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Measuring the Difference Between Pictures From Controlled and Uncontrolled Sources to Promote a Destination. A Deep Learning Approach

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Abstract

Promoting a destination is a major task for Destination Marketing Organizations (DMOs). Although DMOs control, to some extent, the information presented to travelers (controlled sources), there are other different sources of information (uncontrolled sources) that could project an unfavorable image of the destination. Measuring differences between information sources would help design strategies to mitigate negative factors. In this way, we propose a deep learning-based approach to automatically measure the changes between images from controlled and uncontrolled information sources. Our approach exempts experts from the time-consuming task of assessing enormous quantities of pictures to track changes. To our best knowledge, this work is the first work that focuses on this issue using technological paradigms. Notwithstanding this, our approach paves novel pathways to acquire strategic insights that can be harnessed for the augmentation of destination development, the refinement of recommendation systems, the analysis of online travel reviews, and myriad other pertinent domains.

Keywords

Destination Image, Deep Learning, Destination Marketing Organization, Scene Recognition, Natural Language Process.

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I. Introduction

The World Tourism Organization reported that in 2019 the travel and tourism industry generated approximately $1.5 trillion (USD) and was the third-largest export category in the world [1]. This industry is of great importance to many countries around the world that devote considerable resources to the research and promotion of their attractions. It is also important to stress that the paradigms of the tourism sector have changed with the massification of the Internet and social networks. The high availability of information and social media have promoted the surge of new dynamics in tourism [2]–[4]. *Big Social Data* and User Generated Content (UGC) are becoming key sources of well-timed and rich knowledge, supporting data-driven decision approaches that address the management of complex relationships through the use of emerging and comforting technology [5]. Online information on climate, transport, attractions, and accommodation offers to tourists a starting point for planning their holidays, whose decisions are strongly influenced by the opinions of other tourists shared electronically [6].

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One of the main activities of Destination Marketing Organizations (DMOs) is the implementation of marketing campaigns to promote tourism and to design strategies to deal with adverse circumstances affecting the industry [7],[8]. These situations are also present on the internet in the form of information coming from uncontrolled sources, which sometimes deteriorates the projected *destination image*. Monitoring changes in photographs that differ greatly from the projected *destination image* by the DMOs could help to design procedures to mitigate these effects. However, tracking these changes imposes certain limitations, such as the availability of experts and the manpower to overcome the enormous task of analyzing the huge number of photographs daily posted on the internet.

In this work, we propose an approach based on deep learning techniques to automatically measure changes between the photographs used to promote a destination by the DMOs (controlled sources) and those published on the Internet (uncontrolled sources) during adverse events that negatively could influence the projected destination image. To our best knowledge, this is the first effort to propose a method to deal with this problem, which would represent new avenues for collecting and refining strategic information and potential applications for tourists or DMOs.

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II. Destination Image in Tourism

The term *Destination Image* in Tourism or DIT has been around since the 1970s. DIT is the total impression of the destination in the minds of tourists and residents [9]. In a broader sense, the DIT is related to a set of ideas, impressions, and beliefs that a person or group shares about a particular place based on long-term information obtained from various sources that led to the construction of a positive/negative image [10], [11]. Several studies have extensively investigated the process of formation of the destination image. Among these, Gunn [12] influenced and contributed to identifying the levels of image formation based on the type of information available to the tourist. This framework proposes three main levels: organic, induced, and modified-induced. The organic level refers to general ideas that a person has about a particular place; this information can be obtained from multiple sources, such as personal conversations and television. The induced image is formed using information received and processed intentionally by the tourism industry, including brochures and advertisements produced by DMOs. As for the modified-induced image, it refers to the mental reconfiguration of the DIT derived from the travel experience within the destination. These levels are incorporated in the seven steps presented in Fig. 1. According to González-Rodríguez et al. [13], the choice of a particular destination is influenced by a more positive and stronger destination image, which is shaped by different secondary factors such as media on the internet [14], [15]; Frías et al. [16] stressed the importance of the impact of pictures of a destination, because the processing of an image requires less cognitive resources and affects all users; As for social media, the studies of Gallarza et al. [17] and Govers and Go [18] suggested that in the presence of paradigms such Big Data, the destination image perceived by tourists would be influenced by more diverse sources of information, which makes it difficult to quantify this construct because it tends to be complex, relativistic and dynamic.

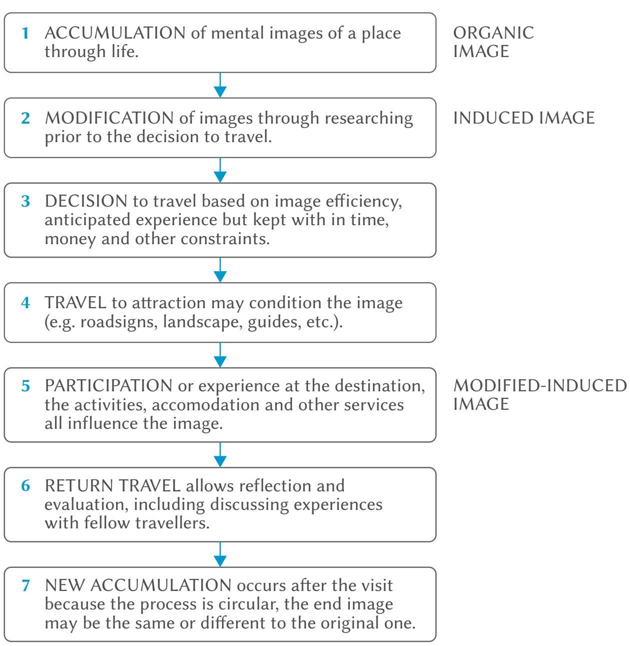

Fig. 1. Stages in the process of DIT formation. Source: [12].

The DIT construct can be classified into different categories. The *projected image* can be defined as the ideas and impressions about a place that is available for the consideration of potential tourists. These secondary images may come from induced sources for the sole purpose of promoting the destination to attract tourists or from autonomous sources (news, travel magazines, social networks, ads, etc.) which are not controlled by DMOs that aim to supply information for travelers [19]. On the other hand, the *perceived images* come from organic sources of two main types: people who talk with their friends and family and UGC on different electronic media. Perceived images are the product of interaction between projected images and the characteristics of potential visitors, but the most credible source is the personal experience of previous visits to the tourist destination [20].

Given the importance of factors such as social networks and the Internet in the image formation, monitoring the variations between the image projected by DMOs and images on the Internet could allow the design of emergency strategies to mitigate the effects of this bad publicity on potential tourists. With new paradigms like Big Data and deep learning, the analysis of different aspects of the destination image in tourism (DIT) construct has been automated and applied to large amounts of information. In our research, we have established a classification for studies. Those who have analyzed DIT's construct using computer techniques can be divided into the following categories: Studies that are aimed at identifying unique attributes of DIT using User Generated Content to get ideas for destination branding [21], [22]; Studies exploring the evolution of the construct using content analysis, such as changes in image perceived during economic crises [23]–[25]; Studies using social media and big data to analyze the construct [26]–[28]; Research interested in understanding the underlying factors influencing the construction [29], [30]; The research focused on the use of multimedia content to achieve better strategies for DMOs [31], [32]; Studies aimed at exploring the factors in tourist attractions to understand the choices of tourists [33],[34]; Finally, another studies do not fall into one category [35], [36]. Based on the many important approaches in the literature, below, we summarize the most influential in our research. The following studies propose methods for analyzing images (photographs):

- Leung et al. [37] carried out a three-stage analysis. In the first, they got pictures of flicker. The second stage tried to find popular places using a clustering method to differentiate images from different users and with certain proximity based on the coordinates of photos. The idea behind this logic was that many tourist photos in the same place mean that such a place is popular. With this data, the authors tried to analyze the patterns of tourist visits and to identify the image of the destination through the analysis of these pictures.
- Nixon [38] proposed a machine learning method to segment the audience of visual destination imagery in order to reflect that different types of audiences will build divergent visual destination images. He used the MachineBox.io service to train a visual classifier for image annotation and to obtain the frequency of these classes. Comparisons between different destination images were made (a ground truth of manually annotated images in comparison to automatic approaches).
- Xiao et al. [39] proposed a method for obtaining a seasonal variation index of the major tourist scenes in the province of Jiangxi in China. The 22 main scenes were analyzed using the Deep learning model Places365 to obtain representative labels of the destination photos, and they applied the Linear Discriminant Analysis (LDA) algorithm to get a distribution of the major themes in those scenes.
- Arabadzhyan et al. [40] presented a method for measuring the dissimilarity among destination images of different places and how such images are influenced by endogenous and exogenous factors. They used the Google Cloud Vision API for image labeling, and distances were calculated as the absolute value of the average distances of the top K labels.

- Bui et al. [41], proposed a big data framework for measuring the DIT construct using machine learning techniques. The framework was able to process textual and visual data, separating it into sub-constructs, seasons, and tourist characteristics. The measure was carried out in each sub-construct (Nature and landscape, people and culture, history, among others) through the frequency of words and sentiment analysis of all information.
- He et al. [42] explored how to analyze UGC to obtain the characteristics in a core-periphery scheme of the destination image to achieve a better selection of images for DMO's to promote the destination. The DeepSentiBank algorithm was used to detect emotions and objects from photos of three different data sets (two of Organization Generated Content and one of UGC). Labels have been processed and used to build a semantic network (with the algorithm NetworkX) for representing the structure of the perceived Destination Image. With this network, the centrality scores were computed to generate a list of major adjectives and nouns ranked. With these metrics as a goodness measure, the best DMO's photos were chosen, and a regression algorithm was used to evaluate their online engagement.

Concerning pertinent studies that have undertaken analogous tasks from a technological perspective and have exerted a notable influence on the current work, a delineation is provided subsequently. The above studies have researched different aspects of the DIT construct and sought marketing information by using tourist segmentation, analysis of popular attractions, and other techniques. The present study aims to measure the discrepancy between photos from controlled sources (DMOs) and those published online for newspapers, magazines, and users (uncontrolled sources) during adverse events that can negatively impact the pre-visit destination image. On considering the above, the following questions have been proposed to guide our research.

- How can images be used to measure differences in the projected destination image between controlled and uncontrolled sources?
- Is our method capable of pointing critical points at measured differences?
- Is our method able to measure those differences for different destinations?

From the analysis of the related work, we have obtained valuable information utilizing the convenience of deep learning and the use of Big Data to derive better tourism intelligence and new potential applications using massive amounts of multimodal data. All these studies influenced our work and the proposed approach is presented in subsequent sections.

III. Proposed Approach

We propose a methodology to automate the process of measuring changes between the photographs used to promote a destination by the DMOs (controlled sources) and those published on the internet (uncontrolled sources) during events that negatively could influence the projected *destination image*. To this aim, we perform a comparative image analysis on three different periods: an analysis of previous the event, an analysis of when the event took place, and a last analysis of when the event has finished. In this way, we can measure the behavior of the uncontrolled sources in comparison to controlled sources.

To automatically perform the image (photographs) analysis, we used a collection of tools and methods based on three stages: scene recognition, characterization of features (feature management), and measurement of the difference between features. Each stage is explained in detail below.

A. Scene Recognition

Scene recognition provides a description of the content of the image rather than listing objects in the scene. The main objective of this task is to assign semantic labels to images and, such labels are defined by real observers to equip computers with the ability to describe scenes like humans [43]. The task of object recognition, on the other hand, is postulated as a representation of the object being investigated with the image features available while rejecting the background features [44]. From the above, we can see that scene recognition provides richer descriptions not only of the objects in the scene but also of their surroundings and context. For these reasons, we opt for using the scene recognition approach. Thus, we choose the well-known Places-CNNs [45], which is a deep learning tool formed by a set of convolutional neural networks. Places-CNN uses different CNN architectures, but according to their results, the most precise are VGG-16 and ResNet152, which likely are at the core of the implementation we used. A typical output of Places-CNN is a set of tags that describe the scene and objects in it. For example, the photograph of a food area in a shopping mall (Fig. 2) is described by Places-CNNs with the terms and strengths in Table I. Tags in *Categories* are the elements discovered on the scene with the deep learning modules. We have named strength to the degree of confidence a neural network has in declaring that a particular element is on the scene. Scene attributes are general descriptions of the image analyzed, such as *closed area*, which means that the action takes place inside. Taking into account the above information, we can imagine Places-CNNs as an advanced device for analyzing huge data loads, recognizing elements in scenes (*attributes*), and with a degree of certainty (*strength*) in this detection process.

Fig. 2. Scene analyzed with Places-CNNs.

TABLE I. Information Obtained by Places-CNNs by Analyzing the Scene in Fig. 2

	Scene Recognition	Strength
Categories	Food_court	0.511
	fastfood_restaurant	0.085
	cafeteria	0.083
	dining_hall	0.040
	flea_market/indoor	0.021
Scene attributes	No horizon	0.903
	Enclosed area	0.495
	Man-made	0.444
	Socializing	0.423
	Indoor lighting	0.211
	cloth	0.151
	Working	0.102
	Congregating	0.081

B. Characterization of the Feature Space

Once a photo is processed by Places-CNN, we use as *photo-features* only the outputs given by the attributes of the scene because, during the experimental phase of this work, we have experienced significant variations in the use of both sets of features (categories and attributes). Therefore, we consider that a more stable performance can be achieved using only *attributes*. That is because they are more descriptive characteristics in a wider scope.

Given a set of features from a set of images, we characterize them as a histogram, where the bins are the label of the features (attributes of the scene), and the sum of the corresponding strength as the *frequency*. Thus, we compute a total of four histograms: one for the set of pictures obtained by the DMOs from a specific destination (controlled photographs), and one for the event on each period to analyze (pre-event, during-event, and post-event), from uncontrolled sources. It is important to note that, the set of photographs does not necessarily have the same number of pictures or features, hence, we normalize the histograms to keep equal scales. In the following section, we briefly explain a method that can be used to quantify the differences between histograms.

C. Measurement of Difference Between Features

To measure the differences between the computed histograms, we use the Earth Mover's Distance (EMD). EMD is a distance metric that measures the dissimilarity of two histograms. The computer vision community has been enthusiastic with this technique [46]. Let's consider two normalized histograms $q = (q_1, ..., q_n)$ and $p = (p_1, ..., p_m)$, each with n and m bins, respectively; q_i and p_j are frequency values of the histograms p and q, for the bin labels i and j, respectively. F is a *flow matrix*, where $f_{i,j}$ is the flow to move from q_i to p_j, and a *cost matrix* C, where $c_{i,j}$ means the cost of moving flow from the bin label i-th of q to the bin label j-th of p. The total cost of moving the unit flow to F and C between the histograms q and p can be defined as:

$$d(q,p) = \sum_{i=1}^{n}\sum_{j=1}^{m} f_{i,j}\, c_{i,j} \tag{1}$$

The ground distance (here called cost matrix) C can be designed, depending on the behind problem, by experts in the field or derived from a formula. It is clear that $c_{i,j} = 0$ and a greater distance between label bins i and j means a greater $c_{i,j} > 0$. As p and q are normalized, then $\sum_{i=1}^{n} q_i = \sum_{j=1}^{m} p_j = 1$, and the EMD between p and q is defined as follows:

$$\begin{gathered} \mathrm{EMD}(q,p) = \min{}_F\, d(q,p), \\ \text{subject to} \\ f_{i,j} \geq 0,\ \forall i \in [1,n] \text{ and } \forall j \in [1,m], \\ \sum_{j=1}^{m} f_{i,j} = q_i, \forall i \in [1,n], \\ \sum_{i=1}^{n} f_{i,j} = p_j \forall j \in [1,m], \\ \sum_{i=1}^{n} q_i = \sum_{j=1}^{m} p_j = 1. \end{gathered} \tag{2}$$

The idea behind the equation (2) is to find the minimum cost to transform q to p. The computed cost represents the difference between histograms, it is to say, if p and q are equal then EMD(q, p) = 0; otherwise EMD(q, p) > 0.

Since a set of photographs is characterized as a histogram, two sets of different photographs can be compared by solving (2). However, a fundamental aspect to consider is the ground distance (or cost matrix C) among each bin label in the histogram. In the problem under study, each bin label of our histograms is a scene attribute, thus obtaining the distance between attribute concepts is not a trivial task. The following section discusses three different approaches to addressing this issue.

1. Ground Distance

As indicated in the previous section, a ground distance matrix must be created to measure the differences between two histograms. When the histograms are about specific entities such as colors, we can use different analytical methods to calculate the differences among them; however, if the histogram is for items like different kinds of wines, an expert or a group of them is needed to provide a measure about how different are a "Pinot noir" and a "Merlot". In the problem at hand, we need to provide a measure of the semantic distance between concepts such as "man-made" and "indoor light", we opted to use two well-known approaches in the field of deep learning and one last rather straightforward. Since there are no available comparisons of the performance of those deep learning approaches for tasks like the one in this study, we have decided to use all of them to observe their suitability for our method. In the following, we explain three different proposals to compute the ground distance C.

WordNet The first proposal to compute Ground distance is based on Natural Language Processing (NLP). This approach is performed by using the WordNet database. WordNet is a large lexical database of English. It contains almost 80,000 noun word forms organized into 60,000 lexicalized concepts. Nouns, verbs, adjectives, and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked utilizing conceptual-semantic and lexical relations [47]. To measure the distance of two concepts, we used the Wu & Palmer similarity measure (*wup*), which calculates the relatedness by considering the depths of two synsets in the WordNet taxonomies, along with the depth of the Least Common Subsumer (LCS) [48]. The LCS of two concepts A and B is the most specific concept, which is an ancestor of both A and B [49]. The calculation of the metric is given by:

$$wup = 2 * \frac{depth(lcs(s_1, s_2))}{depth(s_1) + depth(s_2)} \tag{3}$$

where s_1 and s_2 are the synsets to be compared, depth is the deepness in the taxonomic tree and lcs refers to the Least Common Subsumer.

Word embeddings The second proposal, also based on the NLP approach, was a technique known as *word embeddings*. This technique performs a mapping of a categorical variable (a word) to a vector of continuous numbers. For implementation, we use the well-known Word2Vec method [50]. One of the major advantages of these models is that the distributed representation reaches a level of generalization that is not possible with classic models [50]. A typical n-gram model operates in terms of discrete units that have no intrinsic relationship between them, a continuous model works in terms of word vectors, therefore, similar word have similar vectors. For our experiments, we use the *GoogleNews-vectors-negative300* pre-trained model. This model has been trained on a part of the Google News data set and contains 300-dimensional vectors for 3 million words and phrases [51]. By using a vector representation for each word that preserves semantic meaning, we can approach the quantification of similarity as a simple Euclidean distance between the points in a 300-dimensional space.

Constant Value Finally, for comparison purposes, the last approach to compute Ground distance is assuming that the distance between all elements is constant. This means that the difference between all *scene attributes* is the same. Specifically, we set the value constant equal to 1. For example, the distance between *indoor* and *eating* is 1 and it is the same for *eating* and *man-made*.

D. Summary

Our approach follows a three-stage process: obtain the *attributes of the scene* from a set of pictures, characterize output attributes into normalized histograms, and compute the differences between the histograms (see Fig. 3 and Fig. 4). In the *first stage*, a set of photos

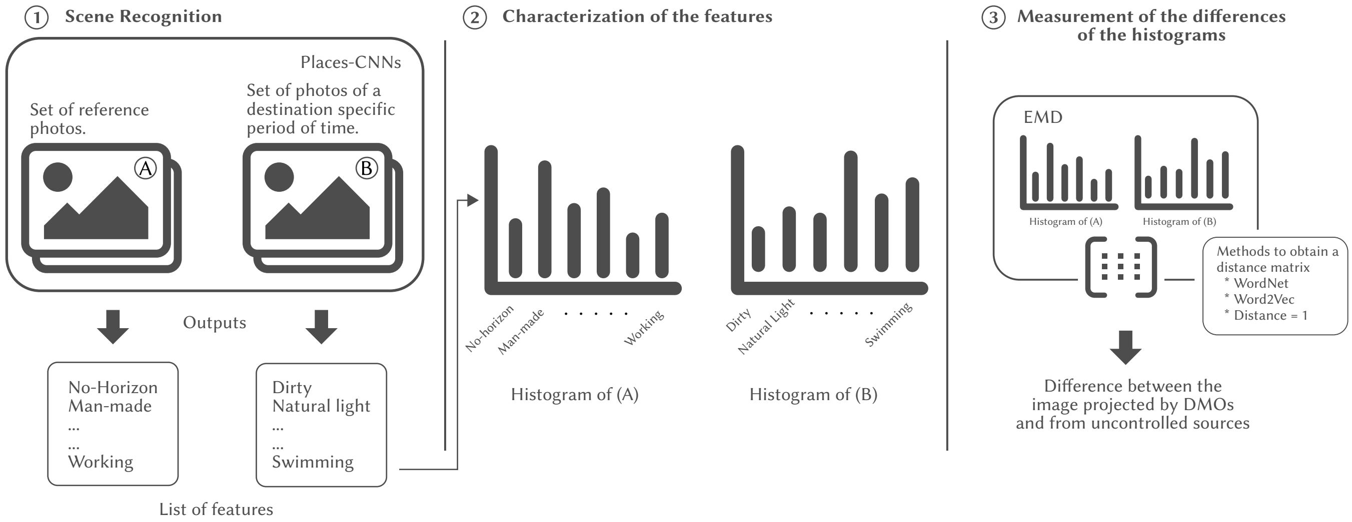

Fig. 3. Graphical description of the phases of the proposed approach.

is processed using the Places-CNN's tool for scene recognition. The result in each picture is a set of attributes and strengths (confidence level of the neural network) of the scene. In the *second stage* the complete set outputs are characterized on a histogram, where the bins are the label of the features (attributes of the scene), and the sum of the corresponding strength as the "frequency". Since the strengths are continuous values and the set of features are not necessarily the same we normalize the histograms to keep equal scales. In order to have a baseline to compare, we built four histograms: from a reference set of a collection of photos of the tourist place, and three from a set of photos (of the same reference place) taken on the internet on different periods of time around an event (pre-event, during event and post-event). The *third step* is to calculate the differences between the histogram obtained on the reference photos of the tourist destination and the histogram from the three periods under evaluation. In this stage, the most important thing is the adequate generation of the distance matrices, which is necessary to calculate the difference between histograms. The result of this step is a symbolic measure of the differences. With the elements in the histograms, we can also perform set operations to know more about each period analyzed.

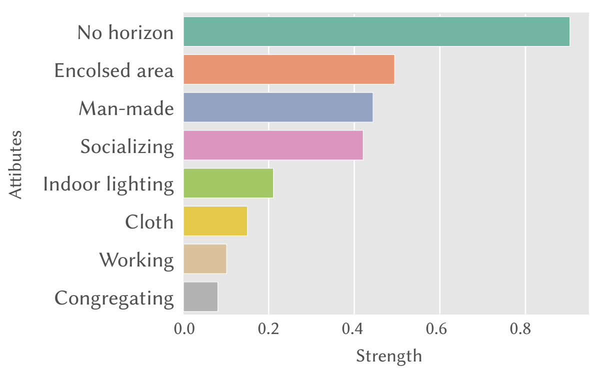

Fig. 4. Example of a histogram of the attributes of Fig. 2.

IV. Experimental Design

A common practice for travelers from all over the world is to search the Internet for details of where they are about to visit, especially photos. Considering the above, we want to know how the pre-visit destination image is affected by pictures of adverse events available on the internet as climatic or social phenomena. To verify whether the changes can be automatically quantified from photographs, we select a set of events with extensive media coverage that took place in Mexico. We employed an approach based on periods, labeled as "*during*" for the time the event took place and "*before*" and "*after*" for the pre- and post-event times. The photos were searched and downloaded manually, and equal proportions of photos were gathered for all time periods. For the collection of images, we implemented a web scraper. This algorithm automates the search and downloads the pictures. We have used Google Images, but any web platform may be employed. The terms used for the search follow the structure shown below:

"City" "streets" "Larger than 800x600" "after:Date_1 before:Date_2"
"City" "beaches" "Larger than 800x600" "after:Date_1 before:Date_2"
"City" "news" "Larger than 800x600" "after:Date_1 before:Date_2"

The term "*beaches*" is used in the sun and beach destinations. The deep learning module needs images of at least "*224x224*" pixels, so the size can be introduced to the search to avoid smaller images. We used both English and Spanish for the terms. The events are described in Section IV.A. To make comparisons, we also need a baseline of the places where the events took place. We used a set of DMO's and Flickr's photographs to build it (see Section IV.B). The results are presented in Section V.

A. Events Under Analysis

To test our method, we select a small sample of adverse events that occurred in different destinations in Mexico. To be able to ensure sufficient content, we choose events with extensive media coverage. We reduced our list only to events that affected tourist destinations and these are Mexico City, Guadalajara, Cancun, Acapulco, and San Blas. Apart from Mexico City and Guadalajara, the others are well-known sun and beach destinations for foreign (Cancun, Acapulco) and domestic (San Blas) tourists. Mexico City and Guadalajara are recognized for their historical relevance and comprehensive range of tourism-related services. Mexico City was recognized by UNESCO as a World Heritage Site in 1987 and the Museo Cabañas in Guadalajara and the surrounding Agave landscape got such recognition in 1997 and 2006 respectively. In addition to its beautiful turquoise beaches, Cancun is known for its World Heritage Maya ruins. In 2019, it was visited by 463,428,131 tourists, being the second most-visited destination behind Mexico City. Acapulco is a tourist attraction in the Mexican state of Guerrero, located on the Pacific coast of Mexico. With an annual average temperature of 28° Celsius, Acapulco is one of the few destinations in the world with year-round pleasant weather. It offers a variety of services to enhance the visiting experience in addition to its natural charms. In 2019 it was the third most popular destination in Mexico with 186,377,996 visitors. San Blas is part of a new tourism development called Riviera Nayarit, which promises to bring tourism development to the coastal region of the municipalities of the region, an area rich in diverse natural and cultural resources. In 2019, above 278,513 tourists visited San Blas. For the occupation data, we have relied on statistical information gathered by the governmental organism in charge of tourism in Mexico, the Secretary of Tourism or SECTUR under the acronym in Spanish [52].

1. Sargassum Season in Cancun 2021

Sargassum is a species of algae that is abundant in tropical zones like the Caribbean coasts [53]. Since 2019, there has been a considerable increase in the proliferation of Sargassum, but the highest concentration occurs during the hottest months of the year. To characterize this event, we selected the photographs posted between March and June 2021. The images for the previous (**before**) period were from January and February of the same year. For the following period (**after**), the months of July and August were taken into account. Fig. 5 presents some thumbnails of representative images of the event. 100 images were collected for each time period for this event. This number of images was chosen to avoid repetitions among the photos and to ensure diversity.

Fig. 5. Representative images of the season of sargassum in Cancun.

2. Protesters in Mexico City During 2021

Before describing this event, we want to state that we are not against the protesters and their struggle for women's rights. Our interest is only from the point of view of tourism to analyze the impact of this social phenomenon on the sector. On March 8, International Women's Day, police and activists clashed in Mexico City during a march [54]. According to the BBC news portal, officers pushed back the protesters with tear gas and riot shields. For the event, we collected photographs from 03-08-2021 to 03-10-2021. The before period was from 02-26-2021 to 02-28-2021. For the after period, the dates range from 04-10-2021 to 04-12-2021. Fig. 6 shows some representative images of the event. 100 images were collected for each time period for this event.

3. The Effects of Hurricane Willa on San Blas, Nayarit (2018)

In October 2018, Hurricane Willa hit 8 of the 20 municipalities in Nayarit State. The climate phenomenon caused the flooding of the San Pedro and Acaponeta rivers, which affected more than 180,000 people [55]. Willa struck the municipality of San Blas on October 24, but their effects were felt a few days before. For this event, the dates envisaged for the periods are as follows: from 10-14-2018 to 10-19-2018 for before, from 10-20-2018 to 10-26-2018 for **during**, and from 11-10-2008 to 11-16-2018 for **after**. Fig. 7 depicts some images representative of the event. 50 images were collected for each time period for this event.

Fig. 6. Protests during InternationalWomen's Day in Mexico City.

Fig. 7. Impacts of Hurricane Willa in San Blas, Nayarit.

4. Protesters in Guadalajara During 2020

On 4 May 2020, a 30-year-old young man, Giovanni López was arrested for assaulting a group of police officers from the municipality of Ixtlahuacán, Jalisco. The next day, he died of damage caused by the police [56]. These events led to civil mobilizations in Guadalajara on days 4, 5, and 6 of June. The dates considered for the periods are: from 05-28-2020 to 05-30-2020 for before, from 06-04-2020 to 06-06-2020 for during, and from 07-01-2020 to 07-03-2020 for after. Fig. 8 presents some representative images. 100 images were collected for each time period for this event.

Fig. 8. Protests in June 2020 at Guadalajara, Jalisco.

5. Violence in Acapulco During 2017

In 2017, the municipality of Acapulco was considered the most violent place for women according to the United Nations. According to the report, the municipality contributed 3.9% of the national homicides, 5.5% above the national average [57]. This wave of violence is still far from over, considering the health contingency of 2020, we think that with fewer people on the streets and the beaches closed, a change can be identified by comparing similar time periods. Therefore, we compared images from the months of April, May, and June in the years 2017 and 2020. We chose these months because of increased tourist arrivals during the warmer months. The representative pictures are in Fig. 9. 50 images were collected for each time period for this event.

April to June, 2017 April to June, 2020

Fig. 9. Images of Acapulco during 2017 and 2020.

B. Reference Pictures

To be able to identify the differences, we also need a reference base for the tourist destinations we want to analyze. To this end, we have collected around 500 photographs of the destinations where the events took place. As reference material, we have used photographs from local DMOs (SECTUR) to promote the destination, and to ensure variety we also used material from Flickr. The selection was done manually to ensure that the photos were from the place of interest and to avoid duplicated or bad-quality material. For our approach, there are no limits to the number of photographs to analyze. The reason behind the choice of 500 photographs is strictly linked to the variety and quality of the material at hand. Fig. 10 shows a set of representative pictures of each considered destination.

Fig. 10. Sample of the reference images of the destinations under analysis.

V. Experimental Results

Three different approaches were used for the ground distance required to measure the similarities between histograms. As mentioned above, two distance matrices were obtained through NLP approaches (WordNet and Embeddings), as a substitute for language experts. The final method was to consider the difference between all the concepts as 1 unit. Fig. 11, Fig. 12, Fig. 13, Fig. 14 and Fig. 15 show the graphs of the calculated difference between the histogram of the reference images and the histograms of the set of pictures on each time frame. There is a chart for each approach adopted for the distance matrix (WordNet, Embeddings, and Distance = 1).

From the figures, we can highlight the existence of a triangular pattern in Cancun, Mexico City, San Blas, and Guadalajara. The *peak* vertex belongs to the "*during*" period in all these charts, and is pointing up in San Blas, and downwards in Cancun, Mexico City, and Guadalajara. The existence of this triangular pattern confirms our hypothesis that during abnormal conditions such as adverse events, the differences between the baseline images (those from the DMOs) and the ones from uncontrolled sources are incremented. On the other hand, despite there being differences between the baseline photos and those from normal conditions, they are shorter than the above. In this context, we refer to normal conditions as the time intervals previous to and posterior to an adverse event for the destination image. The intuition behind this idea is that photographs for such "normal conditions" present the destination with all its pros and cons while during adverse events, photographs reflect more flaws than qualities. Given that controlled sources present just the brighter side of the destination they promote, photographs of non-anomalous periods (posted by uncontrolled sources) will also have a variation regarding the image projected by DMOs but smaller than those resulting from adverse events.

As for Acapulco's charts, it should be noted that the series for 2017 and 2020 shows differences in magnitudes and are separable. It is important to note that the patterns are similar to the three ways to compute the distance matrix. The magnitudes obtained with WordNet and Embeddings are almost the same, and with distance = 1, the differences between the stages are more evident and, therefore the one that we will discuss in this section.

Even if the triangular model in the series is not pointing in the same direction in all destinations, the anomaly is easily identifiable. Table II and Table III present the score given by EMD to each period, the average score of a series, and the rate of change in the critical point given the mean. The rate of change (last column of both tables) presents a statistic of how much varies the score from periods considered "normal" and anomalous periods. This measure can help us understand the level of impact of factors depicted by photos during adverse events. Table II shows that the most drastic change occurred in San Blas (from the destinations in this group), with a change rate of 10.731%. Considering the damages inflicted by Hurricane Willa on this town, it is understandable those variations. Regarding Mexico City and Guadalajara, the damage provoked by the protesters is well reflected in the media and has resulted in significant changes in their scores, with a change rate of 8.876% and 8.299% each. Cancun got the smallest change rate in this comparison (4.115%). Given that Sargassum is just a small flaw in the landscape, this rate of change makes sense. Data from Acapulco (Table III) shows an important separation in the periods evaluated. This situation could be due to pictures in 2017 presenting noise and festive scenes, with different examples of crime and law enforcement. On the other hand, in 2020, with quarantine and closed beaches, images of solitude in the landscape are free of trash and jolly chaos.

It is also interesting to know what attributes were found by the Neural Networks in the scenes corresponding to the critical points. By using this information and the changes in the series, our approach can provide an overview of the current situation. Table IV shows some scene attributes that stand out in critical points, and Table V

Fig. 11. Charts for Cancun. Differences between histograms at each time frame. In the upper right corner, a label is given for each method.

Fig. 12. Charts for Mexico City. Differences between histograms at each time frame. In the upper right corner, a label is given for each method.

Fig. 13. Charts for San Blas. Differences between histograms at each time frame. In the upper right corner, a label is given for each method.

Fig. 14. Charts for Guadalajara. Differences between histograms at each time frame. In the upper right corner, a label is given for each method.

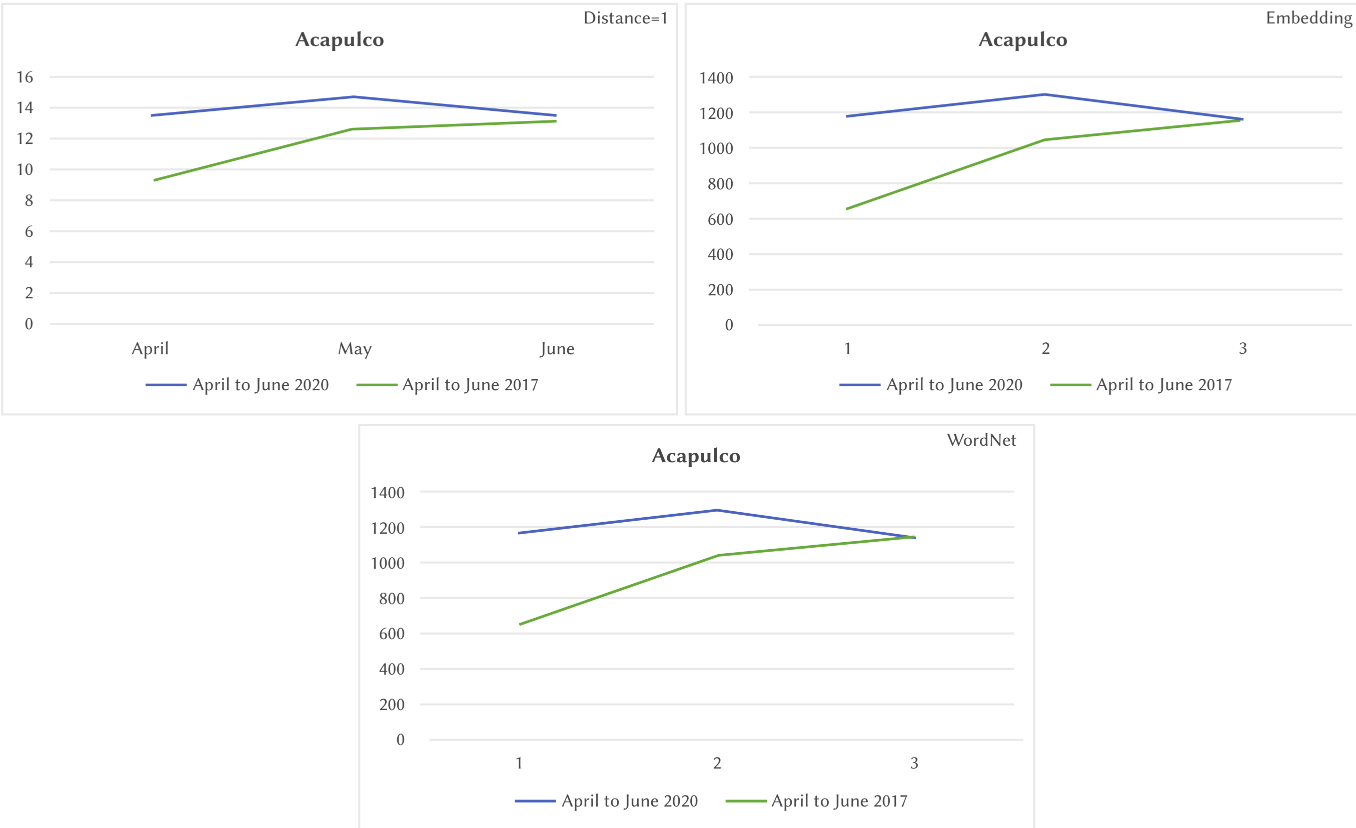

Fig. 15. Charts for Acapulco. Differences between histograms at each time frame. In the upper right corner, a label is given for each method.

TABLE II. Scores for the Differences Between Histograms (Reference and Period) With Ground-distance = 1 for All the Attributes of the Scene

Destination/Period	Before	During	After	Average	Rates of change in the *During* period
Cancun	14.348	13.513	14.418	14.093	4.115%
Mexico City	12.542	10.905	12.455	11.967	8.876%
San Blas	9.102	10.583	8.987	9.557	10.731%
Guadalajara	18.538	16.26	18.397	17.731	8.299%

TABLE III. Scores for the Difference Between the Histograms of Acapulco (Reference and Period). The Ground-distance = 1

Month/Year	2017	2020	Difference	Rates of change in the months considered
April	9.359	13.569	4.210	36.723%
May	12.688	14.764	2.076	15.124%
June	13.240	13.574	0.334	2.491%

presents those attributes that were not present in the scenes of the *during* period but are part of the scenes of the reference photographs for all the destinations. The attributes were obtained through set operations between the items in the reference set and the items in the period under evaluation. It can be seen that the most common faults found by neural networks are *dirt* and *dirty*. These attributes are understandable for mass manifestations, sargassum, crime, and climatological phenomena, however, defects in scenes for Hurricane Willa have been detected by neural networks as bathing scenes. As for the negative image (obtained with the missing attributes in Table V), it can be observed that such elements can tell us about things that are absent in the photographs of a destination. For example, for Cancun, all the photos were aimed at showing the algae problem and did not reflect the fun things about the beaches as surfing or soothing. The same applies to San Blas with pictures showing the damage caused by the hurricane. For better understanding, Table VI shows the complete list of attributes identified in the scenes of the reference images in all the destinations considered. The Acapulco case is interesting, as the chaotic images of people enjoying the beach and those photos that portray law enforcement present different realities side by side, but also show all of Acapulco's strengths at the same time. This series presented a violent season for our country and got a better score by EMD instead of the one that presents the loneliness of the quarantine (series 2020) because the last one presented only a few aspects of the place. We believe that this is one of the reasons behind the best score in the 2017 series. The other and most important reason is that, like in many scene recognition tools, the deep learning module was trained to recognize a wide range of elements, but none is unpleasing to the eye. That's why problems like crime go unnoticed by neural networks, and flood scenes get confused with people bathing. However, despite these flaws, our method can assess the disparity between photographs to promote a destination and those of uncontrolled sources, giving details of attributes that are not reflected in a critical point or the defects that are present in the period under assessment.

TABLE IV. Scene Attributes That Stand Out in the *During* Period in All Destinations

Destination	Attributes
Cancun	Dirty, dirt.
Mexico City	Dirty, dirt, cluttered space, waiting in line, stressful.
San Blas	Bathing, cold, pavement.
Guadalajara	Dirty, dirt, spectating.
Acapulco (2017)	Dirty, dirt, stressful, shingles.
Acapulco (2020)	Dirty, dirt, rusty.

TABLE V. Attributes That Were Not Present in the Scenes of the *During* Period for the Different Destinations

Destination	Attributes
Cancun	Surf, competing, shopping, soothing, vegetation. **Total**: 29 attributes missing.
Mexico City	Symmetrical, soothing, playing, matte. **Total**: 18 attributes missing.
San Blas	Brick, surf, aged, soothing, ocean. **Total**: 17 attributes missing.
Guadalajara	Brick, soothing, glossy, concrete, symmetrical. **Total**: 33 attributes missing.
Acapulco (2017)	Surf, symmetrical, soothing, camping, glossy, sports, hiking, horizontal components. **Total**: 41 attributes missing in the entire series.
Acapulco (2020)	Symmetrical, glossy, rock, playing, grass, shopping, climbing, camping. **Total**: 64 attributes missing in the entire series.

VI. Discussion

According to scores in each time frame for the three employed distances on the destinations, there was a significant difference for San Blas, where the unfortunate event of the Willa Hurricane significantly increased images from uncontrolled sources. In this regard, the DIT of San Blas continues forming through positive and negative images [10], [11]. Also the DIT is related to a set of ideas, impressions, and beliefs about a particular place (San Blas in this case) based on medium to long-term experiences [9], where images from uncontrolled sources play a major role. Thus, the increment of pictures from adverse events impacts the "induced" level (one of the three levels of destination image formation analysis) [12]. Since such images are intentionally published by different uncontrolled media, they influence the processing of the destination image, even if it is based on negative aspects of the destination promotion. Consequently, once the adverse event has occurred, DMOs should resume promotion with positive images intended for potential visitors, particularly cognitive resources that impact more [16]. The aforementioned is also related to perceived changes during adverse economic events where the construction of such destination image changes the decisions of potential visitors [23]–[25].

Concerning the measures given by our approach, differences among histograms show that the rate of change in each critical point, considering the mean between normal and abnormal periods, contributes to understanding the level of influence of the factors behind the analyzed pictures of adverse events. Of the destinations analyzed, San Blas represented the higher rate of change of the places in this study for its images (Huracan Willa), followed by Mexico City (protestors, vandalism), Guadalajara (protestors, vandalism), and Cancun (sargassum). It can be said that adverse periods affecting the DIT by exogenous factors hurt this image [40], which presented a method that measures the dissimilarity between images of different destinations influenced by endogenous and exogenous factors and helps them identify the elements that influence positively or negatively the destination image. In this case, San Blas was severely damaged by the hurricane, and our approach was able to detect the change based on the comparative analysis of the photographs before, during, and after the event. The scene recognition approach that takes into account objects, environment, and context, is therefore preferred over simple object detection frameworks [43].

TABLE VI. Attributes of the Scene From the Set of Reference Photos

Destination	Attributes
Cancun	Surf, dry, horizontal components, cold,biking, cluttered space, glass, enclosed area, cloth, praying, plastic, socializing, sand, rugged scene, eating, railing, competing, shopping, glossy, semi-enclosed area, soothing, natural light, open area, pavement, spectating, vertical components, man-made, wood, indoor lighting, touring, moist, metal, warm, driving, transporting, shrubbery, congregating, vegetation, sports, grass, natural, asphalt, boating, ocean, diving, swimming, far-away horizon, stillwater, sunny, foliage, leaves, clouds, trees, reading, no horizon, aged, climbing.
Mexico City	Warm, fencing, rusty, man-made, cold, semi-enclosed area, sports, glossy, congregating, rugged scene, matte, symmetrical, carpet, dirty, paper, dirt, horizontal components, metal, working, railing, plastic, transporting, soothing, rock, shingles, ocean, playing, stressful, flowers, wire, shopping, driving, swimming, boating, glass, brick, natural light, asphalt, biking, pavement, wood,aged, far-away horizon, cluttered space, socializing, dry, still water, diving, cloth, eating, competing, natural, climbing, shrubbery, touring, praying, using tools, enclosed area, clouds, open area, spectating, moist, no horizon, indoor lighting, leaves, trees, camping, vertical components, vegetation, sunny, foliage.
San Blas	Glass, brick, using tools, indoor lighting, working, dirt, rock, driving, vertical components, transporting, praying, asphalt, wood,natural light, dry, warm, metal, dirty, climbing, surf, cluttered space, open area, shrubbery, grass, shingles, man-made, soothing, shopping, enclosed area, touring, aged, sunny, camping, moist, far-away horizon, congregating, boating, swimming, clouds, no horizon, natural, diving, leaves, cloth, rugged scene, foliage, still water, semi-enclosed area, vegetation, ocean, trees, biking.
Guadalajara	Diving, rusty, metal, paper, brick, soothing, man-made, competing, still water, eating, glossy, congregating, plastic, wood, semi-enclosed area, glass, using tools, scary, railing, concrete, boating, stressful, natural light, socializing, working, waiting in line, moist, dirty, dirt, aged, symmetrical, shopping, camping, cloth, asphalt, horizontal components, carpet, shingles, transporting, driving, dry, warm, pavement, indoor lighting, natural, swimming, open area, climbing, fencing, shrubbery, biking, sand, praying, trees, cluttered space, leaves, rock, touring, grass, enclosed area, vegetation, hiking, far-away horizon, foliage, reading, rugged scene, vertical components, clouds, no horizon, sunny, sports, running water.
Acapulco	Reading, congregating, semi-enclosed area, pavement, cluttered space, socializing, competing, dirty, glass, symmetrical, aged, sand, metal, glossy, natural light, open area, cold, driving, plastic, eating, biking, sports, shopping, horizontal components, playing, asphalt, working, paper, railing, hiking, cloth, enclosed area, praying, warm, wood, using tools, grass, bathing, touring, climbing, transporting, vertical components, spectating, surf, indoor lighting, dry, soothing, foliage, rugged scene, camping, leaves, still water, man-made, rock, vegetation, natural, diving, boating, moist, trees, ocean, shrubbery, dirt, swimming, far-away horizon, sunny, no horizon, clouds.

In the Acapulco analysis, the highest rates of change were observed in April, followed by May and June for 2017 and 2020. Considering that in March of 2017, the Tourism tianguis[1] took place in such destination, promotion images presented the beautiful sides of the city such as natural landscapes, urban landscapes, and related tourist products; Compared to the events that took place in the following months of the same year (insecurity, crime, social agglomerations) and the events of 2020 at the beginning of the SARS CoV-2 pandemic (closed beaches, minimal hotel occupancy, emergency health measures), produced a different picture of the destination. Once more, the scene recognition approach made it possible to provide descriptions of the image and its content that have been useful in distinguishing the observed features presented on images from controlled and uncontrolled sources.

As regards the attributes of critical points in all cities, two coincidences have been noted: "dirty" and "dirt"; Representative characteristics of the identified adverse events (protestors, vandalism, delinquency, sargassum, and climatic factors). Regarding San Blas and the impact of the hurricane, the prominent attributes were "bathing", "cold", and "pavement". Such attributes were misinterpreted by artificial intelligence but they pointed out inundations in the scene, which are negative factors for the destination promotion but that are considered by potential tourists. In this sense, our methodology could improve attribute recognition (or minimize the mistakes) by nesting other specialized computer vision strategies, e.g. [58] [59].

The choice of a destination is strongly influenced by different secondary factors [13], therefore, being able to measure an important part of them, communicated through powerful and simple cognitive resources like the photographs, could help DMOs and other entities to plan countermeasures to mitigate the effects of adverse events for the tourism industry.

VII. Conclusions

In this work, we presented an approach based on deep learning techniques to automatically measure changes between the photographs used to promote a destination by the DMOs (controlled sources) and those published on the Internet (uncontrolled sources) during adverse events that negatively could influence the projected destination image. This approach was designed to automate the tracking of these changes, reducing the burden on experts or to be employed in the absence of them.

Our method uses different computing techniques and employs the Deep Learning paradigm as a cornerstone. Thanks to the synergy of these techniques, our method can detect critical points and also provide information about the scene attributes that stand out in such events. With this information, travelers and/or DMOs can design strategies to attenuate the factors that may discourage potential tourists from visiting a destination. To our knowledge, this is the first work to explore this issue through the use of IT techniques.

As our proposal is a pioneer in dealing with the problem of measuring differences between images from controlled sources versus images from uncontrolled sources, specifically during events that could alter the projected destination image, it is possible that our methodology could be easily adapted to other potential applications, for example:

- Destination development (Dd): Given a set of parameters, the present methodology can be adapted to measure the evolution of a destination's infrastructure using a collection of images. This can also be used for the sustainable development of the destination.
- Recommendation systems (RS): Given the change history tracking in a period over some destination, it is possible to use this information to feedback into an RS to support tourists to avoid unpleasant experiences and to recommend the best periods to travel, minimizing witnessing undesirable situations.
- Online Travel Reviews (OTRs): The analysis of the OTRs has been studied a lot, mainly using Sentiment Analysis. However, the OTRs analysis does not differentiate between normal experience periods and those with adverse events. Thus our approach can be used to segment OTRs depending on the detected changes and have a deeper OTRs analysis.
- Quick response (QS): Taking into account historical records, DMOs, and governments can discover patterns and design strategies to mitigate drawbacks in advance.
- Ranking Systems (RaS): Destinations can be ranked according to their variations in the monitoring of changes. Destinations with fewer variations (according to a baseline) are ranked above those with several variations.
- Measurement of differences in content (MDC): Our methodology can be used to quantify differences between UGC and DMOs' content using photos. With this measure, DMOs can evaluate the performance of their marketing campaigns regarding the experiences shared by tourists.

Finally, the proposed method provided evidence that images can be used to measure differences in the destination image projected by controlled and uncontrolled sources, it can be used for different destinations and it helps to detect critical points on the tracking. Using this method as a cornerstone, our investigation will be able to go to further steps to analyze the impact that those divergences have on tourists' destination image through in situ analyses.

[1] Is an international event for tourism promotion of Mexican destinations held by the federal government.

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