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# Indicators of Flickr Activity as a Proxy for Hospitality Sales: Social Media VGI in Rural Destination Management

**Tracy Michaud, Ph.D.**
Assistant Professor in Tourism & Hospitality
University of Southern Maine
tracy.michaud@maine.edu

**Colleen Metcalf**
Undergraduate Student
Department of Geography-Anthropology
University of Southern Maine
Colleen.metcalf@maine.edu

**Todd Gabe, Ph.D., M.S.**
Professor – Economics
University of Maine
todd.gabe@maine.edu

**Matthew Bampton, Ph.D.**
Professor of Geography
Department of Geography-Anthropology
University of Southern Maine
Matthew.bampton@maine.edu

***ABSTRACT***

*This research evaluates whether and how Volunteered Geographic Information (VGI) from Flickr photo posts can inform rural tourism management, acting not only as a proxy for visitor movement but also for hospitality sales in a destination. The relationship between hospitality sales and Flickr photo and user counts are analyzed in 43 regions in Maine from 2013 to 2020 through scatterplots, regression analysis, and geo-visualizations. Regression results show a positive and statistically significant relationship between hospitality sales and the number of out-of-state Flickr users in Maine. Geo-visualizations of the data suggest slight movements of out-of-state Flickr users and visitor spending away from Maine's most popular coastal destinations to a more inland and rural distribution during the COVID-19 pandemic in 2020. Furthermore, differences in travel patterns and hence hospitality sales are observed between Flickr users from places with and without COVID-19 related travel restrictions into Maine. This type of analysis adds a layer of socio-economic meaning to geo-visualizations of VGI from social media sites such as Flickr. It suggests a new way of providing insight into visitor spending patterns, especially useful for rural destination managers in places with limited access to tourism data and financial resources.*

**Keywords**
Social media, Flickr, hospitality spending, COVID-19, rural destination management, Maine

## INTRODUCTION

Visitor spending at restaurants and lodging (hospitality) businesses has long been used by tourism managers as an indicator of the direct economic impact of tourism (Frechtling, 2006). Volunteered geographic information (VGI) is geo-spatial content generated by online users, particularly of social media (Goodchild, 2007), and is increasingly used to assess visitor spatial behavior as the basis of tourism's impact on a region. This research explores the relationship between hospitality sales and tourist movement through various indicators within social media VGI from the online photo-sharing site Flickr. It builds on previous social geographic theory, ascribing value and meaning to tourist spatial patterns for the management of destinations (Allan et al., 2015; Andrienko and Andrienko, 2011; Garcia-Palomares et al., 2015; Girardin et al., 2008; Heikinheimo et al., 2017; Kadar, 2014; Kadar and Gede, 2013; Levin et al., 2015; Riungu et al., 2019; Spaulding et al., 2017; Wood et al., 2013). By examining the relationship between hospitality sales and indicators of Flickr use, socio-economic meaning in shifting travel patterns can be better understood.

The main problem that motivates this study is that detailed tourism data are sometimes unavailable in rural and emerging destinations. When data are available, there may be a considerable time lag between when information is collected and reported, as it often takes weeks or months to conduct surveys or interviews to obtain comparatively small consumer behavior datasets, and it's costly to purchase data from sources such as cellphones. A possible solution to this problem is to use free data on social media as an indicator of the presence and economic activity of tourists. VGI from social media sites such as Flickr might be in a unique position to provide data to research if it can be used as a proxy for hospitality sales.

## LITERATURE REVIEW

### Volunteered Geographic Information

Since Goodchild (2007) described the rise of private citizens creating online geographic data, the amount of volunteered geographic information (VGI) from georeferenced web sharing platforms has increased exponentially and offers researchers increased granularity when studying people's interaction with each other and their environment (Bugs et al., 2010; Li et al., 2018; Liu et al., 2018). VGI produces datasets of real-time occurrences, usually on digital platforms, that can be easily tracked through time, allowing patterns to emerge, without the need for face-to-face research methodologies (Ding and Hongchao, 2019; Elwood et al., 2013). Such locational data, when combined with other information documenting a person's experience, contributes to the development of meaningful social patterns within a space (Chen et al., 2019), such as who is valuing the place, and when they are going there.

The internet and social media can provide VGI datasets with sometimes millions of data points, called "big data," and this information is increasingly being used by researchers and industry practitioners (McAfee and Brynjolfsson, 2012). The variety of questions to which VGI has been applied, and the ingenuity of researchers in designing methods, has expanded at a rapid pace (Ding and Hongchao, 2019; Flanagin and Metzger, 2008; Yan et al., 2020). Owour and Hochmair (2020) discuss the social media sites most commonly used in VGI research: Twitter, Facebook, Flickr, Foursquare, YouTube, LinkedIn, and Yelp. Each has advantages and disadvantages. A potential issue when using VGI collected from online photo communities is contribution bias, where a minority of users contribute a large percentage of photos. This practice can lead to bias in interpretations that are meant to be representative of a whole group (Li et al., 2018; Nielsen, 2020). To address this issue, this research separately examined individual Flickr users as distinct from the number of photos posted.

### Flickr

The VGI used in this research is composed of the metadata from geotagged Flickr images. Flickr, which merged with Smugmug in 2018, is a photo-sharing social media site that has over 75 million unique users and tens of billions of photos (Flickr.com, n.d.), making it the most popular site used by professional photographers (Girardin et al., 2008). It is recognized that Flickr is not as large or well-recoginzed as other social media platforms such as Instagram and Facebook; however, unlike those popular platforms, accessing Flickr VGI is realtively easy, publically available, and free (Kadar, 2014).

Demographic research shows that while most travelers take photos, social media users posting their images online tend to be younger, more educated, and earn higher incomes than those who do not (Di Minin et al., 2015; Li et al., 2013; Lo et al., 2011; Nov and Ye, 2010). Flickr users are typically well-traveled with a strong understanding of technology, and a larger share of Flickr users are professional photographers as it is the largest photography-focused social media site of professionals (Girardin et al., 2008). Despite the socio-demographic specificity of Flickr users, much research uses Flickr as the primary data source, and has shown that Flickr activity can act as a proxy for broader tourism spatial and movement patterns (Yan et al., 2020). Flickr was chosen for this research due to its focus on photographs and connection to leisure travel, relative ease in obtaining locational data, generous API rate limitation, and previous evidence of how it functions as a proxy for tourist movement (Kadar, 2014; Owour and Hochmair, 2020; Yan et al., 2020).

Flickr photo posts are considered a form of modern, intentional and public communication about the tourism experience (Giglio et al., 2020; Girardin et al., 2008; Riungu et al., 2019; Runge et al., 2020; Straumann et al., 2014; Sun et al., 2015; Walden-Schriener et al., 2018). However, there has been little research making direct correlations between Flickr and socio-economic activity within the tourism management literature (Steinmetz and Fesenmaier, 2018). This research contributes to the understanding of socio-economic activity within a rural destination by investigating the connection of photo VGI to hospitality spending.

### Hospitality spending

While visitor spending is a distinct part of analyzing the economic impact of tourism, details about the components of expenditures are not usually recorded (Wilton and Nickerson, 2006). Tourism researchers and practitioners have used a variety of approaches and methods to estimate hospitality expenditures in general and the economic impact of tourists (Frechtling, 2006). These include analyzing existing administrative data; conducting household, visitor, and tourism business surveys; and developing econometric visitor expenditure models that often analyze the relationship between taxable sales and the number of visitors in a region or the presence of special events (Baade et al., 2008, 2011; Gabe and Lisac, 2014; Gabe and McConnon, 2018; Stynes and White, 2006; Thompson, 2007; Wilton and Nickerson, 2006).

### Maine, USA

The study is based in Maine, which is a longstanding nature tourism destination in the most northeastern point of the United States (Maine Office of Tourism, 2020). Much of Maine is composed of small, rural communities. Maine is within a day’s driving distance of large East Coast U.S. and Canadian cities such as Boston, New York City, and Quebec City, which provide a majority of the travelers to the state. Tourism sales revenue ($6.5 billion in 2019) is one of the largest contributors to the economy (Maine Office of Tourism, 2020). Millions of travelers visit Maine during the summer with concentrations of tourists along the south coast versus its interior forests, mountains, and lakes. Out-of-state visitors typically spend more money than local residents in restaurants and lodging establishments, most of which are along the south coast (Maine Office of Tourism, 2020). Any changes away from this distinct and long entrenched pattern of travel and spending, due to impacts from events such as the COVID-19 pandemic, would be a notable development in Maine. Likewise, it might provide a comparable indicator of change in other similar emerging and/or rural, nature-based destinations during this time.

## RESEARCH QUESTION

The research presented in this paper attempts to answer the question: Are indicators of Flickr activity good proxies for hospitality sales in a rural destination? Developing new ways to provide socio-economic context to tourists’ spatial patterns through social media VGI is important to tourism planners anytime, but particularly helpful during a public health crisis limiting the movement of people, such as that brought by COVID-19, a multiyear pandemic, where timely visitor datasets are needed and in-person research methodologies and budgets might be restricted.

## MATERIALS AND METHODS

The methodology used in this paper focuses on determining the relationship between hospitality sales and the number of Flickr users and photos. This approach builds on past research that uses Flickr posts as a proxy for tourist movement in a region, and econometric studies that have examined aspects of visitor spending. Maine provides an important study destination in that the amount of Flickr posts in the timeframe studied is small (less than 7,000 after data cleaning) compared to other research using Flickr datasets from larger urban areas that are associated with sometimes millions of posts (McAfee and Brynjolfsson, 2012). Therefore, if a connection is suggested between hospitality sales and Flickr activity in a rural place such as Maine, it will support continued investigation of the use of VGI as a proxy for sales in other rural destinations where the VGI “big data” sets are not comparatively so big, as well as those places where they are.

The units of analysis used in the study are Maine’s 43 Economic Summary Areas (ESA), which are regions that are larger than individual municipalities and smaller than counties. ESA are groupings of nearby towns and cities used by Maine Revenue Services to report monthly taxable sales data (Maine.gov, n.d.). Figure 1 is a map of Maine’s ESA.

The empirical analysis in this study focuses on the relationship between hospitality (restaurant and lodging) sales and several indicators of Flickr activity (photo counts from out-of-state and in-state user posts, and out-of-state and in-state Flickr user counts) within Maine’s ESA. Flickr user numbers are determined by counting only one photo attributed to a certain user in each Maine ESA irrespective of the number of photos they posted. A regression panel data set is created with observations for Maine’s 43 ESA across eight years, 2013 to 2020, focusing on six-month totals for the months of March to August. Although the use of individual monthly data may be feasible in larger and more urban states, the six-month totals are needed in Maine because of the relatively small dataset. The March to August timeframe also aligns with Maine’s tourism season and the months most impacted by initial COVID-19 travel restrictions. The data cover years before (2013-2019) and during (2020) the pandemic. The dependent variable in the analysis is the amount of taxable hospitality sales in restaurants and lodging establishments. The objective is not to determine causality but to uncover which, if any, Flickr characteristics are associated with hospitality spending to inform which geo-visualizations of the data might be most representative of hospitality sales patterns. Geo-visualizations of Flickr activity over the seven years from 2013 to 2019 provide a strong baseline of consistent tourist movement and sales along Maine’s south coast during the summer tourist season in order to assess changes in 2020, when the first COVID-19 travel restrictions were in place.

**Figure 1: Maine's 43 Economic Summary Areas (ESA)**

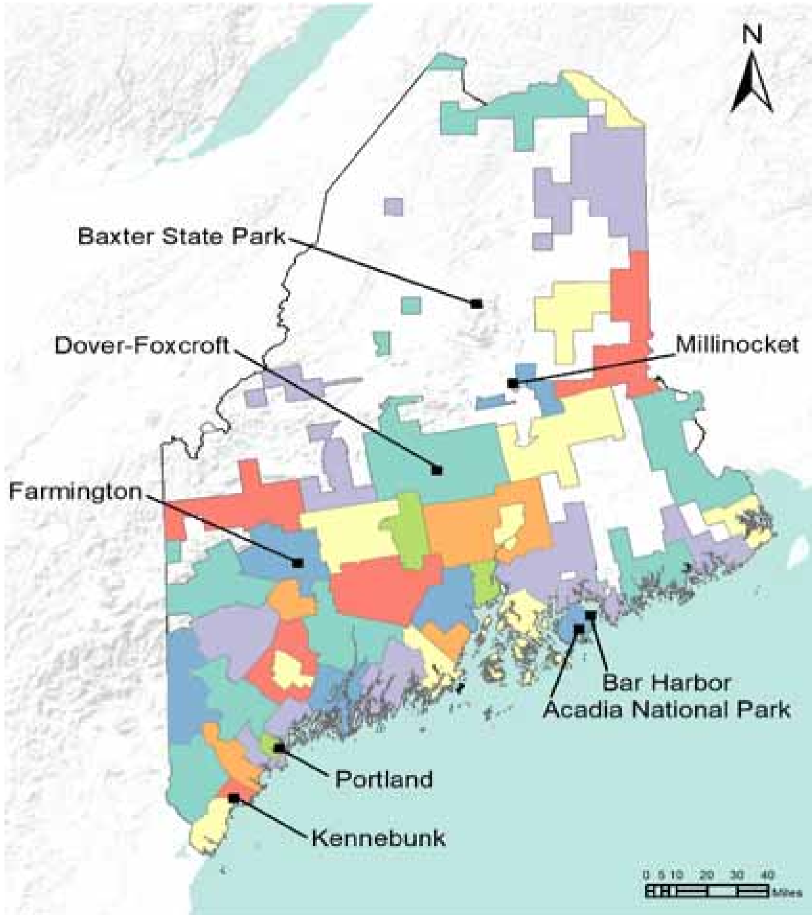


Figure note: Maine ESA are composed of nearby towns and cities that are combined to form a regional sales tax reporting structure. Three rural northern inland and three southern coastal (popular with tourists) ESA are labeled on the map, along with two of Maine's major attractions (Acadia National Park and Baxter State Park).

Along with the various indicators of Flickr activity, the regression analysis includes region-specific dummy variables that control for "non-Flickr" differences in the amount of hospitality sales across Economic Summary Areas and year-specific dummy variables that capture time trends in hospitality sales (Roberts and Whited, 2013). For example, the ESA dummy variables account for differences in tourism attractions and infrastructure, and differences in the popularity of places to tourists, expected to explain much of the variation in hospitality sales across regions. The year-specific dummy variables control for annual patterns in tourism, such as the broad impacts of the COVID-19 pandemic, which affect all regions. The inclusion of the region-specific and year-specific dummy variables provides tight controls to isolate the extent to which the various measures of Flickr activity are good proxies for hospitality sales (Roberts and Whited, 2013).

Using the program Flickrapi, the Flickr API was accessed and the metadata for geotagged photos from March 1 to Aug. 31 for 2013 to 2020, including where users live, was downloaded (Girardin, et al., 2008; Li et al., 2018; Liu et al., 2018). Photos that did not have a user-identified location of residence were dropped, given the interest in separating in-state and out-of-state users. The data were further processed to eliminate duplicate images. The final data set contained 6,863 photos and 921 users. This translates into averages, across the 344 region (i.e., 43 ESA) and year (i.e., 2013 to 2020) combinations, of 19.95 photos and 2.68 users. The economic activity of visitors was measured using taxable restaurant and lodging sales (referred to as hospitality sales) data downloaded from the State of Maine website in October 2020.

## COVID-19 Pandemic

The COVID-19 pandemic brought widespread illness and death to the USA in early 2020. It provides a distinct event to analyze changing patterns of tourist spending within Maine during the following summer. Due to the pandemic, on March 3, 2020, the state of Maine suspended all nonessential government travel, which was followed by a series of travel restrictions on out-of-state leisure visitors from places with higher rates of COVID-19 (State of Maine Office of the Governor COVID-19 Response, n.d.). By July 3, 2020, visitors from Connecticut, New York, New Jersey, New Hampshire and Vermont were the only ones exempt from these COVID-19 travel restrictions, which included a 14-day quarantine or proof of negative test, which remained in place through the end of August 2020. For this research, this meant out-of-state tourists could be grouped into those from places exempt from COVID-19 travel restrictions and those that were not exempt. Due to persistent tourism patterns that were established before COVID-19, Maine provides a unique rural landscape to study VGI and tourism-related economic activity during this event.

# RESULTS

The data collected were separated into in-state and out-of-state users and not surprisingly found to be dominated by out-of-state users. Across all 344 of the ESA region and year combinations, the average number of out-of-state users (2.08) and photos (16.34) account for about 80% of the average number of total users (2.68) and photos (19.95). Likewise, the number of out-of-state users is highly correlated ($r = 0.95$) with the total number of users, and the number of out-of-state photos exhibits a high correlation ($r = 0.97$) with the total number of photos. By comparison, the number of in-state users and total users has a correlation of 0.62, and there is a relatively low correlation ($r = 0.28$) between the number of in-state user photos and the total number of photos.

Two empirical approaches were used to examine the connection between hospitality sales and Flickr data. The purpose was not to uncover a “causal” impact of Flickr activity on restaurant and lodging sales but the statistical relationship between these different indicators of tourism to establish whether the Flickr variables are reasonably good proxies for hospitality sales. The first approach analyzed the simple correlations between hospitality sales and the numbers of Flickr users and photos.

**Figure 2: High Correlation between hospitality sales and Flickr users**

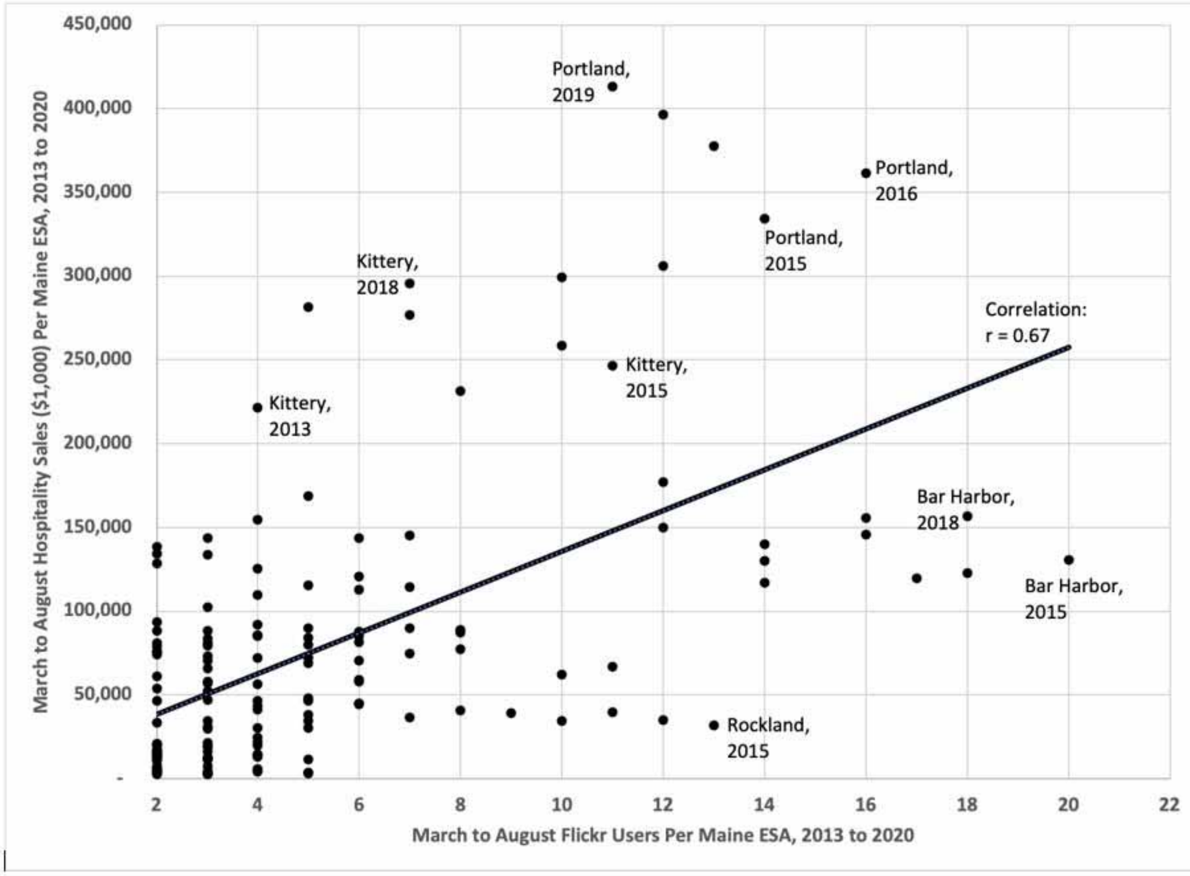


Figure note: The scatterplot has 344 points, which indicate all of the Maine Economic Summary Area (43 regions) and year (2013 to 2020) combinations.

Figures 2 and 3 are scatterplots that show the relationship between hospitality sales (measured from March to August for the years 2013 to 2020) and the number of Flickr users and photos, respectively, tagged to an ESA. The trend line in Figure 2 shows a positive relationship between hospitality sales and the number of Flickr users, and the correlation (r = 0.67) is reasonably high. The relationship between hospitality sales and the number of photos in Figure 3, however, is considerably weaker (r = 0.30).

**Figure 3: Low correlation between hospitality sales and Flickr photos**

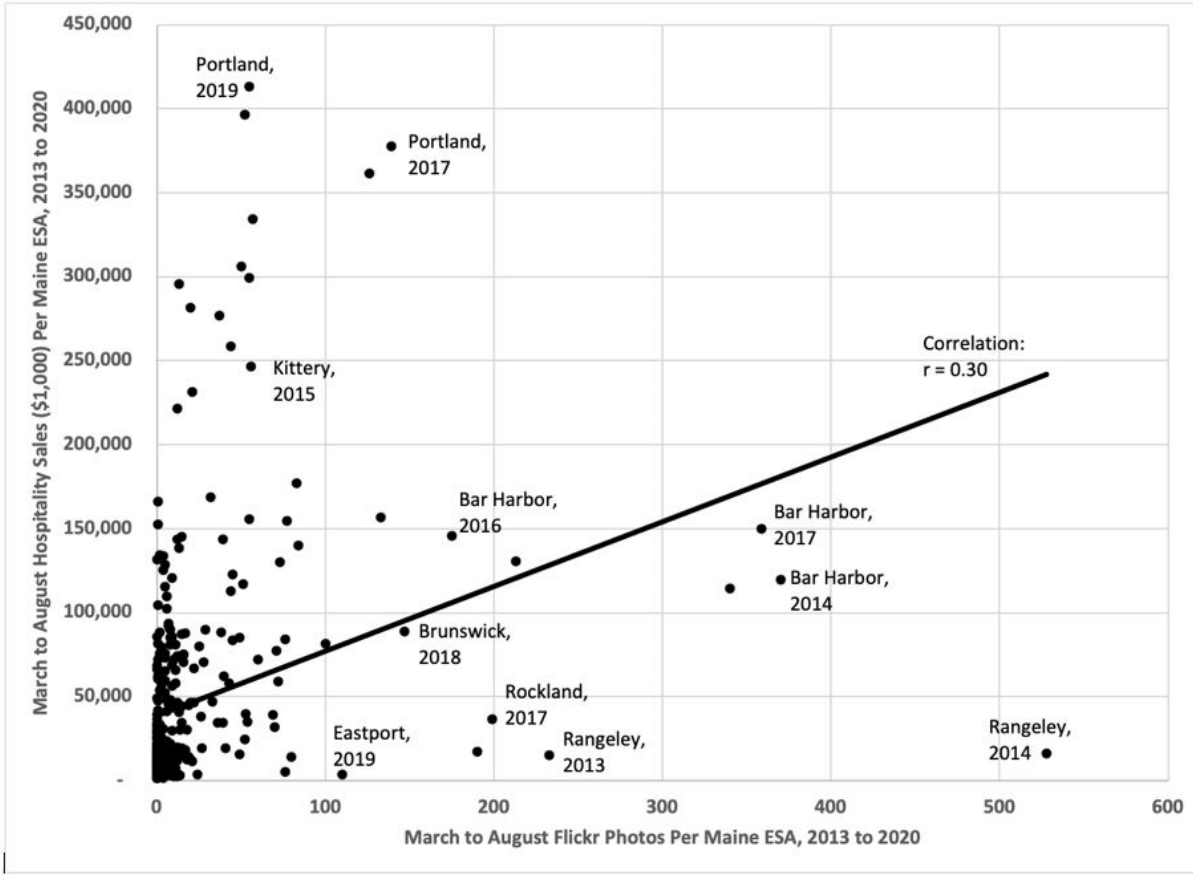


Figure note: The scatterplot has 344 points, which indicate all of the Maine Economic Summary Area (43 regions) and year (2013 to 2020) combinations.

The second approach analyzes in more detail the relationship between hospitality sales and Flickr activity to estimate a set of regression models, the dependent variable being the amount of taxable hospitality sales reported per ESA from March to August over the years of 2013 to 2020. The key explanatory variables of interest are the indicators of Flickr activity, and the models include ESA-level and year-specific dummy variables. As noted, the dummy variables provide very tight controls to isolate the relationship between hospitality sales and the indicators of Flickr activity. In addition, the ESA-level dummy variables account for the attributes of regions (proximity to the coast or mountains, population size, distance to interstate and population centers, natural amenities) that affect the amount of hospitality sales. Likewise, the year-specific dummy variables account for year-to-year trends (COVID-19 pandemic) that affect all regions.

Table 1 shows estimated coefficients from six versions of the regression model, which differ by the combinations of Flickr variables that are included. Estimated coefficients in the far-left column show that a one-unit increase in the number of Flickr users that tagged photos in a Maine ESA (between March and August of a given year) is associated with a $1,168,000 increase in hospitality sales. This does not suggest that an individual Flickr user spends this amount while visiting a region in Maine. Rather, a single Flickr user represents a larger group of tourists that generate about $1.2 million in hospitality spending. Controlling for the number of users (and the other variables included in the regression model), the number of Flickr photos does not have a statistically significant effect on hospitality sales.

In the next two columns of results in Table 1, the relationships between hospitality sales and the numbers of Flickr photos and users are examined separately. Model 2 indicates the number of Flickr photos does not have a statistically significant effect on hospitality sales. Further, the results from model 3 show that the number of photos tagged by either out-of-state users or users from Maine also does not have a statistically significant effect on hospitality sales.

**Table 1: Regression results: relationship between hospitality sales and Flickr activity (n=344)**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| All Users | 1,168** (479) | NA | NA | NA | NA | NA |
| All Photos | 2.63 (20.9) | NA | NA | NA | NA | NA |
| Out-of-State Users | NA | NA | 1,471*** (538) | 1,453*** (543) | NA | 1,447*** (549) |
| Out-of-State Photos | NA | 14.3 (21.7) | NA | 6.01 (21.6) | NA | 5.89 (21.7) |
| In-State Users | NA | NA | 138 (1,053) | NA | 493 (1,225) | 157 (1,221) |
| In-State Photos | NA | -15.7 (79.8) | NA | NA | -32.6 (91.8) | -5.18 (91.6) |
| Year 2020 | -9,000*** (2,967) | -8,443*** (3,017) | -8,427*** (3,005) | -8,294*** (2,963) | -8,783*** (3,040) | -8,356*** (3,026) |
| Year 2019 | 11,428*** (3,085) | 13,731*** (3,037) | 12,120*** (3,137) | 12,329*** (3,002) | 13,217*** (3,150) | 12,218*** (3,167) |
| Year 2018 | 9,955*** (3,068) | 12,128*** (3,038) | 10,683*** (3,131) | 10,876*** (2,990) | 11,654*** (3,150) | 10,766*** (3,156) |
| Year 2017 | 8,452*** (2,988) | 9,454*** (2,998) | 8,646*** (2,985) | 8,672*** (2,967) | 9,407*** (3,010) | 8,639*** (2,997) |
| Year 2016 | 4,384 (3,178) | 7,362** (3,021) | 4,677 (3,180) | 4,825 (3,092) | 7,045** (3,100) | 4,743 (3,201) |
| Year 2015 | 1,874 (3,115) | 4,303 (2,993) | 1,632 (3,112) | 1,702 (3,105) | 4,197 (3,005) | 1,680 (3,128) |
| Year 2014 | (547 (2,999) | 1,570 (2,999) | 594 (2,989) | 570 (2,986) | 1,633 (3,001) | 544 (3,004) |
| Constant | 69,429*** (5,337) | 71,894*** (5,290) | 69,621*** (5,328) | 69,660*** (5,294) | 71,760*** (5,343) | 69,571*** (5,356) |
| ESA Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.965 | 0.965 | 0.966 | 0.966 | 0.965 | 0.966 |
| Adjusted R-squared | 0.959 | 0.959 | 0.960 | 0.960 | 0.959 | 0.959 |

Table Note: Hospitality sales measured in $1,000s. Flickr variables cover the period of March to August in 2013 to 2020. The superscripts ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are shown in parentheses.

The results from models 4 and 5 indicate that out-of-state users are associated with hospitality sales, whereas in-state users do not have statistically significant effects on hospitality sales. Finally, results in the far-right column of Table 1, Model 6, which includes all four indicators of Flickr activity, are consistent with the results from models 2 to 5. Therefore, the number of out-of-state users is the only Flickr variable with a positive and statistically significant effect on hospitality sales. Other results presented in Table 1 show that the dummy variables indicating observations from the years 2020, 2019, 2018, 2017 and, in two of the six regression models, observations from 2016, have a statistically significant effect on hospitality sales, compared to an omitted category of observations from 2013.

To demonstrate the utility of using the number of out-of-state Flickr users to illustrate broad trends in the economic activity of visitors, several geo-visualizations of Flickr user activity were developed alongside maps of actual hospitality sales. In places outside Maine with more robust Flickr data, these types of maps might be able to distinguish even more subtle and nuanced patterns of visitor economic activity across regions and over time.

Figure 4 has two choropleth maps that show the highest densities in the spatial distribution of the yearly average number of out-of-state Flickr users in Maine between March and August of 2013 to 2019 (left panel), compared to the distribution of out-of-state Flickr users over the same six months of 2020. Both maps show the highest concentrations of out-of-state Flickr users along the coast, but the right-hand side map, focusing on 2020, indicates a pattern of slightly more out-of-state Flickr users found in inland, rural and less popular ESA. These visualizations show a shift in travel patterns corresponding to the COVID-19 pandemic, when people looked for less crowded, outdoor, nature-based destinations (Michaud, et al., 2021).

**Figure 4: The distribution of out-of-state Flickr users changed in the COVID-19 period of 2020**

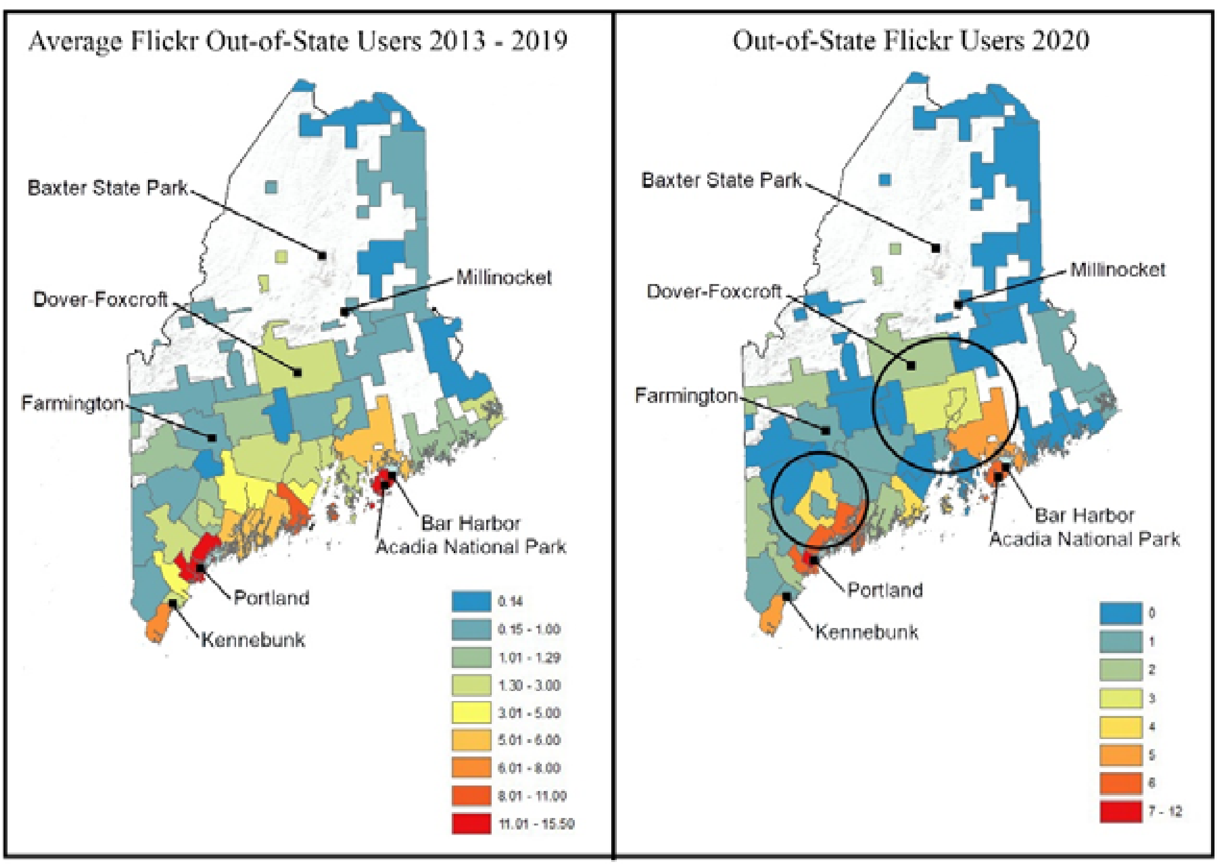


Figure note: Orange and red indicate the highest densities (hotspots) of out-of-state Flickr users. Circles highlight shifts to more inland, rural, and northern Economic Summary Areas.

Despite the use of a dataset with relatively small numbers of out-of-state Flickr users, the patterns demonstrated by comparing the left and right side maps of Figure 4 are similar to the trends revealed by comparing the two maps of the spatial distribution of hospitality sales in Figure 5. The left side map of Figure 5, which represents average March to August hospitality sales between 2013 and 2019, shows hotspots along the Maine coast, similar to the hotspots of out-of-state Flickr users. A comparison of this map to 2020 (right-hand panel of Figure 5) also shows a pattern of tourism economic activity moving from the congested coastal areas to more rural and traditionally less-visited areas. Although the two sets of maps are different in terms of the exact ordering of relative hotspots, the maps of out-of-state Flickr users convey a picture of movement away from popular coastal regions that is very similar to the broad patterns indicated by the hospitality sales data.

**Figure 5: The distribution of hospitality sales changed in the COVID-19 period of 2020**

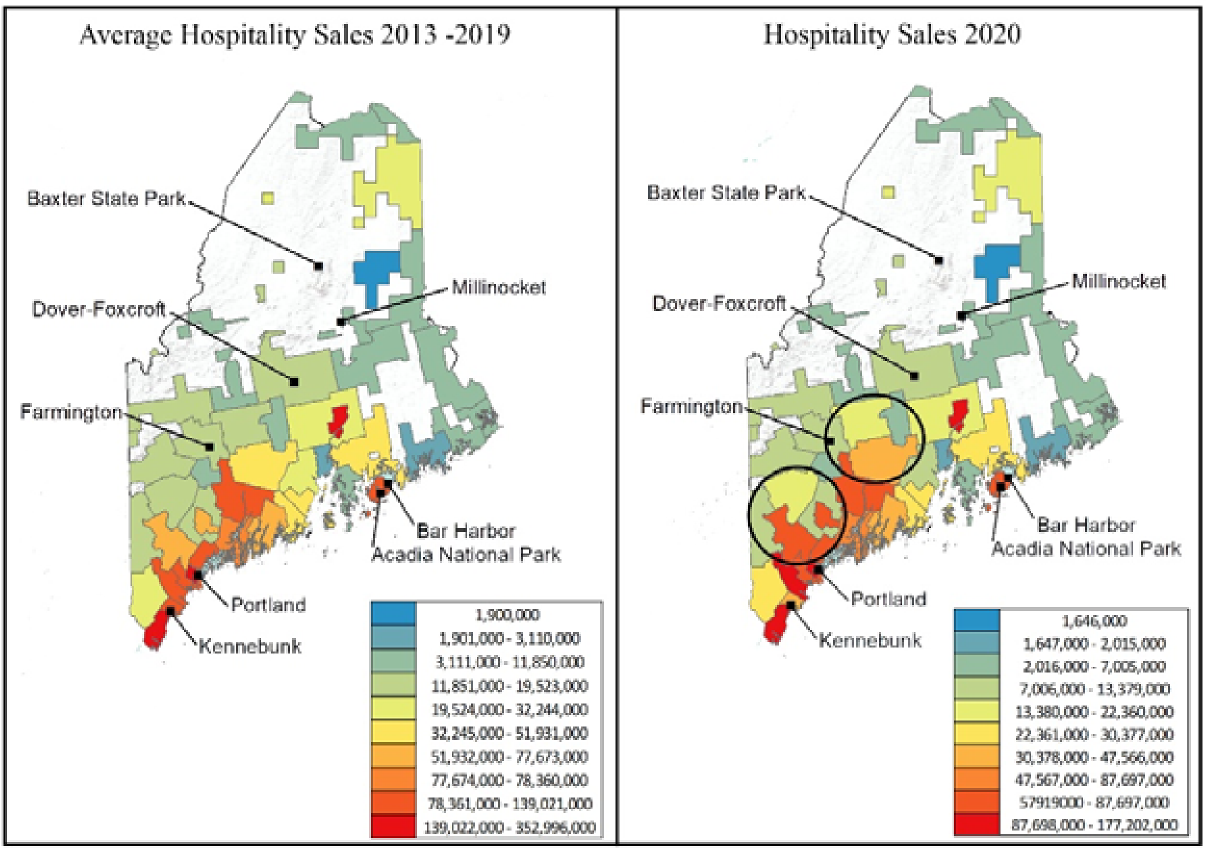


Figure note: Orange and red indicate the highest densities (hotspots) of hospitality sales. Circles highlight a shift to more inland and rural Economic Summary Areas.

Along with its helpfulness in showing overall changes in the distribution of visitor economic activity, the Flickr user data can also be used to analyze patterns of visitor behavior based on where travelers originate. This type of analysis is not possible using the taxable hospitality sales data alone because the origins of spenders are unknown. Out-of-state Flickr users in 2020 were separated into visitors from states that were exempt from COVID-19 travel restrictions and those from places where visitors were not exempt from COVID-related travel restrictions. The left-side panel of Figure 6, which focuses on Flickr users from exempt states, shows the now familiar spatial distribution with hotspots along the south coast. The spatial pattern of out-of-state Flickr users from non-exempt areas (right side of Figure 6) also has hotspots along the coast, but these visitors were relatively more dispersed in rural, inland, and less popular tourism destinations (Michaud, et al., 2021).

Given the correlation found between hospitality sales and out-of-state Flickr users, the differences between the spatial patterns of users from states that were and were not exempt from COVID-related travel restrictions can help explain some of the factors driving changes in hospitality sales during this timeframe. For example, non-coastal ESA attracted a relatively higher number of visitors from non-exempt states and experienced the smallest percentage reduction in hospitality sales from 2019 to 2020 (State of Maine, n.d). This suggests that travelers from non-exempt states were more responsible for the smaller decreases in hospitality sales in the rural and inland regions of Maine. Knowing the origins of tourists who are spending money, and where expenditures occur within a destination, is valuable for tourism managers when assessing the impact of travel restrictions on the economy and deciding whom to focus marketing efforts on in the future. For Maine, it indicates a potential opportunity to capitalize on development opportunities in rural, inland regions with the specific group of people that traveled there during the pandemic. These results demonstrate that VGI is uniquely positioned to provide this additional level of understanding.

**Figure 6: Spatial patterns of Flickr users differed in 2020 between states exempt and non-exempt from COVID-19 travel restrictions**

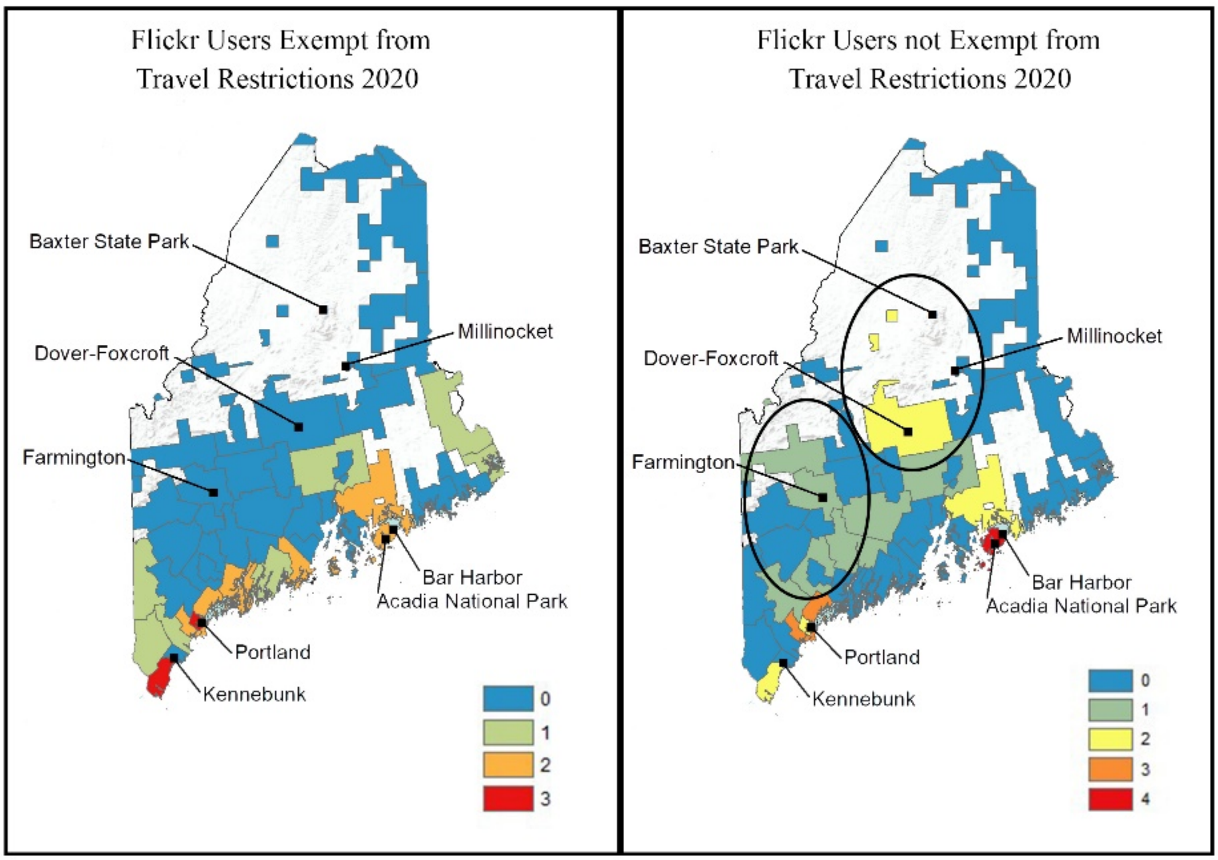


Figure note: Orange and red indicate the highest densities (hotspots) of Flickr users. Circles show that spatial patterns of non-exempt visitors are more dispersed into inland, rural, and northern Economic Summary Areas.

## DISCUSSION

The empirical analysis presented above suggests that the number of out-of-state Flickr users is a good proxy for hospitality sales; however, there is no evidence of a connection between hospitality sales and the number of Flickr photos in a place. Since Flickr users can post wildly variable amounts of photos, this so-called contribution bias may be a reason why the number of photos posted by Flickr users is a relatively poor indicator of spending in the regression models. Additionally, administrative data show that out-of-state visitors typically spend more money than in-state travelers (Maine Office of Tourism, 2020), which may explain — in part — why out-of-state Flickr users are consistently connected to hospitality sales. Given the Flickr VGI dataset used is small (73% of the ESA and year combinations have two or fewer out-of-state users) compared to other "big data" sets, these results show a significant connection and are particularly important to rural or emerging areas where number of tourists and visitor spending are not tracked in detail or readily available.

Spatial analysis of out-of-state Flickr users in Maine provides preliminary evidence related to travel patterns and socio-economic visitor behavior during the COVID-19 pandemic. Geo-visualizations suggest that out-of-state Flickr users spent relatively more time and money in less popular and inland nature destinations in 2020, as compared with earlier years. In addition, these patterns appear to be driven — at least in part — by visitors from states that were not exempt from COVID-19 related travel restrictions in Maine. These geo-visual findings, considered along with our regression results, are consistent with actual changes in hospitality sales where Maine's coastal destinations experienced substantially larger COVID-related percentage declines than rural and inland areas (Maine.gov, n.d.).

## Limitations and Future Research

Although the analysis suggests that certain information collected from Flickr can be a good proxy for hospitality sales, the study is subject to some limitations that provide directions for future research. First, rural Maine has relatively low numbers of Flickr users and photo posts requiring the aggregation of Flickr activity into six-month totals, which influenced the scope of the geo-visualizations that could be performed. Applying similar methods to a larger urban area could allow for more disaggregated and detailed analysis. Nevertheless, the results for Maine suggest our general approach can be successfully applied to study broadly the locational and economic activity of tourists in other rural and emerging destinations.

Another limitation of the study is its use of a single social media platform, which has a smaller user base than, for example, Twitter, Instagram or Facebook. Although Flickr data provides important, no-cost information about the social media user, the number of people who post photos to the platform is lower than those using some other social media sites. While many popular social media platforms do not give public access to its users' metadata, future research could apply methods similar to those used in this study to an analysis of the relationship between hospitality spending and visitor information extracted from other digital platforms or cellphone records, recognizing that the data could be costly to obtain. Another focus of future study could be revisiting the destinations analyzed three years into the pandemic to see whether changing travel and spending patterns were retained.

## Conclusion

When looking to connect economic activity to data collected from Flickr activity, our exploratory research indicates that, at least in rural and emerging destinations with smaller "big data" sets, Flickr out-of-state user counts seem to be a good proxy. Past research suggests the amount of online photo posts indicates the attractiveness and value of a destination (Riungu et al., 2019), this study provides evidence that a plethora of photos does not necessarily translate to higher spending. A Flickr user who posts 100 photos does not necessarily spend 100 times more money in the destination than a visitor who posts only a single image. However, larger numbers of Flickr users do translate into higher hospitality spending in a place. This result has implications for the use of different aspects of big data, VGI, and social media, and adds to the discussion of what geo-visualizations of photo VGI reveal about visitor socio-economic behavior in different places.

Although the results do not provide definitive evidence of the impacts of COVID-19 on tourism sales, this work suggests a useful correlation between a geographic shift in visitor movement and a geographic shift in hospitality sales activity. In Maine, this shift is likely from a specific group of travelers, those not-exempt from initial COVID-19 travel restrictions. It inserts a missing economic layer into discussions on tourist movement seen in VGI maps and sets a foundation for exploration of the reasons for this shift in the future. Immediately though, having this freely available data from Flickr is helpful to inform practical and political decisions on the economics of tourism marketing, investment, development, and policy in rural regions.

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