

Abstract

Event inventories: Estimating the temporality of landscape scenic resources from user-contributed geodata.

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1. Theoretical context

1 Time and space are not separable. Landscapes and their character are in constant flux. This
2 significantly affects human-environment interaction, perceived meaning and value of landscapes
3 (Bell 2012). But, unlike the predominantly perceived spatial aspects, landscape change often
4 occurs subconsciously, underlying our everyday decisions and passing of experiences. This
5 makes evaluation of the temporality of scenic landscape resources difficult. In an attempt to
6 improve the empirical assessment of ephemeral landscape features, Hull & McCarthy (1987)
7 proposed a concept they called “change in the landscape”. While a specific focus is given to
8 wildlife, the authors describe a broad range of processes relating to change: “[...] day changes to
9 night, autumn to winter and flowers to fruit; there is plant succession, bird migration, wind, rain,
10 fire and flood [...]” (ibid., p. 266). These changes are characterized by nine types, such as slow
11 changes (gentrification of neighborhoods, growth of vegetation), sudden (fluctuations of
12 weather), regular (seasonal changes in plants, animal migration, sunrises), frequent (presence of
13 wildlife, wind, sounds), infrequent (fire, flood), long duration (buildings, roads, consequences of
14 natural disasters), medium duration (harvesting of trees, seasons), ephemeral-
15 irregular, -occasional, and -periodic (wildlife, weather, hiking, evidence of other hikers). In their
16 conclusion, Hull & McCarthy (1987) raise a warning that ignoring these conditions causes
17 biasing effects on landscape quality assessments.

18 Since then, conceptually, several frameworks for landscape character assessment with
19 specific emphasis on temporal characteristics have been put forward. Tveit, Ode, and Fry (2006)
20 suggest a scheme of nine visual concepts, with “ephemera” representing a distinct category for
21 human imposed and natural changes in the landscape. For this category, they suggested
22 indicators that are either based on a percentage of land cover affected by seasonal change, or
23 based on the presence of ephemeral features such as wildlife (ibid., p.246). Stephenson (2008)
24 proposes a model of five dimensions in which landscape qualities can be portrayed. The list
25 starts with the most common static-spatial portrayal (emphasis on the physical landscape), to
26 dynamic-spatial (emphasis on interactions at a point in time), static-temporal (emphasis on
27 historic associations), dynamic-temporal (emphasis on interactions over time), and dynamic-

28 spatial-temporal (emphasis on interactions over space and time). In practice, however, common
29 temporal assessments remain focused on physical manifestations of change, such as in biotopes
30 (Käyhkö, Niina, and Helle Skånes 2006) and assessed using remote-sensing technologies
31 (Fichera et al. 2012).

32 A limited number of approaches focus on people's perceptions of, attitudes towards and
33 responses to environment change such as Photo-elicitation (Beilin 2005) and mental mapping
34 (Soini 2001). With the advent of large user-generated content collections shared on the internet,
35 several publications have focused on evaluating temporal aspects. Juhász and Hochmair (2019)
36 compare temporal activity patterns between geo-located posts shared on Snapchat, Twitter and
37 Flickr and find that the different active groups on these platforms elicit significant differences in
38 the spatial patterns observed. Paldino et al. (2016) study the temporal distribution of activity
39 from domestic tourists, foreigners and residents in New York, focusing on daily, weekly and
40 monthly activity patterns and differences between these groups. They use seasonal
41 decomposition as a method to separate measures of attractiveness in time series into trend,
42 seasonality and random variations (noise). Mancini et al. (2018) use 'Wavelet coherence'
43 between two time series collected from social media and survey data. They specifically compare
44 spatial wildlife watching activities and conclude that day trips have the biggest impact on
45 differences between survey and social media data. Tenkanen et al. (2017) demonstrate how
46 Instagram, Flickr and Twitter can be used to monitor visitation of protected areas in Finland and
47 South Africa. Their findings suggest that data volumes and quality vary widely between the
48 three platforms. The biggest agreement with official visitation statistics is found for highly
49 frequented parks and areas.

50 Our own research has focused on a bottom-up conceptualization of events and reaction to
51 events in user-generated content (Dunkel 2019). Many authors argue that events function as the
52 temporal counterpart of objects in the spatial domain (Zacks and Tversky 2007, Chen 2003,
53 Worboys 2005). From this perspective, it can be argued that humans perceive, structure and
54 memorize landscape through a sequence of discrete events of varying experienced importance
55 (Zacks and Tversky 2007, p. 58). In our definition, events range from simple atomic changes that
56 people perceive and react to, such as a rumble of thunder or a sunset (etc.), to more complex
57 events or collections of events, arranged in a particular pattern and sequence (e.g. spring, the
58 Burning Man festival etc.). Individual photographs can be considered as atomic artifacts of these
59 experiences, shared online for purposes of evidence in place and time (Steels 2006).

60 **2. Method**

61 In a recent study on worldwide reactions to the sunset and sunrise (Dunkel 2023), the signed
62 chi equation has been used to visualize spatial over- and underrepresentation. This approach
63 allowed us to identify collectively valued places and areas largely independent of overall
64 visitation frequencies. Conversely, the study showed that the common approach of using
65 absolute counts or proportions (photo count, user days or user count) may mislead practitioners.
66 As a result, landscape preference in urban areas and highly frequented popular places are often
67 overemphasized in studies using user-generated content. The chi equation was developed by
68 Visvalingam (1978) and the UK Census Research Unit (1980) for visualizing relative importance
69 of spatial phenomena. It is based on two components, a generic query (*exp*) to normalize local
70 observations (a single grid cell) of a specific query (*obs*) based on the global (all cells) average
71 ratio of frequencies (*norm*).

$$chi = \frac{((obs * norm) - exp)}{\sqrt{exp}} norm = \frac{\Sigma_{exp}}{\Sigma_{obs}}$$

72 A specific query could be the frequency of photographs in a single grid cell relating to a
 73 specific topic or theme (e.g. number of photos relating to the sunset or the sunrise). A generic
 74 query, on the other hand, ideally requires a random sample of photographs, both globally (all
 75 grid cells) and locally (a single grid cell under investigation). The random sampling is usually
 76 difficult to obtain, given the opaque nature of platform Application Programming Interfaces
 77 (APIs). The easiest way to guarantee randomness is sampling of all photographs of a platform.
 78 For Flickr, this was possible and all photographs that are geotagged have been queried for the
 79 period from 2007 to 2020. The resulting dataset consists of metadata of 350 Million photographs.
 80 For Instagram, a different sampling strategy was used, querying individual places for a random
 81 sample of 20 Million photographs and a five-month period in 2017. Despite these differences,
 82 both datasets produced a strong consistency of spatial preference patterns worldwide for
 83 watching these two events. Selected differences have been observed in places where user
 84 preferences largely differ, such as at the Burning Man festival in Nevada, a place that ranked
 85 second worldwide for watching the sunrise on Instagram, compared to almost no photographs
 86 shared by Flickr users — a pattern that we explain with the different user make-up of these
 87 platforms. In our conclusion, we suggest ‘Event Inventories’, as a means to better capture the
 88 transient nature of human-landscape interactions and landscape change.

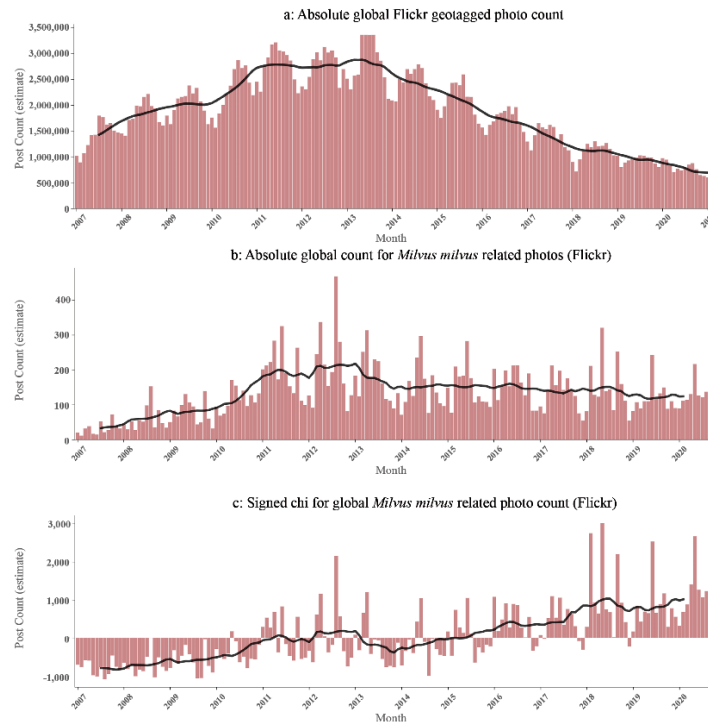


Figure 1. Temporal distribution of (a) all Flickr geotagged photographs globally; (b) *Milvus milvus* related photographs globally; and (c) signed chi for *Milvus milvus* related photographs, normalized based on global Flickr trends. The trend lines were added using seasonal decomposition (Statsmodels).

89 Exploring the idea of ‘Event inventories’ further, a scoping test is shown in Figure 1 for
 90 applying the chi equation to temporal observations. The first graph (Fig. 1a) shows the absolute

91 temporal distribution of all Flickr geotagged photographs globally. Seasonality is clearly visible
 92 from this distribution. The graph also shows a declining popularity of the Flickr platform since
 93 2013. Using seasonal decomposition, a trend line was added, based on the removal of random
 94 and seasonal parts, emphasizing these longer trends in contribution patterns. The second graph
 95 (Fig 1b) is based on a dataset using a specific query, sampled for a study by Hartmann et al.
 96 (2022), who explored the spatial distribution of pictures of the Red Kite (*Milvus milvus*). This
 97 graph is based on absolute counts and not normalized. With frequent peaks during summer
 98 season and lows in winter months, the graph indicates a similar seasonal patterns as is visible for
 99 all photographs, albeit slightly less noticeable. The trend line for these absolute counts suggests
 100 that there is a relatively constant contribution of photographs for the Red Kite, after an initial
 101 growth period till 2012. However, this trend line ignores the global declining trend of Flickr and
 102 may therefore distort interpretations. The last graph (Fig. 1c) was calculated by using the signed
 103 chi equation, based on all photographs per month and the average ratio of Red Kite photographs
 104 across the whole period. Here, it becomes obvious that, indeed, there is an increasing trend for
 105 Red Kite pictures on Flickr. Two interpretations are possible. Firstly, the community of ‘Red
 106 Kite photographers’ on Flickr could be growing, relative to all other photo interests on Flickr.
 107 Secondly, the Red Kite could have become prominently visible in recent years as a photo
 108 subject, with supporting evidence based on a continued population growth for this species in the
 109 last decade (Stevens 2020).

3. Research questions and summary of anticipated results

110 Without corroboration, these interpretations remain speculative. Furthermore, visualizing global
 111 trends is not suitable for assessing individual landscapes. Our research focuses on two questions:

- 112 1. Given a topic or scenic resource, estimate its perceived impact over time and identify
 113 trends, by sampling across different platforms and finding relationships in the same
 114 direction and at similar strength (event valuation).
- 115 2. Given an area or a selection of areas, identify significant events based on common
 116 temporal characteristics from georeferenced topics discussed online (event inventory).

117 Our goal is not to classify events, but to contribute methods to first extract and collect
 118 ‘Event inventories’ for selected landscapes. The term *event inventories* is leaned on the spatial
 119 counterpart “descriptive inventory methods” coined by Arthur et al. (1977). Considering that
 120 volunteered geographic information (iBird, iNaturalist) or crowdsourced social media data
 121 (Flickr, Twitter, Instagram) predominantly captures the human viewer component, we first
 122 expect to be able to characterize common known temporal landscape phenomena, such as the
 123 waterfalls in Yosemite being most impressive in spring, or the regular pattern of California
 124 poppies or Nevada deserts in bloom. Secondly, we hope to be able to identify single events of
 125 particular importance, as a means to supplement and corroborate contemporary landscape
 126 assessments. Examples are classical human-centered events (the Burning Man festival), or
 127 natural events of particular perceived importance (the ‘Firewaterfall’ in Yosemite, occurring not
 128 more than once a year). Lastly, we attempt to contribute to identifying longer trends from user-
 129 contributed data, based on the chi-equation and cross-platform validation. Here, what is
 130 considered as a ‘generic’ query can be modulated based on different contexts. For instance, if
 131 National Parks become the main scope of our analysis, the temporal chi for a specific park can be
 132 normalized based on the ‘global’ average, referring to the posting behavior observed for all parks

133 under investigation. We expect that such an investigation highlights specific trends for individual
134 parks deviating significantly from the norm.

4. Application significance and Conclusions

135 The audience of this research are landscape and urban planners, regional resource specialists
136 and researchers focusing on the human-centered impact of landscape change. Given the
137 exponential rise and availability of user-contributed data, both as publicly available geodata from
138 social media and specific Volunteered Geographic Information (VGI), such as from *iNaturalist*
139 or *eBird*, provides for the first time a basis for evaluating longer trends of ephemeral landscape
140 features and collective perceptions of landscape change. However, the variability in platform
141 popularity and intra-dataset biases pose challenges to data assessments, a core focus of our
142 contribution. In the fields of landscape and urban planning, the results may help to better
143 understand the unique transient characteristics of places, areas and landscapes. The proposed
144 event inventories may particularly support protecting and developing specific ephemeral scenic
145 values, or proposing action for changing negative influences. With an increasing pace of change
146 in the landscape, user-contributed geodata can contribute indicators with high actuality for
147 monitoring of scenic resources over time, directing focus to missed or undervalued patterns, or
148 for corroborating on-site observations, which contributes to a more balanced and representative
149 assessment of landscapes.

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