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Projected and Perceived Tourist Image of a Destination: A Regional-Scale Comparison Based on Travel Guides and Instagram in Senegal

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Abstract

Various studies have analysed the image of tourist destinations on social networks. However, most of them have tended to focus on urban spaces. The current article analyses the presence of tourist images on a wider scale: for the whole of Senegal. Photographs taken by Instagram users are compared with the information presented in travel guides. The results show that although travel guides include a much greater number of attractions than Instagram, it is Instagram that provides much wider spatial coverage. This shows the need for comparative studies between different sources of tourist information and, at the same time, points to the need for approaches that consider the local and regional scales in their analyses.

Keywords: Representative dissonance; travel guides; user-generated content; Instagram; Senegal

Introduction

In major cities, tourism has tended to intensify since the end of the 20th century. Consequently, studies on visitor behaviour have a strong focus on urban spaces (Donaire et al., 2020). However, in this same period, tourism has also increased in other areas. One example of this can be found in Africa where, moving beyond visits to major cities, there has also been an increase in the number of tourists visiting natural spaces and small and medium-sized cities (Donaldson, 2018). The casuistry behind this tourism has received far less attention (Shen et al., 2018). Identifying the tourist image of a whole territory is essential for good tourism management since a destination not being recognised is an important limitation when it comes to projecting its tourist image.

The present work is an example of analysing tourist image beyond that projected by the cities. We analysed a wide context: the whole of Senegal, with a view to helping to improve the spatial knowledge of relationships in which the tourist simultaneously acts as both the producer and consumer of images (Urry & Larsen, 2011). As a result, the projected images (based on travel guides) and perceived images (content generated by Instagram users) were compared. To be more precise, on the one hand, we analysed the limited number of locations projected by the travel guides. These were generic and simplified images that give the tourist a false sense of total understanding, order and stability, and of having everything under control. And on the other hand, there is Instagram, a piece of social network that allows a diversification of the tourist points that are usually promoted, thanks to information compiled by different users (Alsheikh et al., 2021). A social network that has hitherto been relatively little used by the academic community (Smith, 2018).

The present work contributes to the comparative studies between different sources of tourist information and, at the same time, points to the need for approaches that consider the local and regional scales in their analyses. Comparing projected and perceived images makes it possible to identify similarities and differences between the sources analysed and to contribute to the ongoing debates about the strong and weak points of the spatial distribution of tourism, and to an analysis of the effects that the tourism can have on wider territories.

Theoretical framework

The projected image and the perceived image

When a tourist interacts with a destination, they do this guided by the full set of images that they have of it. This interaction can occur in the form of text, or take a more creative form (Urry & Larsen, 2011). Tourism researchers have long been interested in the interaction between projected and perceived image (He et al., 2022). Given that tourism is an activity that tends to be spatially oriented in terms of its destinations (Lee et al., 2017), this situation will suppose a different spatial behaviour based on whether the tourist follows the pre-established images or creates their own itinerary within the city (Paül i Agustí, 2020).

The creation of a tourist image and its impact on the destination continue to be one of the basic themes of tourism research (Yu & Egger, 2021). Tourist destinations have images that contribute to their positioning as destinations. This image is formed on the basis of several different sources; induced (tourist brochures, mass media, travel agency staff, and webpages), organic (friends and relatives), and autonomous (guidebooks, news, articles, reports, and programs) (Beerli & Martin, 2004). These sources play an important role in the choice of destination. However, these images remain uncertain until they are verified by experience (Arefieva et al., 2021). When the tourist moves to a place, they personally verify the degree of similarity between the projected image and how it is experienced. At the same time, with their experience, the tourist contributes to the diffusion of a new image of the destination that is visited.

The coexistence of various sources is also evident in the online world, where completely new types of social media platform have now emerged: blogs, virtual communities, wikis, social networks, collaborative tagging, and media files shared on sites like YouTube. The importance of these different types of online publication has led to companies, institutions and tourists being present in this environment via their websites and channels and, above all, via the web 2.0. This has allowed the creation of tourism content on a massive scale (Marine-Roig & Ferrer-Rosell, 2018).

This process has added to the diversification of the images shared via social networks, but it has also engendered a series of other changes. The main one has been an increase in the distrust that tourists have for traditional forms of tourist information, which are perceived as being biased and as mainly providing content related to the tourism industry (Xiang & Gretzel, 2010). As a result, tourists have tended to give greater credibility to images created by other users. Even so, the proliferation of social media platforms has also brought with it a change in the perception of the trustworthiness, credibility and current accuracy of information created by users (Zeng & Gerritsen, 2014). This is something that has been particularly noted with the existence of tourism companies and organisations that pay external people, who have a presence on social networks, to create what are known as "sponsored posts" (Snee, 2013). This is a casuistry which brings information created by users nearer to that generated by traditional travel agents.

Despite the variety of tourist information sources, the majority of studies tended to focus on only a single source. This situation was particularly evident in the analysis of the spatial differences between the projected image and perceived image, in which studies based on several sources are extremely limited (Marine-Roig & Ferrer-Rosell, 2018). This is a particularly relevant deficiency given the clearly spatial orientation of tourist activity (Lee et al., 2017).

Several studies have analysed the tourist image based on the Internet. However, focusing on a single source may condition the results of the research and even more so when it has been underlined that analysing several sources tends to highlight significant differences. This is what is known as representative dissonance: several agents project different representations in response to multiple purposes. These are differences that condition the representativeness of the results (Ji & Wall, 2015).

The objective of the present research was therefore to analyse the spatial distribution of the tourist attractions comparing the projected image (travel guides) and the perceived image (user-generated content, or UGC, on Instagram). In this way, we obtained information that reflected the complexity of the tourist image in a more suitable way.

The location of tourist activity

Traditionally, tourist areas have been analysed using quantitative data based on aspects such as the density of occupation of tourist activities or visitor flows (Marmolejo & Cerda, 2017). However, it is normal for a wide number of small attractions to be present in the same area, which are difficult to identify based on general data. Mapping the different sources allows us to analyse and characterize the different aspects linked to tourist activity in greater detail (Raun et al., 2016), transforming them into a tool of the highest order for achieving a good management of the urban space (Salas-Olmedo et al., 2018).

Locating the tourist images helps to achieve a better management of tourism. A photograph of a particular place, whether in a travel guides or Instagram, express an interest in that specific point. Various authors have opted for a form of spatial analysis that groups together the different images of a given area (Paül i Agustí, 2018). In this way, it is possible to make an analysis in which – along the lines identified by Tobler (1970) - everything is related to everything else, but things that are closer together are more closely interrelated than those which are farther apart. However, the geolocation of different images on a map may not be enough to identify tourist behaviours. It is necessary to incorporate indicators to represent the complexity of each area and also the possible interrelations that exist (Paldino et al., 2015). Various studies have demonstrated the viability of analysis base on image densities. However, there have been few studies with a wide territorial approach, whether at the regional or state scale. In analyses that look beyond the urban scale, it is only possible to highlight articles about natural spaces (Tenkanen et al., 2017). The present study adopts an approach at the state scale, analysing the whole of Senegal, thereby contributing a wider case study to the existing literature.

Tourist activity in Africa

Very few studies have analysed African tourism (de Beer et al., 2022). Most articles tend to focus on South Africa and, to a lesser extent, English-speaking African countries. Some sources noted that South Africa has concentrated 60% of the articles published, followed – at a distance – by Zimbabwe and Ghana (Rogerson & Rogerson, 2019). According to the same source, other countries, including the one studied by the present article, Senegal, have had no previous articles about them. Furthermore, most tourism studies on Africa have focused on the economy (Rogerson & Visser, 2014) and the environment (Shen et al., 2018). Or have been based on a fairly negative focus: wars, natural disasters and epidemics (Avraham & Ketter, 2017) and pro-poor tourism and slum tourism (Rogerson & Visser, 2014). In addition, some authors have underlined how the image that is projected in networks like Instagram sees tourist destinations as being available for possession and consumption, effacing local place and identity (Smith, 2018).

In recent years, this image has, however, changed towards more positive aspects (Bunce, 2016). This aspect tends to be observed in non-urban settings, such as in the study of cultural tourism or heritage tourism (Rogerson & Van der Merwe, 2016). Along the same lines, certain tourism themes have also been analysed, such as business tourism, visiting friends and relatives, and religious pilgrimages (Cohen & Cohen, 2014). This is a tendency that will foreseeably continue in the coming years, thanks to the rapid development of the African tourism sector (Avraham & Ketter, 2017). A general trend that can also be observed in some countries, like Ethiopia (Muluneh et al., 2022) or Mozambique (Abdula et al., 2021). One factor that has played an important role in this change of perception has been the increase in infrastructure that allows access to the Internet (The World Bank, 2020). A situation that has contributed to tourist companies normally using social media platforms like Instagram (Moodley & Naidoo, 2022). This has allowed the Internet to show richer and more dynamic images of Africa than traditional media (Avraham & Ketter, 2016).

Methodology

The study area

Recent changes in tourism in Africa have highlighted the interest in analysing this destination. The present research focused on the Republic of Senegal: a country of 16,209,125 inhabitants in 2019 and with a surface area of 196,712 km^2. There are, however, important inequalities. The capital, Dakar (0.3% of the surface), concentrates most of the population: 3,732,284 inhabitants (23%). The adjacent region of Thiès (3.4% of the surface area) contains another 2,105,707 inhabitants (13%). Outside the area of the capital, the population tends to be located in the departments located along the Atlantic coast. The interior area is noticeably less populated, with regions like Kédougou covering 16,800 km^2 and with 184,275 inhabitants.

Senegal is one of the most visited sub-Saharan African countries. In 2017, it had 1.365 million international tourist arrivals, most of whom were European (47.5%) and African (31.6%). However, in terms of income from tourism, the country is located in the lower fringe, receiving US$ 419 million (World Tourism Organization, 2019). Senegal has a long history of tourism, with a tradition dating back to the 1960s (Diombéra, 2017). Its aerial interconnections and the level of security have tended to be better than in the neighbouring countries. As far as the main tourist attractions are concerned, they are of several types: cities, like Dakar and Saint-Louis; natural parks; ecotourism; safaris; business trips; golf; beaches; islands; pilgrimages; and museums, amongst others.

With reference to Internet connectivity, which is basic for access to social networks, Senegal has an infrastructure that surpasses that of other countries in the area. According to data from The World Bank (2021), in 2019, in Senegal, there were 109 mobile phones for every 100 inhabitants. Its access to Internet increased from 26% (2016) to 46% (2019). This importance of tourism sector, combined with its relevant presence on Internet, make Senegal an excellent country in which to analyse the spatial behaviour of tourist image.

Data collection

The study compared the attractions of Senegal described in the travel guides and in the UGC on Instagram. In the case of the guides, the most recent entries in English (Connolly, 2019), French (Gloaguen, 2018) and Spanish (de la Carrera, 2014) were analysed. Also, given its tradition, the Lonely Planet guide was analysed, although its latest edition in English dedicated exclusively to Senegal was published in 2009 (Kane, 2009). Given the time that has passed between the publication of some of the guides and their analysis, there could be some variations in the elements treated. Even so, we did not find any significant differences between the guides published in 2009 and those published in 2019. For this reason, it was considered that if these changes existed, they would be limited.

In the travel guides, we located all of the resources mentioned. To do this, they were read in depth, highlighting data such as the number of words in the description and, if it was the case, the dimensions of any images or maps referring to the attraction. The data obtained were quantified based on the formula proposed by Serrano i Miracle & Imbert-Bouchard (2009: 391). In this way, we obtained comparable values between different sources, in a ranking between 0 (null impact) and 10 (maximum impact):

Impact factor = ((A*10/Amax) *0.4) + ((B*10/Bmax) *0.2) + ((C*10/Cmax) *0.2) + ((D*10/Dmax) *0.2)

A = Number of words written about the attraction
B = Size of any photographs and/or graphics related to the attraction
C = Rough map showing the location of the attraction
D = Objective treatment (data referring to schedules, businesses or accommodation) or subjective treatment of the attraction (description).
max = maximum values obtained in the different fields analysed

In the case of UGC (Instagram), it was not possible to retrieve all of the information. For this reason, we analysed the images posted between 5th and 19th December 2019. This month corresponds to the high season in Senegal. An analysis of this period offers the maximum level of comparison with the information provided in tourist guides because most of the country's tourism products are promoted to the maximum at that time. In other months of the year, some tourist attractions could be closed. However, we must also be aware of the fact that establishing this time limit could impose certain limitations. For example, some tourist events which are held outside this period may not be reflected in the study. Our data must therefore be considered to refer to the country's high season.

Instagram allowed an automatic search by location. In this investigation, we used the reference 'Senegal'. This name was the one that presented the greatest level of activity: around 1,200 images per day, which implied 17,820 images.

In order to identify tourist-taken images, it was necessary to differentiate them from those taken by local residents. This differentiation was carried out by identifying the location of the images posted by the users in the month previous to the image analysed. If territorial mobility was observed, the photographer was considered a tourist. If the image was of the same area, they were considered a local resident. If the identity of the photographer was not sufficiently clear, the image was discarded. By applying this filter, it was possible to establish that 1,273 tourist images (7.14% of the total) were posted during the period analysed.

The next step was to geolocate the images. We began with the idea of eye-catchers, in which 50% or more of the space was occupied by an element that caught the attention (Pritchard & Morgan, 1995). When it was not possible to territorialize this element (faces, detailed zooms, sun sets or clouds) they were discarded on the basis of not being considered tourist attractions. The other points were located using three different procedures:

- Commentaries in which users referred to the place where the image was taken.
- Recognition of locations (the image contained the names of streets or monuments).
- An analysis of Google images. The results showed pages with similar images, where the location often appeared.

Despite being quite time-consuming, this semiautomatic procedure offered greater guarantees of exactitude. Automatic locations of social media images are not always accurat (Toivonen et al., 2019). The geolocation proposed by Instagram was based on a pre-defined list of locations that could be excessively wide (urban areas, regions or natural parks) and prevented a precise location.

We geotagged 423 images captured by tourists (33.23%) which were mapped using the ArcGis 10.4.1 program. Given that the repercussion on Instagram can vary according to the level of engagement, an impact factor was calculated for each image. We differentiated between images with very little tourist projection and those that were more descriptive, shared and followed, which could reach a broader public:

Impact factor = ((A*10/Amax) *0.4) + ((B*10/Bmax) *0.2) + ((C*10/Cmax) *0.2) + ((D*10/Dmax) *0.2)

A = Word count of the commentary caption
B = Number of likes
C = Number of hashtags
D = Treatment as a Top Post (Dmax = 1)
max = maximum values obtained in the different fields analysed.

In order to validate the sample, we calculated that the 423 georeferenced images, with respect to 1,273 posted by tourists, would represent a margin of error of 3.9%, with a level of confidence of 95%. These data showed the representativeness of the sample. In order to ensure the reliability of the different classifications, we followed Stylianou-Lamber (2012). A series of guidelines were established to avoid subjectivity. Two different coders used the same categories to code 0.5% of the sample. If the degree of coincidence in the classification was of more than 95%, the criteria were validated. These values were in line with those cited by other authors (Paül i Agustí, 2019; Wacker & Groth, 2020).

Data analysis

The cartographic analysis was based on two methods: Kernel Density Estimation (KDE) and Inverse Distance Weighting (IDW). KDE it's a non-parametric method to estimate the probability density function of a random variable (Terrell & Scott, 1992). KDE has been used in the field of tourism, to analyse tourist behaviour (Miah et al., 2017). KDE is based on an inference process from a sample of known points to estimate the local densities of the set of points. In the present study, we used the default values of ArcGIS 10.4.1. This process assigns more weight to the most significant points and penalises exceptional behaviour. As a result, it tends to be considered a good method for synthesising behaviour within areas.

IDW is a common interpolation method that enable discrete measurements to be converted into a continuous spatial distribution. As far as IDW is concerned, several tourism studies have used this calculation, for example, to identify the potential interrelationships between tourism and wetlands (Lupei et al., 2017). It has also been used to analyse social networks like Instagram (Paül i Agustí, 2018). From a set of sample points (L1, L2, ... Ln) IDW calculates the value for a new location L. IDW interpolation explicitly works on the assumption that things that are close to one another tend to be more similar than those that are further apart. This approach also allowed us to include examples of exceptional behaviour within the data set, such as places with a high impact factor located in areas with few sights. For IDW calculations, we also used the default values proposed by ArcGis 10.4.1. The interpolations were established on the basis of the 12 spatially closest values.

These calculations were made for each of the sources, travel guides and Instagram. The geographical location of the elements was compared obtaining a Z-weighting value corresponding to the impact factor of each of the two sources. The observed differences were mapped using the resulting raster.

The previous data were analysed by territory, based on population density. We used data from The World Bank (2017), in which population density was shown by pixel at a resolution of 100 metres, in 2015. We were conscious of the limitations of this index, if other indicators, such as economic ones, were not taken into consideration (Potts, 2017). However, the density of population allowed a detailed territorial approach which other sources, expressed at the municipal level, were unable to provide. In Senegal, the official definition of urban municipality was based on a limit of 10,000 inhabitants (Potts, 2017). However, inequalities in the size of the *commune* (the basic municipal level for the Senegalese administration) advised against our using them. The *communes* in the interior of the country tended to have very large surface areas. This was able to generate great surface areas that were practically uninhabited and to locate them in urban municipalities, thereby losing much of the detail of the research.

Results

Attractions identified

The analysis of the travel guides and Instagram allowed us to identify 325 tourist attractions in Senegal: the guides identified 172 attractions and Instagram 156 (table 1). However, the comparison between sources showed very few coincidences in the attractions identified. Only 28 spaces (8.6% of the total) appeared in both the guides and on Instagram. These data implied important differences between the sources and reinforced the idea that the analysis of a single source would only allow a partial vision of the tourist attractions of a given destination.

Table 1. Main tourist attractions

	Number of attractions	% on total
Total number of attractions mentioned in some of the sources	325	100
In travel guides	172	52.9
On Instagram	156	48.0
Mentioned in travel guides & on Instagram	28	8.6
Mentioned only in travel guides	169	52.0
Mentioned only on Instagram	129	39.7

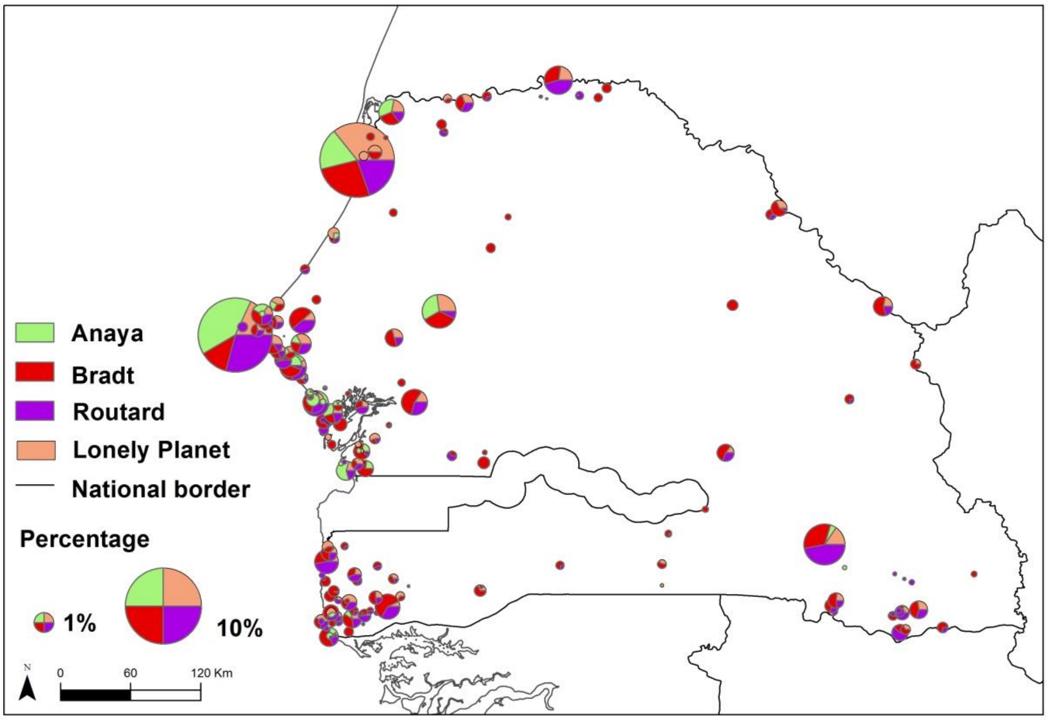
The travel guides promoted 169 points whose images were not found on Instagram: points that were not sufficiently attractive to tourists to get them to visit, photograph, or share them. On the other hand, we found 129 points that were photographed by tourists, but which did not appear in the travel guides.

As far as the comparison of the impact factor of the points described was concerned, a moderate correlation was identified: 0.567. The correlation between the Brandt guides and Instagram was the lowest: 0.351, whereas the highest was between the Anaya guide and Instagram: 0.631. In all of the cases, the level of confidence was 95%, the margin of error was 5% and there was a significant correlation at 99.9% ($p < 0.01$). This data set shows the need to analyse different sources in order to identify all of the spaces with potential interest for tourists.

Location of the attractions

The spatial distribution of the attractions also exhibited differences. In the travel guides, the points that had the greatest presence were Dakar, the capital, and Saint-Louis, the ancient capital, located to the north. Each of these points concentrated approximately 10% of the total information described in the guides (in agreement with the impact factor). The presence of departmental capitals, like M'bour, Thiès and Podor (approximately 1% of the information) was also important. The other points were described much more briefly. However, the majority of these spaces that were briefly described were located on the coast to the south of the capital and in that of Casamance (Figure 1). Outside these spaces, we only found a few very specific attractions. These were basically natural parks, amongst which the most outstanding was the National Park of Niokolo-Koba (the 4th most described attraction) and some border crossing points.

Figure 1. Attractions identified in the travel guides (impact factor)

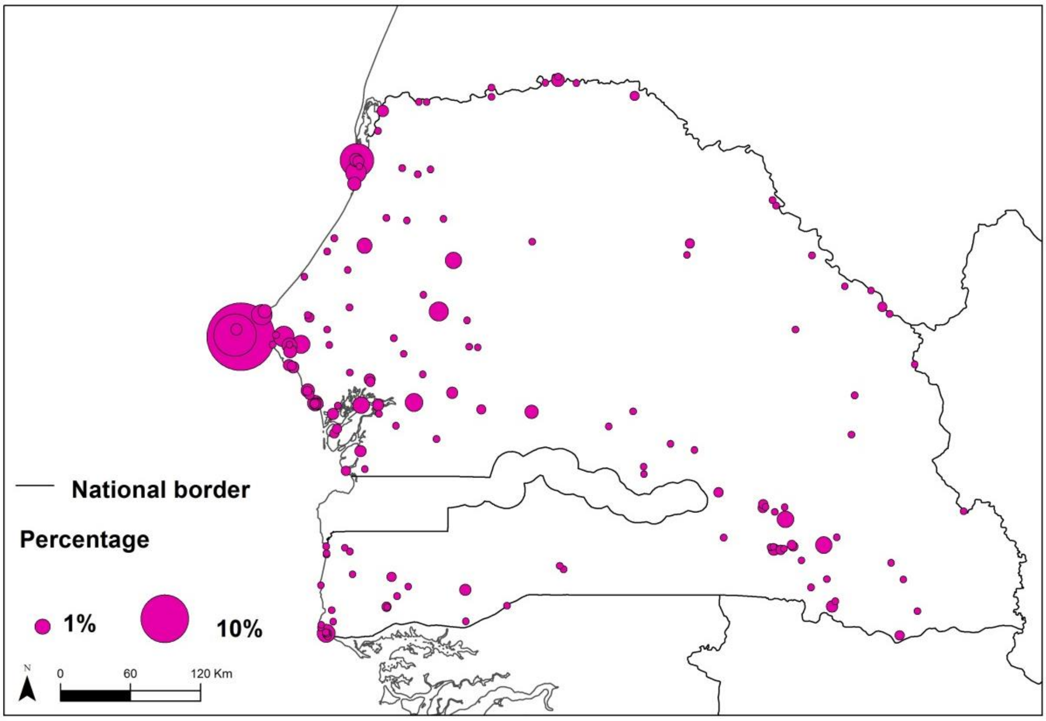


We also observed differences in the attractions reviewed according to the guide. We only located fifteen attractions (4.6%) that appeared in all four of the guides analysed. Most of these attractions were the ones with the greatest impact factor. On the other hand, 92 attractions (28.3%) were only identified in one guide, often with only a testimonial presence, which showed an important concentration, both in terms of territory and of the volume of information. This situation was in line with the long tail pattern of Pan & Lii (2011), according to which a limited number of attractions are recognised by all tourists, with the others tending to be more specialised.

As far as the images obtained from Instagram were concerned (Figure 2), the points with greatest impact factor tended to coincide with those highlighted in the travel guides. The only significant difference was the island of Gorée, located opposite Dakar. This island concentrated 21.5% of the images taken by tourists, as opposed to 4.2% of the information in the guides. At the other end of the spectrum, we found 129 points (39.7%) that only appeared on Instagram. As in the case of the guides, the long tail pattern was verified. While the 10 most photographed attractions concentrated 46.9% of the images, 94 attractions (60.3%) had only one image (19.8% of the images).

These rarely photographed attractions showed a territorial distribution that differed from that of the guides. In fact, only 11 of the 94 attractions with one or two photographs on Instagram appeared in the guides. In all of them, with the exception of Ziguinchor, a city in the south of the country, the description tended to be brief.

Figure 2. Attractions identified in Instagram images (impact factor)



Generally speaking, the attractions only identified on Instagram tended to be natural spaces, small settlements, or points located along the roads that linked attractions, and especially points of sale or travelling food and drink services. In contrast, amongst the spaces that were only identified in the guides, descriptions of urban spaces, like Thiès, Saly and Kafountine, predominated. This situation showed how travel guides tended to prioritize describing urban spaces, despite the fact that in several cases no tourist images were identified in these cities. On the other hand, they ignored reviews relating to non-urban spaces, and especially those in which there was no regulated tourist activity.

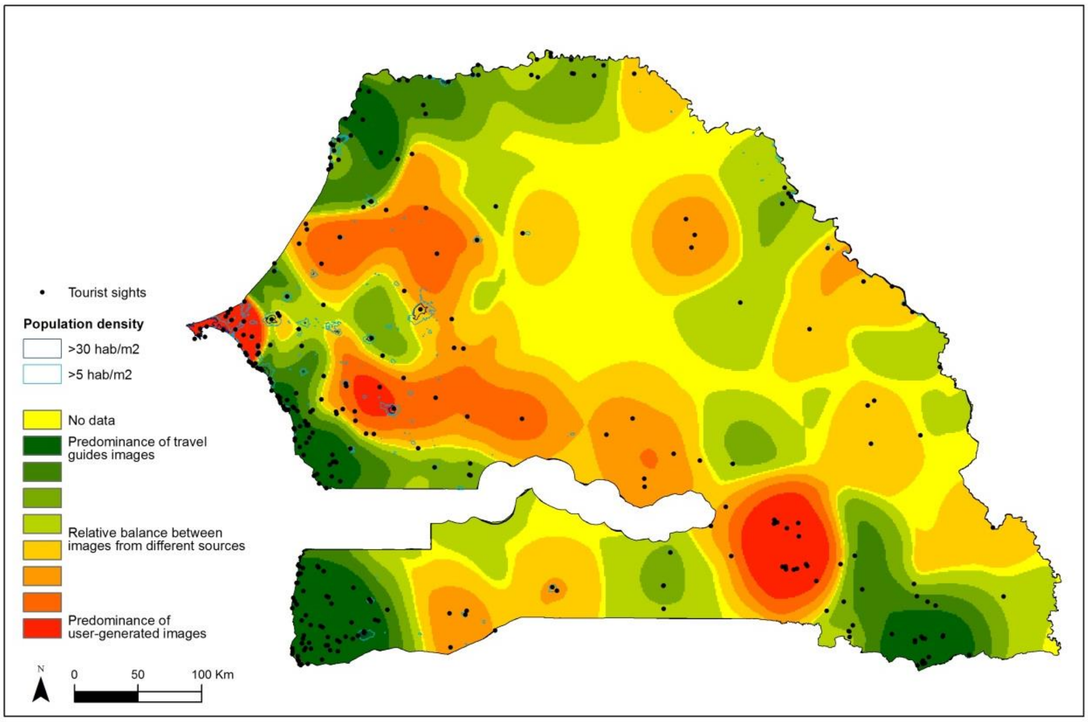
Discussion

Different spatial behaviours between projected and perceived images

Summarising the previous information in a single map allowed us to identify coincidences between the projected image and the perceived image. This comparison was made using an estimation of Kernel density in which the points space at which each of the analysed sources played a predominant paper were spatially identified (Figure 3).

The result showed differences in the predominant image that depended on the area of the country. The weight of the images on Instagram was clearly predominant in the capital and in some of the neighbouring cities and areas (Gorée and Lac Rose). It was also noticeable in some cities in the interior, such as Kaolack, and in the Niokolo-Koba National Park. In other areas of the country, such as the Kaolack-Tambacounda corridor, the presence of images of Instagram was predominant, albeit less clearly than in the previously mentioned zones. In contrast, the attractions promoted by the guides showed a clear predominance for the coastal area, both from Dakar to The Gambia and along the coast of Casamance. They also heavily featured Saint-Louis and the border area around Dindéfelo, in the south-east of the country. Other small cities, and especially those with frontier posts (such as Matam and Kidira) also tended to be overrepresented in the guides, largely because their descriptions included recommendations about how to enter the country.

Figure 3. Summary of the results from the sources analysed (KDE based on differential impact factor).



In spite of this, their intensity was clearly smaller than that of the major cities and the coast. Finally, we must highlight the fact that in an important part of the country, and especially in the interior area of the Sahel, we did not identify any tourist images, either in the travel guides, or on Instagram.

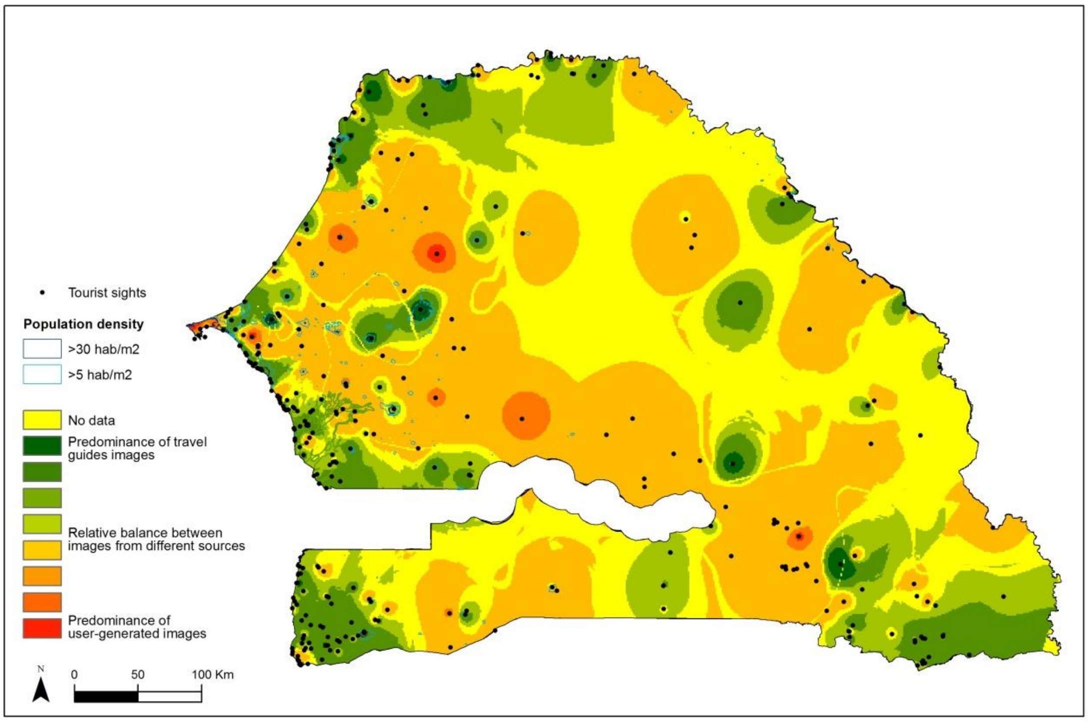
Generally speaking, we observed how the image predominantly promoted by the travel guides tended to focus on urban and coastal spaces. In contrast, the image projected by the UGC tended to correspond more to inland spaces. We were, therefore, faced with a differentiation between the image projected in the guides and on Instagram. This was a differentiation that segmented the country in terms of tourism. There was a north-south continuum promoted by the guides existed, with the image of Senegal as a destination related to the sun and beach. This show that the durability of the traditional image in tourist guides and the existence of images that are only promoted on Instagram: specific images, such as trees, areas of water, landscapes, and photographs of people and of local markets. These are things that are rarely highlighted in tourist guides, partly due to their status as micro-sites (very specific places at specific points) and their changing nature (a landscape may be the subject of a photograph at a certain time of year yet not arouse any interest at another), but which show the existence of other possible attractions, which could help to diversify the tourist image of Senegal. In spite of this, the presence of several of these destination on Instagram would seem to show that there is tourism outside the spaces predominantly promoted via the guides. This is something that must be considered when managing regional tourism.

The data obtained from the KDE were used to summarise different spatial behaviours. The results were therefore influenced by specific behaviour, as witnessed by the clear overrepresentation of the island of Gorée (21% of the images on Instagram as opposed to 4% of references in the guides). This is a concentration that IDW tends to clarify, as we shall now see.

The locally important tourist attractions

IDW allows the data to be analysed not in isolation but in relation to data in the environment. In the case of tourist image, IDW made it possible to clearly define the behaviour of locally important tourist attractions, but a predominantly regional analysis could cause distortions. We therefore obtained an approximation based on local behaviour (Figure 4).

Figure 4. Summary of the results from the sources analysed (IDW based on the differential of the impact factor)



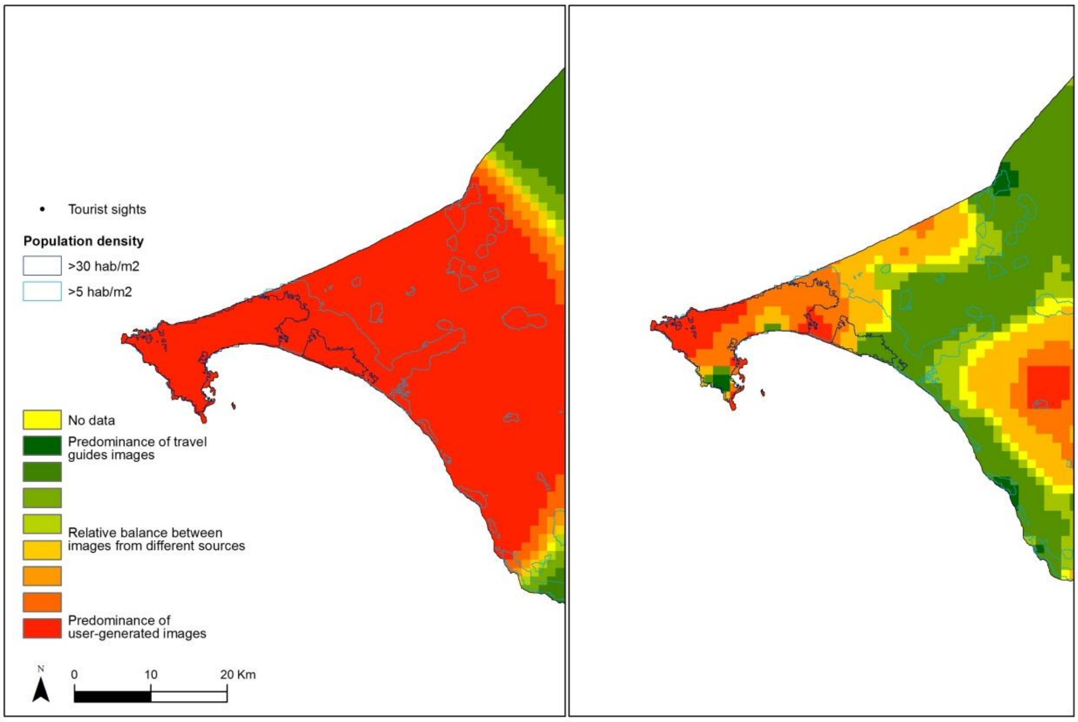
The IDW results broadly confirmed the distribution of KDE data. The images promoted by the travel guides tended to give greater weight to the coastal and border areas; Instagram tended to have a greater presence in inland spaces, while a significant part of the interior area did not have any tourist images.

However, IDW did add some important nuances. Although some points continued to have significant differences (for example, the clear predominance of Instagram at Boulal's Sylvo-Pastorale Reserve and the Niokolo-Koba National Park), the differences between the travel guides and Instagram were smaller. This is another aspect that reinforces the need to analyse multiple sources to obtain a complete vision of the tourist image of a country.

Another point at which nuances are introduced, and which demonstrates the existence of specific types of behaviour that we could ignore if we limit our analysis to the regional scale, was observed in the Dakar region (Figure 5). KDE, with its more regional analysis, showed a predominance of Instagram, which also extended into the adjacent departments. On the other hand, IDW, with an analysis that permits a more local focus, clarified this situation and limited the clear hegemony of Instagram to the Island of Gorée and the northern coast of the peninsula. IDW also made it possible to identify significant differences at the urban scale. For example, it was observed how the historical centre of Dakar (south of the peninsula), which has been highly promoted in travel guides, had only a testimonial presence on Instagram.

This was an example of how IDW made it possible to incorporate exceptional behaviour. A regional analysis could conclude that the Dakar region has a strong presence on the Internet. However, if we analyse the local scale, this presence remains limited to certain areas. This is a demonstration of the need for analyses that bear in mind different sources and scales in order to obtain a correct interpretation of the tourist image generated by a country.

Figure 5. Comparison of KDE (left) and IDW (right) maps of the Dakar region



Conclusions

Various studies have shown the importance of analysing multiple sources in order to have a good understanding of the tourism phenomenon. We can cite, amongst others, research undertaken in the field of the contents promoted or semiotics (Marine-Roig & Ferrer-Rosell, 2018). The present article shows how, in the field of the analysis of the regional spatial distribution of the tourist attractions, it is also recommendable to follow an approach that includes various sources.

An analysis of the tourist image based solely on a single source could give a biased view of the tourist reality of the country. The use of several sources was used to enable us to analyse this image in greater detail. It also shows how, in order to analyse the tourist image, it is necessary to adopt an approach that includes several different scales. If we do not combine the local and regional scales, there is a risk of missing some locally relevant types of behaviour.

Along these lines, the difference between the image obtained from the travel guides and that from Instagram shows how visiting a place can help change the image of this destination (Beerli et al, 2017). Within a context in which diffusion via social networks is on the increase, the gap between the projected image and the image perceived by the tourist is reinforced. Even so, studies of tourist image cannot only be focused on the UGC. Several studies have shown that the projected images of a destination tend to be so strong that they can come to condition the perceived image (Almeida-García et al., 2020). This is something that reinforces the need for comparative studies between different sources.

The study also serves to show some types of behaviour that differ from that previously described in the academic literature. Several previous studies, which have given little attention to the African context, have tended to report high tourist density spatial clusters in historic centres (Hayllar & Griffin, 2009). However, the results obtained in Senegal differ, show hardly any presence of UGC in these spaces. It also shows the presence of UGC outside the spaces most traditionally associated with tourism, which is a sign of greater tourist mobility.

The article also contributes a source: Instagram, which has hitherto been relatively little used in African context. However, using Instagram presented some limitations. The main one was that, unlike other social average, Instagram does not allow public access to data. As a result, this study does not analyse all of the Instagram users but only those who have a public profile on the network. At the same time, we must be mindful that the popularity of Instagram varies from country to country, which could influence the study results. Focusing this study on a period of 15 days could also have been a limiting factor. The article cannot, therefore, be regarded as reflecting the interests of all the tourists who visit Senegal, but only of those who visit the country in its high season. However, despite these limitations, recent studies have shown that Instagram outperforms Twitter and Flickr in representing monthly visitor patterns for various natural parks (Tenkanen et al., 2017), an aspect that encouraged us to use it.

The methodology used here therefore opens up future lines of research for the comparison of the spatial distribution of tourism based on different sources. Along these lines, it would be possible to move towards a more segmented analysis, comparing travel guides and users from different countries and identifying differences based on the nationality of the tourist in question. It would be equally interesting to be able to segment users based on whether they are first-time visitors or more habitual visitors. The resulting territorial distribution of these segmentations would help us to gain a better understanding of the behaviour of tourists. Finally, future research will also need to analyse how COVID may have affected the distribution of tourism in Senegal. The variations in the locations of the tourist images according to the source used shows the need to incorporate this approach into the analysis of tourist space. This is an approach that contributes spatially relevant information which should help to improve the spatial management of tourism.

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