

Fine-scale Landscape Variability of Cotonou City, Benin: Insights From Three Contrasted Urban Neighborhoods

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Abstract

Urbanization consist in a complex and deep human-driven environmental change that strongly impacts the ecology and evolution of living organisms, including pathogens, reservoir and vector species hence human health. Quantitative proxies of urban landscapes may be very useful to sum-up such a complexity and to guide fundamental and applied research as well as urban planning programs. Geographic Information Systems (GIS) provide landscape and uses metrics which can be investigated through multivariate analyses, thus providing pertinent synthetic landscape descriptors. As such, our study describes the fine-scale modelling of three urban neighborhoods of Cotonou city, Benin, using GIS, landscape metrics and Principal Component Analysis (PCA). Spatial variability between and within neighborhoods revealed different levels of variability, with elements differentiating the three areas from each other, while local neighbourhood-specific variations were also evidenced. We found that Cotonou landscapes are strongly influenced by their history, the natural environment in which they develop as well as the urban planning trajectories. This case study shows that PCA-analyzed of GIS-based metrics may be very relevant to describe and understand the variability of urban landscapes at different scales, thus constituting a valuable tool for urban management of African cities.

Introduction

Cities are booming, especially in Africa where planning policies hardly keep up with unbridled urban growth (UN-WUP 2018). This may result in the emergence of large unsanitary areas lacking adequate infrastructures (Acuto 2018) and/or of marginal spaces often located at the cities' outskirts (Halligey 2020). In such environments, where formal (e.g. roads, formally subdivided neighborhoods with hard-built houses, etc.) and informal (e.g. slums with precarious houses illegally built on sites that are sometimes unsuitable for settlement) settings may coexist, social, economic and health inequalities are glaring (Linard et al. 2012).

Urbanization represents a complex, extreme human-driven environmental change that strongly impacts the ecology and evolution of living organisms, hence biological interaction networks, through deep modifications of land use (Sun et al. 2020a), air quality (Liang and Gong 2020), hydrographic networks (Pradela and Zygmuniak 2017; Andreev et al. 2021; Molbert et al. 2021), temperature (Zhou et al. 2017) and available resources (reviewed in Rivkin et al. 2019). Some of the urban-dwelling species may be vectors or reservoirs of infectious agents; consequently, urban-associated eco-evolutionary changes may have important consequences in terms of human health, for example through increased human/animal interactions (Hassell et al. 2017; Dobigny and Morand, submitted).

The possible modeling and quantification of the landscape through Geographic Information Systems and associated mathematical treatments offer unique opportunities to rigorously characterize, and therefore to guide the arrangement of landscapes towards sustainable city building and management (Hu and Zhang 2020). Within the two last decades, these approaches have been undergoing significant conceptual and methodological development, together with the implementation of new tools that permit

quicker processing of increasingly massive datasets (Dumas et al. 2008; Ibrahim Mahmoud et al. 2016; Baker and Smith 2019; Akin and Erdogan 2020; Siqi and Yuhong 2020; Zhang et al. 2020; Javanbakht et al. 2021). Landscape metrics (Turner et al. 2001) provide numerical data describing the composition and physiognomy of landscapes and are well suited for even deeply modified environments such as the urban ones (Turner et al. 2001; Rossi et al. 2018). However, such approaches have rarely, if ever, been used to study intra-urban landscape variability in Africa.

Cotonou is a coastal city subject to seasonal flooding, and displays a high human density (8,593 hbts/km² in 2013); its extant population reaches 1,23 million inhabitants, a value that is expected to reach >1,6 million in 2030 (INSAE 2018). It is characterized by an overall low household economic situation, rather poor infrastructures as well as inadequate management of solid waste. In many areas, these features altogether contribute to degraded socio-environmental conditions which may be associated with important infectious risks (e.g. cholera and other diarrheal diseases, malaria, leptospirosis, etc.). The habitat in which certain poor neighborhoods of Cotonou have been sprawling (e.g. seasonally floodable lowlands) may further exacerbates the precariousness of the population and reinforces inequalities in terms of environmental exposure, hence welfare and health. In addition to public urban policies, improvement of inhabitants' life conditions within such spaces could rely on locally-conducted management actions, thus requiring good knowledge of the context, including fine-scale landscape descriptions that allows one to guide and evaluate management strategies.

In this study, we provide a quantitative exploration of the landscape variability in Cotonou city, Benin, based on the extraction of synthetic landscape descriptors and their analysis through subsequent multivariate analysis. To do so, we rely on Principal Component Analysis (PCA) which allows for the simultaneous analysis of a large number of landscape metrics (Rossi and Dobigny 2019; Lemoine-Rodriguez et al. 2020), in order to model the urban landscape of three neighborhoods at a fine scale, something that has been rarely, if ever, performed in Africa. We then explore their individual characteristics and spatial variability with the aim of identifying synthetic landscape descriptors for each of these neighborhoods and testing whether they could be helpful to potential research and management programs in the future. We found that the multivariate analysis of such metrics are indeed well adapted to the study of a rapidly changing urban spaces such as those found in Cotonou, thus bringing additional tools for urban ecologists and epidemiologists as well as urban planners and decision makers dealing with city policies and development strategies in Africa.

Material And Methods

Cotonou city and studied neighborhoods

Cotonou is located in the southern part of the Republic of Benin, between 6°20' and 6°24' North latitude and 2°20' and 2°30' East longitude. Before the colonial period, the current Cotonou area was probably home to a few isolated villages of Toffinou fishermen (Ciavolleta and Choplin 2018). Its location, favorable to the slave trade and then to the maritime trade of various commodities, is at the origin of the

first European settlements (Ciavollela and Choplin 2018). Its territory was ceded to France in 1868 (Brasseur-Marion 1953; Houngnikpo and Decalo 2013) and the construction of a wharf as early as 1900 in order to facilitate the transboarding of merchandises and people fueled the intensification of its role as an exchange hub (Janin 1964) and the development of the associated urban space. Though initially slow, Cotonou growth increased following the extension of the wharf in 1952 and the commissioning of a deep-water seaport in 1960 (Ciavollela and Choplin 2018). From there, its demography rapidly accelerated to reach 57,000 inhabitants in 1980, i.e. three times more than in 1945 (Capo 2008). Between 2002 and 2020, it grew from 665,000 to 1,190,000 inhabitants (INSAE 2018).

The city is compressed between Lake Nokoué at North, and by the Atlantic Ocean at South, thus undergoing spatial and demographic expansion to the East (towards Sémè-Kpodji, Porto Novo then Nigeria), to the West (towards Godomey, Cococodji, Cocotomey, Ouidah then Togo) and to the North on the West bank of Lake Nokoué (Abomey-Calavi). The sprawl of Cotonou thus participates to the formation of a wide urban area that occupies most of coastal Benin (INSAE 2017) and is part of the even larger, coastal so-called "Abidjan-Lagos corridor" that is in the process of giving rise to one of the largest African megacities expected to house up to 40 million inhabitants by 2050 (URBACOT 2017; Sun et al. 2020a). The core city has essentially sprawled into a low level sandy plain associated with a dense hydrographic network. Together with 1,200 mm of average annual rainfall, this results in repeated and sometimes long-lasting flooding events during most rainy seasons (Okou 1989).

In 2017, three model neighborhoods in Cotonou were investigated (Supplementary Information 1) as part of a broader program on small mammal-associated (essentially rodent-associated) zoonotic risks in urban and peri-urban settings of southern Benin. They were selected from previously established socioeconomic typologies (Dansou 2006) as well as our own observations to be representative of major neighborhoods profiles of the city. In Cotonou, flooding is an aggravating factor of households' precariousness and poor socio-environmental condition. Each year, they regularly force the poorest inhabitants to abandon their homes for several days when not weeks (PCUG3C 2012). The three neighborhoods studied here are also representative of the major flooding regimes that characterize the different areas of Cotonou.

Agla is a neighborhood in the process of rapid human densification and formalization. Some areas lack basic services (e.g. access to drinking water and electricity supply) and are home to economically poor households who inhabit very precarious housing structures. These zones correspond to large shallows that are humid all year round, but which sometimes overflow, from the beginning of the main rainy season onwards, due to the accumulation of rainwater. (NB: Agla has been the subject of many infrastructure developments since our work).

Ladji is a poor and densely populated informal settlement bordering and extending over Lake Nokoué (i.e., on-stilt cabans). Formal basic services are rare and housing range from hard-built to very precarious housing. Like almost all of the neighborhoods bordering the lake, it floods partially by overflowing of the lake several weeks/months a year, especially at the end of the rainy season. Waste produced throughout

the Cotonou city is partly dumped in vast unmanaged dumpsites, or sometimes used to fill-in the shallows and banks of the lake.

Saint-Jean is an old colonial-type neighborhood, formally subdivided and equipped with drinking water and electricity networks; however, hygiene conditions remain poor in many homes. In this neighborhood, rainwater accumulates in large puddles that sometimes persist during a few days, but the area does not undergo lasting floods *per se*.

Mapping the landscape: land covers and associated social uses

Land covers were defined a priori on the basis of preliminary prospections in the field and our own knowledge of Cotonou (Table 1; Supplementary Information 1). Spaces constituted of a unique continuous land cover were considered as homogeneous landscape units. The collect of landscape units were performed by foot, alley by alley, over a surface area of 529,931 m² in Agla, 223,873 m² in Ladj and 256,030 m² in Saint-Jean. To do so, we used an Android smartphone on which tools developed within the Open Street Map community (OSM, i.e. a collaborative project aiming to provide free open access mapping data) were installed: the KoBoCollect APK v1.23.3k suite of the KoBoToolbox (Harvard Humanitarian Initiative), ODK Collect 1.7.1 and OSM Tracker 0.6.11.

Table 1
Land covers that were collected, with their abbreviations in brackets

Land covers
Hard-built houses (Hard): closed enclosure buildings, made of permanent material (i.e. breeze blocks) and often cement / breeze block roofs.
Precarious houses (Preca): closed enclosure made of precarious material (raffia, bamboo, steel sheet, plastic).
Precarious spaces and roofed (Psr): spaces covered by steel sheets or raffia, but open on at least two sides.
Bush (Bush): dense, bushy vegetation cover.
Grassy-cover (Gras): herbaceous vegetation cover.
Sanitation (San): modern or traditional sanitation infrastructure (sewers, water-collector, culverts).
Wild dumps (Wdum): informal dumping sites.
Lake Nokoué (Nok): lake.
Cemented soils (Csoil): asphalt roads, paved roads, cemented terraces.
Bare soil (Bsoil): bare soils outside the buildings.

In addition to land uses, nine social uses associated with buildings were defined from field observations and further categorized according to the presence or absence of food stocks and/or foodstuffs, the presence or absence of humans at night as well as the presence of traded or manufactured non-food products (Table 2). During the mapping process in the field, each building (i.e., both hard-built and precarious houses) was systematically characterized for its social uses. Exceptionally, some buildings were characterized by two or more social uses (up to four uses for a single building), thus representing 7.4%, 3.3% and 11.6% of buildings of Agla, Ladji and Saint-Jean, respectively. In such cases, we relied on an a priori presumed attractiveness of social uses for small mammals (the focus of the wider program), particularly rodents, in order to retain only the most pertinent one. This led us to consider the following hierarchy, by decreasing attractiveness for rodents: presence of grain and other foodstocks = food shops > night dwelling > restaurant = bar > artisanal craft > non-food shops > services and offices. As an example, a building showing both the “dwelling” and “presence of grain and other foodstocks” social uses was finally associated with “presence of grain and other foodstocks”. In doing so, we were able to assign a unique social use to each building.

Table 2

Social uses associated with buildings, with their abbreviations in brackets. See text for details

Social uses associated with buildings
Services and office (Serv): buildings that do not contain food storage, are not shops neither occupied at night (e.g. offices, schools, religious buildings).
Dwelling (Dwel): buildings that are occupied at night (e.g. houses, hotels).
Food storage and cooking space (FsCs): food storage, cooking and/or processing spaces, non inhabited at night (e.g. fish roasting sites, doughnut cooking, restaurants, food shops, butcher shops, grain and condiment mills, street kiosks/cafeterias, bars).
Manufacturing space (Manu): spaces dedicated for trade, manufacturing or storage of non-food materials (e.g. craft mechanical workshops and woodworking shops), hardware stores, printing works, sawmill).
Shop (Shop): non-food items store (ex. clothes, shoes, bags, thrift store).
Breeding-pens (Bpen): livestock infrastructures (livestock pens, hen houses).
Uninhabited (Uhab): uninhabited, neglected and/or empty buildings (i.e., houses under construction, abandoned houses).
Toilet (Toil): hard-built permanent buildings used as a public toilet.
Cars station (CarS): bus station, parking lots.

All land cover and associated social uses were digitized on a 2016 Spot 7 (multispectral) satellite image base, 6m resolution. UTM projection to WGS 84 was implemented in QGIS v3.16.2 software. This digitizing process resulted in shapefiles (Supplementary Information 1) which were then converted to 0.5

m resolution raster files (Supplementary Information 2) where each pixel is characterized by a specific value corresponding to landscape unit.

Computation of landscape metrics

Rasters were processed under R (R Core Team 2020) in order to allow for the extraction of local mini-landscapes following a moving window strategy (McGarigal et al. 2012). Mini-landscapes were represented by circular buffers which were preferred to square ones due to equidistance between the center and all edge points. In Cotonou, mapping of the above-mentioned landscape units was carried out on a perimeter covering an area whose edges were at least 100 meters away from the sampling sites (the most distant) – the latter being selected as part of a broader program on zoonotic risks in urban and peri-urban areas in southern Benin. On a square grid of 5 m mesh size, a series of 30m radius buffers (mini-landscapes) were extracted from 20,398 points in Agla, 8,213 points in Ladjì and 9,766 points in Saint-Jean. In order to avoid edge effects (i.e., the influence of “incompleteness” of edge-located buffers on the metrics calculation), all buffers that were crossed by the edges of the neighborhoods right-of-way were removed.

Landscape metrics (Table 3) were computed using the R package "landscapemetrics" (Hesselbarth et al. 2019) on all individual buffers for the 10 landscape units and the 9 social uses associated with buildings described here above. The class-level landscape proportion (PLAND) was calculated for each landscape unit in order to quantify the composition of the landscape through the proportion of area covered by each land cover type. The Modified Simpson’s Evenness Index (MSIEI) and the Edge Density Index (ED) were measured for both land covers and social uses in order to obtain synthetic indices of landscape diversity and complexity, respectively, thus reflecting of the intermingling of the different patches (Gerbeaud Maulin and Long 2008). Altogether, the landscape was thus described by 23 quantitative metrics.

Table 3

Landscape metrics used to describe the urban neighborhoods landscape within Cotonou (adapted from McGarigal et al., 2012). Level indicates if the metrics are computed for land-cover classes or for landscape taken as a whole. See text for details

Names (acronyms)	Levels	Descriptions	Units	Extents
Percentage of landscape (PLAND)	Class	Measures the proportional abundance of each landscape unit type in the landscape: landscape composition	Percentages	$0 < \text{PLAND} \leq 100$
Modified Simpson’s Evenness Index (MSIEI)	Landscape	Measures the level of diversity achieved in the landscape	None	$0 < \text{MSIEI} \leq 1$
Edge density (ED)	Landscape	Measures the length of the contours of all landscape units per unit area	Meters per hectare	$\text{ED} \geq 0$, with no upper limit

Principal Component Analysis (PCA) of landscape metrics

The Principal Component Analysis allows one to explore the relationships between a large set of descriptors (here, the metrics used as variables) as well as to identify and quantify the sources of landscape variability (see Rossi and Dobigny 2019, for an urban example).

A first PCA analysis (PCA-Cot) was conducted at the scale of the Cotonou city by pooling the three studied neighborhoods, namely Agla, Ladjì and Saint-Jean datasets. Three other analyses were conducted at the neighborhood scale, i.e. on each neighborhood considered independently (PCA-Agl for Agla; PCA-Lad for Ladjì; and PCA-Jea for Saint-Jean).

Mapping of scores on principal components

The coordinates (scores) of each mini-landscape along the principal components (PC) were used to map the landscape characteristics as identified by the PCA (Supplementary Information 2). To do this, each pixel of the map was associated with its score along one of the different PCs. A colored gradient was used to reflect the range of scores, and allowed us to visualize the spatial variability of the PCA scores across the urban space (Rossi and Dobigny 2019). Such a spatial projection of the PCA scores was used to visualize the landscape variability within each of the three neighborhoods, either when analyzed together (PCA-Cot) or separately (PCA-Agl, PCA-Lad and PCA-Jea).

Results

At the Cotonou city scale (PCA-Cot)

In PCA-Cot pooling all three neighborhoods, PC1 (19.10%), PC2 (9.72%), PC3 (7.97%) and PC4 (7.09%) accounted for 48.88% of the total inertia. The distribution of the buffers along the scores of the PCA largely overlapped, especially towards the positive values of PC1 (Fig. 1a). The cloud of points that correspond to Saint-Jean appeared more compact than those representing the other two neighborhoods (Fig. 1a). Ladjì cloud of points stretched towards the negative side of PC1 and PC2. The Agla cloud of points was also strongly stretched towards the negative values of PC1.

When looking at the contribution of variables to PCs (Fig. 1b), overlaps between neighborhoods appear associated with the hard-built houses (Hard) with multiple uses (Ed.U, Msiei.U) including dwelling (Dwel). Nevertheless, Saint-Jean partly differed from the other two neighborhoods with some pixels showing the preponderance of hard-built dwellings with multiple uses (Hard, Ed.U, Dwel, Msiei.U, Ed.C). In the same manner, many points from Agla was distinguished from Saint-Jean and Ladjì by the importance of bushy shallows (Bush), while some areas of Ladjì appeared distinct due the presence of Lake Nokoué (Nok) and some shallows.

Along PC3 (Supplementary Information 3), shallow areas with a few hard-built houses (towards positive values of the axis) contrasted with bare soil (Bsoil) areas dotted with precarious roofed spaces (Psr) and houses (Preca) (towards negative values). Along PC4, the grassy-cover (Gras) often used as wild dumpsites (Wdum) and/or breeding-pens (Bpen) (positive values) was opposed to the lake and its banks (Nok, Preca, Msiei.U; negative values) (Supplementary Information 3).

The projection on the map of the three neighborhoods of each pixel scores retrieved on PC1 and PC2 of the PCA-Cot is presented in Figure 2: several landscape elements could be clearly identified, such as the hard-built dwellings (represented by positive values on PC1), Lake Nokoué in Ladji, the shallows and wild dumps in Agla and Ladji (negative values on PC1), as well as the streets in Saint-Jean (negative values). Along PC2, bare soil, offices and various services (positive values), precarious houses, grassy-cover used as wild dumps in Agla and Ladji, and Lake Nokoué in Ladji were represented by negative values (Fig. 2b).

At the neighborhood scale (PCA-Agl, PCA-Lad and PCA-Jea)

In PCA-Agl that focuses on Agla landscape metrics (Fig. 3a), PC1 (24.23%) and PC2 (11.15%) accounted for 35.38% of the total inertia. The PC1-PC2 plan explicitly separated low-diversity areas with shallows (Bush) that regularly served as wild dumpsites (Wdum) (towards negative values of PC1 and positive values of PC2) from high-diversity (Msiei.U), complex (Ed.U, Ed.C) and dwelling-dominated (Dwel) areas, especially those with hard-built and precarious houses (Hard and Preca) (positive values of PC1 and negative values of PC2). The spatial projection of the PC1 scores of PCA-Agl (Fig. 3a) confirmed this clear segregation between the inhabited areas (which represent most of the pixels) and the shallow areas. PC2 showed more clearly the spatial separation between bare soil areas with precarious houses and areas with hard-built houses dominated by vegetation and shallows.

The first and second principal components of PCA-Lad (Ladji; Fig. 3b) accounted for 22.93% and 13.25% of the total inertia, respectively. Along PC1, complex areas (Ed.U, Ed.C) with hard-built dwellings (Hard, Dwel) on dry land (Bsoil) (positive values) were opposed to the permanent waters of Lake Nokoué (Nok). Along PC2, the wild dumpsites (Wdum) covered with grass (Gras) and often surrounded by bare soil (Bsoil) (negative values) were distinct from areas composed of precarious dwellings (Preca, Dwel) with multiple uses (Msiei.U and Ed.U) and frequently located at the edge of Lake Nokoué (Nok). The spatial projection of PC1 scores on the Ladji landscape PCA-Lad is shown in Figure 3b. The Lake Nokoué area (negative values) is clearly distinguishable from the complex and diverse dry land area, with many hard-built dwellings (positive values). The same dichotomy as well as the opposition between grass-covered dumpsites (negative values) and precarious dwellings (positive values) were clearly visualized with the projection of the scores obtained along PC2.

PC1 (23.95%) and PC2 (12.58%) accounted for 36.53% of the total inertia of the PCA-Jea conducted on the Saint-Jean dataset (Fig. 3c). Along PC1, hard-built dwelling areas (Hard, Dwel) (positive values) were distinguished from bare soil (Bsoil), cemented soils (Csoil) and sewers or sewage collector (San). Along PC2, precarious houses (Preca) and craft workshop (Manu) lying in an environment dominated by bare soil (Bsoil) (negative values) were opposed to cemented soils (Csoil) and hard-built houses mainly used

for services and offices (Serv). The structure detected by the PCA was well illustrated by its projection on the physical map of Saint-Jean, since PC1 scores clearly retrieved the large open sewage collector (negative values) and the blocks of dwellings (positive values) separated by well-defined roads (negative values). In addition, PC2 showed the spatial separation between precarious houses, craft workshop areas dominated by bare soil (negative values) and cemented soils areas (positive values) (Fig. 3c).

Comparison of the city-wide and local PCAs

The PCA correlation circles that show the variables most involved in the PC1 and PC2 constructions of the inter-neighborhood (Fig. 1; PCA-Cot) on the one hand, and the intra-neighborhood (PCA-Agl, PCA-Lad, and PCA-Jea on Fig. 3a, b, and c, respectively) analyses on the other hand, was quite similar. They point towards the same variables that stretched PC1 at both the Cotonou and the local (i.e., at each neighborhood) scales: "hard-built houses", "dwelling" and "complex and diverse" were opposed to "shallows", "Nok" and "bare soil" in both analyses. In the same manner, a few common variables (e.g. "bare soil," "precarious houses," and "Nok") characterized many of Ladji's points both globally (PCA-Cot) and locally (PCA-Lad) along PC2.

Discussion

Landscape variability

Landscape metrics are important tools as they allow for the quantification and analysis of landscape variability, both between and within cities (Lechner et al. 2020). Examples of between-cities differences in urban landscapes are numerous (e.g. Ding 2021). Using multivariate analyses of metrics, we here provide a clear illustration of within-city variability that was detected between as well as within urban neighborhoods, thus demonstrating the usefulness of such approaches for fine-scale studies.

First, the three neighborhoods studied here contrasted sharply. The Saint-Jean neighborhood, with its many hard-built houses and formal organization, differed from Agla, which was dominated by the presence of vast areas of shallows that often sheltered a thick vegetation within which dwellings develop in a sometimes quite anarchic manner. The two previous neighborhoods differed from Ladji which is primarily characterized by the presence of Lake Nokoué and the associated constraints imposed to the riverside spatial and social organization. This first level of variability was clearly detected by the multivariate analysis of metrics implemented from land and building-associated social uses. This remained true whatever the PCAs were conducted globally (PCA-Cot; i.e. with the three studied sites pooled) or locally (PCA-Agl, PCA-Lad and PCA-Jea; i.e. with the three sites investigated independently and compared a posteriori).

Second, we also revealed finer levels of landscape variability within each neighborhood. In Agla, our analysis succeeded in showing that shallows are often associated with wild dumpsites and are spatially dissociated from the spaces where habitations stand. More subtly, the hard-built dwellings in vicinity of shallows were opposed to the precarious houses that are rather located in bare soil areas (mostly

representing streets and multi-family dwellings courtyards). Agla is currently undergoing very rapid changes. Indeed, this neighborhood was a shallow area and was only recently colonized by the inhabitants of Cotonou (<30 years). It is now one of the most densely populated areas of the city and continues to grow very rapidly with large areas of shallows gradually disappearing in favor of human settlements. Huge quantities of garbage from other neighborhoods of Cotonou city are brought in and dumped in the shallows to serve as fill (our own observations). Major works in progress (started after our field surveys) aim at formalizing the development of the area, and at improving its sanitary situation, in particular by collecting and channeling part of the rainwater that used to be at the origin of the vast annual floods. Ladji is an outlying neighborhood located on the shore of Lake Nokoué. On the dry land, we could distinguish spaces occupied mainly by hard-built dwellings from those characterized by dwellings made of precarious material as well as grassy-covered wild dumpsites. This is indeed characteristic of this neighborhood, although a vast development project may accompany the construction of a major road and an interchange within this particularly unhealthy informal area. Finally, in Saint-Jean, the synthetic landscape indices efficiently retrieved a clear spatial segregation between hard-built dwellings, bare soil surfaces and cemented soils. These elements correspond perfectly to the formal and rectangular street grid (cemented soils or bare soil) of this central and relatively old neighborhood on the one hand, and the dwellings blocks that are characterized by a majority of definitive material housings (i.e., hard-built houses) organized around large sandy courtyards (i.e., bare soil) on the other hand.

Impact of Cotonou history on the current landscape of its neighborhoods

The landscapes of Cotonou neighborhoods are strongly impacted by their history and the socio-environmental context in which it took place. As an example, being of colonial origin, the neighborhood of Saint-Jean was one of the first neighborhoods in Cotonou to benefit from major development work (e.g. design of formal streets, construction of hard-built houses, large sewage collector). So, the global structure of Saint Jean landscape is characterized by the well-aligned blocks of hard-built buildings, cemented streets and sandy alleys that regularly subdivide the area. The local name of Agla (Agla houn, bo wa! in the Fongbé language - "if you are bold, then come") refers in part to the many shallows that make human settlement difficult. Indeed, its hydromorphic soil and bowl topography make the area particularly prone to flooding today, especially since some adjacent neighborhoods (e.g. Houehiyo) have been filled in, developed and extensively cemented (Okou 1989). Originally, only a few indigent residents lived there. From the 1980s and especially from the 1990s, the area progressively densified against the shallows (URBACOT 2018), which is consistent with the outputs of our synthetic landscape proxies, i.e. the marked opposition of shallow spaces to spaces dominated by human settlements.

Similarly, the demographic growth of Cotonou over the last few decades and the urban sprawl that followed have inexorably caused the Cotonou city to move in the direction of Ladji ("where we land" in the Toffinou language) on the edge of Lake Nokoué. Initially occupied by xwla fishermen's villages installed on the lake (on-stilts cabans) or along the banks, Ladji was overtaken by the expansion of the Cotonou city from the 1980s onwards, then rapidly densified thereafter (URBACOT 2018). The presence of many

Toffinou populations accustomed to living on or near the lake (Ciavolletta and Choplin 2018), the difficulties of developing this informal and marshy space and the chronic poverty of often marginalized populations translate into clearly visible landscape signatures detected by our analysis, such as the lake, a mosaic of hard-built and precarious houses and the presence of several grassy-covered wild dumping sites on the dry land.

Urban landscape variability at various scales

Each neighborhood displays specific landscape features that were described above. But, interestingly, our comparative analysis of the global (PCA-Cot) and local (PCA-Agl, PCA-Lad, and PCA-Jea) PCAs also allowed us to detect landscape elements that were common to all three neighborhoods. For instance, the partial overlap of the Agla, Ladji and Saint-Jean clouds in PC1 as well as the sharing of variables strongly involved in the construction of the components of PCA (global and local) point towards quantitative landscapes elements that are shared across the city (e.g. hard-built houses, dwelling, complex and diverse). This further confirms that the method employed here is relevant to describe and to understand urban landscape variability at various scales.

Importance of urban landscape characterization

Cities are drastically transformed habitats that are strongly marked by human activities. As such, they are unique ecosystems with highly significant and complex eco-evolutionary effects on the organisms living there (Johnson and Munshi-South 2017; Rivkin et al. 2019; Alberti et al. 2020). Unfortunately, the urban environment is often considered a single homogenous entity, as illustrated by very recent meta-analyses that typically and simplistically contrast the urban vs. the non-urban environment (e.g. Gibb et al. 2020; Werner and Nunn 2020; Albery et al. 2021), sometimes with an intermediate category, hardly defined neither, i.e., the peri-urban environment (Amirinejad et al. 2018; Kryvobokov et al. 2020). Yet, sources of landscape variability between (e.g. Li et al. 2021) and within cities (e.g. Rossi and Dobigny 2019; this study) may be numerous, multi-factorial and complex. GIS-based approaches (such as that of the present study) allow one to investigate the interactions between urban landscape and a wide spectrum of sociological features, patterns and processes (e.g. human actions and interactions: Rijke et al. 2020; attractiveness and vitality of human environments: Wu and Niu 2019; Kang 2020; population density: Wu and Niu 2019; Song et al. 2021). Urban pattern may also influence local temperature variations (e.g. Zhou et al. 2017; Liu et al. 2018; Sun et al. 2020b), air pollution (e.g. Jaafari et al. 2020; Liang and Gong 2020), the structure and dynamics of communities of organisms that feed and/or live, and thus evolve in cities (e.g. Alberti 2015; LaPoint et al. 2015; Johnson and Munshi-South 2017; Rivkin et al. 2019; Alberti et al. 2020; Hassel et al. 2021), thus impacting many animal, environmental infectious, and zoonotic diseases ecology (e.g. Rossi et al. 2018; Murray et al. 2019). The spatial variability of the urban landscape is typically accompanied by social inequalities (e.g. spatial segregation between rich and poor: Najib 2020; Le Roux et al. 2020; land and rental value of real estate: Lejeune et al. 2016; Kryvobokov et al. 2020) that translate into a wide panel of health and well-being inequalities, such as heat-related mortality (Ellena et al. 2020), household water accessibility and usage patterns (Satur and Lindsay 2020), and burden of

infectious diseases such as malaria (Gomes et al. 2020), dengue (Machado et al. 2009; Carabali et al. 2020) or leptospirosis (Blasdel et al. 2019; Minter et al. 2019; Yusof et al. 2019; Biscornet et al. 2021).

These examples highlight the importance of quantitative characterization of urban areas that provides a repeatable and objective measure of urban landscape variability. It should be systematically considered in both urban research and city management. One of the immediate applications consists in the design of sampling strategies that would explicitly take the urban diversity of landscapes, particularly within the same city, into account (Rossi and Dobigny 2019). For instance, in the present study, the difference in working scales (city-wide vs. local) could open the gate to a neighborhood-specific sampling design that would encompass all landscape variations. Other applications include the use of quantitative proxies for the set-up and follow-up of urban management, thus providing robust elements for decision, for the design, implementation and monitoring of urban planning actions (e.g. Aguilerra et al. 2011; Yang et al. 2019; Hu et al. 2021). The quick and efficient visualization of urban landscape variability through metric-based PCAs may also be a major asset to greatly facilitate dialogue and close collaboration between experts from the different disciplines involved (e.g. biologists and physicians, geographers, sociologists and anthropologists, climatologists, hydrologists, etc.) and the actors in charge of city policies.

Conclusion

All in all, our results thus illustrate how an approach based on PCA analysis of landscape metrics allows one to describe the structure and evolution of city landscapes at very local scale, even in the case of quickly changing urban areas. Consequently, such multivariate investigation of landscape metrics appear quite useful to detect and to describe both inter-neighborhood as well as fine-scale intra-neighborhood landscape variability, thus providing an interesting tool for the description and monitoring of urban organization. A major obstacle to the generalization of this approach lies in the tedious collection of field data (i.e., field mapping). Nevertheless, it can also be applied to data acquired in a more automated way (e.g. satellite images, drone-mediated acquisition), although this does not generally allow for the integration of certain data, such as usage data that were included here based on the Open Street Map toolkit (OSM 2017). The latter is freely available and allows easy-to-implement mapping directly from the ground; in addition, participative approach may make possible the acquisition of more and more numerous and the cartography of increasingly vast areas (<https://www.openstreetmap.org/#map=17/6.36396/2.41592>).

Declarations

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Author's contributions

Henri-Joël DOSSOU (HJD), Jean-Pierre ROSSI (JPR) and Gauthier DOBIGNY (GD) designed the study. HJD and Mariano Davy SOSSOU (MDS) conducted the mapping in the field as well as the management of collected data. HJD and JPR performed the analyses. All authors contributed to the writing of the manuscript.

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Competing Interests

The authors declare no competing interest.

Data and materials

Data and materials are available from the corresponding authors upon request.

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Figures

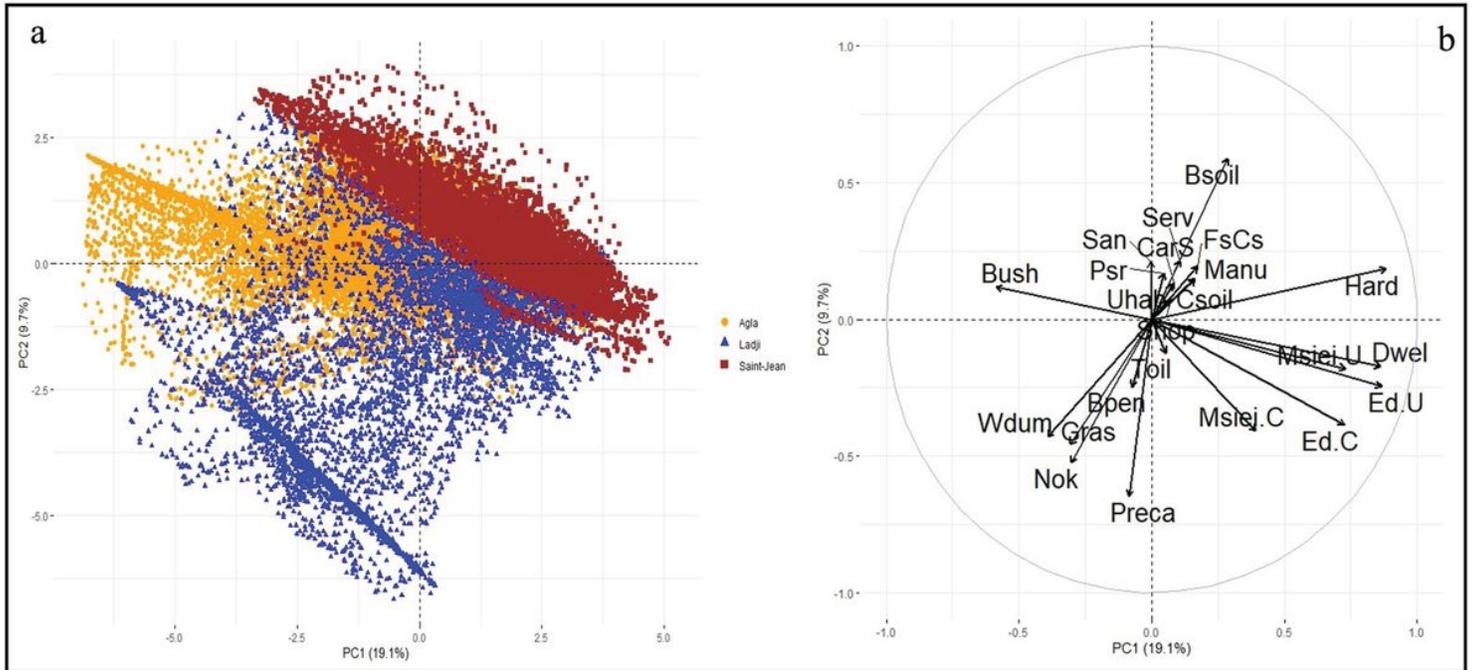


Figure 1

PC1-PC2 plan of the PCA-Cot on the 23 landscape metrics at the Cotonou city scale. (a) Graphical representation of the sampling points, and (b) Graphical representation of the associated variables

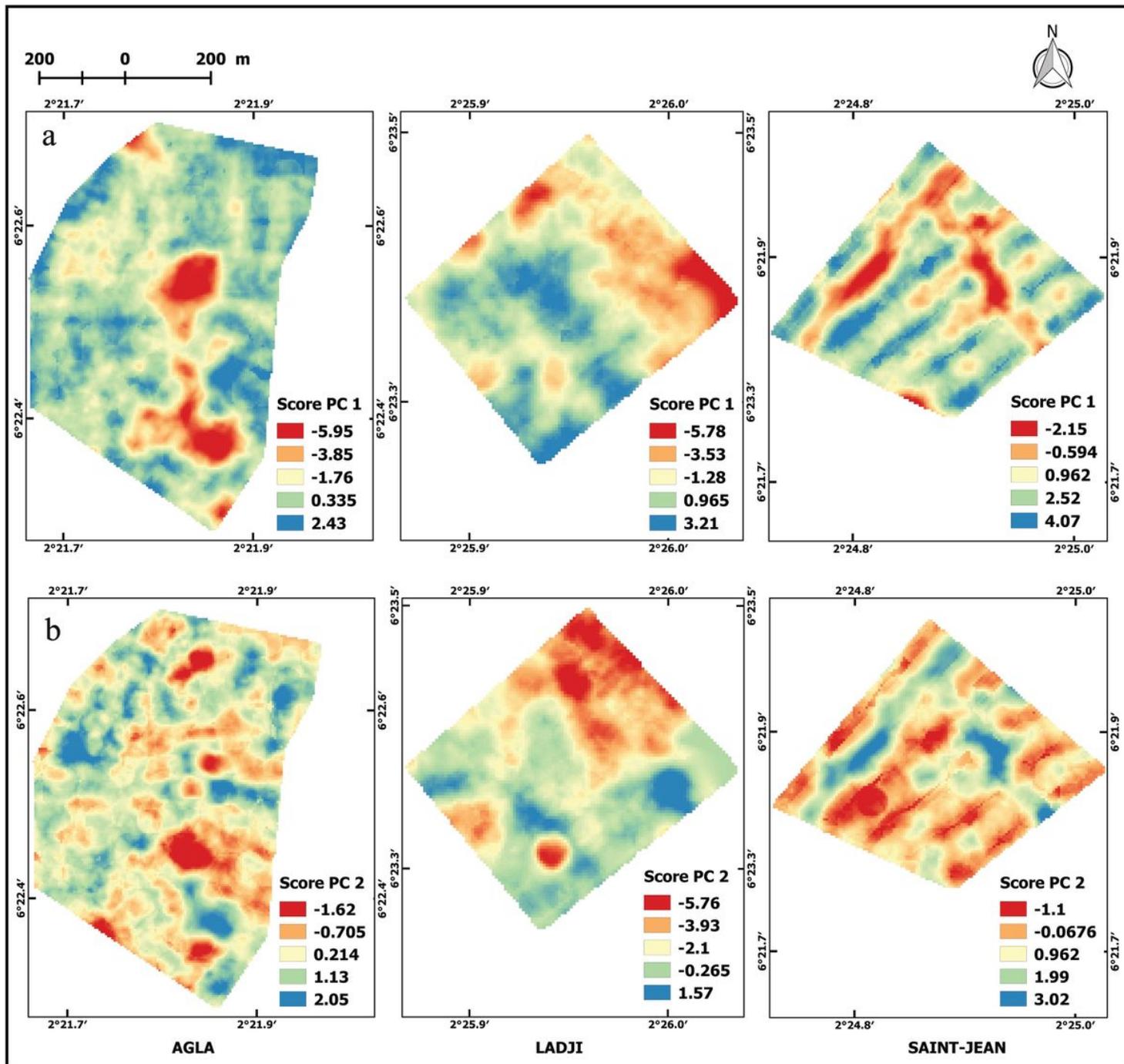


Figure 2

Mapping of each pixel's (i.e. buffer) scores along PC1 and PC2 retrieved from PCA-Cot analysis. (a) Mapping of PC1 and (b) PC2

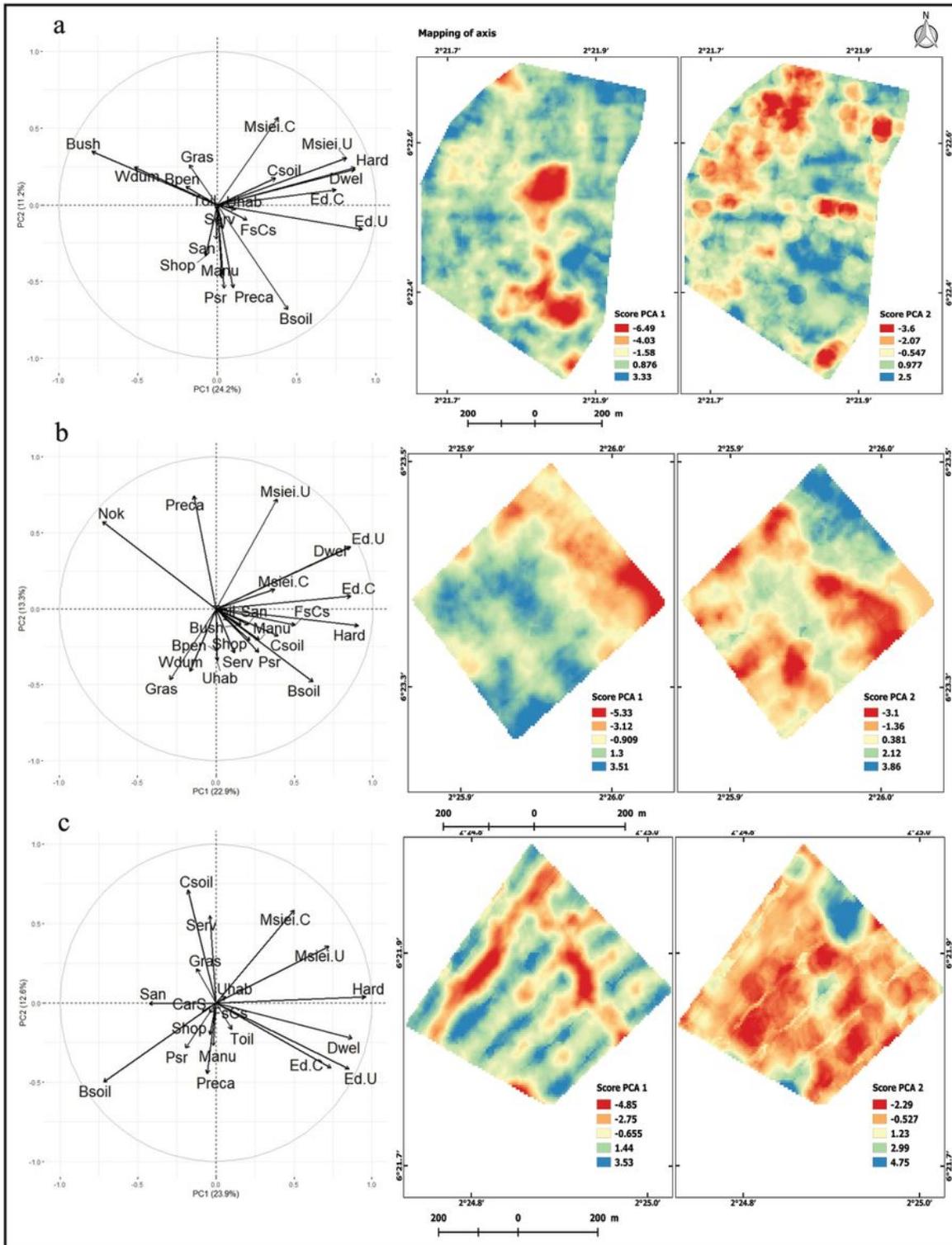


Figure 3

PCA-Agl, PCA-Lad and PCA-Jea of the landscape metrics of the Agla (a), Ladji (b) and Saint-Jean (c), and mapping of respective scores along PC1 and PC2 in each neighborhood

Supplementary Files

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