor in some cases (ids: 26, 43, 55, 70, 73), but the association with dengue cases was also observed as statistically non–significant (ids: 4, 13, 20, 30, 65), and positively associated (id: 35), which might reveals the high density of *Aedes* or vector-borne disease in the area. No clear relationship was generally associated with construction materials: e.g., wood can appear as non–significant (ids: 26, 55), positively (ids: 70, 73) or negatively (id: 71) associated to dengue cases according to the study. Concrete, stone, or brick do not appear to be protective factors (ids: 55, 65, 70, 71, 78). Entomological observations are generally positively associated with the presence of dengue: direct *Aedes* observations of adults, *pupae*, *larvae*, or infested and discarded containers (id: 1, 25, 34, 60). *Aedes aegypti* is much more cited than *Ae. albopictus* in the included articles. In the domestic environment of a house, the presence of shaded and vegetated areas, and the lack of street drainage appear as exposure factors (ids: 26, 30).

5.2. Mapping of Relationships at Neighborhood Level

At the neighborhood level, it is possible to define an urban typology associated with an area, by considering the housing type and the building functions (Figure 8). This led the authors to propose various urban ecotypes, and to consider the residential, commercial, or social function of a construction, after taking into consideration transportation or ecological aspects like density of roads or vegetation. Despite the difficulty in comparing authors' self-definitions, the mix of residential and highly frequented areas, associated with multi-scale human mobility (e.g., road network density, ids: 14, 37), with vegetation in the surrounding areas generally show the strongest associations to dengue occurrences (ids: 10, 14, 19, 28, 35, 37, 51, 57). Considered separately as individual proxies, urban functions are generally not significant (ids: 18, 35). Slum–like or informal settlement areas may be positively associated with the presence of dengue (ids: 14, 28, 51, 53, 73), but not systematically (ids: 3, 49). Well structured urban areas, defined by a "quality index", may have protective effects (id: 32). The height of buildings could have an influence: low-rise buildings may be more exposed than high-rise buildings (ids: 49, 58). Few articles considered human density directly as a proxy at neighborhood level, and it appears non significant or positively related to dengue cases (ids: 7, 26, 35). Entomological observations are fewer than at household-level, and may show significant (e.g., with *Aedes* house index) or non–significant relationships (e.g., with *Aedes* eggs, larvae, and pupae abundance, or Breteau index, defined as the number of positive containers per 100 houses inspected).

5.3. Relationships at Administrative Units

The authors considered a small administrative level to integrate data from institutional sources at fine scale (Figures 9 and 10). A co-occurrence network shows some similarities with the neighborhood level, highlighting the role of human density through residential area mapping (ids: 16, 19), and the importance of mixed areas, characterized by coming and going of people with some hot spots or a context favorable to the persistence of *Aedes*: urban villages (id: 10), deprived areas with medium-high density (id: 38, 44, 63), residential areas with commercial and industrial areas (id: 23), or informal settlement areas (id: 23). With regard to infrastructure level, it is useful to consider waste management and the state of the sewage networks (ids: 15, 27, 65), as well as road structure and density (ids: 10). The orientation of a street, the presence of empty houses, or the use of gutter rain are urban characteristics that could play a role in maintaining *Aedes* (id: 27, 74). Building height is also a variable of interest (id: 46). Some authors have information on human mobility, generally significantly associated with dengue cases, which highlights the usefulness of estimating human fluxes (ids: 11, 22, 77). Historical epidemiological data are scarce, but allow for the study of dengue urban patterns over time, and are especially significant when associated to DEN serotypes (id: 35). Entomological observations are not aggregated or available at the level of administrative units. The presence and density of the *Aedes* mosquitoes are addressed through prior knowledge on vector bio-ecology and remotely-sensed environmental data: (i) the classical index NDVI is used as a proxy of the vegetation, and is positively associated to dengue cases in two of the three studies (ids: 10, 42, 50), (ii) urban surface temperature was not significant (id: 42). At larger administrative levels, authors considered the influence of altitude, which is negatively correlated to dengue occurrences (ids: 21, 34, 44, 64). This result illustrates the influence of the temperature gradient on *Aedes* ecology. Human mobility is also correlated with dengue cases (id: 20, 22). Vegetation also seems positively associated with dengue occurrence (id: 36), although NDVI is associated with a negative relationship to dengue in two cases (id: 3, 45), which could be due to a decrease in residential surfaces in respect to vegetation surfaces.

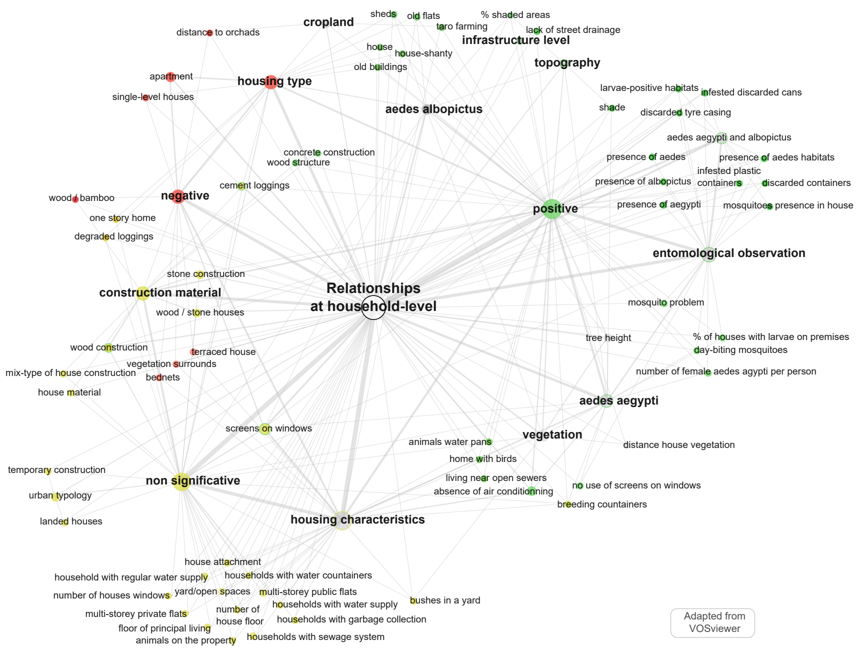

Figure 7. Co-occurrences network mapping of the self-defined keywords related to the landscape factors considered at household-level.

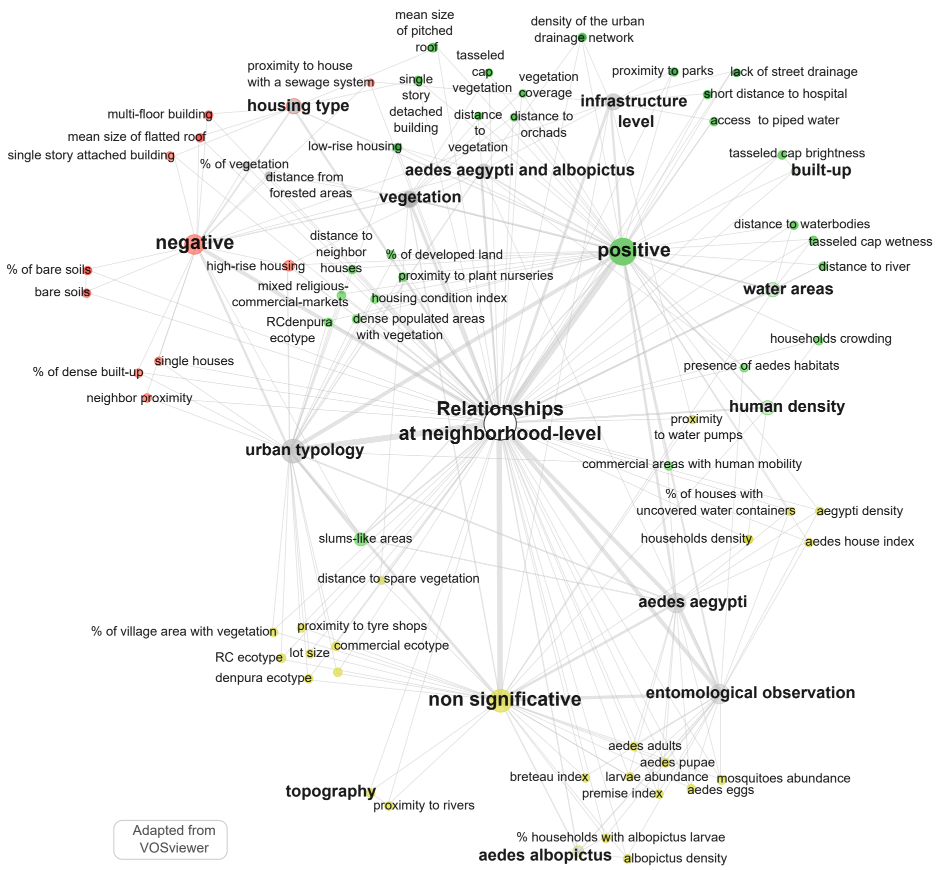

Figure 8. Co-occurrences network mapping of the self-defined keywords related to the landscape factors considered at neighborhood-level.

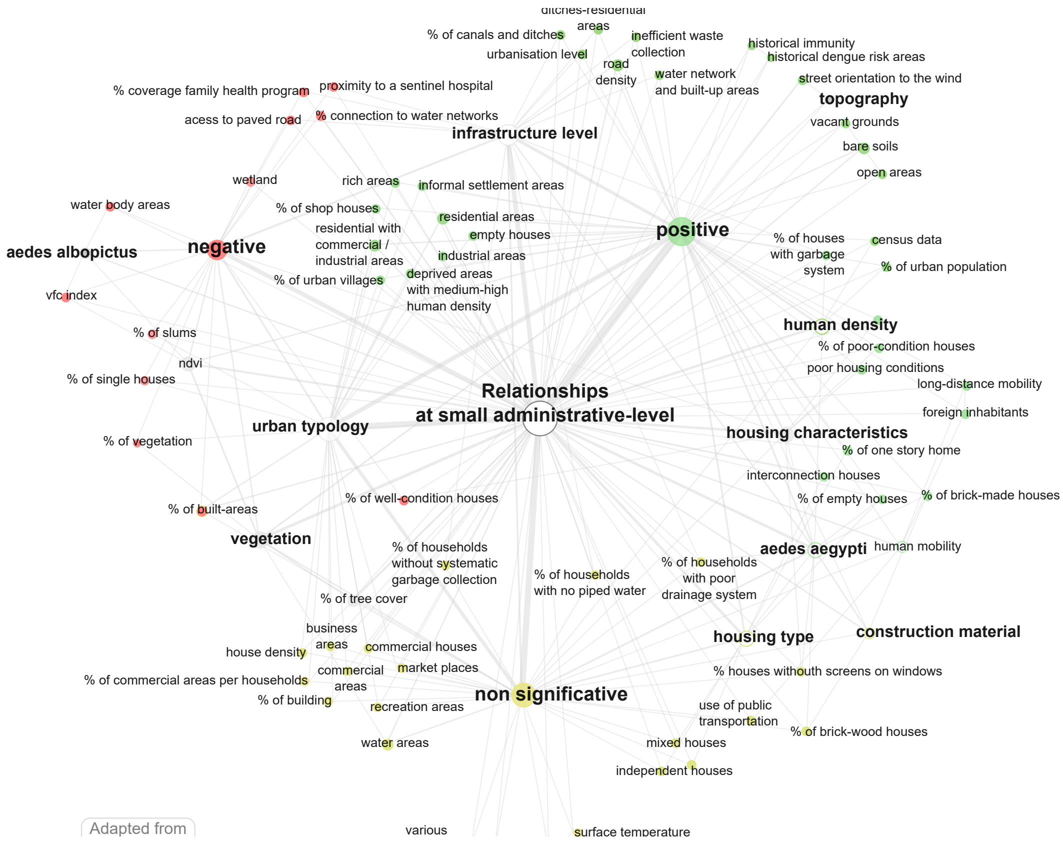

Figure 9. Co-occurrences network mapping of the self-defined keywords related to the landscape factors considered at small administrative-level.

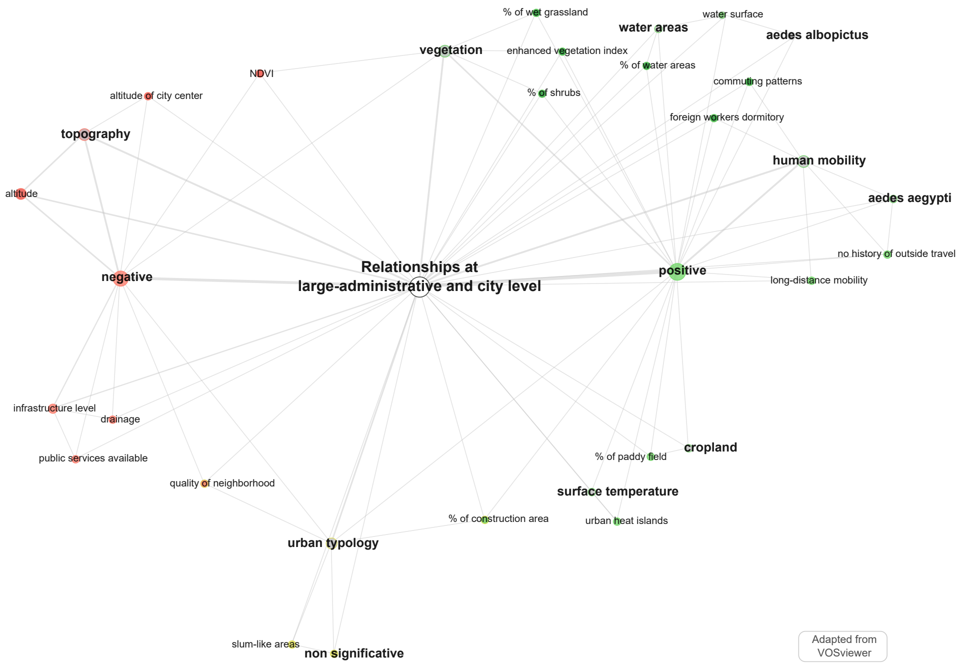

Figure 10. Co-occurrences network mapping of the self-defined keywords related to the landscape factors considered at large-administrative and city-level.

6. Discussion

6.1. Methodological Considerations

The expansion of evidence-based practice across scientific disciplines has led to an increasing variety of review types. We chose a mapping review, which enables the contextualization of in-depth systematic literature reviews within broader literature and identification of gaps in the evidence base [40]. The network, based on calculating the barycenter of the structured textual information, is aimed at proposing a coherent synthesis in a graphical way. The forms of the network graph are however quite dependent on the way information is sorted, structured and grouped. Our work is limited to a broad descriptive and qualitative level, and thus may oversimplify the considerable variations (heterogeneity) between studies and their findings [40]. Mapping reviews do not usually include a quality assessment process to preselect the articles, which could limit considerably the quality of the information and analyses produced. To provide an assessment of the risk of bias, we proposed here a simple checklist on key features based of metadata completeness, and an overall appraisal of the level of contributive information respect to the topic "dengue–relationship characterization" (Supplementary Materials). In addition, we did not include conference papers, which could contain some relevant information at the front-line of the research. We focused on urban areas, but rural areas could contribute at least as much to the dissemination of dengue fever as cities [56]. In a context of significant increase of dengue publications over time [57], our study highlights that specific research on spatial epidemiology, like dengue landscape factors, is not at the front line compared to virology, biochemistry or molecular biology research areas. Surprisingly, we did not find any articles which follow our inclusion criteria related to other *Aedes*-borne diseases, like Zika and Chikungunya when we swap dengue to one of them. These can be relativized by the recent character of the massive outbreaks associated to the Zika flavivirus [58,59]. We found only one study concerning Africa, which might be due to (i) many other competing public health problems (e.g., malaria or Ebola) and limited resources [60], which cause a lack of diagnostic testing and systematic surveillance [61] and (ii) a less suitable environment for dengue [62], with potential differences in terms of vector efficiency and viral infectivity between Africa and other dengue-endemic regions [63]. However, depending on location, rapidly increasing urbanisation, and/or higher temperatures and increased rainfall could increase dengue incidence in the following decades [62,63]. In general, only one article mentioned a given landscape factor, which prevented us from performing a more in depth meta-analysis, and limited us to the present qualitative analysis.

6.2. Potential limitations in Dengue-Landscape Studies

6.2.1. Limitations Associated with Epidemiological and Entomological Data

Through this review, we noted that passive notification cases, reported by official health systems, and dengue serostatus surveys, performed by research teams, can show two different realities of dengue occurrences, relativizing in this way the comparison between the factors proposed in the types of studies. Passive case notification datasets present strong identified biases due to (i) the absence of asymptomatic cases (ii) the absence of symptomatic cases when patients do not consult because of, particularly, the distance to health centers, or their cultural habits, and (iii) misdiagnose based on insufficient medical evidence. On the other hand, intra-urban dengue seroprevalence surveys are based on a sampling strategy where assumptions and representativeness may be inaccurate, and could limit interpretation: lack of demonstrable spatial variation between self-defined areas (id: 8), complexity to define an appropriate urban ecosystem (id: 35), relative influence of contextual indicators versus individuals (id: 48), and limitation to school children population (ids: 49, 67). Unknown socio-demographic drivers, the retrospective nature of questionnaires, and associated recall bias are other issues that should be mentioned (id: 49).

Four distinct serotypes of DENV have been identified, and infection from one serotype confers protective immunity against that serotype but not against other serotypes [64]. Acquired immunity may therefore introduce a bias in any dengue pattern study. From that perspective, historical studies of dengue epidemics can provide valuable information. However, such data are scarce, and few studies have performed both IgM and IgG analysis in the correct time window. Early tests (up to day 7) using Reverse Transcription Polymerase Chain Reaction (RT–PCR) should be preferred because their specificity is much higher than serology, but only one study has performed a Plaque Reduction and Neutral Test (PRNT) to distinguish between dengue serotypes (id: 36). In one study, two time–periods have been considered to distinguish potential infections by DENV-1 and DENV-2 (id: 16).

Underreporting in dengue surveillance systems has been identified in various studies [65–67] demonstrate, through a systematic review, that a large proportion of the data from any affected population has not been captured through passive routine reporting—misdiagnosis or subclinical cases, non-users of health services, users of private versus traditional sectors, or certain age groups. In high endemic settings, however, if the dengue cases are geographically representative and laboratory confirmed, dengue data may be representative, to some extent, and possibly corrected by calculating an expansion factor. Improvements in dengue reporting could come from improvement in indicators/alert signals, laboratory support, motivation strategies, shifts in dengue serotypes or genotype surveillance, and data forms/entry/electronic-based reporting [66].

Dengue cases were rarely associated with entomological data, probably due to the difficulty in obtaining these data in a cost-effective way. Except for household-level studies, mosquitoes were generally considered from prior knowledge, and not from *in situ* observations. *Aedes* were sometimes considered as composed of a unique species, without differentiating *albopictus* from *aegypti* despite their different ecological behaviours. This point could however be relativized because of the remarkable ecological plasticity of both species, especially to urban settings [10,11].

6.2.2. The Difficulty in Defining a Geographical Unit of Spatial Analysis

The first requirement in performing a relationship between dengue cases and environmental determinants is the geolocation of the cases. Most of the selected studies do not go into detail on that point, except when an automated procedure has been implemented (id: 42). Generally, a hypothesis is made after dengue cases have been located at a patient's home address as the transmission may have occurred at home or in the vicinity of the household. *Aedes aegypti* and *Ae. albopictus* are day time biting mosquitoes, which implies to consider human commuting pattern. Such hypothesis might be strengthened when considering an age stratification, as the mobility of elderly persons or young children mobility can be limited for example (ids: 17, 70). If the dengue cases are located within a given area, the probability of the transmission may increase up to a threshold distance, but it might become more difficult to identify the correct environmental determinants associated with the transmission. These proximity-hypotheses are consistent with local, density dependent transmission as key sources of viral diversity, and with home location being the focal point of transmission [68]. Using geolocated genotype and serotype data, Salje et al. [68] showed that in Bangkok (Thailand), dengue cases came from the same transmission chain for (i) 60% of cases living in less that 200 meters apart, and (ii) 3% of cases separated by 1 to 5 kilometers. At distances closer to 200 meters from a case, the authors estimated the effective number of chains of transmission to be 1.7, and that this number rises by a factor of 7 for each 10-fold increase. As in the large majority of ecological-related issues ([69], Modifable Area Unit Problem), the choice of an appropriate spatial unit to associate a relationship between dengue cases and their risk factors has a strong influence on effective analysis. We identified various type of infra-urban areas of spatial analysis in the 78 included articles (e.g., buffers around the infected households, census tracts, health regions, small and large administrative areas), which varied according to authors' choices, data sources and availability. Dengue cases and landscape factors are often aggregated to an administrative level or census tracts to perform comparisons with socio-economic or demographic datasets. When considering an administrative area, there is a risk of disruption with dengue transmission mechanisms as it does not represent a spatial homogeneous area for vector ecology or the human exposures to *Aedes* bites. According to the specific objectives and time period of the study, the use of an administrative unit as an analysis area could be justified [70], but the inevitable simplification that occurs when attempting to model real-world phenomena should be considered and systematically discussed, independent of the type of spatial units or chosen methods [38].

6.3. Highlights and Perspectives to Improve the Frame of Urban Dengue-Landscape Relationships Studies

Our purpose was originally to identify studies based on remote sensing techniques to produce landscape factors, so we opened our search to all kinds of information sources, including survey questionnaire and GIS data. Such strategy is guided by the consideration of a holistic conceptual risk and vulnerability framework [71], to allow for the identification of new factors that would be potentially achievable by using remote sensing techniques. The main purpose was to identify what makes a given landscape "pathogenic" or not, in respect to dengue transmission [72]. We privileged a "Built City" approach, i.e. a city as a physical entity, [44], to avoid direct socio-economic considerations in landscape factors. Discursive links between dengue and poverty may have contributed to an inappropriate transfer of globally dominant dengue control strategies to non-poor local environment [73]. From this perspective, the quantification of human exposure to *Aedes* bites through salivary antibody-based biomarkers may be a promising method for estimating the influence of the bio-physical environment on human–*Aedes* contact [74]. Only two articles used landscape metrics to explore the impact of more in-depth ecological characteristics of an urban landscape on dengue transmission (ids: 57, 69). Landscape metrics have been separately applied to malaria transmission for assessing the influence of landscape factors relative to exposure risk [75,76]. The representativeness of sampling strategies during intra-urban dengue seroprevalence surveys may be improved by the use of GIS and remote sensing techniques ([77], e.g., urban environmental clustering and *Aedes* density); ([78], e.g., Urban typology) and help to objectify the choice of geographical units ([70], e.g., criteria of intra-unit homogeneity, areal and population size, compactness); ([71,79], e.g., Concept of integrated geons). Public health services could also benefit from original visualization techniques to map metrics or indexes related to dengue vectors or occurrences ([80], e.g., Ring mapping).

Id 22 highlighted the importance of human movement, and time spent in places at various scale in human exposition and DENV spreading. Id 37 showed that high-density road network is an important factor to the direction and scale of dengue epidemic, and that the dengue cases were mainly concentrated in the vicinity of narrow roads. Id 63 insisted on the "forest fire" signature of DENV epidemiology in the context of Dehli (India), while id 61 refers to a "silent epidemic in a complex urban area" in the context of Salvador (Brazil), where "high rates of transmission were observed in all studied areas, from the highest to the lowest socio-economic status." Many authors referred to the necessity of an improvement in the individual geolocalisation capacity to estimate human mobility patterns, since an "importation of infected individuals into a frequented area could lead to a local foci of infection included with a low *Aedes* density". Id 12 considered that "dengue transmission occurs, not at a fixed entomologic figure/quantity but rather at a variable level based on numerous factors including seroprevalence, mosquito density and climate." Entomological indices may be good proxy of DENV occurrences at household-level (ids: 4, 34, 68, 75), but seem less significant when aggregated at coarser resolutions (ids: 6, 26, 28, 59), or when considering only larvae (id: 5). Some important data relative to vector borne diseases are exclusively accessible by field survey, e.g., type of material construction or screens on windows, but their knowledge do not seem so critical in the case of *Aedes* borne disease (ids: 4, 13, 70, 73). Many survey questionnaires based studies confirmed the large inadequacy of remote sensing techniques to properly identify potential dengue risk factors in link with *Aedes* habitats, characterized by a fine or micro-scale level: empty houses, sewage system, garbage system, street drainage, water pumps, water containers, open sewers, tyres, water puddle, ditches, cans (ids: 8, 9, 17, 18, 33, 65, 68, 74). However, remote sensing techniques should be now in capacity to provide more than land cover information, and could help to systematically inform on land use and urban typology, without the need of a questionnaire, as (i) proxies of human presence and activity, or as (ii) macro-scale hotspot proxies of *Aedes* habitats e.g., cemeteries (id: 17), construction site (id: 36), vegetation height (ids: 26, 73), shade (ids: 26, 73), or roof shape (id: 54). Based on sound statistical machine learning, such complex urban typology could be labeled from space at neighborhood or small administrative level: informal settlement areas (ids: 23, 28, 49), urban villages (52), quality of neighborhood index (ids: 32, 52), or multiple association of urban functions (ids: 18, 19, 23, 35, 57), especially if completed by building height (ids: 58, 46, 75). Such improvement could help to explicit the multiscale geographical framework where DENV transmission occurs as a result of a multifactorial process. At the same time, remote sensing products could help to guide the questionnaire during the field survey, while GIS provide the framework to combine all spatialized information and performs geo-analysis (id: 10). Although remotely sensed radiometric measures like NDVI or LST could provide conflicting conclusions (ids: 3, 10, 42, 44, 50, 69), their use in a sound methodological framework could be of some interest, especially when available at higher resolutions. Digital archiving in GIS context of geocoded and confirmed dengue cases should help to easily inform on historical dengue risks areas (id: 35). Such digital layers could provide an interesting proxy of dengue transmission patterns when DENV-serotype is known.

As was apparent during this review, we were not able to identify a set of land cover and land use classes unequivocally related to dengue risk factors. This is consistent with the fact that reliable predictors for dengue have not yet been established in the literature [36], and the *Aedes* presence and density are not sufficient to determine dengue epidemics [13], which justifies the scope of this review, centering on dengue cases. DENV transmission is complex, and the relationship between vector density and risk is not static nor adequately characterized through periodic entomological surveillance [81]. However, even if *Aedes* indicators serve as surrogates of true exposure [81], vector control will remain the primary prevention strategy in most dengue endemic settings [1], including when an effective dengue virus (DENV) vaccine would become commercially available [18]. To better target surveillance programs, effective control of *Aedes* could benefit from available evidence-based guidance by considering an Integrated *Aedes* Management framework ([82,83], IAM).

Some specific factors are unachievable using remote sensing techniques due to their limited spatial dimension and should continue to be acquired by field and entomological surveys, e.g., decimetric spatial resolution for breeding sites or for gutter rain, or because they are hidden from the sensor perspective. However, building detection remains a central task as it allows human presence and density to be identified, and is constrained geographically to the urban area. Building environment, e.g., vegetation or water areas, is also of interest since it could influence *Aedes* ecology or human activities. Building function, e.g., residential or commercial, can give important information about human activities and human presence related to time. Road and transport networks may also constraint *Aedes* and DEN virus diffusion, and can be related to patterns of human commuting. Land use data related to human movement and places visit frequency should help in reducing the difficulty of acquiring detailed knowledge about “the non-random nature of encounters” [8]. In this way, urban mapping, particularly by including land use, could provide the geographical context in which, with adequate parameters that compensate for missing information, dengue-related processes could be modelled ([36], Review on modeling tools for dengue risk mapping; [84–86], Getis-Ord Gi in GIS context; [87–89], Spatial Mechanistic Modeling of *Aedes* Mosquito Vectors; [90], Spatial agent-based simulation model of the dengue vector *Aedes*; [91], Environmental hazard index mapping methodology of *Aedes* aegypti; [92], Modeling Dengue vector population using remotely sensed data and machine learning; [93], Comparison of stochastic and deterministic frameworks in dengue modelling).

To improve surveillance and monitor of dengue occurrences and *Aedes* mosquitoes, intercomparison model projects could help to identify the most general and efficient models considering various geographical contexts and data set: ([94], e.g., Airborne spread of foot-and-mouth disease – Model intercomparison; https://www.theia-land.fr/en/anisette-tracking-mosquitoes-that-carry-disease/, e.g., Inter-Site Analysis: Evaluation of Remote Sensing as a predictive tool for the surveillance and control of diseases caused by mosquito, and future impacts of climate and/or land use changes may also be considered; [95], e.g., Malaria and climate; [17,23,96], e.g., Urbanization). Review of literature are also needed to update the ever-increasing output of scientific publications, and lead to new synthetic insights ([97]; [10], e.g., Determinants of Aedes Mosquito Habitat for Risk Mapping, [98], e.g., New frontiers for environmental epidemiology in a changing world, [99], e.g., Current challenges for dengue; [100], e.g., Mosquito-Borne Diseases: Advances in Modelling Climate-Change Impacts; [101], e.g., A 10 years view of scientific literature on *Aedes aegypti*; [102], e.g., Satellite Earth Observation Data in Epidemiological Modeling).

The potential of satellite images and remote sensing techniques should continue to be explored. As mentioned in this review, the images used often corresponded to old missions or end-of-life satellite sensors, and methodologies should consider more state-of-the-art-approaches:

- the native pixel resolutions were often aggregated at a coarser resolution during the mapping production (Figure 11). Recent satellite missions should bring greater possibilities to fit spatial resolution and temporal windows over urban areas, for example the Copernicus Sentinel program ([103], Monitoring Urban Areas with Sentinel-2A Data), or on demand very high-resolution sensors ([104], Pléiades satellite potential for urban tree mapping);
- image processing was previously limited to spectral indices (NDVI, VFC), or some supervised pixel-based classifications mostly based on the maximum likelihood algorithm (ids: 57, 69, 70, 71). Only one study considered object-based classification for building extraction purposes (id: 77). Such approaches could benefit from methodological advances, especially from the urban mapping community—([105], Comparison of Deep Neural Networks, Ensemble Classifiers, and Support Vector Machine Algorithms) ([106], "Compared with the traditional rule-based and ML [Machine Learning] methods, the DL [Deep learning]-based classification method has significant advantages in terms of classification accuracy, especially in complex urban areas") ([47], Google Earth Engine Platform), ([107], VHR and landscape-structure heterogeneity), ([108], Urban change detection), ([109], Street-level imageries) ([110], VHR images and slums detection);
- two studies have exploited the thermal sensors from Landsat-TM and MODIS instruments, and used them to retrieve land surface temperature (LST) parameters (ids: 3, 19). This is particularly useful to detect urban heat islands that could indicate improved conditions for *Aedes* viability and dengue virus replication, due to the potentially amplified higher temperatures (typically greater than 30° C), and resulting in a reduction of the extrinsic incubation period from 12–14 days to 7 days ([111], id: 3). New thermal sensors with higher spatial resolution may promote consideration of thermal sensors, such as the CNES-TRISHNA mission [112,113], even if methodological issues remain: that is, hotspot effects, separation of temperature and emissivity parameter.
- dengue is often spread in tropical or subtropical regions, where the presence of clouds and cloud shadows result in missing data in optical images. Synthetic aperture radar SAR images could penetrate such barriers and might be combined with optical sensors for overcoming this issue. Such an approach to optical and SAR fusion has been applied in the studies of malaria [114,115];
- very high resolution imagery may be more suitable for extracting the direct dengue-related landscape factors, such as (i) the type of vegetation near human settlements [104,116] (ii) the footprint of built-up areas [46,117], and (iii) land use types, such as slum areas [118,119];
- from high-resolution built-up area detection, population growth estimation due to urbanization could be assessed, improving the estimation of census and incidence rates [120,121]. In this regard, only one article proposed a proxy for a spatially-corrected population density by digitizing and excluding inhabited areas (id: 24). To improve the population density assessment, cities should be considered in their verticality and volume, through the use of a digital height model, potentially generated from unmanned or satellite remote sensing stereo imagery [122–124];

- although we did not consider meteorological factors here, surface air temperature or soil moisture, traditionally measured by *in situ* weather stations, could be derived from satellite passive microwave radiometry [102,125].

The temporal dimension remains largely absent in the spatio-temporal relationship studies of this review. Populations commute, as well as mosquitoes. If a decrease in mean distance between dengue cases may generally correlates with activity, and could lead up to an outbreak, a decrease in temporal distance between dengue cases may increase geographic spread of the disease [126]. Landscape changes associated with human mobility, like transportation infrastructure changes, may create favorable conditions for the establishment of dengue virus [127]. However, relationship investigations are usually done under a stationary analysis scheme, and the mapping of dengue patterns often ignore "temporal kinetics" (id: 32). A complementary approach to this static view should be to consider human mobility in relation to *Aedes*-bites exposure, and not only to mosquito dispersal associated with its flight, as this former could affect significantly the spread of infection [128]. Adams and Kapan [129] enhanced the fact that hubs and reservoirs of dengue infection can be places people visit frequently but briefly. Authors from id 74 found that most of the space-time distances of non-commuting dengue cases clustered within 100 m and one week, whereas commuting cases clustered within 2 to 4 km and one to five weeks. Human commuting patterns may be estimated through the use of GPS data-logger (id: 22) [130] or regularly logged cellphone tracking data [131], which could be in the next decade generalized in the so-called Smart City model ([132] Real Time Health Monitoring, [133] Smart Health care Internet of Things and *Aedes* monitoring, [134] Geospatial artificial intelligence).

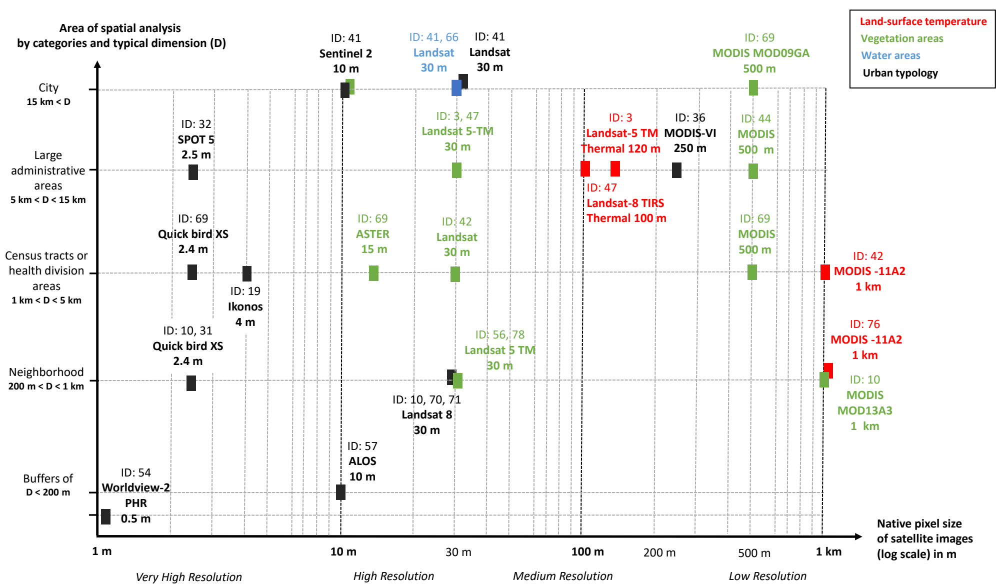

Figure 11. Comparison between pixel size (x axis, in log scale) and typical dimension of geographical area used to perform relationships with dengue cases (Y axis, in qualitative dimension).

7. Conclusions

We propose here a mapping review which focuses on the landscape factors potentially related to urban dengue transmission. By analysing the 78 included articles that satisfied these criteria, we found that the landscape mapping linked to human dengue infection was mainly guided by (i) vector ecology-based considerations through vegetation and water surface mapping and (ii) human presence and activities deducted from the settlement typology.

We extracted each of the specific landscape features that have been assessed in the context of DENV transmission. We proposed a systematic three-valued interpretation of the relationships performed between each landscape factors and dengue occurrences, and provided a representation in a graphical way according to the considered spatial scale of the studies. Even if some characteristics appear essential, as human density and movement pattern, or the presence of a minimum vegetation in the surrounding, considering only one landscape factor at a time should be avoided, as we highlighted the complexity of the "pathogenic landscape" associated to dengue transmission. In a broad and simplified approach, relevant landscape is characterized by a mix of residential and highly frequented areas, associated to multi-scale human mobility, with an entomological thresholds that can be low. From a remote sensing perspective, there is a need to identify land uses more than solely land covers to characterize more complex urban environment: informal settlement, building typology, transportation network, and consider the vertical dimension of the city. Up to now, these kinds of information have been more often retrieved from costly and time-consuming survey questionnaires than from automatic remotely-sensed approaches. To provide a realistic geographical context in dengue modelling and to take into account the complexity and the multi-factorial nature of DENV transmission in tropical environments, remote sensing approaches need to be promoted through the use of recent HR and VHR sensors such as, Copernicus (Sentinel) or Orfeo (Pleiades) programs, a combination of optical, including stereo, and RADAR approaches, and state-of-the-art image processing algorithms, including deep learning techniques when possible. A strengthening of relations between environmental epidemiology and urban mapping communities should help to standardize the mapping of the urban typology of interest, and therefore enable better assessment of the influence on dengue transmission.

As integrated approach combining remote sensing, GIS, and field survey preferable when possible, since health data and entomological observation availability and quality would probably remain the main limiting factors if landscape and urban typology mapping, including human movement pattern, continue to improve. Due to the silent characteristics of DENV presence within the city, dengue control still requires above all an active search and an early detection of new cases, including serotype detection, associated to an entomological control at fine scale involving both citizen and health agencies.

Supplementary Materials: The following are available online at http://www.mdpi.com/2072-4292/12/6/932/s1.

Author Contributions: Conceptualization: R.M., Z.L., N.D., H.G.; Methodology, formal analysis, software use: R.M.; Writing—review and editing: R.M., Z.L., T.C., E.R., N.D., M.M., L.X., J.G., P.H., A.T., L.D., J.-F.F., J.J.C., B.D., V.H.; Supervision and funding acquisition: N.D., Z.L. and P.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Project No.: 41801336). This research was also partially supported by a denotion from Delos Living LLC to Tsinghua University, and by the APUREZA project (CNES-TOSCA 2016–2018 call).

Acknowledgments: The authors would like to thank the members of the work-groups from the Environment, Societies and Health Risks inter-disciplinary (ESoR, http://www.espace-dev.fr/index.php?option=com_content&view=article&id=37&Itemid=193), and from the *ANalyse Inter-Site* CNES-TOSCA project (ANISETTE, https://anisette.cirad.fr/), particularly Eric Daudé and Renaud Misslin, for the constructive discussions that considerably enriched the paper. We also thank the administrative and technical supports.

Conflicts of Interest: The authors declare no conflict of interest. The founders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A. Raw Descriptive Tables of the 58 Included Articles

Appendix A.1. Identification and Localization Table of the 58 Included Articles

Table A1. Extraction of the publication meta-data (first author, date of publication, title, name of the journal), and description of the geographical contexts (country, city, geographical unit) of the 78 included studies.

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	Date	Title	Journal	Country	City	Geographic Units of Spatial Analysis
1 [135]	Ali	2003	Use of a geographic information system for definin	The American journal of tropical medicine and hygiene	Bangladesh	Dhaka	**8820 Households (within 90 wards)**
2 [136]	Al-Raddadi	2019	Seroprevalence of dengue fever and the associated	Acta Tropica	Saudi Arabia	4 cities:Makkah, Al Madinah, Jeddah, and Jizan	**6397 Households**
3 [137]	Araujo	2015	Sao Paulo urban heat islands have a higher incidence of dengue than other urban areas	The Brazilian Journal of Infectious Diseases	Brazil	Sao Paulo	**Districts**
4 [138]	Ashford	2003	Outbreak of dengue fever in Palau, western pacific: risk factors for infection	The American Journal of Tropical Medicine and Hygiene	Palau	5 hamlets of Palau	**(270) Households**
						Koror and five hamlets of Palau	**(189 of 865) Households**
5 [139]	Barbosa	2010	Spatial Distribution of the Risk of Dengue and the Entomological Indicators in Sumaré, State of Sao Paulo, Brazil	Revista da Sociedade Brasileira de Medicina Tropical	Brazil	Tupa	**Neighborhoods**
6 [140]	Barbosa	2014	Spatial Distribution of the Risk of Dengue and the Entomological Indicators in Sumaré, State of São Paulo, Brazil	PLOS Neglected Tropical Diseases	Brazil	Sumare Sao Paulo state	**Neighborhoods**
7 [141]	Barrera	2000	Estratificación de una ciudad hiperendémica en dengue hemorrágico	Revista Panamericana de Salud Pública	Venezuela	Maraquay	**(349) Neighborhoods**
8 [142]	Braga	2010	Seroprevalence and risk factors for dengue infection in socio-economically distinct areas of Recife, Brazil	Acta Tropica	Brazil	Recife	**Households**
9 [143]	Brunkard	2007	Dengue Fever Seroprevalence and Risk Factors, Texas–Mexico Border, 2004	Emerging Infectious Diseases	USA Mexico	Brownsville, Texas Matamoros, Tamaulipas	**(300) Households Neighborhoods**
10 [144]	Cao	2017	Individual and Interactive Effects of Socio-Ecological Factors on Dengue Fever at Fine Spatial Scale: A Geographical Detector-Based Analysis	International Journal of Environmental Research and Public Health	China	Guangzhou	**(167) Townships-streets**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	Date	Title	Journal	Country	City	Geographic Units of Spatial Analysis
11 [145]	Carbajo	2018	The largest dengue outbreak in Argentina and spatial analyses of dengue cases in relation to a control program in a district with sylvan and urban environments	Asian Pacific Journal of Tropical Medicine	Argentina	Tigre	**Census tracts**
12 [146]	Chadee	2009	Dengue cases and Aedes aegypti indices in Trinidad	Acta Tropica	Trinidad	County Victoria	**(50) Households**
13 [147]	Chen	2016	Who Is Vulnerable to Dengue Fever? A Community Survey of the 2014 Outbreak in Guangzhou, China	International Journal of Environmental Research and Public Health	China	Guangzhou	**Households**
14 [148]	Chen	2019	Spatiotemporal Transmission Patterns and Determinants of dengue fever: a case study of Guangzhou, China	International Journal of Environmental Research and Public Health	China	Guangzhou city	**Grid-level 1km**
15 [149]	Chiu	2014	A Probabilistic Spatial Dengue Fever Risk Assessment by a Threshold-Based-Quantile Regression Method	PLoS ONE	China	Kaohsiung Fongshan	**Li (Smallest Administrative Unit)**
16 [150]	Chuang	2018	Epidemiological Characteristics and Space-Time Analysis of the 2015 Dengue Outbreak in the Metropolitan Region of Tainan City, Taiwan	International Journal of Environmental Research and Public Health	China	Tainnan	**BSA, village (Small Admnistrative newline Unit)**
17 [151]	Delmelle	2016	A spatial model of socioeconomic and environmental determinants of dengue fever in Cali, Colombia	Acta Tropica	Colombia	Cali	**(323) Neighborhoods**
18 [152]	De Mattos	2007	Spatial Vulnerability to Dengue in a Brazilian Urban Area During a 7-Year Surveillance	Journal of Urban Health	Brazil	Belo Horizonte	**(2548) census tracts**
19 [153]	Dom	2013	Coupling of remote sensing data and environmental-related parameters for dengue transmission risk assessment in Subang Jaya, Malaysia	Geocarto International	Malaysia	Subang Jaya	**Locality (Small Admnistrative Unit)**
20 [154]	Ellis	2015	A Household Serosurvey to Estimate the Magnitude of a Dengue Outbreak in Mombasa, Kenya, 2013	PLOS Neglected Tropical Diseases	Kenya	Monbasa	**(701) Households**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	**Date**	**Title**	**Journal**	**Country**	**City**	**Geographic Units of Spatial Analysis**
21 [155]	Escobar-Mesa	2003	Determinantes de la transmisión de dengue en Veracruz: un abordaje ecológico para su control	Salud Pública de México	Mexico	Veracruz	**(1249) Localities**
22 [156]	Falcon-Lezama	2017	Analysis of spatial mobility in subjects from a Dengue endemic urban locality in Morelos State, Mexico	PloS one	Mexico	Axochiapan city	**Trajectory in and out of the city**
23 [157]	Garcia	2011	An examination of the spatial factors of dengue cases in Quezon City, Philippines A Geographic Information-System GLS based approach 2005 2008	Acta Medica Philippina	Philippines	Quezon	**Barrangay (Small Admnistrative Unit)**
24 [158]	Hapuarachchi	2016	Epidemic resurgence of dengue fever in Singapore in 2013–2014: A virological and entomological perspective	BMC Infectious Diseases	Singapore	Singapore	**150 m buffer around clusterized cases**
25 [159]	Hayes	2003	Risk factors for infection during a severe dengue outbreak in el Salvador in 2000	The American Journal of Tropical Medicine and Hygiene	Salvador	Aguilares (Las Pampitas)	**(106) Households**
26 [160]	Hayes	2006	Risk factors for infection during a dengue-1 outbreak in Maui, Hawaii, 2001	Transactions of The Royal Society of Tropical Medicine and Hygiene	USAHawaii	Nahiku Hana	**Households**
27 [161]	Heukelbach	2001	Risk factors associated with an outbreak of dengue fever in a favela in Fortaleza, north-east Brazil	Tropical Medicine & International Health	Brazil	Fortaleza Favela Serviluz	**Self-defined districts**
28 [162]	Honorio	2009	Spatial Evaluation and Modeling of Dengue Seroprevalence and Vector Density in Rio de Janeiro, Brazil	PLoS Neglected Tropical Diseases	Brazil	Rio de Janeiro	**(3) Neighborhoods**
29 [163]	Huang	2018	Spatial Clustering of Dengue Fever Incidence and Incidence and its association with surrounding greeness	International Journal of Environmental Research and Public Health	China	Tainan Kaohsiung	**Districts**
30 [164]	Kennesson	2019	Social-ecological factors and preventive actions decrease the risk of dengue infection	PLOS Neglected Tropical Diseases	Ecuador	Machala	**Households**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	**Date**	**Title**	**Journal**	**Country**	**City**	**Geographic Units of Spatial Analysis**
31 [165]	Kesetyaningsi	2018	Determination of environmental factors affecting dengue incidence in Sleman District	African Journal of Infectious Diseases	Indonesia	Sleman District	**200 m buffer**
32 [166]	Khormi	2011	Modeling dengue fever risk based on socioeconomic parameters, nationality and age groups: GIS and remote sensing based case study	Science of The Total Environment	SaudiArabia	Jeddah	**(111) Districts**
33 [167]	Kim	2015	Role of Aedes aegypti and Aedes albopictus during the 2011 dengue fever epidemics in Hanoi, Vietnam	Asian Pacific Journal of Tropical Medicine	Vietnam	Hanoi	**(8) Districts (1200) 50 m-buffers around Households**
34 [168]	Koopman	1991	Determinants and Predictors of Dengue Infection in Mexico	American Journal of Epidemiology	Mexico	70 localities under 50,000 inhabitants	**(3408) Households**
35 [169]	Koyadun	2012	Ecologic and Sociodemographic Risk Determinants for Dengue Transmission in Urban Areas in Thailand	Interdisciplinary Perspectives on Infectious Diseases	Thailand	Chachoengsao's province cities	**(1200) Households considering (4) ecotypes**
36 [170]	Li	2013	Abiotic Determinants to the Spatial Dynamics of Dengue Fever in Guangzhou	Asia Pacific Journal of Public Health	China	Guangzhou	**(12) Districts**
37 [171]	Li	2018	Spatiotemporal responses of dengue fever transmission to the road network in an urban area	Acta Tropica	China	Guangzhou Fushan	**500 m distance from roads**
38 [172]	Lippi	2018	The social and spatial ecology of dengue presence and burden during an outbreak in Guayaquil, Ecuador, 2012	International Journal of Environmental Research and Public Health	Ecuador	Guayaquil	**Census tract**
39 [173]	Liu	2018	Dynamic spatiotemporal analysis of indigenous dengue fever at street-level in Guangzhou city, China	PLOS Neglected Tropical Diseases	China	Guangzhou	**Street-level**
40 [174]	Mahmood	2019	Spatiotemporal analysis of dengue outbreaks in Samanabad town, Lahore metropolitan area, using geospatial techniques	Environmental Monitoring and Assessment	Pakistan	Samanabad	**Union Council**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	**Date**	**Title**	**Journal**	**Country**	**City**	**Geographic Units of Spatial Analysis**
41 [175]	Mala	2019	Implications of meteorological and physiographical parameters on dengue fever occurrences in Delhi	Science of The Total Environment	India	Delhi city	**City**
42 [176]	Martinez	2017	Relative risk estimation of dengue disease at small spatial scale	International Journal of Health Geographics	Colombia	Bucaramanga	**(293) Census tracts**
43 [177]	McBride	1998	Determinants of dengue 2 infection among residents of Charters Towers, Queensland, Australia	American journal of epidemiology	Australia	Charters Towers	1000 **Households**
44 [178]	Mena	2011	Factores asociados con la incidencia de dengue en Costa Rica	Revista Panamericana de Salud Pública	Costa Rica	Various cities	**(81) Cantones**
45 [179]	Meza-Ballesta	2014	The influence of climate and vegetation cover on the occurrence of dengue cases (2001-2010)	Revista de Salud Pública	Colombia	Various cities	**(30) Municipios**
46 [180]	Mondini	2008	Spatial correlation of incidence of dengue with socioeconomic, demographic and environmental variables in a Brazilian city	Science of The Total Environment	Brazil	Sao Jose do Rio Preto	**Census tract**
47 [181]	Ogashawara	2019	Spatial-Temporal Assessment of Environmental Factors related to dengue outbreaks in Sao Paulo, Brazil	GeoHealth	Brazil	Sao Paulo	**District-level**
48 [182]	Pessanha	2010	Dengue em três distritos sanitários de Belo Horizonte, Brasil: inquérito soroepidemiológico de base populacional, 2006 a 2007	Revista Panamericana de Salud Pública	Brazil	Belo Horizonte	**Households**
49 [183]	Prayitno	2017	Dengue seroprevalence and force of primary infection in a representative population of urban dwelling Indonesian children	PLOS Neglected Tropical Diseases	Indonesia	26 cities	**Neighborhoods**
50 [184]	Qi	2015	The Effects of Socioeconomic and Environmental Factors on the Incidence of Dengue Fever in the Pearl River Delta, China, 2013	PLoS neglected tropical diseases	China	7 mains cities of Pearl River Delta, Guangdong	**(402) streets and towns**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	Date	Title	Journal	Country	City	Geographic Units of Spatial Analysis
51 [185]	Qu	2018	Effects of socio-economic and environmental factor	Geospatial Health	China	Guangzhou city	**Township-level**
52 [186]	Reiter	2003	Texas Lifestyle Limits Transmission of Dengue Virus	Emerging Infectious Diseases	USA-Mexico	Laredo, Texas Nuevo Laredo Taumalipas	**(622) Households**
53 [187]	Ren	2019	Urban villages as transfer stations for dengue fever epidemic: a case study in the Guangzhou, China	Emerging Infectious Diseases	China	Guangzhou city	**1 km square grid**
54 [188]	Rinawan	2015	Pitch and Flat Roof Factors' Association with Spatiotemporal Patterns of Dengue Disease Analysed Using Pan-Sharpened Worldview 2 Imagery	ISPRS International Journal of Geo-Information	Indonesia	Bandung	**Buffer 50 m**
55 [189]	Rodriguez	1995	Risk Factors for Dengue Infection during an Outbreak in Yanes, Puerto Rico in 1991	The American Journal of Tropical Medicine and Hygiene	Puerto Rico	Yanes (Florida)	**65 households**
56 [190]	Rotela	2007	Space–time analysis of the dengue spreading dynamics in the 2004 Tartagal outbreak, Northern Argentina	Acta Tropica	Argentina	Tartagal	**Residential block addresses**
57 [191]	Sarfraz	2014	Near real-time characterisation of urban environments: a holistic approach for monitoring dengue fever risk areas	International Journal of Digital Earth	Thailand	Muang	**Buffer 200 m**
58 [192]	Seidahmed	2018	Patterns of Urban Housing Shape Dengue Distribution in Singapore at Neighborhood and Country Scales	GeoHealth	Singapore	Singapore Geylang	**200 m-grid 1 km-block**
59 [193]	Stewart-Ibarra	2014	Spatiotemporal clustering, climate periodicity, and social-ecological risk factors for dengue during an outbreak in Machala, Ecuador, in 2010	BMC Infectious Diseases	Ecuador	Machala	**(253) Neighborhoods**
60 [194]	Sulaiman	1996	Relationship between Breteau and house indices and cases of dengue/dengue hemorrhagic fever in Kuala Lumpur, Malaysia	Journal of the American Mosquito Control Association	Malaysia	Kuala Lumpur	**6 zones of 1 million inhabitants**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	Date	Title	Journal	Country	City	Geographic Units of Spatial Analysis
61 [195]	Teixera	2002	Dynamics of dengue virus circulation: a silent epidemic in a complex urban area	Tropical Medicine & International Health	Brazil	Salvador	**(30) Neighborhoods**
62 [196]	Teixera	2008	Socio-demographic factors and the dengue fever epidemic in 2002 in the State of Rio de Janeiro, Brazil	Cadernos de Saúde Pública	Brazil	Rio state	**(90) Municipios**
63 [197]	Telle	2016	The Spread of Dengue in an Endemic Urban Milieu–The Case of Delhi, India	PLOS ONE	India	Dehli	**(1280) Colonies**
64 [198]	Teurlai	2015	Socio-economic and Climate Factors Associated with Dengue Fever Spatial Heterogeneity: A Worked Example in New Caledonia	PLOS Neglected Tropical Diseases	New Caled.	Various cities	**City**
65 [199]	Thammapolo	2008	Environmental factors and incidence of dengue fever and dengue haemorrhagic fever in an urban area, Southern Thailand	Epidemiology and Infection	Thailand	Songkhla	**Enumeration district**
66 [200]	Tian	2016	Surface water areas significantly impacted 2014 dengue outbreaks in Guangzhou, China	Environmental Research	China	Guangzhou	**City**
67 [201]	Tiong	2015	Evaluation of land cover and prevalence of dengue in Malaysia	Tropical Biomedicine	Malaysia	15 cities	**Buffer 10 m**
68 [202]	Toan	2014	Risk factors associated with an outbreak of dengue fever/dengue haemorrhagic fever in Hanoi, Vietnam	Epidemiology & Infection	Vietnam	Hanoi	**(73) Households**
69 [203]	Troyo	2009	Urban structure and dengue incidence in Puntarenas, Costa Rica	Singapore Journal of Tropical Geography	Costa Rica	Punta-renas	**Health region**
70 [204]	Van Benthem	2005	Spatial patterns of and risk factors for seropositivity for dengue infection	The American journal of tropical medicine and hygiene	Thailand	(Ban Pa Nai Ban Pang) Mae Hia	**Buffer 200 m**

Table A1. *Cont.*

ID [Ref.]	Publication Meta-Data				Geographical Context		
	First Author	Date	Title	Journal	Country	City	Geographic Units of Spatial Analysis
71 [205]	Vanwambeke	2006	Multi-level analyses of spatial and temporal determinants for dengue infection	International Journal of Health Geographics	Thailand	(Ban Pa Nai Ban Pang) Mae Hia	**Buffer 200 m**
72 [206]	Wanti	2019	Dengue Hemorrhagic Fever and House Conditions in Kupang City, East Nusa Tenggara Province	Kesmas: National Public Health Journal	Indonesia	Kupang	**Households**
73 [207]	Waterman	1985	Dengue Transmission in Two Puerto Rican Communities in 1982	The American Journal of Tropical Medicine and Hygiene	Puerto Rico	Manati Salinas communities	**(60) blocks of 6 households**
74 [208]	Wen	2012	Population Movement and Vector-Borne Disease Transmission: Differentiating Spatial—Temporal Diffusion Patterns of Commuting and Noncommuting Dengue Cases	Annals of the Association of American Geographers	China	Tainan city	**266 "Villages" (smallest administrative division)**
75 [209]	Wong	2014	Community Knowledge, Health Beliefs, Practices and Experiences Related to Dengue Fever and Its Association with IgG Seropositivity	PLOS Neglected Tropical Diseases	Malaysia	Various cities	**1400 Households at 3 km of the schools**
76 [210]	Yue	2018	Spatial analysis of dengue fever and exploration of its environmental and socio-economic risk factors using ordinary least squares	International Journal of Infectious Diseases	China	Guangzhou city	**1 km square Grid**
77 [211]	Yung	2016	Epidemiological risk factors for adult dengue in Singapore: an 8-year nested test negative case control study	BMC Infectious Diseases	Singapore	Singapore	**Households**
78 [212]	Zellweger	2017	Socioeconomic and environmental determinants of dengue transmission in an urban setting: An ecological study in Nouméa, New Caledonia	PLOS Neglected Tropical Diseases	New Caledonia	Noumea	**(36) Neighborhoods**

Appendix A.2. Epidemiological Characteristics and Vectors Mention (M) or Observation (O) in the 58 Included Articles

Table A2. Data extracted from the 78 articles on the epidemiological context (time-span of the outbreak or of the serosurvey, data provider, method used to identify dengue virus, number of cases ([n]) or incidence (I) or prevalence (P), spatial distribution of the dengue occurrences). In last column, we indicate if vectors are only mentioned (M) or observed (O) in the study.

ID [Ref.]	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
1 [135]	2000	Self-reported dengue cases	NA	NA	NA	Clustered in the southern part (hospitals location)	***Aedes aegypti and Aedes Albopictus (O)***
2 [136]	Sep 2016–Jan 2017	Sero-prevalence survey	IgG (ELISA)	NA	% by city	NA	**Mosquitoes (M)**
3 [137]	2010–2011	Passive notification (COVISA)	IgG (ELISA)	NA	N=7415	Heterogeneous	***Aedes aegypti (M)***
4 [138]	1995	Passive notification (Palau Hospital)	Clinical and IgM and IgG	NA	N = 254	Heterogeneous	***Aedes aegypti albopictus, and hensilli (O)***
	Jan–Jun 1995	Passive notification (PHD) and cross-survey	IgM (ELISA) and Virus isolation		N = 817 P = 75%		
5 [139]	Jan–2004–Dec–2007	Passive notification (PCD)	Clinical and Lab. confirmed	NA	I = 281 per 100,000	NA	***Aedes aegypti (O)***
6 [140]	Jan–Sep–2011	Passive notification (SINAN)	Clinical and Lab. confirmed	DENV-1 DENV-2 DENV-3	N = 195	Heterogeneous	***Aedes aegypti (O)***
7 [141]	1993–1998	Sero-incidence	Clinical signs	NA	N = 10,576 N = 2593 (DHF) N = 8 (Death)	Observed Patterns	***Aedes aegypti (M)***
8 [142]	2005–2006	Sero-prevalence survey	IgG (ELISA)	NA	P = 91% P = 87% P = 74%	Socio-eco stratified	***Aedes aegypti (M)***
9 [143]	Oct–Nov 2004	Sero-prevalence survey	Double IgM-IgG (ELISA), and PRNT	DENV-2 DENV-1	N = 6 (Recent), N = 119 (Past) N = 22 (Recent), and N = 235 (Past)	NA	***Aedes aegypti, albopictus, Culex quinque, fasciatus (O)***
10 [144]	2014	Passive notification (CDCP)	Clinical, IgM, and PCR	NA	N = 37,322	4 clusters 1 Hotspot 3 cold spots (Moran's I)	***Aedes albopictus (aegypti) (M)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	DATA Source	Diagnostic Method	DENV-Type	Number of Cases	Spatial Variation	Vectors Mention
11 [145]	2016	Passive notification (CDCP)	Ns1 IgM	NA	N = 83	Mild	***Aedes aegypti (albopictus) (M)***
12 [146]	2003–2004	Sero-prevalence	Clinical signs IgM Seroconversion	NA	N = 33	NA	***Aedes agypti (O)***
13 [147]	Jul–Aug 2014	Passive notification (NNIDRIS)	Clinical IgG PCR	NA	N = 165	NA	***Aedes albopictus (aegypti) (M)***
14 [148]	Jan–Dec 2014	Passive notification China CDC	Clinical or laboratory diagnosis	NA	37 386	Spatially clusted in central districts	***Aedes (M)***
15 [149]	2004–2011	Passive notification (CDC)	IgM	NA	NA	Heterogeneous	***Aedes aegypti (albopictus) (M)***
16 [150]	2015	Passive notification (CDC)	IgM	NA	N = 22,740 P = 12.06 per 1000	3 Clusters (Moran's I)	***Aedes aegypti and albopictus (M)***
17 [151]	2010	Passive notification (SIVIGILA)	Clinical signs	NA	N = 9287	3 Clusters Heterogeneous (Moran's I)	***Aedes aegypti (M)***
18 [152]	1996–2002	Passive notification (SINAN) (SISVE)	Clinical	NA	N = 89,607	Heterogeneous	***Aedes aegypti (M)***
19 [153]	2006–2010	Passive notification (DHO) (SJMC)	NA	NA	NA	5 Hotspots	***Aedes (aegypti) (M)***
20 [154]	3–11 May 2013	Sero-incidence	IgM RT-PCR	DENV-1 DENV-2 DENV-3	N = 210 of 1500	No clustering	***Aedes aegypti (M)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
21 [155]	1995–1998	Passive notification (IPEEDP)	NA	DENV-3 and co-circulation	N = 26,423 I = 112.7 per 100,000 (1997)	Heterogeneous	***Aedes aegypti (M)***
22 [156]	May-Sep 2012	Sero-prevalence survey	IgM or IgG capture ELISA	NA	37 386	42 cases, 42 intradomestic, and 42 population controls	***Aedes (M)***
23 [157]	2005–2008	Passive notification (DOH)	NA	NA	N = 8812	Heterogeneous	***Aedes (M)***
24 [158]	2013–2014	Passive notification (MOH)	Clinical NS1 or RNA-PCR	DENV-1 (dominant) and DENV-2	N = 22,170 I = 410 (2013) N = 18,338 I = 335 (2014)	NA	***Aedes aegypti (albopictus) (O)***
25 [159]	18–19 Aug 2000	Primo and secondary Sero-incidence	IgM IgG	DENV-2	I = 98 per 1000	NA	***Aedes (O)***
26 [160]	Oct 2001	Sero-incidence	Clinical IgM IgG	DENV-1	I = 389 per 1000	Confined area	***Aedes albopictus (O)***
27 [161]	1 Jun–31 Jul 1999	Passive notification (PHCC)	Clinical IgM	DENV-1 DENV-2	N = 34 clinical N = 16 IgM	NA	***Aedes aegypti (M)***
28 [162]	Jul–Nov 2007 Apr 2008	Sero-prevalence and recent cases survey	Clinical IgM IgG RT-PCR	DENV-2	NA	Hotspots patterns	***Aedes aegypti (albopictus) (O)***
29 [163]	2014–2015	Passive notification Taiwan Centers for Disease Control (CDC)	IgM, nucleotide sequence, viral isolation	NA	15 394 for 2014, 42 932 for 2015	Hotspots of dengue epidemic in urban areas	***Aedes aegypti and Ae. albopitus (M)***
30 [164]	Jan–Sep 2014, Mar–Jun 2015	Sero-prevalence	RT-PCR, NS1 test, ELISA and IgM	NA	72	Heterogeneous	***Aedes aegypti (M)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	DATA Source	Diagnostic Method	DENV-Type	Number of Cases	Spatial Variation	Vectors Mention
31 [165]	2008–2013	Passive notification DF and DHF cases, HD of Sleman district, and PHC	NA	NA	1150	Dengue incidents are clustered for each year	***Aedes aegypti (M)***
32 [166]	2006–2010	Passive notification (JHA)	Clinical	NA	NA	Heterogeneous	***Aedes aegypti (M)***
33 [167]	1 Aug–21 Dec 2011	Passive notification (NHTD)	Clinical signs RT-PCR	DENV-2 DENV-1	N = 140	24 infectious foci	***Aedes (O) (95%) aegypti (5%) albopictus***
34 [168]	March–Oct 1986	National sero-prevalence survey	Antigens test	NA	NA (age < 25)	Stratified	***Aedes aegypti (O)***
35 [169]	Aug–Oct 2007	Sero-incidence (Hospital and PHO)	IgM, IgG, and clinical signs	NA	1200	NA	***Aedes (aegypti) (M)***
36 [170]	May–Nov 2002	Passive notification (CDCPG)	NA	NA	N = 1069	2 clusters	***Aedes aegypti and albopictus (M)***
37 [171]	2014	Passive notification China CDC	NA	NA	40 379	Spatio-temporal dengue kernels	***Aedes aegypti (M)***
38 [172]	2012	Passive notification	Clinical signs	NA	P = ? per 10^5	Heterogeneous.	***Aedes aegypti (albopictus) (M)***
39 [173]	2006–2014	Passive notification China CDC	Clinical signs, and lab. confirmed	NA	NA	Spatio-temporal clustering	***Aedes albopictus (M)***
40 [174]	2012–2015	Passive notification, the Punjab Health Department	NA	NA	377 for 2012, 871 for 2013, 133 for 2014 and 49 for 2015	NA	***Aedes aegypti and Ae. albopictus (M)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
41 [175]	2006–2015	The Health Department of Municipal Corporation of Delhi	NA	NA	NA	NA	***Aedes* mosquitoes (M)**
42 [176]	2008–2015	Passive notification (SIVIGLIA)	Clinical signs	NA	N = 27,301 P = 1359 per 10^5	NA	***Aedes aegypti (M)***
43 [177]	May–Sept 1995	Serosuvey	Hemagglutination inhibition assay, Clark and Cassals	DENV-2	[n = 203]	Foci	***Aedes aegypti (M)***
44 [178]	1999–2007	Passive notification Ministerio de Salud	Clinical and serologic	NA	N = 137,719	Heterogeneous.	***Aedes aegypti (M)***
45 [179]	2001–2010	Passive notification SIVIGILA	NA	NA	NA	NA	***Aedes aegypti (M)***
46 [180]	1994–1998 1998–2002	Passive notification A.L.	NA	NA	N = 13,998	Heterogeneous, clusters (Moran's I)	***Aedes aegypti (M)***
47 [181]	2011–Aug 2017	The State Secretariat of Health	NA	NA	From 475 to 43,359 yearly	NA	***Aedes aegypti (M)***
48 [182]	Jun–2006 Mars 2007	Sero-prevalence survey	SN	NA	709 11.9%	Heterogeneous	**NA**
49 [183]	Oct–Nov 2014	Sero-prevalence survey	IgG ELISA	NA	N = 3194 children I = 69.4%	NA	***Aedes (M)***
50 [184]	2013	Passive notification China CDC	Clinic IgG PCR	NA	I = 28,896 per 10^5	Highly clustered Hot and cold spot	***Aedes albopictus (aegypti) (M)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
51 [185]	2014	Passive notification China CDC	NA	NA	37,380	Space-time clustering	***Aedes albopictus (M)***
52 [186]	1999	Sero-prevalence	IgM	NA	Prevalence(IgM) P = 1.3% (Laredo) P = 16% (Nuevo Laredo)	Across the boarder	***Aedes aegypti (O)***
53 [187]	2012, 2013, 2014, and 2017	Passive notification China CDC	Clinical or laboratory diagnosis	NA	36 344 for 2014, NA for other years	Spatially clusted for the each year	***Aedes albopictus (M)***
54 [188]	Jan–Dec 2012	Passive notification	NA	NA	1058	Hotspots patterns	***Aedes (M)***
55 [189]	Nov 1991	Sero-incidence survey (primary and secondary cases)	IgM IgG	NA	I = 18% (N = 59 of 331)	Agglomerated	***Aedes aegypti (O)***
56 [190]	24 Jan 11 May 2004	Passive notification (SiNaVE)	PCR IgM IgG	NA	N = 487	Hot spots	***Aedes aegypti (M)***
57 [191]	2005–2010	Passive notification (DOH)	NA	NA	NA	Heterogeneity	***Aedes (M)***
58 [192]	2010–2015 (Geylang) 2013–2015 (Singapore)	Passive notification Ministry of Health	NA	DENV 1-2-3-4	N = 353 (Geylang, 2014–2015)	13 Clusters in Geylang (Moran's Index)	***Aedes aegypti and albopictus (O)***
59 [193]	2010	Passive notification (NIMH)	NA	DENV-1	N = 2019 I = 84 per 10^5	Hotspots patterns	***Aedes aegypti (M)***
60 [194]	1994	All hospitals notifications	Hemagglutination inhibition test of Clarke and Casals	NA	0 to 21 cases monthly	All areas	***Aedes aegypti and albopictus (O)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
61 [195]	May–Jun 1998	Sero-prevalence	NA	DENV-1 and 2	P = 68.7%	NA	***Aedes aegypti (O)***
	1998-1999	Sero-incidence			I = 70.6%		
62 [196]	2002	Passsive notification SINAN	Clinical signs	DENV-1 DENV-2	N = 368,460	Highly Heterogeneous	***Aedes aegypti (M)***
63 [197]	2008–2009–2010	Passive Delhi surveillance system	IgM	NA	N = 5998 (2010)	Spatio-temporal clusters	***Aedes aegypti (M)***
64 [198]	1995–2012	Passive notification (DASS)	Clinical signs Lab. confirmed	NA	N = 24,272	Highly Heterogeneous	***Aedes aegypti (M)***
65 [199]	Jan–Dec 1998	Passive notification (Health Department)	WHO criteria	NA	N = 287 DH/DHF	Some points clustering (Moran's I)	***Aedes (O)***
66 [200]	1978–2014	Passive notification (NIDRS-CDC)	Phylo-genetic.	DENV-1	NA	NA	***Aedes albopictus (O)***
67 [201]	2008–2009	Sero-prevalence survey (Malaya University)	IgG ELISA	NA	N = 1,410 childrens	NA	***Aedes (M)***
68 [202]	2009	Passive notification Hanoi Hospital	Clinical signs	NA	N = 73 DF/DHF	NA	**Mosquitoes (O)**
69 [203]	2002	Passive notification (Health Department)	Clinical signs	NA	N = 1,434	NA	***Aedes aegypti (M)***
	2003				N = 2017		
70 [204]	May–Sep 2001	Sero-incidence survey	IgM (ELISA)	NA	N = 1750 I = 6.5% and I = 3.1%	One Sero-Positive cluster	***Aedes aegypti (M)***

Table A2. *Cont.*

ID [Ref.]	Epidemiological Context						
	Start–End Years	**DATA Source**	**Diagnostic Method**	**DENV-Type**	**Number of Cases**	**Spatial Variation**	**Vectors Mention**
71 [205]	2001–2003	Sero-incidence survey	IgM	NA	NA	4 clusters	***Aedes (M)***
72 [206]	2011–2015	Sero-prevalence	NA	NA	240 DHF patient cases	NA	***Aedes (M)***
73 [207]	July 1982	Sero-incidence survey	Hemagglutination	DENV-1 DENV-4	I = 35% (Salinas) I = 26% (Manati)	NA	***Aedes aegypti (O)***
74 [208]	Jun 2007–Jan 2008	Passive notification (Taiwan-CDC)	Clinical signs Lab. confirmed	NA	N = 1403	Various space-time clusters	***Aedes aegypti and albopictus (M)***
75 [209]	Mar 2011–May 2012	Sero-prevalence survey	IgG	NA	N = 156 school children (age 7–18)	3 clusters	***Aedes mosquitoes (M)***
76 [210]	Jan–Dec 2014	Passive notification China CDC	Clinical sign, lab. or viral isolation	NA	30,553	High density in several districts	***Aedes albopictus (M)***
77 [211]	Apr 2005–Feb 2013	Sero-incidence survey	RT-PCR IgM-IgG conversion	DENV-1 DENV-2 suspected	N = 395 of 1703 (age $\geq$ 18)	Spatial gradient	***Aedes aegypti (M)***
78 [212]	Sep 2008–Aug 2009	Passive notification (DASS)	Clinical signs IgM PCR NS1 analyses	(DENV-1) DENV-4	N = 2310 I = 23.7 per 1000	North to South gradient clusters (Moran's I)	***Aedes aegypti (M)***
	2012–2013			DENV-1	N = 3369 I = 34.5 per 10^3	Widely homogeneous	

Appendix A.3. Landscape Factor Production and Landscape-Dengue Relationships Table

Table A3. Data extracted from the 78 articles on the landscape factor production (type of source), on the landscape factor classification according to groups and subgroups, and on the dengue-landscape relationship (three-valued interpretation: +, −, or NS, and statistical method performed).

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
1 [135]	Survey questionnaire	Entomological observation		*Aedes albopictus* larvae	+	Vector breeding sites (at household level)	Correlation and simple regression model
				Aedes aegypti larvae	NS		
	GIS data	Land use	Infrastructure level	Proximity to the hospitals	+	Virus screening (at wards level)	
2 [136]	Survey questionnaire	Housing type and chracteristics	Housing type	Villa w/o garden	NS	Human–Vector encounter (at household-level)	Odds ration Multivariate logistic regression
				Villa with garden	NS		
				Apartment	−		
		Land use	Infrastrucutre level	Presence of a sewage network	−	Vector breeding sites (at household-level)	
		Entomological observations		Presence of mosquitoes at home	+	Exposure to mosquitoes bite (at household-level)	
		Human immunity		Previous history of Dengue	+	Virus Exposition (at household-level)	

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
3 [137]	Landsat 5 TM image	Land cover	Surface Temperature	Urban heat islands	+	Vectors resting sites and virus replication (at large-admin level)	Multiple cluster analysis
			Vegetation	Normalized Difference Vegetation Index (NDVI)	−	Vectors breeding and resting sites (at large-admin level)	
	Survey questionnaire	Land use	Urban Typology	Slums-like areas	NS	Human-Vector encounter (at large-admin-level)	
4 [138]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Screens on windows	NS	Vectors exposure (at household-level)	Univariate and Multivariate Analysis
		Land use	Construction material	Mixed type of house construction	NS	Vector breeding site (at neighborhood-level)	
			Cropland	Taro farming	+		
		Entomological observation		Presence of *Aedes albopictus*	+	Vector exposure (at household-level)	
				Presence of *Aedes aegypti*	+		
				Larvae-positive habitats	+		
		Housing type and characteristics	House characteristics	Animals water pans	+	Vector breeding site (at household-level)	
		Entomological observation		Presence of *Aedes*	+	Vector exposure (at household-level)	
5 [139]	Survey questionnaire	Entomological observation		Larvae abundance	NS	Vector breeding site (at neighborhood-level)	Cross-lagged correlation

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
6 [140]	Survey questionnaire	Entomological observation		*Aedes* Eggs indicators	NS	Vector breeding site (at neighborhood-level)	Generalized additive model
				Aedes Pupae indicators	NS		
				Aedes Adults indicators	NS	Vector exposure (at neighborhood-level)	
7 [141]	GIS data	Human density		Human density	+	Human exposure to virus (at neighborhood-level)	Linear statistic stratification
8 [142]	Survey questionnaire	Housing type and characteristics	Housing type	Apartment	−	Vector exposure (at household-level)	GLMM GAM
				House	+		
			House characteristics	Households with water supply	NS	Vector breeding site (at household-level)	
				Households with regular water supply			
				Households with water containers			
				Households with a sewage system			
				Households with a garbage collection			
9 [143]	Survey questionnaire	Housing type and characteristics	House characteristics	Absence of air conditioning	+	Vector exposure (at household-level)	Multivariate logistic regression
		Land use	Infrastructure level	Lack of street drainage	+	Vector breeding site (at neighborhood-level)	
		Entomological observation		Presence of *Aedes* habitats	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
10 [144]	Landsat 8 image	Land use	Infrastructure level	Urbanization level	+	Human-Vector encounter (at small-admin level)	Linear correlations, and Coefficient of Geographical detector
	GIS data			Road density	+	Human mobility at small-admin level	
	MODIS image	Land cover	Vegetation	NDVI and VFC	−	Vectors breeding and resting sites (at small-admin level)	
	GIS data		Water-areas	Water-body areas	−		
	Landsat 8 and Quickbird images	Land use	Urban Typology	% of urban villages	+	Human-Vector encounter (at small-admin level)	
11 [145]	Survey questionnaire	Human mobility	Long-distance human mobility	Foreign inhabitants	+	Human and Virus mobility (at small-admin level)	GLM
12 [146]	Survey questionnaire	Entomological observations		Adults and immatures *Aedes*	+	Exposure to mosquitoes bite (at household-level)	G-test on contingency tables
				Rate of *Aedes* pupae per person	+		
13 [147]	Tele-interview survey questionnaire	Housing type and characteristics	Housing type	Old flats	+	Vector exposure at household-level	Logistic regression models and Odds Ratio (OR)
				Sheds	+		
			Housing characteristics	Screens on windows	NS		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
14 [148]	2.5m SPOT 5 image GIS data (Baidu map)	Land use	Infrastructure level	Road network density	+	Human-vector encounter (at neighborhood level)	Geographical detector
				Subway lines network density	+		
				Aging infrastructure	+		
			Water-areas	Ponds area	+	Vector breeding site (at neighborhood level)	
			Human density	Number of the people on the building	+	Human exposure to virus (at neighborhood level)	
15 [149]	GIS data	Land use	Infrastructure level	% of canals and ditches	+	Vectors breeding sites (at small admin-level)	Quantile regression
				Interaction ditches-residential areas	+	Human-Vector encounter (at small admin-level)	
16 [150]	GIS data	Land use	Urban Typology	Residential area	+	Human-Vector encounter (at small admin-level)	Quantile regression
				Recreation area	NS		
				Business area	NS		
		Land cover	Cropland	Agriculture area	NS	Vectors breeding sites (at small-admin level)	
			Water areas	Wetland	−		
				Water areas	NS		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	Data Group	Data Sub-Group	Landscape Factors	Three-Valued Interpretation	Potential Proxy of (at Unit Level)	Statistical Method
17 [151]	GIS data	Land use	Infrastructure level	Proximity to parks	+	Human-Vector encounter (at neighborhood-level)	GWR
		Topography		Proximity to rivers	NS		
		Land use	Urban Typology	Proximity to tyre shops	NS		
			Infrastructure level	Proximity to water pumps	NS		
			Urban Typology	Proximity to cemeteries	NS		
				Proximity to plant nurseries	+		
			Infrastructure level	Proximity to houses with a sewage system	−		
18 [152]	Survey questionnaire	Land use	Infrastructure level	% of households with no piped water	NS	Vectors breeding sites (at small-admin level)	Multivariate regression
				% of households without systematic garbage collection	NS		
		Human density		Population density	NS	Human exposure to virus (at small-admin level)	
		Land use	Urban Typology	Ratio (Nb commercial) (Nb Households)	NS	Human-Vector encounter (at small-admin level)	

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	Data Group	Data Sub-Group	Landscape Factors	Three-Valued Interpretation	Potential Proxy of (at Unit Level)	Statistical Method
19 [153]	IKONOS image GIS data	Land use	Urban Typology	Residential areas	+	Human-Vector encounter (at small-admin level)	Layers super-imposition
				Industrial areas	+		
				Commercial areas	NS		
		Land cover	Bare soils	Open areas	+		
		Housing type and characteristics	Housing type	Interconnection houses	+		
				Independent houses	NS		
				Mixed houses	NS		
		Land use	Urban Typology	Commercial houses	NS		
				Residential with commercial and industrial areas	+		
20 [154]	Survey questionnaire (assisted by Google Earth imagery)	Human mobility		Long-distance mobility	+	Human and virus mobility (at regional-level)	OR (95 % CI) Logistic regression
		Housing type and characteristics	Housing type	One story home	NS	Vector exposure (at household-level)	
		Land use	Urban Typology	Temporary construction	NS		
		Housing type and characteristics	Housing characteristics	Screens on windows	NS		
		Entomological observation		Breeding containers	NS		
21 [155]	Topographic data	Topography		Altitude	–	Vector mobility (at regional-level)	Bivariate statistics
	Census data	Land use	Infrastructure level	Drainage	–	Vector breeding sites (at large-admin level)	
				Public services availability	–	Human-Vector encounter (at large-admin level)	

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
22 [156]	GIS data (GPS data logger)	Human mobility		Number of visits out of the municipality's administrative limits	+	Human and virus mobility (at city level)	Conditionnal and multiple logistic regression
23 [157]	GIS data	Land use	Urban Typology	Residential with commercial industrial areas	+	Human-Vector encounter (at small-admin level)	Layers super-imposition
			Infrastructure level	Water network and built-up areas	+		
			Urban Typology	Informal settlements areas	+		
24 [158]	Survey questionnaire GIS data	Entomological observation		*Aedes* house index	+	Vector exposure (at neighborhood-level)	Linear correlation (Spearmann)
25 [159]	Survey questionnaire	Entomological observation		Discarded containers	+	Vector breeding sites (at household-level)	Univariate and Multivariate analysis (Odds Ratio)
				Discarded tire casings	+		
				Infested discarded plastic containers	+		
				Infested discarded cans	+		
26 [160]	Survey questionnaire	Housing type and characteristics	Construction material	Wood-construction	NS	Vectors exposure (at household-level)	Multiple logistic regression (Odds ratios)
			Housing type	Single-level houses	–		
		Land cover	Vegetation	Tree height	+	Vectors resting sites (at household-level)	
		Topography		% Shaded	+		
		Land use	Urban Typology	Lot size	NS	Human density (at neighborhood-level)	
				Neighbor proximity	–		
		Land cover	Vegetation	Distance house-vegetation	+	Vector exposure (at household-level)	
		Entomological observation		% households with *Aedes albopictus* larvae	NS	Vector breeding sites (at neighborhood-level)	
		Housing type and characteristics	Housing characteristics	Home with birds	+	Vector exposure (at household-level)	
				Screens on windows	–		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
27 [161]	Survey questionnaire	Topography		Street orientation to the wind	+	Vectors mobility (at small-admin level)	Odds ratios
		Housing type and characteristics	Housing characteristics	Gutter-rain water	+	Vector breeding sites (at small-admin level)	
		Land use	Infrastructure level	Inefficient waste collection	+		
28 [162]	Survey questionnaire	Land use	Urban Typology	Slum area	+	Human-Vector encounter (at neighborhood-level)	Generalized Additive Model (GAM)
		Entomological observation		Mosquito abundance	NS	Vector exposure (at neighborhood-level)	
		Land use	Urban Typology	Commercial activity areas with human movements	+	Human-Vector encounter at neighborhood-level	
29 [163]	MODIS image	Land cover	Vegetation	NDVI	−	Vector breeding and resting sites (at city level)	Spearman correlation GLMM
	GIS data			Forest	−		
				Grassland	−		
		Land use	Cropland	Agricultural areas	−		
			Urban typology	Park	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production			Dengue-Landscape Relationship			
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
30 [164]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Highly shaded patio	+	Vector breeding site (at household level)	Bivariate analysis using Chi-square, Fisher's Exact or t-tests
				Proximity to abandoned property	+		
				Lack of piped water inside the house	+		
				Daily garbage collection	−		
				Standing water in various recipient types	NS		
				Screens on all windows	NS	Vector exposure (at household level)	
31 [165]	Quickbird image	Land cover	Urban typology	% of built-up area with vegetation surrounding	+	Human-vector encounter (at neighborhood-level)	Spearman and Pearson correlation
				Only built-up area	−		
	Topographic data	Topography		Altitude	−	Vector mobility (at large admnistrative-level)	
32 [166]	SPOT 5 image	Land use	Urban Typology	Quality of neighborhood	−	Human-Vector encounter (at large-admin level)	GWR
33 [167]	Survey questionnaire	Entomological observation		*Aedes aegypti* population density	+	Vector exposure (at neighborhood-level)	Spearman correlation coefficient
				Aedes albopictus population density	NS		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
34 [168]	Survey questionnaire	Entomological observation		% of houses with larva on the premises	+	Vector exposure (at household-level)	Odds ratios
				% of houses with uncovered water containers	+	Vector breeding sites (at neighborhood level)	
	Topographic data	Topography		Altitude	−	Vector mobility (at regional level)	
35 [169]	Survey questionnaire	Land use	Urban Typology	Commercial ecotype	NS	Human-Vector encounter (at neigborhood-level)	Uni, multi-variate hierarchical logistic regression
				DENPURA ecotype	NS		
				RCDENPURA ecotype	+		
				RC ecotype	NS		
		Human immunity		Historical dengue risk areas	+	Virus exposition (at small-admin level)	
		Housing type and characteristics	Housing characteristics	Number of house floors	NS	Vector exposure (at household-level)	
				Floor of principal living	NS		
			Construction material	Construction material of house	NS		
			Housing characteristics	Number of house windows	NS		
				Having screens for house windows	+		
				Having a yard/open space	NS		
				Having bushes in a yard/ open space	NS		
				House attachment	NS		
36 [170]	MODIS-VI image	Land use	Urban Typology	% of construction area	+	Human-Vector encounter (at large-admin level)	Generalized linear model logistic regression
		Land cover	Vegetation	% of shrubs	+	Vector resting and breeding sites (at large-admin level)	
			Water-areas	% of wet grassland	+		
				% of water area	+		
		Land use	Cropland	% of paddy field	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
37 [171]	GIS data	Land use	Infrastructure level	High-density road networks	+	Human and virus mobility (at neighborhood-level)	Analysis of Variance (ANOVA)
				Proximity to narrow roads	+		
38 [172]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Poor housing condition	+	Human-Vector encounter (at small-admin level)	(Moran's I) Negative binomial model
		Land use	Infrastructure level	Access to paved road	−		
		Housing type and characteristics	Housing type	Unoccupied houses	NS		
39 [173]	Survey questionnaire (the National Bureau of Statistics of China)	Land use	Urban typology	Urban, urban-rural and rural communities	NS	Human-vector encounter (at neighborhood-level)	Univariate logistic regression Stepwise logistic regression
40 [174]	Google earth	Land cover	Urban Typology	% of built-up area	+	Human-vector encounter (at large admin-level)	Descriptive statistical analysis
41 [175]	Landsat 7, Landsat 8, IRS-P6, and Sentinel-2	Land cover	Urban typology	Built-up density	+	Human-vector encounter (at city-level)	Poisson regression
			Water areas	Distance from water bodies	−	Vector breeding site (at city-level)	
			Vegetation	Vegetation density	−	Vector resting site (at city-level)	
	Topography data and high resolution satellite images	Land use	Infrastructure level	Distance from drainage networks	−	Vector breeding site (at city-level)	

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
42 [176]	Landsat	Land cover	Vegetation	Normalized difference vegetation index (NDVI)	+	Vectors breeding and resting sites (at small-admin level)	Pearson coefficient Bayesian model
	MODIS		Surface Temperature	Urban heat islands (UHI)	NS	Vectors and Virus replication (at small-admin level)	
43 [177]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Presence of house screening	−	Human-Vector encounter (at household-level)	Stepwise logisticregression analysis (odds ratio)
				Presence of rainwater tanks on the property/two residential blocks	+		
				Presence of evaporative cooling units	NS		
		Human immunity		Presence of a suspected case of dengue household / two residential blocks	+		
44 [178]	Census data	Human density		Human density	+	Human-Vector encounter (at small-admin level)	Pearson, Spearmann, and multiple analysis
		Housing type and characteristics	Housing characteristics	% of well-condition house	−		
				% of poor-condition house	+		
	MODIS	Land cover	Vegetation	Enhanced Vegetation Index	+	Vectors breeding and resting sites (at large scale)	
	Topographic data	Topography		Altitude of city center	−	Vector mobility (at large scale)	
45 [179]	Landsat image	Land cover	Vegetation	NDVI	−	Vector breeding and resting sites (at city level)	Simple linear regression

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
46 [180]	Survey questionnaire	Housing type and characteristics	Housing type	% of one-story home	+	Vector exposure (at small-admin level)	Spatial regression
47 [181]	Landsat 8-OLI TIRS	Land cover	Vegetation	NDVI	NS	Vector breeding or resting sites (at large amnistrative-level)	Linear stepwise regression
			Water areas	NDWI	NS		
			Urban typology	NDBI	NS	Human-vector encounter (at large amnistrative-level)	
			Surface temperature	LST	NS	Vectors and virus replication (at large amnistrative-level)	
48 [182]	Survey questionnaire	Housing type and characteristics	Housing type	Apartment	–	Vector exposure (at household-level)	OR (95% CI) Logistic regression
				House/shanty	+		
49 [183]	Survey questionnaire	Land use	Urban Typology	Temporary/unplanned/slum	–	Human-Vector encounter (at neighborhood-level)	Uni, multi-variate hierarchical logistic regression
		Housing type and characteristics	Housing type	Multi-floor building	–		
				Single story attached building	–		
				Single story detached building	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
50 [184]	Census data	Infrastructure level	Urban Typology	Prefectural boundary	+	Human-Vector encounter (at small-admin level)	GAM
		Land use		Urban and rural	+		
		Human density		Human density	+	Human exposure to virus (at small-admin level)	
	GIS data	Land use	Infrastructure level	Road density	+	Human mobility (at small-admin level)	
	Remote sensing images (unknow sensor)	Land cover	Vegetation	Normalized Difference Vegetation Index (NDVI)	+	Vectors breeding and resting sites (at small-admin level)	
51 [185]	GIS data	Land use	Urban typology	Urban village	+	Human-vector encounter (at large amnistrative-level)	Generalized additive model (GAM)
				Urban-rural fringe areas	+		
			Infrastructure level	Road density	+	Human mobility (at large amnistrative-level)	
	Remote sensing images (not clear)	Land cover	Vegetation	NDVI	−	Vector breeding or resting sites (at large amnistrative-level)	
52 [186]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Absence of air conditioning	+	Vector exposure (at household-level)	Univariate and Multivariate analyis
		Human mobility		No history of outside-travel	+	Human mobility (at regional-level)	
		Land use	Urban Typology	Distances to neighboring houses	+	Human-Vector encounter (at neighborhood-level)	

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
53 [187]	GF-2 satellite image ?	Land use	Urban typology	Urban villages associated to public transport	+	Human-vector encounter (at large amnistrative-level)	Pearson correlation and Geographically weighted regression (GWR)
54 [188]	World View 2 image	Land use	Urban typology	Mean size of pitched roof	+	Vectors breeding and resting sites (at neighborhood-level)	(Moran's I) GWR
				Mean size of flatted roof	−		
55 [189]	Survey questionnaire	Entomologic observations		Number of female *Aedes aegypti* per person	+	Vector exposure (at household-level)	Univariate and multivariate logistic regression methods
		Housing type and characteristics	Construction material	Concrete construction	+		
				Wood construction	NS		
			Housing characteristics	Animals on the property	NS		
				No air conditioner device	+		
				No use of screens on windows	+		
56 [190]	LANDSAT 5 TM satellite image	Land cover	Water-areas	Distance to river	+	Human-Vector encounter (at neigborhood-level)	Visual interpretation Pearson correlation coefficient
			Vegetation	Distance to Vegetation	+		
			Vegetation	Tasseled cap vegetation	+	Vectors breeding and resting sites (at neighborhood-level)	
			Water-areas	Tasseled cap wetness	+		
			Built-up	Tasseled cap brightness	+	Human presence (at neighborhood-level)	

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
57 [191]	ALOS Google Earth GIS data	Land use	Urban Typology	Dense populated areas surrounded by vegetation	+	Vector exposure (at neighborhood-level)	Geo-spatial analysis
				Institutions 40%, religious places (18%) market (15%)	+	Human-Vector encounter (at neighborhood-level)	
58 [192]	Census, OSM and GIS data	Land use	Urban Typology	High-rise housing	−	Human-Vector encounter (at neighborhood-level)	Chi-square test
				Low-rise housing	+		
			Infrastructure level	Density of the urban drainage network	+	Vectors breeding sites (at neighborhood-level)	
	Entomological survey	Entomological observation		Pupal density per 1000 population	NS	Vectors breeding sites (at neighborhood-level)	Pearson Coefficient
59 [193]	Census data	Land use	Urban Typology	Composite normalized housing condition index	+	Human-Vector encounter (at neighborhood-level)	Global linear model
			Infrastructure level	Short distance from hospital	+	Dengue reporting (at neighborhood-level)	
				Access to piped water	+	Vectors breeding sites (at neighborhood-level)	
	Entomological survey	Entomological observation		Breteau Index	NS	Vectors breeding sites (at neighborhood-level)	
60 [194]	Entomological survey	Entomological observation		Breteau index	NS	Vectors breeding sites at household-level	Correlation coefficient
				House index	NS		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
61 [195]	Census data	Human density		Human density	+	Human exposure to virus (at neighborhood-level)	Pearson cooefficients
	Entomological survey	Entomological observation		Premise index	NS	Vectors breeding sites at neighborhood-level	Risk ratio
62 [196]	Census data	Human density		% of urban population	+	Human exposure to virus (at small-admin level)	Spearmann coefficient Multi-linear regression
		Land use	Infrastructure level	% of population connected to water network	–	Vectors breeding sites (at small-admin level)	
				% of coverage by Family health program	–	Human exposure to virus (at small-admin level)	
63 [197]	Census data	Land cover	Vegetation	Distance from forested areas	–	Human-Vector encounter (at neighborhood-level)	
		Land use	Infrastructure level	Proximity to a sentinel hospital	–	Virus observation (at small-admin level)	
			Urban Typology	Deprived areas with medium-high human densities	+	Human-Vector encounter (at small-admin level)	
				Rich areas	+		
64 [198]	Topographic survey	Topography		Mean Altitude	–	Vector mobility (at city-level)	Pearson Coefficient

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
65 [199]	Survey questionnaire	Land use	Urban Typology	House density	NS	Human-Vector encounter (at small-admin level)	Pearson coefficient
		Land use	Urban Typology	% of shop-houses	+		
			Urban Typology	% of single houses	−		
		Land cover	Urban Typology	% of building	NS		
		Land use	Urban Typology	% of slum	−		
		Housing type and characteristics	Housing type	% of empty houses	+		
		Housing type and characteristics	Construction material	% of brick-made houses	+		
		Housing type and characteristics	Construction material	% of brick-made/wood houses	NS		
		Land use	Infrastructure level	% of houses with garbage system	+		
		Land use	Infrastructure level	% of houses with poor drainage system	NS		
		Housing type and characteristics	Housing characteristics	% of houses without window screens	NS		
66 [200]	Landsat image	Land cover	Water-areas	Water surface	+	Vector breeding sites and vector mobility (at city-level)	Linear correlation
67 [201]	Google Earth	Land use	Urban Typology	% of developed land	+	Human-Vector encounter (at neighborhood-level)	Spearman correlation coefficient
		Land cover	Vegetation	% of Vegetation	−		
		Land cover	Water-areas	% of water surface	NS		
68 [202]	Survey questionnaire	House type and characteristics	House characteristics	Living near open sewers	+	Vector exposure (at household-level)	Odds ratios
		Entomological observation		Mosquitoes presence in the house	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
69 [203]	MODIS-ASTER	Land cover	Vegetation	EVI-NDVI	–	Vectors breeding and resting sites (at small-admin level)	Pearson coefficient
	Quickbird	Land cover	Urban Typology	% Built area	NS	Human-Vector encounter (at small-admin level)	
			Vegetation	% Tree area	NS	Vectors breeding and resting sites (at small-admin level)	
			Urban Typology	% Built area	–	Human-Vector encounter (at small-admin level)	
			Vegetation	% Tree cover	+	Vectors breeding and resting sites (at small-admin level)	
70 [204]	Survey questionnaire	Housing type and characteristics	Construction material	Wood Households	+	Vector exposure (at household-level)	Logistic regression
				Stone and concrete	NS		
				Combination of stone and wood	NS		
			Housing characteristics	Screened windows	–		
	Landsat image	Land use	Cropland	Distance to orchards	+	Human-Vector encounter (at neighborhood-level)	
			Vegetation	Distance to sparely Vegetation	NS		
		Land cover	Urban Typology	% of densely built area in 200 m	–		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
71 [205]	Survey questionnaire	Housing type and characteristics	Construction material	Wood/bamboo Households	−	Vector exposure (at household-level)	Logistic regression
				Stone Households	+		
				Combination of stone and wood	+		
			Housing characteristics	Bednets	−		
		Land use	Cropland	Distance to orchards	−		
	Landsat 5 image and GIS data	Land cover	Water-areas	Distance to waterbodies	+	Human-Vector encounter (at neighborhood-level)	
			Bare soils	% of bare soil in 200 m-buffer	−		
		Land use	Urban Typology	% of village area with Vegetation	NS		
72 [206]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Housing size	NS	Vector exposure (at household-level)	Bivariate analysis using t-test (ratio scale) and chi square (test nominal) scale
				Non permanent wall	+	Vector breeding site (at household-level)	
73 [207]	Survey questionnaire	Land use	Urban Typology	Slum housing	+	Human-Vector encounter (at neighborhood-level)	Univariate and Multivariate analysis
		Land cover	Vegetation	Tree height	+	Vectors resting sites (at household-level)	
		Topography		Shade	+		
		Housing type and characteristics	Housing Characteristics	Screens on windows	−	Vector exposure (at household-level)	
			Construction material	Wood structure	+		
		Entomological observations		Day-biting mosquitoes	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
74 [208]	Survey questionnaire	Land cover	Bare soils	Vacant grounds	+	Vectors breeding and resting sites (at small-admin level)	Univariate and Multivariate analysis
		Land use	Urban Typology	Empty house	+		
				Markets-parks	NS	Human-Vector encounter (at small-admin level)	
		Human density		Population density	+		
		Human mobility		Commuting patterns	+	Human and virus mobility (at regional level)	
75 [209]	Survey questionnaire	Land use	Urban Typology	High rise residential apartment	+	Human-Vector encounter (at neighborhood-level)	t-test analysis analysis of variance, chi square, Uni-variate and multivariate logistic regression
		Housing type and characteristics	Housing characteristics	Terraced house	−	Vectors breeding and resting sites (at household-level)	
				Vegetation surround	−		
		Land use	Urban Typology	Single house	−	Human-Vector encounter (at neighborhood-level)	
		Entomological observation		Mosquito problem	+	Vector exposure (at household-level)	
76 [210]	GF-1 image	Land cover	Water	NDWI	+	Vector breeding and resting sites (at neighborhood-level)	Spearman rank correlation and Ordinary least square (OLR)
	MODIS image		Surface water	LST day	+	Vector resting site and virus replication (at neighborhood-level)	
				LST night	+		

Table A3. *Cont.*

ID [Ref.]	Landscape Factors Production				Dengue-Landscape Relationship		
	Data Source	**Data Group**	**Data Sub-Group**	**Landscape Factors**	**Three-Valued Interpretation**	**Potential Proxy of (at Unit Level)**	**Statistical Method**
77 [211]	Survey questionnaire	Housing type and characteristics	Housing characteristics	Multi-storey public flats	NS	Vector exposure (at household-level)	Multi-level logistic regression
				Multi-storey private flats	NS		
		Land use	Urban Typology	Landed houses	NS		
		Human mobility		Use of public transportation	NS	Human mobility (at small-admin level)	
				Foreign workers dormitory or hostel	+	Human mobility (at regional level)	
78 [212]	Landsat 7 ETM+ image	Land cover	Vegetation	Vegetation coverage	+	Vectors breeding and resting sites (at neighborhood-level)	Univariable and multivariable generalized linear model
	Census data	Housing type and characteristics	Human density	Households crowding	+	Human-Vector encounter (at neighborhood-level)	
				Households density	NS		
		Housing type and characteristics	Housing type	Old buildings	+	Vector exposure (at household-level)	
				Degraded loggings	NS		
				Apartment 2008–2009	−		
				Apartment 2012–2013	−		
			Construction material	Cement loggings 2008–2009	NS		
				Cement loggings 2012–2013	+		

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