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Mapping tourist hot spots in African cities based on Instagram images

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Abstract

Knowing in which areas tourists concentrate is fundamental for managing its effects. However, to date, research in this subject has mainly been carried out only in European and North American cities. The current article, in contrast, focuses on six African cities. We have analysed the spatial concentration of the images captured by Instagram users to identify the most visited locations. The results obtained show how there is a strong spatial concentration of images in African cities, little territorial continuity between the spaces visited, and a predominance of private attractions. These are important differences with respect to what has been described in the literature in other contexts.

KEYWORDS

African cities, Instagram, spatial analyst, urban tourism, user-generated images

1 | INTRODUCTION

The growth in the number of tourists at the global level is a constant. According to data from the World Tourism Organization (UNWTO, 2019), the number of international tourists in the world passed from 595 million in 1996 to 1,401 million in 2018. During this same period, the "African region" went from receiving 22 million tourists a year (3.7% of the total) to 67,1 million (4.8%). Even so, certain barriers remain that restricts the development of tourism in this region, where there are relatively few countries that receive important volumes of tourists. For example, in 2018, only Morocco, Tunisia, and South Africa received more than three million international tourists. There are also significant local conditioning factors, such as the fact that only 3% of Africans travel abroad (International Air Travel Association, 2014). Despite these difficulties, Africa has, however, been gaining weight in terms of tourism (UNWTO, 2019).

However, despite this growth, only a few studies have analysed the tourist behaviour in Africa (Saayman, Viljoen, & Saayman, 2018). This lack of data has conditioned the possibilities of obtaining replies to questions such as: Which spaces do tourists visit? Do they concentrate in certain specific spaces, or are they well-distributed across the territory? Are there any similarities between the types of places visited in different countries?

To respond to these questions, the current article analyses the situation in six different African cities via geolocalized information based on the images that tourists have posted on the Instagram social media site. Instagram allows us to easily access geolocalized information about tourist hot spots (Brantner & Rodriguez-Amat, 2016), and by using Instagram, it is possible to identify relationships between tourists and the urban space (García-Palomares, Gutiérrez, & Mínguez, 2015; Paül i Agustí, 2018). These are complex relationships, in which the tourist is both the producer and consumer of images (Urry, 1990).

Despite these strong points, the use of Instagram presents several limitations. The first of these is that the popularity of Instagram varies from country to country, which is a factor that could influence the obtained results. Moreover, unlike other social media which have been used in other studies (such as Twitter), Instagram does not offer free access to information. This makes its exploitation more difficult. In more general terms, there is also a limitation of deriving the prior selection of the images that its users wish to share via the Internet. Furthermore, it is not possible to access the private profiles of its users without prior authorization. This could condition the selection of the places shared on the Internet (Bauder, 2016). Finally, there is also a time limitation. Searching for historical Instagram images has its limitations and tends to condition the total number of days that can be considered. Even so, recent studies have shown that Instagram outperforms Twitter and Flickr in representing monthly visitor patterns for various natural parks (Tenkanen et al., 2017). To a large extent, this is due to the fact that "Instagram acts both as an archive for discourse about a destination and as a vector through which experience can be performed" (Smith, 2018, p. 3).

Although Instagram is considered as one of the most popular social networks worldwide, this source has hitherto been relatively used little by the academic community (Smith, 2018; Tenkanen et al., 2017). Instagram images have been used to analyse tourist behaviour in various different cities. That said, in the majority of cases, these have been western cities, with long traditions of tourism: cities in the USA (Pat, Kanza, & Naaman, 2015), Europe (Loiseau, Djebali, Raimbault, Branchet, & Chareyron, 2017), Asia (Hu et al., 2015) or the Americas (Paül i Agustí, 2020). The present research adds the study of six African cities to the existing literature. In this way, we wish to add knowledge about this area to the on-going debate about the effects of tourism on the urban space. More specifically, we show how user-generated images can provide a very useful tool for analysing the strong and weak points of the spatial distribution of tourism in major African cities.

2 | THEORETICAL FRAMEWORK

2.1 | Tourist images

The image of a tourist destination tends to be socially constructed (Watkins, 2005). It is based on a complex relationship which includes "the sum of beliefs, ideas, and impressions that a person has of a destination" (Crompton, 1979, p. 18). Thanks to this, its study constitutes an important tool for analysing place (Hunter, 2016).

Photographs taken by tourists form part of this image. When tourists visit a city, they have normally acquired a series of information via images created by various tourism-related agents (projected image) (MacKay & Fesenmaier, 1997). However, tourists do not automatically reproduce the projected image. They are capable of creating new images that show their own personal experiences (Stylianou-Lambert, 2012). In this way, a study of tourist-generated images allows us to obtain a much richer insight into the analysed urban reality.

Although some actors question the weight of the image of a destination due to lack of its concreteness (Hughes & Allen, 2008), or question the role of the tourist in creating the image of the destination (Govers & Go, 2005), the majority of authors accept the image of the destination as a multidimensional concept (Gallarza, Saura, & Garcia, 2002). That said, there are differences of focus regarding how to study this. Different studies all too often analyses the image in an individual way, based—for example—on the number of photos, comments and/or likes that a particular tourist attraction receives. This may prove a limitation, as it does not take into account the complexity of the relationships in the urban space (Capone & Boix, 2008). Georeferencing the images provides more territorial approximation in which the existing spatial interrelationships are clearly identified.

2.2 | The image and its representation in the space

The appearance of social networks has resulted in a change in the way that we can study the relationships between tourism and space. The availability of georeferenced images revealing tourist behaviour has, in a certain way, "democratized" the process of creating and disseminating images relating to tourism (Lo, McKercher, Lo, Cheung, & Law, 2011). This has meant that social networks have become an element that mediates in travel experiences and influences the places that tourists visit (Zheng & Gretzel, 2010).

Every tourist generates their own social spaces on their social networks (Watkins, 2005). The large number of images present on social networks makes it possible to map tourist behaviour and experiences within a wide urban space (Su, Chen, Yixuan, & Zhongliang, 2016). As a result, we had able to identify areas where tourists move freely and others that they rarely visit (Cesario et al., 2016). In short, "geospatial data reveals important structural ties between photographs, based on social processes influencing where people take picture" (Crandall, Backstrom, Huttenlocher, & Kleinberg, 2009, p. 761).

In this way, it is possible to incorporate a new aspect into the debate about the impact of tourism on the urban space. Mapping Instagram images make it possible for us to identify links between cities and the spatial behaviour of the tourists who visit them (Gilbert & Barton, 2013). For example, new tourist attractions can be recognized that do not appear in the images projected by traditional media (Paül i Agustí, 2020) and this can transform traditional conceptions of public space (Brantner & Rodriguez-Amat, 2016). Furthermore, this also makes it possible to establish relationships between the different places preferred by tourists. As Crompton (1979) observed, two nearby tourist attractions may both attract some visitors who had initially planned to visit only one of them.

The existing academic literature has analysed the image portrayed via social networks based on three main approaches (Zhang, Chen, & Li, 2019): (a) Giving priority to metadata and, above all, GPS coordinates (García-Palomares et al., 2015; Hays & Efros, 2008); (b) Using an approach based on text tags and geospatial data (Crandall et al., 2009; Stepchenkova & Zhan, 2013); and (c) Analysing image content (Hays & Efros, 2008; Mak, 2017). Each of these approaches can be followed by adopting a relatively conventional manual approach or one using IT tools.

The IT approach allows us to handle a high volume of information with a clear level of standardization. However, such analyses are conditioned by two important factors: the need for powerful IT resources and for social networks that provide free access to the required information. Furthermore, the coding and machine training phase requires an important degree of dedication. For certain studies, this time can be comparable with that required for manual codification. On the other hand, the conventional approach offers a relatively mature conceptual and theoretical framework (Zhang et al., 2019). With this in mind, our study has mainly relied on manual codification. We carried out a first level of data collection based on the automatic treatment of GPS data made by Instagram. Then, the final analysis of the location was based on combining the image content with the associated text.

2.3 | The study of tourism in African capitals

The number of academic studies that have focused on Africa is rather limited (Avraham & Ketter, 2017; Shen et al., 2018). The majority of articles have analysed the case of South Africa and, to a lesser extent, English-speaking African countries. Few studies have looked at French-speaking or Portuguese-speaking countries. Some sources have quantified this English-speaking predominance by pointing out that South Africa has concentrated 60% of the articles published, followed—at a distance—by Zimbabwe and Ghana. Other countries (the ones studied by the present article include Kenya, Tanzania, Mozambique, and Uganda) have either only had a testimonial presence or have had no previous articles about them (e.g., Senegal) (Rogerson & Rogerson, 2019). Furthermore, the majority of the articles published have been case studies rather than comparative analyses. As a result, we find ourselves faced with very limited previous research into African urban tourism (Shen et al., 2018).

Furthermore, articles on Africa and its tourism have tended to give a fairly negative focus: wars, natural disasters, and epidemics (Avraham & Ketter, 2017). In recent years, this image has, however, changed towards more positive aspects (Bunce, 2016). In the field of tourism, the predominant themes have been related to the economy (Rogerson & Visser, 2014) and the environment, including such topics as sustainable tourism, wildlife tourism, and ecotourism (Shen et al., 2018). Cities have, however, only been the focus of a partial analysis, and one framed within analyses focusing on pro-poor tourism or slum tourism (Coles & Mitchell, 2009; Rogerson & Visser, 2014; Shen et al., 2018). Even for thematic areas in which, in the western context, the presence of cities is habitual, African experiences have tended to focus on non-urban settings, such as in the study of cultural tourism (Manwa, Moswete, & Saarinen, 2016) or heritage tourism (Rogerson & Van der Merwe, 2016). This has limited our knowledge of urban tourism in Africa.

The Internet somewhat has changed this situation. Internet is a source that also shows the urban image of Africa. Access to mobile Internet, which is a basic requirement for the use of social networks, has undergone major growth, particularly in the largest cities (The World Bank, 2019). This implies that this area has the necessary infrastructure to allow tourists to share their photos on Instagram. Thus, the diffusion of the images of African cities in Internet can help to show a richer and more diverse landscape. In this way, the images posted on social networks help to promote the economic, social, and environmental development of African cities.

2.4 | Methodology

2.4.1 | Case studies

This study was based on the Africa region of the World Tourism Organization (UNWTO). This region is approximately equivalent to the whole of the African continent, but excluding Egypt. The region receives 5% of global international tourist arrivals and 3% of international tourism revenue. This was the region which exhibited the greatest growth in the number of arrivals of international tourists in 2018 (UNWTO, 2019).

Within this region, we excluded the countries along the Mediterranean coast (Algeria, Morocco, and Tunisia) and also South Africa. These countries alone represent 51% of the arrivals of internationals tourists to this region. We considered that these were therefore much better consolidated tourist destinations than the rest of the region and that they probably followed a series of different logics to those that we wished to study.

From the rest of the countries, we selected cities that appeared in the MasterCard Global Destination Cities Index (MasterCard, 2018). This index ranked the world's top 162 destination cities in terms of visitor volume and spending for the calendar year 2017. The cities chosen were Accra (Ghana), Nairobi (Kenya), Maputo (Mozambique), Lagos (Nigeria), Dakar (Senegal), Dar es Salaam (Tanzania) and Kampala (Uganda). We finally discarded Lagos, however, due to the lack of tourist images that presented its profile on Instagram.

The cities chosen shared the fact that they are large cities, each with over a million inhabitants, with Dar es Salaam having a population of more than four million. The majority of these cities are state capitals, with the exception being Dar es Salaam. Although it has not been the seat of its national assembly since 1996, this city continues to host various government offices and acts as the country's de facto capital.

2.4.2 | Data collection

The data analysed were obtained from the social network Instagram. Instagram was chosen on account of the highly representative nature of its results. The choice of this social network was largely justified by the fact that recent studies have shown how it outperforms Twitter and Flickr in representing monthly visitor patterns for various African natural parks (Tenkanen et al., 2017).

For the purposes of our research, only publicly available images were used. This study assumed that tourists had previously made a selection of the images that they posted. Some studies have identified a source of potential bias given that users only cover a fraction of the entire sample (García-Palomares et al., 2015). That said, the academic literature assumes that the images posted on these profiles coincide with the photographs that tourists take on their travels (Stepchenkova & Zhan, 2013; Donaire, Camprubí, & Galí, 2014; Su et al., 2016). Therefore we must be conscious of the fact that this is not a study of all the photographic images that have been generated. It is a study that analyses a certain collection, relating to users of the Instagram social network.

Instagram allowed us to carry out research based on the places where the photos had been taken. In our study, the research criteria were the name of the city and the name of the country. We collected images for the week of 11th to 17th March, 2019. We limited our study to just 1 week for two main reasons. First, accessing more images and over more days would have caused problems on the

Instagram network, and second, longer time intervals could have captured changes occurring in these cities, or in the use of the social network (Feick & Robertson, 2015). Working in this way, we wanted to avoid "seeing patterns where none actually exist, simply because enormous quantities of data can offer connections that radiate in all directions" (Boyd & Crawford, 2012, p. 668). This period did not include any national festivities which could also have modified the results obtained.

During the week analysed, more than 90,000 images of the chosen cities were captured (Table 1). Dar es Salaam was the most photographed city, accounting for one third of all the images; in contrast, Maputo was the city with least protagonism on Instagram, and with fewer than 3,000 images.

The images were later analysed to differentiate between those taken by residents and those by tourists. The source used was the user profile information provided by Instagram, or—to be more precise—the location information of the images previously posted by the user. If the images corresponding to previous weeks were of the same city, they were considered to have been taken by a resident; if they were of other cities, they were considered to have been taken by a tourist. If the identity of the photographer was not sufficiently clear, the photograph was discarded. Following Stylianou-Lamber (2012, p. 1825), in this selection and in subsequent ones, a series of guidelines were established to avoid subjectivity. Two different coders used the same categories to code 0.5% of the sample. The clarity of the criteria resulted in the level of coincidence exceeding 96%. These values were in-line with those cited by other authors (Paül i Agustí, 2018; Wacker & Groth, 2020).

Once the images had been analysed, 3.5% of the total (3,183 photographs) were deemed to have been taken by tourists. The most photographed city was Nairobi, with more than thousand photographs. The least photographed was Maputo, with fewer than 200.

The next step was to map the images. The basic principle followed was the "eye-catchers" approach (Pritchard & Morgan, 1995, p. 28). This process could only be followed in the case of photographs with spatial content. Bearing this in mind, we discarded images with photographs of fine details, sunsets, and/or selfies. If over 50% of the image was occupied by some of these elements, the photograph was discarded.

The remaining images were spatially located. This was done in three different ways. First, we referred to comments made on the app, which allowed us to directly identify the different places in question. Second, we were able to recognize some of the locations in the images (due to photographs showing the names of shops or addresses, etc.). Thirdly, we used the Google images app that allows users to search for images; the results obtained provided us with links to pages with similar images, from which the location was often identified.

In total, we were able to locate 1,605 images; this represented 50.4% of the total number of potentially locatable images. The margin of error, which was calculated based on the total number of tourist images in each city, was less than 5%, with a confidence level of 95%.

2.4.3 | Data processing

The study area was defined by applying criteria that permitted the comparison of data from different cities. To be more precise, we grouped the information together in 200-m hexagons. In this way, we obtained groups of tourist areas that allowed multiscale spatial analysis (Feick & Robertson, 2015). The data were processed using ArcGIS 10.6.

A buffer zone, reaching 12 km from the centre of each city, was established. The city centre was defined based on the location of the historic city hall. The only exception was the case of Dakar, where the city hall occupies an eccentric position on the peninsula that houses the capital. In order to avoid losing part of the metropolitan area, the centre was therefore based on the city hall of Grand Dakar, one of the arrondissement communes within the city of Dakar. To prevent edge effects, the different indicators were calculated based on a buffer with a 10 km radius from the city centre. Water surfaces (lakes and oceans) were discarded to prevent them from distorting the results.

On this base, we calculated various statistical descriptors: standard distances (SDs) and spatial distribution patterns. The SD of the photographs enabled us "to measure the degree to which features were concentrated or dispersed around the geometric mean centre" (García-Palomares et al., 2015). The Getis-Ord General G statistic and the Global Moran's I statistic were calculated to identify spatial distribution patterns. The former measures the degree of clustering of either high or low values. The latter simultaneously measures spatial autocorrelation based on both feature locations and feature values.

TABLE 1 The number of images identified

City	Country	Total no of images	Tourist images	Georeferenced images	Margin of error
Accra	Ghana	16,310	288	189	4.19
Dakar	Senegal	7,245	651	253	4.82
Dar es Salaam	Tanzania	30,765	272	174	4.47
Kampala	Uganda	6,825	441	292	3.34
Maputo	Mozambique	2,940	215	208	3.78
Nairobi	Kenya	26,544	1,316	489	3.51
Total		90,629	3,183	1,651	

Contiguity by edges was the method employed to define different neighbourhoods.

3 | RESULTS

3.1 | Intensity

We were only able to identify tourist images in 327 of the 13,587 hexagons (2.4%) (Table 2). The city with the greatest spatial diffusion of images was Nairobi, where we located images in 97 different spaces (3.1%). The city with the greatest percentage of spaces with images was Dakar, with 3.5% of the city hexagons containing at least one photograph. In contrast, the greatest concentrations of images were found in Maputo (in 39 different hexagons, 1.79%) and Kampala (with a percentage of 1.76%).

The concentration of the photographs was even more evident if we consider that only 100 of the hexagons (0.7%) contained five photographs or more. In Table 3, we have included a frequency table in which we have individualized the most visited points.

The maximum values obtained tended to be quite low. For example, the hexagon with most photographs in Dar es Salaam (corresponding to the area between the Azania Front Church and the Sheraton Hotel) contained only 12 photographs. In fact, there was only one point with a significant number of photographs; this was the island of Gorée, in Dakar, with 42 identified photographs. This minimal repetition of images indicated us that the majority of resources were hardly known (Donaire et al., 2014). Tourists do not feel the need to photograph a specific place. This shows the need to improve the touristic projection of some of these resources.

The greatest concentrations of images were located in the historic and functional centres of the cities. There were also, however, concentrations of images in other spaces too. In the cities with waterfronts, a significant presence of photographs was observed in these areas (especially in Accra and Dakar, but also to a lesser extent in Dar es Salaam and Maputo). These photographs tend, except in the case of Dakar, to coincide with the presence of private resorts, where there were also an important number of images corresponding to beaches.

We also identified other points with high values. These were points that tended to coincide with hotels and shopping centres. This followed the logic of the important presence of business tourists in African cities. In the case of the cities analysed, this type of tourism would be particularly important in Accra and Nairobi (Rogerson & Visser, 2014), where it was possible to observe a greater spatial diffusion of amenities related to business tourism. The greater safety of enclosed spaces would also contribute to there being a greater number of images of them on Instagram (Paül i Agustí, 2020).

With the exception of Nairobi, the rest of this peripheral area was practically devoid of images. The presence of the Nairobi National Park, in the south of the study area, no doubt explains the presence of points with a large number of photographs taken outside what would be habitual areas in other cities. It would also have been reasonable to predict that some images would have been located in the neighbourhood of Kibera. It lies to the south-west of the centre of Nairobi and is a typical place for slum tourism, although we did not identify any images that had been taken there.

TABLE 2 Frequency table showing the 10 most cited places in the images that were identified for each city

	City		City
Tourist images	**Accra**	**Tourist images**	**Dakar**
15	Accra Mall	18	Marché aux posions
13	Labadi beach	15	Statue de la Libération de l'Esclavage
8	Kwame Nkrumah Memorial Park & Mausoleum	14	Monument de la Renaissance africaine
7	Ashiedu Keteke Beach	14	Musée des esclaves
7	Independence square	10	Mosquée de la Divinité
6	Bojo Hotel	10	Plage de Gorée
5	Mamma Mia Pizzeria	7	Zoo
4	James Town Light	7	Église Charles Borromée
4	Harbour Close	6	Grande Mosquée
4	Arts center	6	Plage de Yoff
	Dar es Salaam		**Kampala**
8	Samaki	15	Baha'i House
6	National museum	12	Kampala Old Taxi Park
6	The waterfront	8	Kampala Central Mosquee
5	Zanzibar Shopping center	7	The Acaccia Mall
5	Kariakoo Market	7	Casino Simba
5	Bahari Zoo	6	Sheratton
5	Ledger Bahari Beach Hotel	5	Aponye center
5	Kipepeo	5	Metroplex
5	St Joseph Cathedral	5	Forest Mall
5	Chef's Pride	5	Kampala Boulevard
	Maputo		**Nairobi**
12	Fortaleza de Maputo	12	Nairobi National Park entrance
8	Jardim Botânico Tunduru	10	Nairobi National Museum
8	Praça da Independencia	10	University of Nairobi Towers
7	Museu de História Natural	8	Giraffe center
7	Centro Cultural Franco-Moçambicano	7	The Village Market
7	Train Station	7	David Sheldrick Elephant & Rhino Orphanage
6	Camara Municipal	7	Britam Tower
6	Southern South	7	Jamiaa Mosquee
5	Catedral de Maputo	7	Havana Restaurant
5	Katembe Bridge	7	Kilimanjaro

TABLE 3 Distribution of the mapped photos

	Photos	Number of hexagons	Hexagons with photos	Density (photos per hexagon)	Hexagons with photos (%)	STD	CV	Max
Accra	189	1,858	54	3.50	2.91	0.82	8.46	15
Dakar	253	1,135	40	6.33	3.52	1.75	7.85	42
Dar es Salaam	174	2,219	43	4.05	1.94	0.61	8.91	12
Kampala	292	3,059	54	5.41	1.77	0.99	10.37	29
Maputo	208	2,176	39	5.33	1.79	1.00	10.46	23
Nairobi	489	3,140	97	5.04	3.09	1.19	8.51	26
Total	1,605	13,587	327	4.91	2.41			42

Abbreviations: CV, coefficient of variation.

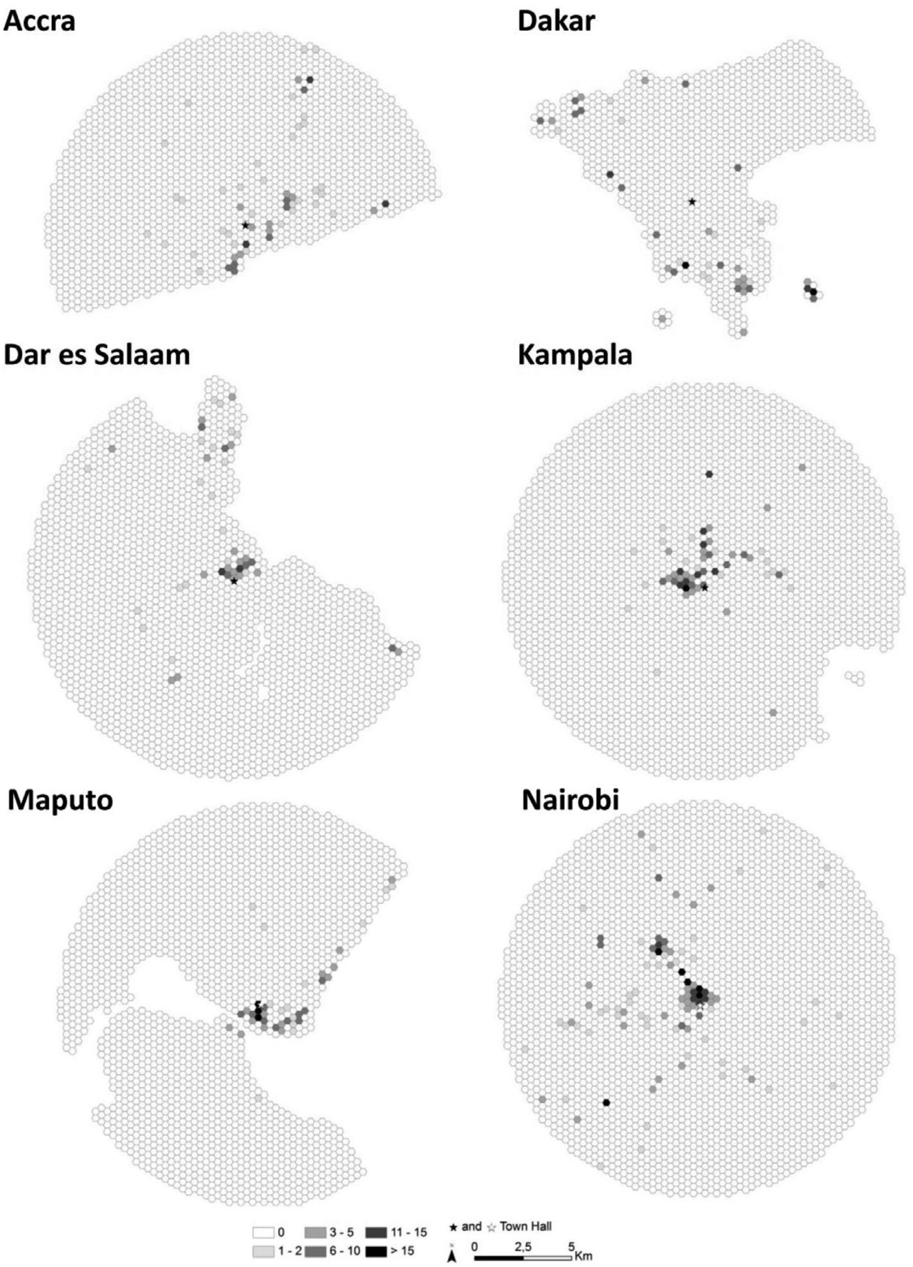

FIGURE 1 Density of tourist photos

This distribution implied that the coefficient of variation (CV) (Table 3) produced low values, which points to a high degree of dispersion. Only Maputo and Kampala had slightly higher values, which would seem to indicate a greater level of spatial concentration. Even taking into account the specific histories and urban morphologies of the cities studied, the distribution of the tourist images that we observed (Figure 1) show important differences with respect to the existing bibliography. African cities present a concentration of photographs taken at few, very specific, locations, although these points could be spread across a relatively extensive part of each metropolitan area. In contrast, in European cases, there has been a tendency to describe a distribution of tourist images that includes practically the whole of the city (García-Palomares et al., 2015). In the cases of Mexico and Brazil, it is possible to speak of a concentration around the economic and functional centres of cities and along seafronts (Paül i Agustí, 2020).

3.2 | Distance

Another measure that identifies the degree of concentration and diffusion is the SD. Table 4 shows the values for a one-standard-deviation circular polygon. This value covers approximately 68% of the features.

Some of the specific characteristics of African cities, such as the rapid growth that they have experienced over recent decades, would perhaps lead us to expect a greater degree of coincidence with cities from South and Central America. Even so, the distribution of tourist images in African cities tends to be closer to that of European and North American cities than to those of Central and South America.

In general terms, the values obtained tend to be high, especially at Dakar. This is a consequence of the presence of photographs along the coast of the peninsula, where the city is located. More specifically, the values for Dakar (5,936 m) are comparable with those for cities like Madrid (5,861 m) and London (6,143 m), obtained using methods similar to those used by García-Palomares et al. (2015). The French influence upon the urban morphology of Dakar could explain these differences, although new research would be required to confirm this.

The lowest values were found at Maputo (2,321 m) and Kampala (2,466 m), cities which would have a greater concentration of tourist images. This concentration would not, however, be as great as in some Mexican tourist cities, such as La Paz (781 m) and Los Cabos (1,617 m); it would be more in line with cities like Acapulco (2,646 m) (Paül i Agustí, 2020).

3.2.1 | Spatial autocorrelation and spatial clusters

To analyse the presence of clusters in the cities studied, we used the Getis-Ord General G Statistic and the Anselin Local Moran's I statistic. The p-value obtained for the six cities was <.05. We were consequently able to reject the null hypothesis that the phenomenon analysed was randomly distributed.

The results showed large clusters with a high degree of statistical significance. The Anselin Local Moran's I statistic calculations distinguished High-High Clusters (statistically significant clusters of high values—HH), Low–Low Clusters (statistically significant clusters of low values—LL), High–Low Clusters (outliers in which a high value was surrounded by low values—HL), and Low–High Clusters (outliers in which a low value was surrounded by high values—LH). As shown in Table 5, the number of clusters identified was relatively limited. Most were HH, and in a few cases, they were HL or LH. We did not, however, observe any LL clusters.

In Figure 2, we mapped the results obtained from the Anselin Local Moran's I statistic calculations. In the majority of cities, a clear concentration of HH clusters was observed in the areas around the city halls. Such areas also tend to coincide with those delimited by the SD.

However, as previously noted, this spatial concentration was accompanied by other points with an important presence of images. In the majority of cases, these correspond to beaches and hotels located along the coast: at Dakar, we found the island of Ngor and beaches on the northern part of the peninsula, and the island of Gorée to the south; at Dar es Salaam and Maputo, there were beaches to the north. In other cases, we identified areas associated with leisure activities, such as restaurants to the east of Kampala and to the west of Nairobi. The images also featured shopping centres, to the west of Nairobi, to the south of Dar es Salaam, and to the north of Accra. These spaces included a sufficient number of images for them to be considered statistically significant clusters. In some cities, these spaces were found separated from each other by quite large distances (15,691 m at Dar es Salaam and 15,972 m at Dakar). This is a demonstration of the capacity of areas located outside the central tourist space to attract visitors. That said, the majority of the points identified were found to be interconnected by high-capacity roadways. Infrastructure is therefore a differentiating factor that favours certain spaces that are far from the centre in detriment to others.

Another aspect to highlight was the size of the spaces considered HH clusters; with an average of 27 hexagons per city. This value falls far short of the average of 137 hexagons reported for European cities by García-Palomares et al. (2015, p. 416), yet it easily exceeds the

TABLE 4 Standard distances (in metres)

	Standard distance
Accra	4,016.02
Dakar	5,936.41
Dar es Salaam	4,646.01
Kampala	2,465.54
Maputo	2,320.51
Nairobi	3,648.67

TABLE 5 Clusters according to the Anselin Local Moran's I statistic (number of hexagons)

	HH	HL	LH	LL	Not significant
Accra	22	3	0	0	1,833
Dakar	18	1	3	0	1,113
Dar es Salaam	23	1	1	0	2,194
Kampala	34	1	0	0	3,024
Maputo	25	0	1	0	2,150
Nairobi	40	2	0	0	3,098
Total	162	8	5	0	13,412

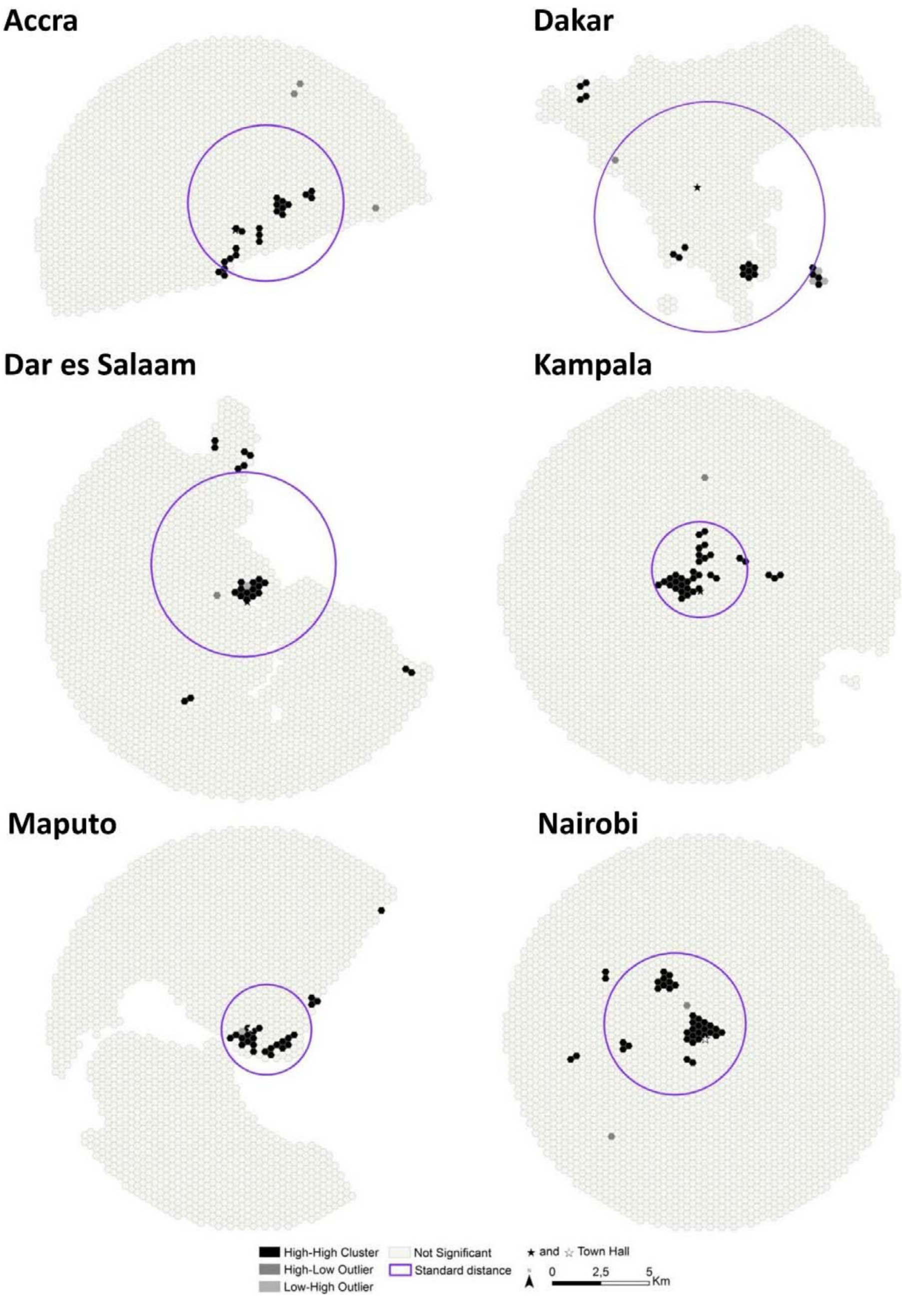

FIGURE 2 Clusters according to the Anselin Local Moran's I statistic [Colour figure can be viewed at wileyonlinelibrary.com]

average of 17.5 reported for Mexican and Brazilian cities (Paül i Agustí, 2020, p. 165). The attractions photographed by tourists in the African cities were more than just a few sights.

In the case of HL clusters, we identified only eight. In general, these were relatively isolated points, in areas with few identified images. In some cases, they were points that attract a large volume of visitors on account of their unique nature. They included, for example, the Bahá'í House of Worship, in Kampala, and the Nairobi National Park. In other cases, they were economic activities, such as hotels, restaurants, and commercial spaces. This all seems to indicate that these spaces could become future points of tourist interest. This would, however, call for good tourism management to develop it.

Finally, we only identified five LH points. In general, these were spaces located near places where a large number of photographs were taken. Even so, the presence of large areas of private and/or inaccessible spaces (including certain areas on the island of Gorée and the Gymkhana Club of Dar es Salaam) meant that it was difficult to reach a number comparable with those in their immediate vicinity.

The data therefore showed a diffusion of tourist images in African cities that extended beyond the traditional urban centre and coastal area. Mapping also made it possible to visualize areas with important voids, particularly in the more central zones and in some coastal spaces. This pointed to the possible existence of areas with tourist potential in other parts of cities, but which have not been featured in tourist photographs. This is something that could act as an indicator for those who administer tourist spaces; it could reveal problem areas to them, where tourism behaves in a different way to in their most immediate area.

4 | CONCLUSIONS

The results of this research show the specific characteristics of African cities and the need for an approach that goes beyond the study of European and American cities. The spatial behaviour of tourists may vary according to a number of different, local, and casuistic factors. As result, if we wish to obtain a truly global view of the impact of tourism, it is necessary to analyse cities in all the different contexts. At the same time, there is a need for studies that go beyond individual cases. The comparison made in this article between six cities makes it possible to identify some of the tendencies that would be relevant to consider for research on a wider scale.

Along these lines, the present article identifies some of the differences between European and American cases and their African counterparts. In the case of Europe and America, tourism tends to be concentrated at a single point, which is generally the historic centre of the city in question, from which it then spreads out like oil. This pattern does not occur in African cities, where tourism apparently spreads across multiple neighbourhoods. Even so, within this territorial diffusion, there is a clear concentration around certain very specific spaces, although these tend to be geographically separated from each other. These tend to be predominantly private spaces (hotels, shopping centres, and/or conference centres) that tourists visit without necessarily visiting other tourist attractions near to them. Furthermore, the spaces visited by tourists in historic centres and along the coast in Africa tend to have a lesser weight than in other contexts.

This demonstrates the importance of business travel and a type of tourism that focuses on visiting friends and relatives in the African city context (Cohen & Cohen, 2014). This is a type of tourism that tends to use specialized amenities and to be associated with specific needs (such as the celebration of special leisure or other events involving family and friends). This has created a distribution pattern that is clearly different from that of the leisure tourism that predominates in other contexts.

This different distribution pattern also points to some deficiencies that could affect the development of tourism in these cities, such as problems with spatial security, a lack of amenities, or even an extremely limited projection of the potential tourism resources of these areas. Future, more detailed studies of the different spaces analysed would help to confirm their causes and to help find potential solutions.

The results of this work could help to improve the planning of tourism in African cities. Knowing the spaces in which tourists move, and also those that they avoid, could help planners to create new projects to strengthen tourism. The results also open the door to future lines of research into urban tourism in Africa, while increasing the possibilities of offering answers to problems that differ from those found at other destinations.

The article also contributes a source: Instagram, which has hitherto been relatively little used in urban studies. The exploitation of data from social networks has proven a useful instrument for analysing contexts in which access to more traditional data is limited. However, it is also important to underline some of the possible limitations of the approach employed. Restricted access to Instagram data meant that it was necessary to resort to the manual collection and exploitation of the information used. The automatization of these processes would enable us to increase the number of cases analysed and, for example, to segment the information presented in line with factors such as the points of origin of the tourists, the period of their visits, or the visits that they may have previously made. This would help to improve our knowledge of tourist behaviour. The source used may also impose some limitations on research; for example, not everyone uses Instagram. Similarly, not all Instagram profiles are public, nor does everyone post images during or just after their visit. This may limit the visibility of certain collectives who, as a result, may not be appropriately represented in the sample.

Even so, due to a focus based on spatial statistical techniques, the objective approximation to Instagram data allowed us to obtain comparable results for cities located in very different contexts. It also allowed us to compare our results with those from other territories. In this way, we were able to conclude that tourism in African cities has the potential to spread to new areas. Even so, for this to be possible, it will be necessary to improve the physical infrastructure available and also the quality of life of the inhabitants of the different areas which currently receive few visits. In this way, it will be possible to promote a better quality of life for local citizens, while at the same time achieving a more diffuse presence of tourism and the possibility of contributing to the creation of new businesses, activities, and visions of urban spaces.

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