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

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Abstract

The exponential growth and availability of user-contributed data, both as publicly available geodata from social media and as specific Volunteered Geographic Information (VGI), such as from iNaturalist or eBird, provides a comprehensive basis for assessing ephemeral landscape features and collective perceptions of landscape change. However, variability in platform popularity and other biases pose challenges to data assessment. In this study, we first explore how intra- and inter-dataset comparisons can be used to assess the temporality of landscape scenic resources, such as identifying seasonal characteristics for a given area or selection of areas. Then, by focusing on the consistency and reproducibility of temporal patterns for a selected scenic resource from filtered data, we aim to contribute to the development of methods for quantifying the perceived impact of events and trends. The proposed techniques can help focus attention on overlooked or underappreciated patterns of landscape change, or corroborate field observations, and provide indicators with a high degree of timeliness for monitoring scenic resources over time.

Introduction

It is common to think of landscape as a specific arrangement of objects in space. Observations of these objects can then be collected, inventoried, and mapped (e.g., for purposes of environmental planning and natural resource management). To shift the perspective to a process-oriented view, anthropologist Tim Ingold (1993) coined the term landscape temporality. According to Ingold, this concept encompasses both the human viewer component and the physical manifestation of objects in space and time. Landscape temporality can therefore refer to both human and phenomenal change. This is similar to concepts in landscape and urban planning, where 'experiential' approaches aim to describe how people perceive and interact with the landscape (Dakin 2003). It is generally accepted that both human and phenomenal change can significantly influence human-environment interactions and the perceived meaning and value of landscapes (Bell 2012). However, the human viewer component in particular complicates the assessment of landscape scenic resources. Landscape and environmental planners need to assess not only physical changes (including ephemeral features), but also how people respond to these changes, which in turn affect landscapes. This includes temporal characteristics, trends, and collective perceptions of landscape change. In this study, we examine temporal patterns in publicly shared user-generated and georeferenced content from five platforms (Reddit, Flickr, Twitter, Instagram, and iNaturalist). In particular, we interpret the results from a human-centered perspective, with the goal of potentially complementing and corroborating traditional landscape scenic resource assessments.

Background and Literature Review

In an attempt to improve the empirical assessment of ephemeral landscape features, Hull & McCarthy (1987) proposed a concept they called "change in the landscape". While the authors give a specific focus to wildlife, they describe a wide range of processes associated with change: "[…] day changes to night, autumn to winter and flowers to fruit; there is plant succession, bird migration, wind, rain, fire and flood [...]" (ibid., p. 266). These changes are characterized by nine types, such as slow changes (gentrification of neighborhoods, growth of vegetation), sudden changes (weather fluctuations), regular changes (seasonal in plants, animal migration, sunrises), frequent (presence of wildlife, wind, sounds), infrequent (fire, floods), long duration (buildings, roads, consequences of natural disasters), medium duration (harvesting of trees, seasons), ephemeral-irregular, -occasional, and -periodic (wildlife, weather, hiking, evidence of other hikers). In their conclusion, Hull & McCarthy (1987) warn that ignoring these conditions leads to biased assessments of landscape quality. In practice, however, common temporal assessments continue to focus on physical manifestations of change, such as those observed in biotopes (Käyhkö & Skånes 2006), which are often assessed using remote sensing technologies (Fichera et al. 2012).

A number of approaches investigate people's perceptions, attitudes, and responses to environmental change (Daniel 2001). With the emergence of large collections of user-generated content shared on the Internet, several studies have attempted to assess temporal aspects. Juhász & Hochmair (2019) compare temporal activity patterns between geolocated posts shared on Snapchat, Twitter, and Flickr and find that the different active groups on these platforms induce significant differences in the observed spatial patterns. Better understanding the source and nature of these differences has become a central focus of research around VGI. Paldino et al. (2016) study the temporal distribution of activity by domestic tourists, foreigners, and residents in New York City, analyzing daily, weekly, and monthly activity patterns and differences between these groups. Mancini et al. (2018) compare time series collected from social media and survey data, concluding that day trips have the greatest impact on the differences between survey and social media data. Tenkanen et al. (2017) show how Instagram, Flickr, and Twitter can be used to monitor visits to protected areas in Finland and South Africa. Their findings suggest that the amount and quality of data varies considerably across the three platforms. In a relatively new direction, ecologists are increasingly relying on unstructured VGI for biodiversity monitoring. Rapacciuolo et al. (2021) demonstrate a workflow for separating measures of actual ecosystem change from observer-related effects such as changes in online communities, user location or species preferences, or platform dynamics. In particular, they find that trends in biodiversity change are difficult to separate from changes in online communities.

In a recent study, we examined responses to sunset and sunrise expressed in the textual metadata of 500 million photographs from Instagram and Flickr (Dunkel et al. 2023). Despite differences in data sampling, both datasets revealed strong consistency in spatial preference patterns for viewing these two events worldwide. Selective differences were observed in locations where user preferences differed significantly, such as the Burning Man festival in Nevada, a location that ranked second globally for sunrise viewing on Instagram, while Flickr users shared very few photos, a pattern we explain by the different user composition of these platforms.

Goals and Objectives

Building on these earlier findings, this scoping study addresses two tasks specific to the temporal assessment of scenic resources:

- Given an area or selection of areas, identify common temporal characteristics and cyclical phenomena from georeferenced topics discussed online (event inventory).

- Given a topic or scenic resource, quantify its occurrence over time and identify trends by sampling across platforms and finding relationships in the same direction and similar strength (event assessment).

Methods

A key task in analyzing user-generated content is to reduce bias in the data to increase representativeness. Bias can include factors such as uneven data sampling affected by population density, or highly active individual users skewing patterns through mass uploads, as well as changes in platform incentives that affect how and what content is shared (Mancini et al. 2018). There are a number of methods that can help compensate for these effects. However, these methods can also introduce bias and further reduce the amount of data available, making interpretation more difficult. For this reason, Rapacciuolo et al. (2021) divide approaches into two broad categories that are not mutually exclusive but tend to have opposite effects: filtering and aggregation (ibid.). Filtering increases precision, which helps to derive more reliable and useful inferences. However, filtering also tends to reduce the available variance, richness, and representativeness of the data. Aggregation, on the other hand, minimizes bias in the overall data by, for example, increasing quantity by sampling from a larger, more representative number of observers and by integrating data from different platforms. However, this comes at the expense of precision. Often, aggregation and filtering approaches can be combined.

To explore these different analytical contexts, we use data from five platforms in three examples. The first example illustrates cross-platform analysis by sampling and aggregating data from Instagram, Flickr, Twitter, and iNaturalist for 30 biodiversity hotspots in Germany. The total number of photos and observations is 2,289,722. In this example, we do not apply any filtering techniques, and the results show the absolute frequencies of photos, tweets, and animal and plant observations, respectively. A second example is based on a single data source, Reddit, where different seasonal communication trends for 46 national park subreddits are evaluated through within-dataset comparisons and relative measurements. This dataset contains 53,491 posts and 292,404 comments. In the third example, we look at global observations of the Red Kite (Milvus milvus) and use a variety of filtering techniques to examine temporal patterns. Specifically, we apply the signed chi normalization to temporal data. This equation was originally developed by Visvalingam (1978) to visualize overrepresentation and underrepresentation in spatial data.

$$chi_t = \frac{\left((obs_t * norm) - exp_t\right)}{\sqrt{exp_t}} \qquad norm = \frac{\Sigma_{exp}}{\Sigma_{obs}}$$

Applying this normalization allows analysts to distinguish properties of filtered subsets of data from phenomena or biases found in the entire data set (Visvalingam 1978). The two components can also be described as a generic query (expected) and a specific query (observed). A specific query might be the frequency of photographs related to a particular topic or theme (e.g., all photographs of the red kite). A generic query, on the other hand, ideally requires a random sample of data. Observed and expected values are usually evaluated for individual "bins", which can be spatial grid cells or temporally delimited time periods. Based on the global ratio of frequencies between observed and expected (norm), individual bins are normalized. Positive chi values indicate overrepresentation and negative values indicate underrepresentation of species observations in a given time interval. Randomness of the generic query is typically difficult to achieve due to the opaque nature of platform application programming interfaces (APIs). For example, it is not always clear how data has been pre-filtered by algorithms before being served to the user (Dunkel et al. 2023). The easiest way to ensure randomness is to sample all data from a platform. For Flickr and iNaturalist, this was possible, and all geotagged photos and observations were queried for the period from 2007 to 2022. The resulting dataset we use for “expected” frequencies consists of metadata for 350 million (Flickr) and 57 million (iNaturalist) photographs. Observed frequencies are based on 22,075 Flickr photos and 20,561 iNaturalist observations. All data and code used to generate the plots below are made available in a separate data repository (Dunkel & Burghardt 2023) along with five Jupyter notebooks (S1-S5).

Results

Figure 1 shows stacked frequency bar plots of average seasonal user frequency for three of 30 biodiversity hotspots in Germany. All hotspots show divergent patterns, with user frequencies varying widely over the year and across the four platforms. For example, the "Ammergebirge, Niederwerdenfelser Land und Obere Isar" (hotspot 2) appears to be a popular holiday destination at the turn of the year and for Instagram (e.g., winter sports tourism). At the same time, this region shows a relatively constant flow of visitors across all platforms in all seasons. In contrast, the "Limestone and Volcanic Eifel" (hotspot 14), a region known for its attractiveness to nature lovers and hikers, attracts a disproportionately high number of animal and plant observers, especially in summer (iNaturalist), according to our data. Other regions, such as "Mecklenburg-Brandenburgisches Kleinseenland" (hotspot 25), are primarily characterized by summer tourism. Many of the remaining figures, available in Supplementary Material S5 (Dunkel & Burghardt 2023), can also be assigned to these three categories. In our data, Twitter and Instagram tend to show the least variation in frequency throughout the year, while iNaturalist and Flickr users tend to share more data, relatively speaking, during the summer months.

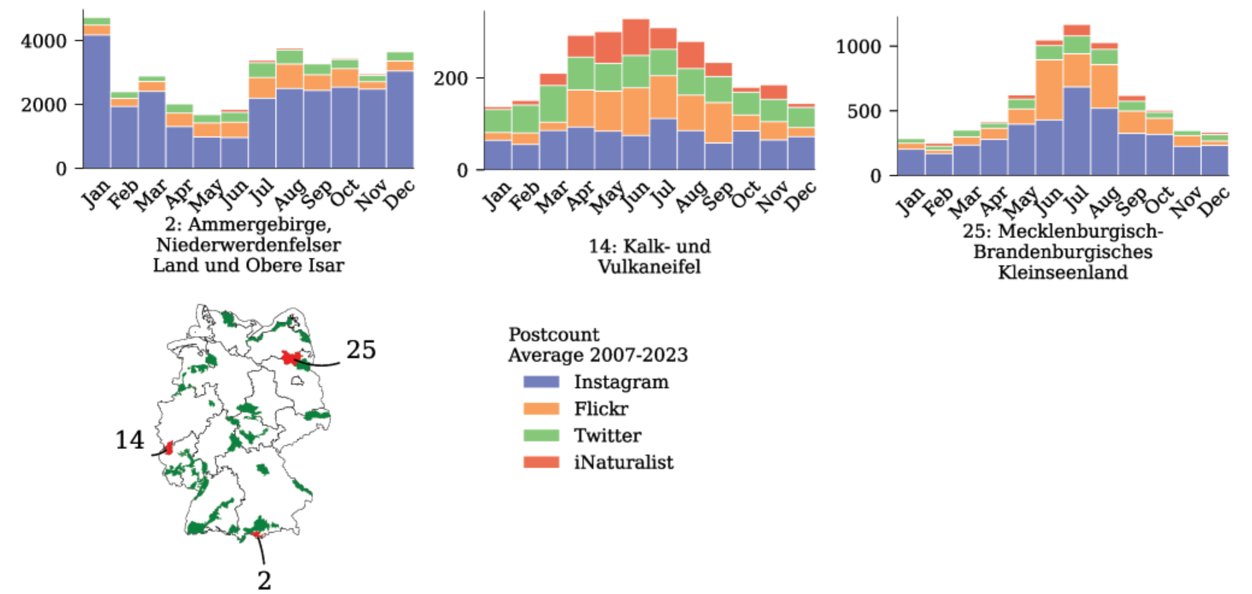

Figure 1. Monthly average number of users for three of 30 biodiversity hotspots in Germany, measured from the intersection of georeferenced posts (2007-2022) from four platforms with hotspot areas (see S5, Dunkel & Burghardt 2023).

Looking at these graphs, it is clear that different platforms represent different user groups with different interests that affect how and when data is shared. In these cases, sampling across platforms can reduce bias and increase the trustworthiness of the data. Unfortunately, rigid area delineation of hotspots requires coordinates of sufficient accuracy, which are only available from a limited number of platforms. As a second example, we looked at Reddit, a discussion platform that does not support explicit georeferencing. However, spatial information can be inferred, for example, from subreddits that refer to different spatial regions. We manually matched 46 subreddits related to US national parks and collected comments and posts from 2010 to 2022. Figure 2 shows how each park's monthly pattern differs from the norm (the average monthly frequency for each park), based on the number of unique users sharing posts and comments. Many subreddits do not have enough data, so we limit our analysis to the top 50% of parks.

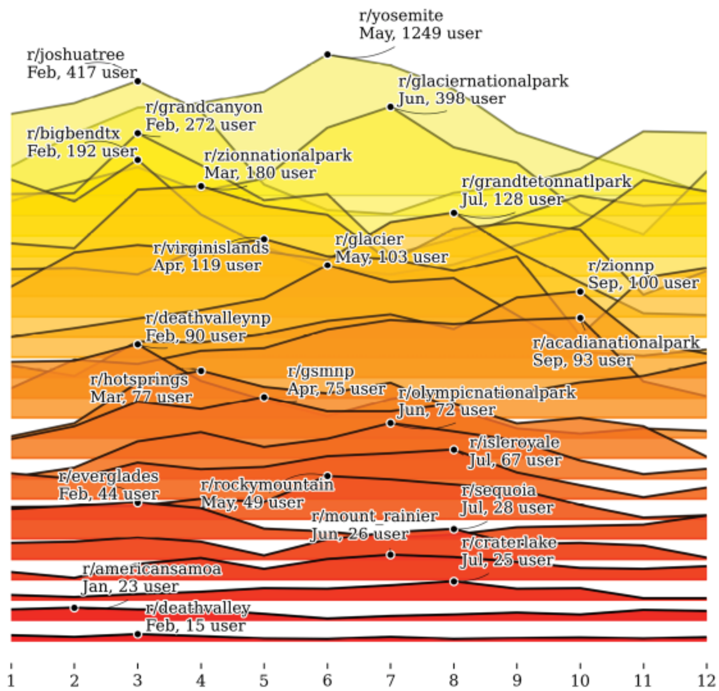

Figure 2. A Joyplot visualizing seasonal communication trends for selected national parks based on unique user counts from subreddits. Mountain peaks are used as a metaphor for the volume of monthly patterns that deviate from the norm (the average monthly frequency for each park), and distance/order and absolute height of the peaks are used to symbolize the total available volume of data, which increases with distance (see S2, Dunkel & Burghardt 2023).

Contrary to what one might expect, Reddit park rankings (order of peaks) do not follow official visitation statistics. For example, Great Smoky Mountains National Park is ranked #1 in official visitation statistics, while it is ranked #14 based on the volume of posts and comments on Reddit (r/gsmnp). One explanation for this may be that the Reddit community hosts a younger community that is more attracted to the selection of top-ranked parks in our dataset (e.g., Yosemite, Yoshua Tree). Ignoring this overall bias, the contribution patterns for individual parks confirm our expectations that seasonal preferences are evident in communication trends. For example, Yosemite, Glacier, and Grand Teton National Parks are difficult to visit in the winter due to harsh weather conditions, which is reflected in the communication trends on Reddit. Similarly, Joshua Tree, Zion, Grand Canyon, Big Bend and Death Valley national parks are popular during the winter season when temperatures are more moderate.

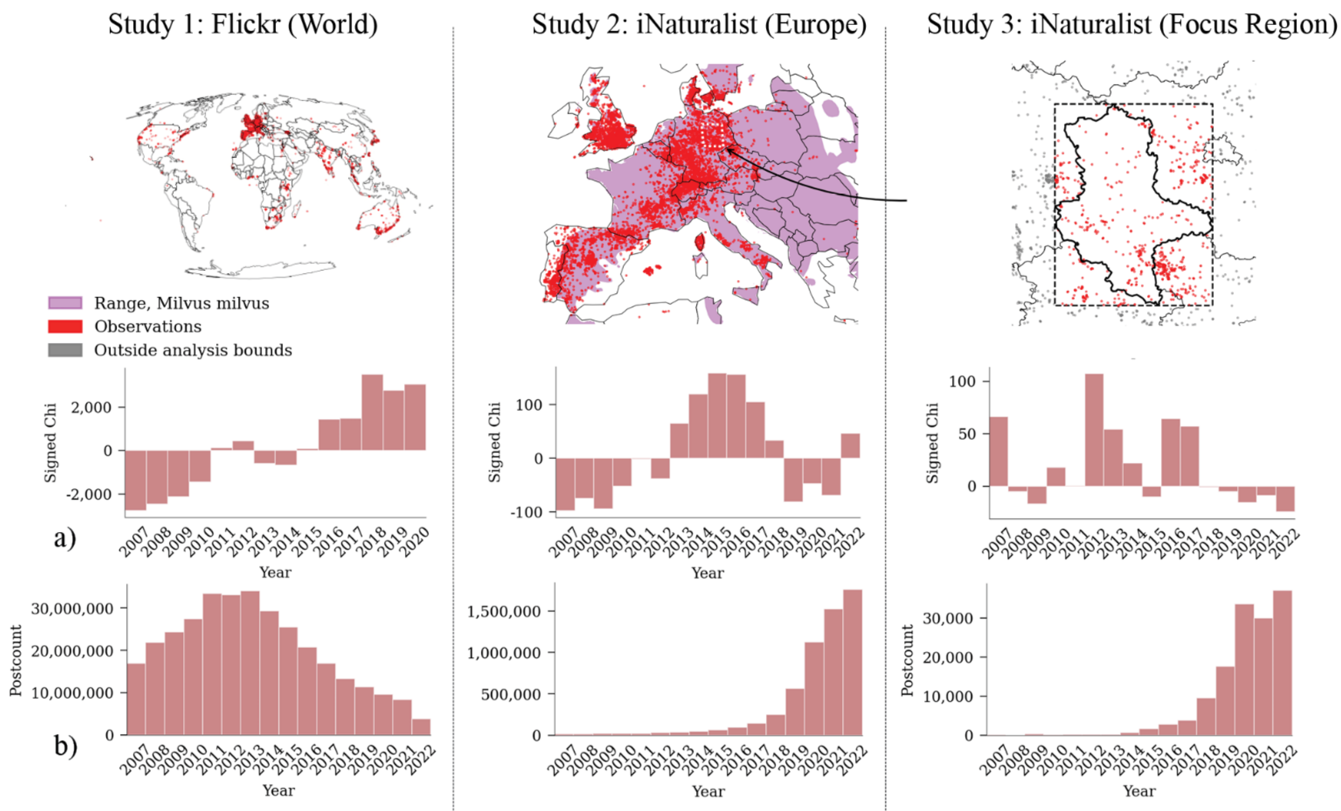

Figure 3. Three separate studies showing (a) signed chi over time for all red kite related photos on Flickr (Study 1) and iNaturalist (Study 2 and 3), calculated using expected data based on (b) all geotagged photos within these areas and for these platforms (see S1 and S4, Dunkel & Burghardt 2023).

In addition to these seasonal patterns, we wanted to explore long-term temporal trends for a selected theme or landscape resource. Figure 3 visualizes a narrow ephemeral event, red kite sightings, for three different study areas based on data from Flickr and iNaturalist. While iNaturalist allows filtering by taxonomic species name, Flickr required a term-based search. This type of sampling is more prone to error and usually requires significant data cleaning (see Hartmann et al. 2023). For example, because the range of the red kite is limited to Europe, false positives in the Flickr dataset outside of this range can be expected. We did not correct for these errors in this study. We used the signed chi measure (Fig. 3a) to adjust for decreasing (Flickr) and increasing (iNaturalist) overall platform popularity over the same time period (Fig. 3b). Based on the signed chi, a consistent relative upward trend can be observed for red kite images on Flickr globally. On iNaturalist and for Europe, a different trend can be seen, with the frequency of red kite observations increasing in significance between 2013 and 2018, and decreasing thereafter. Finally, Saxony-Anhalt, the area with the largest population of officially reported red kites, is difficult to interpret from our data due to the small number of observations available. In particular, the trends for Europe and the focus region are not consistent with the continuous population growth reported for this species over the last decade based on structured survey data (Stevens 2020).

Discussion and Conclusions

Building on previous work, this study addressed two tasks common to scenic resource management: (1) identifying temporal characteristics for a given area or region, and (2) characterizing and identifying temporal trends for selected scenic resources. Generic queries and integration of multiple data sources can reduce bias and increase representativeness, which helps to increase the trustworthiness of the data. In particular, comparisons between data from different platforms help to better understand tourist flows for different user groups. However, only unspecific and broad interpretations are possible, such as identifying and confirming common, recurring seasonal visitation patterns for selected areas and regions. Our results show this for two examples of US national parks and for 30 biodiversity hotspots in Germany. On the other hand, it proved difficult to identify trends for selected themes or scenic resources. Similar to the conclusions of Rapacciuolo et al. (2021), our interpretation is that overall platform changes (e.g., popularity) or changes in subcommunities (e.g., bird photographers or the group of "red kite photographers" on Flickr and iNaturalist) have a stronger influence on the observed patterns than phenomenal changes, such as the actual growth of the red kite population.

From a broader perspective, we see variable specificity as a key challenge in capturing landscape change through user-generated content, including ephemeral features and how people respond to these changes. Depending on the definition, events can range from simple atomic changes that people perceive and respond to, such as a single rumble of thunder or a sunset, to more complex events or collections of events arranged in a particular pattern or sequence (Dunkel et al. 2019). The level at which events and landscape change needs to be assessed can vary widely. From an analyst's perspective, integrating and comparing data from multiple sources can increase representativeness, but it can also produce only general results, leading to broad and non-specific interpretations that are difficult to translate into decision making. Conversely, specific queries can produce results of higher specificity, with the trade-off of increased bias and reduced representativeness. Rapacciuolo et al. (2021) propose individual data workflows to reduce bias in selective biodiversity monitoring. Specifically, they recommend the use of "benchmark species" to normalize observed data for the species under investigation, such as the red kite. Applying this concept to landscape change monitoring could mean first considering observations from umbrella communities, such as all "bird photographers" on a given platform, as the expected value in the signed chi equation. This generic query can then be used to compensate for within-community variation to visualize corrected trends for specific observations (e.g., to normalize observations of specific bird species). In the fields of landscape and urban planning, such normalized observations over time can help to better understand the unique transient characteristics of places, areas and landscapes, to protect and develop specific ephemeral scenic values, or to propose actions to change negative influences.

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