Landscape Image H.A.C.K.: Human Activity Captured Kernels

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Abstract

In this twenty-first century, social media has introduced digital disruption as online methods created to consume services. Responsible for this are the people who do not subscribe to traditional ways of procuring services; they opt to use the internet instead, such as having an online photo album in Facebook. Through these online activities, big data is created – information that are accessible for designers of the landscape. Using the internet for design purposes has been a regular part of the landscape design process – mood boards created to provide visualization for the client in design conceptualization. This research explores the use of big data as a source of information with the Instagram platform. Since Instagram is the most popular image-sharing platform online, designers can also take advantage of the volume of its content. What makes Instagram unique is that its images come from accounts of the online community. Information from every active account leads to a glimpse to what they hold valuable through the act of posting an image they took. There has been a method developed in a Master in Tropical Landscape Architecture (MTLA) at the University of the Philippines Diliman to evaluate landscape representation from Instagram landscape images (Bimbao, 2017). To further the research on this online resource, this paper considers scrutiny of the human representations included within the studied landscape representations. The connections of human and landscape representation in a landscape image inform and remind the landscape designer to appreciate the landscape use of the online community. Through the methodology, the following were revealed; a more passive landscape usage, importance of water elements, and the need to develop a specific human activity recognition method for landscape analysis.

Keywords: Instagram content analysis, Human Activity Recognition, Landscape Value, Landscape Image

I. Introduction

The dependence of the public to social media platforms shows how digital disruption impacts industries. An industry is "disrupted" when people who use certain services are provided with an online option to consume or deliver products of the industry (Macy and Thompson, 2011). Examples of these web platforms are AirBnb for accommodation, Grab for transport, and Facebook for news. The list goes on and on with more platforms being developed that increase disruption in many industries. The information that is being aggregated through these services hold a unique value as the online community or online public operates as both producer and consumer of information (Macy and Thompson, 2011). The data is made by the public and produced for the public – what researchers face now would be to be able to identify what data points or kernels should be examined.

The author takes interest in exploring further the landscape design industry, another field digitally disrupted by technology. The emergence of new technology finds its way in the landscape design process such as the computer aided design (CAD) for drawing production that has rendered majority of the drafting tables in design offices obsolete. CAD offered plenty of advantages to designers in delivering their works over traditional methods of manual drafting. A more recent addition to this digital disruption in the practice is when the landscape architect makes use of the internet as a tool in conceptualization. It is common practice for design professionals to scan the internet for media that can be used as design inspiration. To continue to be a relevant service provider, professionals need to be able to integrate disruptions brought by technology to the practice they can offer. This means using digital disruption for the benefit of improving the landscape design process.

One contribution to landscape architecture of digital disruption is landscape representation, specifically how users of social media capture the environment. This act reveals landscapes that hold or have a certain value to the online community. These aid in creating relevant mood boards in the landscape design process. It leads to more inclusive consideration of the values of the online public. An evaluation using content analysis to generate value from landscape representations of the online community was presented by the author as an MTLA thesis (Bimbao, 2017).

Landscape representation has been historically proven to be significant in understanding how humans relate to the environment. Landscape is the stage for any human activity. Sharing images online that have landscape

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representation shows what landscape and landscape activities are valuable. This is important for professionals involved in landscape design because their end product is landscape. There is a circular framework that continuously connects users, the landscape or environment, and the designer (See Figure 1).

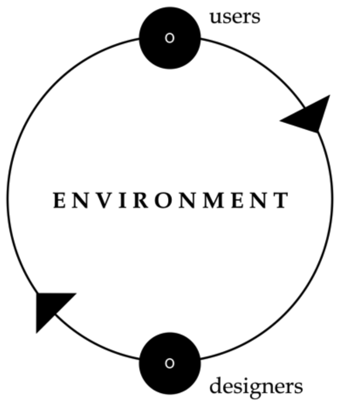

Figure 1. Conceptual Framework

From the beginning of defining what is "landscape" in the 16th century, the evolving themes of land use have been reflective of values - from romantic, to picturesque, to romantic-rebellion, to conservation, ecology and preservation (Bimbao, 2017). One notable part of this progression is the change of who produces and consumes the media of landscape representation - it eventually becomes produced and consumed by the public reflective of landscape use throughout history. Since the turn of the 21st century, landscape representation is still at an early stage to be defined with multiple themes.

In this contemporary time, the public has been instrumental in the development of the designed and built environment. Inclusivity is a design goal that reflects values of the majority. Effective design strategies ensure inclusivity, giving consideration to the inputs of the public. It is sensible to explore how the online community, a significant part of the public, values their environment to provide suitable landscapes.

In a methodology designed to harness landscape values embedded in Instagram for landscape design, comparison to the other image search engines was conducted that resulted with curated content, the option to search geo-tagged images has removed biases that other search engines have. Inclusivity of the values of the online community is ensured because its content make up the collected data. The method looks into how landscape was represented in the frame. Content analysis is used to provide evaluations for the landscape based on the theory of information processing of Kaplan and Kaplan (1979), which is established by looking into four factors in the landscape - coherence, complexity, legibility, and mystery.

An alignment tool was also designed to observe how the rating system of the images compares to how professionals would rate the landscape based on the same factors. The conclusion revealed that images with more landscape information or landscape patterns would have higher value, and landscape architects can align themselves to identify higher value images provided that they are guided.

To further enrich the method, this research would like to capture beyond the landscape representation to look at the other captured element in the frame of the data set, which is human representation. The scrutiny of this other element of the landscape image would capture the meaning of the entire frame.

The goal is to investigate human activities in the landscape from the online content posted on Instagram. The following objectives are to: (1) recognize human activity within the landscape image, (2) create typologies of activity to group landscape images with similar characteristics, (3) relate human activities to the landscape representation, and (4) critique landscape image rating results from Bimbao's methodology (2017) to the human activities.

The human activity captured within the frame of the landscape image shall be indicative of landscape representation ratings from the methodology (Bimbao, 2017). The relationship between high rating images, images that reflect the aesthetic of Instagram users, and the human activity captured within the same frame will reveal highly preferred landscape use by the online community.

II. Methodology

The framework of the methodology (See Figure 2) followed a linear step by-step process based on the objectives of the research. The image presented the sequence of the method from sampling up to how the human activities relate to the landscape ratings. The yellow highlights on the first step showed how the landscape image data set was sampled. The second to the fourth steps with the yellow highlight describes how content analysis was used to scrutinize the image content. The landscape image sampled in Figure 2 has the following content: kind of human activity – standing; typologies human activity – isolated, full body, daytime setting, and in a natural environment setting; landscape image rating range – 71-80.

The landscape image data set (Bimbao, 2017) was used for data gathering on human activity. This data set was produced during a daily nine o'clock evening sampling from the date of July 17, 2017 until July 23, 2017. For the purpose of this research, July 17, 2017, Monday, was marked as Day 1. The data gathering continued up to Day 7, July 23, 2017, Sunday.

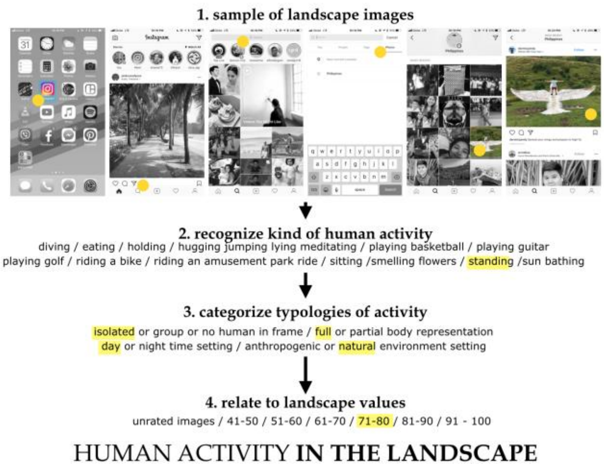

Figure 2. Methodology

The sampling process from Bimbao (2017) was done by launching the Instagram application with a Samsung J7 2017 mobile phone, went to the "Places" tab, entered the search query "Philippines" went to the most recent window, and screen captured all landscape images in that finite set of recent images. Landscape images were defined as images taken outdoors. The search technique was implemented to get recent public images posted that have the geo-tags within the country.

The first objective was to recognize human activity within the landscape image. The field of Human Activity Recognition (HAR) was utilized to identify how users were captured in the frame (Geetha and Samundeeswari, 2018). HAR has been instrumental in fields such as video surveillance, human-computer interaction, healthcare, and sports analysis (Dobhal, Shitole, Thomas, and Navada, 2015). This research borrowed some techniques implemented in HAR to meet the goal.

To interpret the human activity, the Activity Theory (Kaptenlinin and Nardi, 2017) aided in understanding how humans act in the image. There was a relationship that this theory presented – a subject or "S" and an object or "O." The subject was the tangible human component while the object was the interpreted activity (Akintunde, 2017). This research employed manual interpretation of activity by observing all human representation within the image.

Figure 3. Sample Image from Bimbao (2017)

The second objective was to create typologies of activity to group landscape images with similar characteristics. The characteristics that were observed through manual processing of the data set were kind of human activity, type of human activity, human representation within the frame, time setting, and environment setting.

The kind of human activities was recorded. There are two HAR related literature that identified various human activities. Geetha & Samundeeswari (2018) have identified the following; bending, catching, crouching, dancing, falling, jack, jumping, kicking, lying, phoning, playing instruments, playing golf, reading, riding a bike, riding a horse, running, side[view], sitting, skipping, standing, squatting, taking a photo, throwing, using the computer, and walking. Alex, Ravikumar, Selvaraj, and Sahayadhas (2018) on the other hand have identified asleep, awake, eating, walking, falling, and phoning. These words were considered for classifying what human activities were captured with the data set (Bimbao, 2017). If there were other activities that were not part of the list of words, those activities were also added to the list because this research was open to encountering activities specific to landscape activities.

The type of human activities noted if the activity was done alone or in a group. This gave insight on the preferred activities of the users. For cases without any humans captured within the frame, the images were still included in the study as having that image meant that there was a human activity of taking the photo.

Human representation within the frame was observed if the human body was entirely captured. This gave insight to the human representation needed to capture a specific activity.

The time setting noted whether the activity captured was during daytime or nighttime. Since the online sampling was conducted during the evening, publishing online content was not expected to be instantaneous. The data set also contained images taken during the daytime. This gave insight as to when users use the landscape.

The environment setting noted whether the landscape was anthropogenic or naturalistic. This gave insight to where users went to do activities in the landscape. Bimbao (2017) identified the setting based on the recorded landscape elements. Anthropogenic classification occurred when there were more man-made landscape elements (51 percent) while naturalistic classification occurred when there were more natural landscape elements.

The third and fourth objectives were to relate the human activities to the landscape representation and to critique landscape image rating results from Bimbao (2017) to the activities. Relationships between the image ratings of landscape representations were then correlated to the human activity data collected. The discussion of this research focused on relationships that can be revealed.

The data were separated per day to explore trends that occurred for an entire week for the first two objectives. The intent was to capture the shift of human activity in the landscape from weekday to weekend. On the other hand, the data were clustered following the landscape ratings from the evaluation of Bimbao (2017) that met the last two objectives. The ratings were clustered every ten points to compare batches of high rated images from low rated images.

Figure 3 was used as an example for the methodological process. Through the content analysis the following data points were established: (1) kind of activity – meditation, (2) type of activity – isolated, (3) human representation – full body, (4) time setting – during the day, (5) environment setting – naturalistic, and (6) rating of landscape representation – 72 points. The collected information from the entire set of 218 landscape images was discussed in the Results.

III. Results and Discussion

A. Human Activity Recognition

Table 1 indicates the different activities taken from the related literature and the comparison from the image data set. The unique activities listed are activities that people online engage in or have captured in the landscape. These words on the third column show landscape specific activities. Some of these have been identified through observation of the landscape representation within the image. For example, the unique activity "playing basketball" is identified through the basketball court landscape element and the basketball jersey attire of the human in the image. Compared to standard HAR methodologies that isolate humans entirely from the photo, taking note of activity with landscape use requires a different strategy as the environmental factors take a role in helping define and validate specific human activity. The use of Activity Theory supports the relationship of human representation as subject and human representation as object. Without consideration of landscape representation, the "playing basketball" activity would be categorized as simply "standing."

Table 1. List of Human Activities.

HAR related literature	Bimbao (2017) data set	Unique activities in the landscape
asleep	diving	diving
awake	eating	holding
bending	holding	hugging
catching	hugging	meditating
crouching	jumping	playing basketball
dancing	lying	playing guitar
eating	meditating	riding an amusement park ride
falling	playing basketball	smelling flowers
jack	playing guitar	sun bathing
jumping	playing golf	swimming
kicking	riding a bike	
lying	riding an amusement park ride	
phoning	sitting	
playing instruments	smelling flowers	
playing golf	standing	
reading	sun bathing	
riding a bike	swimming	
riding a horse	using a computer	
running	walking	
side[view]		
sitting		
skipping		
standing		
squatting		
taking a photo		
throwing		
using the computer		
walking		

B. Typologies of Human Activities in the Landscape

There are two typologies generated by isolating the two representations within a landscape image – human and environment. Tables 2, 3, and 4 present data taken by isolating the former while tables 5 and 6 present data taken by isolating the latter.

Standing and sitting – these activities have been identified everyday during the entire week. These are categorized as usual movements in HAR literature. Walking is almost captured throughout the span with the exception of Day 6 and 7. In practice, landscape architects usually consider these common activities (including walking) as passive and low impact.

Table 2. Human Activities Captured.

Day	Number of images	Human activities
1	34	diving lying meditating playing basketball sitting standing sun bathing walking
2	50	holding sitting smelling flowers standing sun bathing swimming walking
3	26	sitting standing sun bathing swimming walking
4	35	jumping playing golf riding a bike riding an amusement park ride sitting standing swimming walking
5	21	diving holding standing swimming using a computer walking
6	22	sitting standing sun bathing swimming
7	30	diving lying playing guitar standing sitting
Total	218	-

Water-related activities – the seven-day span have at least one water-related activity occurring, namely, diving, swimming, and sun bathing. These show the value of water elements in the landscape for the online community.

There are more varied activities captured during the weekdays with the peak during Day 4, Thursday. During that day, the list of activities also features more active use of the landscape with play courts/fields. A speculation of this trend is that the online community engages in activities for recreation during the workweek as a break from their workload.

Towards the weekend, the activities shift to a more passive nature. Only the water-related activities continue the active form of landscape use.

Images with no human representation, as discussed in the methodology are still included as all images in the data set are attributed to have human activity. For images without human representation, the human activity is the capturing of the image. These images peaked during Day 1 and dipped to its lowest value in Day 3. Throughout the week, it could be observed that images go beyond the average of 27.1 percent on three days, Days 1, 2, and 6. During these days, it could be speculated that the activities are captured during the weekend, as it is a common practice not to publish images instantaneously.

Table 3. Isolated and Group Activities.

Day	Activities done in isolation (percent per day)	Activities done in groups (percent per day)	No human representation (percent per day)
1	44.1%	20.6%	35.3%
2	34.0%	32.0%	34.0%
3	46.2%	38.4%	15.4%
4	22.9%	54.2%	22.9%
5	42.9%	38.1%	19.0%
6	27.3%	40.9%	31.8%
7	46.7%	30.0%	23.3%
Total 100%	37.2%	35.7%	27.1%

Table 3 compares the kind of human activities, if these activities are done in isolation or in groups. Overall, the activities are almost equal with the total of 37.2 percent for activities done in isolation and 35.7 percent for activities done in a group. The largest differences between the two kinds occur during Days 1, 4, and 7 with more than 15 percent difference. Day 1 and Day 7 show more individual posts that can be attributed to the weekend activities, while Day 4 presents the opposite with more group activities. The values added with the percentage of images without human activities result to a total of 100 percent.

The comparison between full body and partial body representation is important in the identification of human activity. Table 4 verifies that human activity from the entire data set can be recognized regardless of how much of the body is captured if recognition was implemented manually. This also gives the idea of focal distance and field of view between the camera used and the subject. In total, full and partial body percentages are almost similar with 31.7 percent full body human activities and 33.9 percent partial body human activities.

Table 4. Full and Partial Bodies Captured.

Day	Full body representation (percent per day)	Partial body representation (percent per day)	No human representation (percent per day)
1	44.1%	20.6%	35.3%
2	40.0%	26.0%	34.0%
3	73.1%	11.5%	15.4%
4	31.4%	45.7%	22.9%
5	33.3%	47.7%	19.0%
6	9.1%	59.1%	31.8%
7	26.7%	50.0%	23.3%
Total 100%	37.6%	35.3%	27.1%

The comparison between full body and partial body representation is important in the identification of human activity. Table 4 verifies that human activity from the entire data set can be recognized regardless of how much of the body is captured if recognition was implemented manually. This also gives the idea of focal distance and field of view between the camera used and the subject. In total, full and partial body percentages are almost similar with 31.7 percent full body human activities and 33.9 percent partial body human activities.

The trend of partial bodies captured rises above the average as activities head towards the weekend. Landscapes might have been more congested, hence limiting focal distance between subject and image taker. The other trend of full bodies captured occurs mostly at the start of the week. This might signify that landscapes are less congested for human activities as the workweek begins.

Overall, the entire week exhibits more activities captured during the day compared at night. Day activities still dominate Table 5 despite daily sampling at the peak hour of online engagement at nine o'clock.

A notable trend happens when activities at night go beyond their average of 27.1 percent. These are from Days 3 to 6, Wednesday to Saturday. A reason for this might be that due to having more responsibilities or tasks such as school or work, the online community use the evenings for landscape activities during the workweek.

During the entire sampling, more activities occur in an anthropogenic setting. Days that almost have equal weights of the two settings are Days 1, 2, and 7, Sunday to Tuesday. There might be an influence on the weekend activities when members of the online community are able to explore more naturalistic areas.

Table 5. Day and Night Activities.

Day	Daytime activities (percent per day)	Nighttime activities (percent per day)
1	79.4%	20.6%
2	82.0%	18.0%
3	65.4%	34.6%
4	71.4%	28.6%
5	66.7%	33.3%
6	54.5%	45.5%
7	76.7%	23.3%
Total 100%	72.9%	27.1%

Table 6. Anthropogenic and Naturalistic Settings for Activities.

Day	Activities done in anthropogenic setting (percent per day)	Activities done in naturalistic setting (percent per day)
1	55.9%	44.1%
2	48.0%	52.0%
3	73.1%	26.9%
4	60.0%	40.0%
5	76.2%	23.8%
6	68.2%	31.8%
7	53.3%	46.7%
Total 100%	59.6%	40.4%

C. Human and Landscape Representation

The data presented from Table 1 to 6 illustrates the shift of landscape use of the online community during the entire week. Landscape uses during weekdays are more anthropogenic, encourage more group activities, and have an increased nighttime use. The shift occurs during the weekend and would sometimes spillover at the beginning of the week when landscape users do more activities on their own, have a chance to seek naturalistic settings, and have daytime to do landscape activities.

D. Human Activities and Landscape Value

The human activity data collected for this research are then categorized with their landscape value from the data on Tables 7 to 11. There are images without a landscape rating.

Table 7. Activities and Landscape Ratings.

Image Rating	Number of Images	Human Activities	Image: Activity Ratio
No Rating	15	jumping sitting standing walking	4:1
41-50	20	sitting standing sun bathing swimming walking	4:1
51-60	34	eating holding lying playing golf sitting standing swimming walking	4.5:1
61-70	38	holding playing basketball riding a bike sitting standing swimming using a computer	5:1
71-80	54	diving lying meditating playing guitar riding an amusement park ride sitting smelling flowers standing sun bathing swimming walking	5:1
81-90	50	diving sitting standing sun bathing swimming walking	8:1
91-100	7	sitting standing walking	2.3:1
Total	218	-	-

These are the images that did not satisfy the landscape filter that required more than 50 percent landscape representation found in the frame. These 15 images are included in this research since the focus is on human activity.

Across all value ranges, these activities are present: sitting and standing. Walking is also present in all value ranges with the exception of the 61-70 values. These three activities are not unique in the landscape and are usually considered passive activities.

There is one landscape specific activity that is found across all ranges with the exception of the unrated images – swimming. Landscapes that allow this type of activity are usually recreational. It seems that this activity has popularity in the online community.

The value range starting from the unrated images up to images with an evaluation of 80 points exhibits similar occurrence of a specific or unique activity with around four to five images examined before a new activity is revealed. These explain that despite the higher counts of unique activities on the middle value range of 51–80 points, the diversity of activities remains constant because of the number of processed images.

The higher values from processed ratings from 81–100 points break the trend. The value range of 81-90 requires eight images before a new unique activity is revealed, while the range of 91–100 needs 2.3 images for a certain activity. A reason of breaking the trend might be their higher ratings. The landscape representations that have been rated by Bimbao (2017) would require to focus more landscape patterns rather than human activity. This might have limited the online community in terms of variety of activities to engage in. For the top ratings, on the other hand, the low number of images compared to the other value ranges suggests that it would be difficult to speculate with the current data.

Table 8. Isolated or Group Activities and Landscape Ratings.

Image Rating	Activities done in isolation (percent of images)	Activities done in groups (percent of images)	No human representation (percent of images)
No Rating	13.3%	66.7%	20.0%
41-50	42.9%	23.8%	33.3%
51-60	40.6%	34.4%	25.0%
61-70	33.3%	31.3%	35.4%
71-80	42.6%	34.4%	23.0%
81-90	41.2%	35.3%	23.5%
91-100	14.3%	57.1%	28.6%
Total 100%	37.2%	35.8%	27.0%

The difference between activities done in isolation and activities done in groups is almost equal. Going through the various ranges, it is almost constant that there is a slight increase in frequency of activities done in isolation. Activities done in groups are only more frequent in the range of 91-100 points and in the unrated images. These values show a balanced used of the landscape whether alone or in a group.

Table 9. Full or Partial Bodies Captured and Landscape Ratings.

Image Rating	Full body representation (percent of images)	Partial body representation (percent of images)	No human representation (percent of images)
No Rating	26.7%	53.3%	20.0%
41-50	38.1%	28.6%	33.3%
51-60	34.4%	40.6%	25.0%
61-70	31.3%	33.3%	35.4%
71-80	44.3%	32.7%	23.0%
81-90	41.2%	35.3%	23.5%
91-100	42.9%	28.5%	28.6%
Total 100%	37.7%	35.3%	27.0%

Similar with Table 8, Table 9 shows an almost equal value of human body representation whether partial or full. A trend that could be observed is that from images with a processed rating of 71 points and higher, there are more full body representations than partial body representations.

Full body representations are captured with a wider field of view and a longer focal length. These camera settings relate to the landscape as these also mean more landscape patterns captured.

Partial body representations, in contrast, usually have more human represented in the frame and a shorter focal length. These characteristics limit the landscape representation in the frame leading to a lower processed value or discarded as unsatisfactory landscape image.

Table 10 shows that majority of landscape activities are done during the day. The online community uses the landscape mostly when the sun is up. The exception is the unrated images that have more nighttime images rather than daytime images.

The environment setting of most activities is anthropogenic. Images with ratings higher than 60 points and the unrated images have a setting with more anthropogenic elements than natural. Most activities that humans do in the landscape require anthropogenic elements. This would also lead to a higher rating as anthropogenic patterns add value to the landscape elements.

The naturalistic landscape becomes more dominant in lower ratings from 41–60 points. The naturalistic surroundings have lesser landscape pattern as these are areas that have more natural than man-made elements. Landscape information becomes more limited in images with these ratings.

Table 10. Full or Partial Bodies Captured and Landscape Ratings.

Image Rating	Daytime activities (percent of images)	Nighttime activities (percent of images)
No Rating	46.7%	53.3%
41-50	85.7%	14.3%
51-60	65.6%	34.4%
61-70	70.8%	29.2%
71-80	73.8%	26.2%
81-90	85.3%	14.7%
91-100	71.4%	28.6%
Total 100%	72.9%	27.1%

Table 11. Full or Partial Bodies Captured and Landscape Ratings.

Image Rating	Activities done in anthropogenic setting (percent of images)	Activities done in naturalistic setting (percent of images)
No Rating	73.3%	26.7%
41-50	28.6%	71.4%
51-60	46.9%	53.1%
61-70	58.3%	41.7%
71-80	62.3%	37.7%
81-90	73.5%	26.5%
91-100	100%	0%
Total 100%	59.6%	40.4%

IV. Conclusion

Landscape images from social media, specifically found in the platform of Instagram are beneficial material for landscape design. These images offer the designer a lens on how the online community values and uses the landscape. This research presents a method on how to understand human activities captured within landscape images.

HAR methodologies can also be used for analysis of landscape use. Currently, these methods are not yet able to specify how landscape is used since it is mainly used for healthcare, surveillance, and sports analysis. As the technology improves, along with new methods that can be programmed, HAR shows potential to extend its purpose for landscape design use.

The manual survey of human activity from the landscape images introduces landscape-specific activities that are not usually included with identified human activities from related literature. Notable among the landscape-specific activities are water-related activities such as diving, sun bathing, and swimming. Since these activities encompass almost the entire span of the survey from Day 1 to Day 7 and the landscape value ranges from 90 and below, it can be considered a widespread landscape use preferred by the online public.

Along with the prevalence of water-related activities are passive activities such as sitting, standing, and walking, which gave an idea on how landscape is used. For passive activities, it could be attributed to the photography culture or practices in photography of posing in front of the camera.

There are notable changes on how the online public uses landscape from weekdays to weekends and to days right after the weekend. The shifts can be observed if they use the landscape alone or in groups, focal distances that capture their full or partial bodies, and time and environment settings. These are observed through the use of content analysis of the image.

The image content used by the data set has two patterns: images with both landscape and human representation and images with only landscape representation. In co-relating images with both landscape value and human representation, it could be observed that lower rated images reveal more activities. The middle ranges of landscape values show the larger variety of activities, while higher ranges of landscape values show a more limited list of activities – which disproves the hypothesis of the research. This might be due to the balance of content in which a landscape image contains.

The frame is a finite space that shares landscape and human representation. The more space one type of representation takes up, the lesser space can be allotted for the other. The landscape rating methodology of Bimbao (2017) relies on landscape patterns from landscape representation. If there is a reduction of space to capture the different landscape patterns, then the image rating drops. Exception to this would be naturalistic scenery that captures very few landscape patterns such as a view of the ocean of the entire image. This research makes middle rated images useful to a designer who attempts to add to the landscape valuation method by considering human activity in the design process.

Similar to the findings of Bimbao (2017), these landscape representations show a general theme of tourism and recreation as the landscape use. In designing more specific project types, it would be important to tweak the sampling query to better fit the design requirements.

To further explore this research, it is recommended to streamline the methodology, HAR, and big data sampling through autonomous or semi-autonomous techniques. This study was limited to a manual mode as the priority was to test the methodologies.

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