# Classifying and Mapping Cultural Ecosystem Services Using Artificial Intelligence and Social Media Data

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## Abstract

Quantifying and mapping cultural ecosystem services are complex because of their intangibility. Data from social media, such as geo-tagged photographs, has been proposed for mapping cultural use or appreciation of ecosystems. However, manual content analysis and classification of large numbers of photographs is time-consuming. The potential of deep learning for automating the analysis of crowdsourced social media content is still being explored in CES research. Here, we use a new deep learning model for automating the classification of natural and human elements relevant to CES from Flickr images. This approach applies a convolutional neural network architecture to analyze over 29,000 photographs from the Lithuanian coast and uses hierarchical clustering to group these photographs. The accuracy of the classification was assessed by comparison with manual classification. Over 37% of the photographs were taken for the landscape appreciation class, and 28% of the photographs were taken of nature, of animals or plants, which represent the nature appreciation class. The main clusters were identified in urban areas, more precisely in the main coastal cities of Lithuania. The distribution of the nature photographs was concentrated around particular natural attractions, and they were more likely to occur in parks and natural reserves with high levels of vegetation and animal cover. This approach that was developed for clustering the photographs was accurate and saved approximately 100 km of manual work. The method demonstrates how analyzing large numbers of digital photographs expands the analytical toolbox available to researchers and allows the quantification and mapping of CES at large geographical scales. Automated assessment and mapping of cultural ecosystem services could be used to inform urban planning and improve nature reserve management.

**Keywords** Cultural ecosystem services mapping · Crowdsourced data · Flicker data · Images classification · Machine learning · Convolutional neural networks · Lithuanian coast

## Introduction

For decades, the concept of ecosystem services (ES) has been known as the "usefulness" of nature for people and society (Newton et al. 2018; Khomalli et al. 2020; Retka et al. 2019). ES and natural capital were considered necessary elements of sustainable development within this concept in the 1990s (Braat and de Groot 2012); thus, the ES concept has begun to gain popularity with the scientific community (Retka et al. 2019). The Millennium Ecosystem Assessment (MEA) (Millennium Ecosystem Assessment 2005) established the classification of ES as natural support systems that maintain human existence.

Cultural ecosystem services (CES) are a subset of ES that are non-material, such as the values of the existence of a species or the recreational possibility of wildlife (Richards

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and Friess 2015). CES have a relational component that emerges from interactions between cultures and ecosystems. This means that the benefits of CES are experienced directly and personally. Accordingly, (Hernández-Morcillo et al. 2013) CES are an ecosystem's contribution to the non-material benefits that arise from the human—ecosystem interaction. Their identification can be used to improve support for the sustainable management of natural areas and the conservation of biodiversity conservation (Hernández-Morcillo et al. 2013).

Due to their intangible and subjective nature, CES have been underestimated in academic research (Hernández-Morcillo et al. 2013). The assessment of CES depends on a trade-off between the spatial level and the time required to carry them out. Commonly used traditional approaches such as surveys, interviews, and focus groups (Pleasant et al. 2014; Zoderer et al. 2016) can provide high-quality information on CES usage, but are often costly, time-consuming to carry out, and rarely provide spatially explicit information (Hernández-Morcillo et al. 2013). For a CES evaluation, more recent indices derived from geographical data have been offered.

Each year, social media networks such as Facebook, Twitter, and Instagram receive billions of postings from millions of users, including geotagged photographs, videos, and text (Hausmann et al. 2018). Compared to traditional research methods, which involve more human resources, social media data is almost free, and there are often trade-offs between the level of information and the amount of time available for examination (Richards and Friess 2015; Hausmann et al. 2018). Social media enables access to unstructured big data and is seen as a source of "determinate innovation," allowing advancements in data-driven science (Kitchin 2014). Recent years have seen a determined push to harness the potential of social networks for monitoring tourism and recreational activities, as indicated by the growing volume of studies using social media to assess CES. Compared to other CES valuation approaches, such as direct observation and surveys, the "social media-based methodology" is relatively new (Cheng et al. 2019). This includes biodiversity preferences gleaned from Instagram and Flickr, where (Hausmann et al. 2018) discovered no statistically significant difference between them and those gleaned from conventional surveys. The geographical distribution of Instagram photographs in Copenhagen was discovered to reveal the city's major hotspots (Guerrero et al. 2016). Seresinhe et al. (n.d.) employed crowdsourced picture extraction to identify exterior components that were deemed scenic, and geo-tagged photographs from Flickr were used in various studies as a proxy for visiting.

Nonetheless, social media content analysis in the context of CES relies on the manual classification of photos or texts shared by social media users (Cheng et al. 2019), with a few recent exceptions (Havinga et al. 2021; Richards et al.

2021). This manual categorization of massive data sets is time-consuming and costly, particularly when applied to vast geographic regions, time periods, and audiences. State-of-the art models for automated image classification through deep learning computer vision have recently been suggested as an important new tool for CES research (Weinstein 2018). Convolutional Neural Networks (CNNs; Lusch et al. 2018) are especially promising because they can learn to recognize similarities in the information content of an image in a way that is similar to a biological brain. Examples of CNN applications in ecology include the identification of species and other taxa from images (Weinstein 2018), such as those gathered via citizen science platforms (Terry et al. 2020) and camera traps (Ferreira et al. 2020). However, to date, CNN tools used to analyze CES represented in crowdsourced social media data are not freely available in their full versions (Egarter Vigl et al. 2021; Gosal et al. 2019), thus restricting their usage by researchers, managers, and decision-makers. Therefore, there is an urgent need for strong and openly accessible deep learning methods for CES assessment in order to enhance their use and promote methodological innovation across academic and practitioner groups.

CES evaluation should be conducted with the aim of expanding comparability while preserving context specificity (Gosal et al. 2019). The existing photograph density may be used to do large-scale evaluations of coastal CES, as well as to provide information about the most frequently visited regions. However, density alone cannot tell us about a site's cultural significance or the reasons for society's appreciation of it as a cultural activity. To include this essential component, we must evaluate the cultural activities that people engage in when they take photographs, as well as the environment's most attractive characteristics. Content analysis of images on social networks enables the identification of social preferences and the mapping of geographical patterns. It also enables us to find a method's suitability, advantages, and shortcomings for CES research. As a new source of data, although still in its infancy in terms of serving CES research, geolocated social media is expected to change the situation whereby CES have been neglected in the study of ecosystem services due to their lack of direct connection to ecosystem processes. The specific goals of this paper are (1) to examine the feasibility of using geolocated social media data as a proxy of visitation, since visitation volume is frequently regarded as a comprehensive representation of CES values. (2) To use photo content analysis to find CES categories. (3) To model the spatial and temporal patterns of actual CES usage. (4) To monitor and analyze actual CES usage. (5) To explore the impacts of environmental attributes, social attributes, and facilities on the spatial and temporal distributions of CES. This research will attempt to reveal the spatial and temporal patterns of CES and find theoretical explanations for them.

## Material and Methods

### Study Area

Lithuania, which is located in the southeastern part of the Baltic Sea, covers an area of 65.3 km² and has a population of 2,8 million inhabitants. The Lithuanian coast is one of the most significant places for recreation and tourism in Lithuania; it is the shortest coastline (90.6 km in length) out of all the Baltic Sea countries (Fig. 1). The Bounding Box at 20.71 N, 55.231 E, 21.95 S, 56.10 W is affiliated with our study area. The Lithuanian climate is semi-continental with cold winters and mild, moderately rainy summers; hence, favorable weather conditions are a crucial factor with regard to tourism and outdoor activities. The mean annual air temperature is 18 °C in July and -1.5 °C in January; the mean annual rainfall is 675 mm (Gomes et al. 2021). The Klaipeda Strait divides our study area into two sections, a 51.03 km-long section on the Curonian Spit and a 38.49 km-long mainland section (Jarmalavičius et al. 2007). The mainland coast is relatively densely populated (228,384 inhabitants, approximately 8% of the total population of

**Fig. 1** Locations of the Flickr photographic dataset along the Lithuanian coast
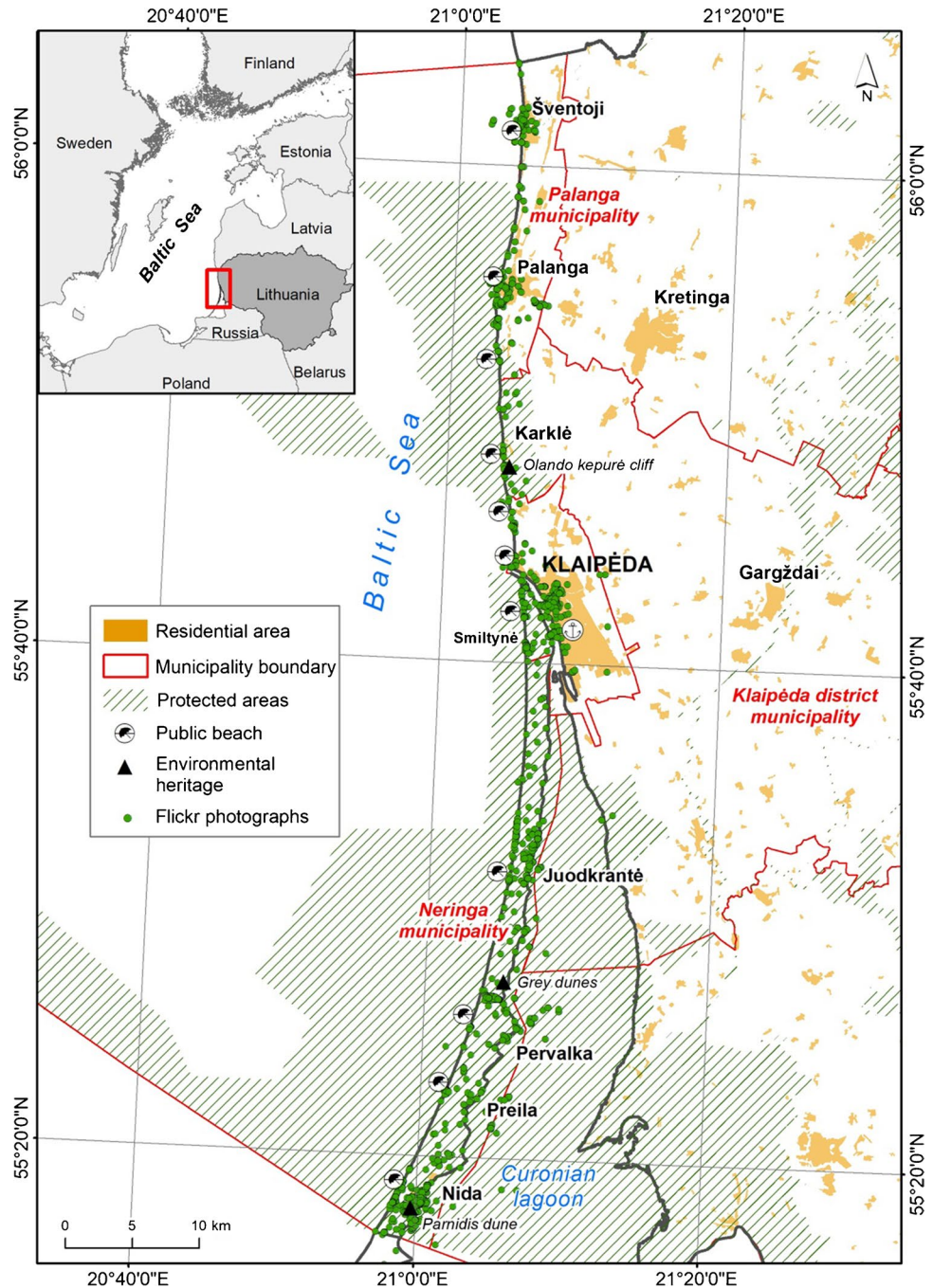
Lithuania) compared to the Curonian Spit (3,782 inhabitants) (Lithuanian Census data 2021). The Lithuanian coastal municipalities comprise approximately 54% agricultural land, 28% forestland, and 1% wetland (EEA, 2018). Our study area includes Klaipeda seaport, the most important and biggest Lithuanian transport hub and the third most populous city in Lithuania with148,348 inhabitants (Lithuanian Census data 2021). The coastal town of Palanga is the most popular resort in Lithuania. Approximately 369,800 tourists (16.6% of the country's total number of tourists) visited the municipality of Palanga in 2021. It is also the most popular destination for domestic tourists (Lithuanian Census data 2021). Approximately 75,000 tourists visit Neringa annually (3.4% of the country's total number of tourists) (Lithuanian Census data 2021). The Lithuanian coast is a typical example of a micro-tidal low-lying coastline formed out of Quaternary deposits where sandy sediments prevail on the mainland coast, while glacial (moraine) deposits are exposed in abrasional cliffs in the central section, which serves as an attraction for visitors (Bitinas et al. 2005; Jarmalavičius et al. 2007). The Curonian Spit is included on the list of UNESCO World Heritage sites and its terrestrial and nearshore sections have several protection statuses (reserves, parks, Natura 2000). All the coastal municipalities have approximately 780 objects of archaeological, architectural, and artistic heritage (most concentrated in Klaipėda), as well as 30 objects of environmental heritage (springs, hills, dunes, moraine cliffs, stones) that serve as major tourist attractions. The area is also divided into three strict reserves, 24 reserves, and two national and regional parks.

The Lithuanian coastal zone was chosen for this study due to its complex usage regarding the exploitation of natural resources (sand extraction, fishery, planned offshore wind energy parks, oil extraction, etc.), intensive seasonal recreation (including blue flag beaches and several resorts), industrial infrastructure (oil terminals, ports, shipping lanes, underwater cables, etc.), and extensive nature conservation across several protected areas.

## Dataset

The data was collected from the Flickr website (https://www.flickr.com/). We developed a script in the Python environment with the Flickr Application Programming Interface (API) to facilitate repeatable requests to the Flickr API. The functions in this approach make a call to the Flickr API and return both the raw photo download links (URL S, URL O, URL SQ…) and all their additional metadata, stored in a CSV table. The script feature allows users to define a set of search criteria that are then queried using the Flickr database. In our case study, we used the Bounding Box coordinates 20.7076 N, 55.2352 E, 21.9485 S, 56.102 W. The images were downloaded with the associated metadata,

including longitude and latitude, the dates and times the photographs were taken, and the photographers' user IDs. 29,000 images uploaded by 2,456 users between 2017 and 2021 were downloaded. The limitations of this package created in the Python environment are usually connected to the level of photo searches via the Flickr API, which only returns 4,000 unique results per search criterion and which limits one's ability to easily access data for spatially or temporally large searches. For this purpose, it is recommended that the request must contain a deadline and a maximum date (minimum date taken and maximum date taken). When using a simple query with no date margin and searching for more than 4,000 results, the API appears to get metadata for each of them. However, the Flickr API only returns data for the first 4,000 images, after which the subsequent pages of data are doubled by the first 4,000. This means that users can get what appears to be more than 4,000 results but end up only having the metadata of the first 4,000 unique images repeated several times.

## Data Categorization and Pre-Processing

The 29,000 photos were randomly split into three sections. An objective coding technique based on prior CES research and tailored to the Lithuania coastal environment was used on the first segment, which included 1,000 photos. The categories were first adopted from the CES typologies defined by the (Ministério do Meio Ambiente Instituto Chico Mendes de Conservação da Biodiversidade 2016) and (Richards and Friess 2015), and were also somewhat influenced by the asset stewardship framework presented by (Jepson et al. 2017). A total of eight categories were used to classify each photograph (Table 1).

The objective coding technique was used in order to gain a general understanding of the cultural multi-services presented by the photographs, and then to integrate them into a supervised learning algorithm that would allow us to annotate the large numbers of images which constitute the training data. The K-nearest neighbors (KNN) algorithm is a supervised machine-learning algorithm that can be used to solve classification and regression problems. In our case study, we used the KNN algorithm as an automatic annotator, which received the first annotated images section as the output, whereby it would be able to train and define the prediction model. The KNN algorithm prediction was carried out with some manual annotation corrections to perform the most precise annotations possible (Fig. 2). The algorithm uses similarities between the longitude and latitude features to predict the CES classes of 9,000 collected photographs, which also means that new photographs will be annotated based on how close they are to the CES classes in the training set. 80% of the annotated data was used for training and 20% for testing, bearing in mind that the training set size of all the images was 10,000 photographs.

**Table 1** Classification categories of the cultural ecosystem services (Richards and Friess 2015)

| CES category | Description |
| --- | --- |
| Artistic or Cultural Expressions and Appreciation | Photographs representing people in artistic activities (e.g., painters, sculptors), cultural activities (e.g., artisanal fishing, folk dancing), or their products (e.g., painting, pottery) |
| Historical Monuments | Photographs depicting historical infrastructure (e.g. historical buildings, ruins) |
| Landscape Appreciation | Photographs where the main focus is a broad and large-scale view of the landscape |
| Nature Appreciation | Photographs focusing on animals, plants, and other living organisms |
| Religious, Spiritual, or Ceremonial Activities and Monuments | Photographs representing religious or spiritual monuments or activities (e.g., churches, indigenous rituals) |
| Social Recreation | Photographs that represent groups of people in an informal or non-dedicated recreational (i.e., not sport) social environment |
| Infrastructure Appreciation | Photographs that primarily depict aspects of buildings |
| Recreational Fishing | Photographs that depict people fishing |
| Other | Photographs that do not fit any of the above criteria |

## Model Training

### Convolutional Neural Networks (CNNs) Model

After carrying out several CNN architecture and transfer learning approaches such as VGG and AlexNet, we proposed a new convolutional architecture for classifying the images. As illustrated in (Table 2), its input was RGB images with a size of (170*120*3) trained beforehand with supervised methods (KNN). The architecture has two Convolution, Pooling, and Dropout layers followed by a Flatten layer, which is usually used as a connection between the Convolution and the dense layers.

**Convolution** The first Convolution layer was used to extract the various feature maps from the input images. A mathematical convolution operation was performed in this layer between the input image with a filter with a size of 32 and a kernel of $5 \times 5$. By sliding the filter over the input image using a stride of $1 \times 1$, the dot product was taken between the filter and the parts of the input image. Then, the Convolutional layer applied a rectified linear unit (RELU) as an activation function. The RELU returns 0 if it receives any negative input, but for any positive value it returns that value back.

$$z^L = h^{L-1} * w^L \tag{1}$$

**Max-Pooling** Besides Convolution layers, CNN often uses Max-Pooling layers. It is primarily used to reduce the size of the tensor in order to speed up calculations. This layer selects the maximum value from each region with a size of $(2 \times 2)$ and transfers them to the next layer.

$$h^L_{xy} = max_i = 0, \dots, s, j = 0, \dots, s h^{L-1}_{(x+i)(y+j)} \tag{2}$$

**Dropout** Overfitting occurs when a particular model works so well on the training data that it causes a negative impact on the model's performance when used on new data. To overcome this problem, a dropout layer of 0.3 is used whereby a few neurons are dropped from the neural network during the training process, resulting in a reduced size of the model.

**Dense** A Dense Layer is a simple layer of neurons where each neuron receives input from all the neurons of the previous layer. It is used to classify images based on output from convolutional layers. In our case, 512 neurons were used along with RELU as an activation function, in order to extract as many feature maps as possible. The SoftMax function was used as an activation function that predicts a multinomial probability distribution of nine classes in the output layer. As an optimizer, we used the NADAM algorithm, which is another variation of the ADAM algorithm, resulting in a slightly faster training time than the ADAM. The parameters used in the NADAM optimizer are (learning rate = 0.001, beta 1 = 0.9, beta 2 = 0.999, epsilon = 1e-07). Since we were dealing with nine classes, categorical cross entropy was used as a loss function.

In order to monitor the training, we used Early Stopping as a trigger to stop the training process based on the validation loss metric with a patience of nine, once the chosen performance measure stopped improving. However, the model at the end of training may not be the model with the best performance in the validation dataset. In this regard, we managed to use the Model Checkpoint, which monitors training in order to keep the model that has achieved the best performance.

### Model Performance Evaluation

In order to measure the performance of the trained model, we relied on the testing phase, where we used 20% of the data. In general, choosing an appropriate measure is
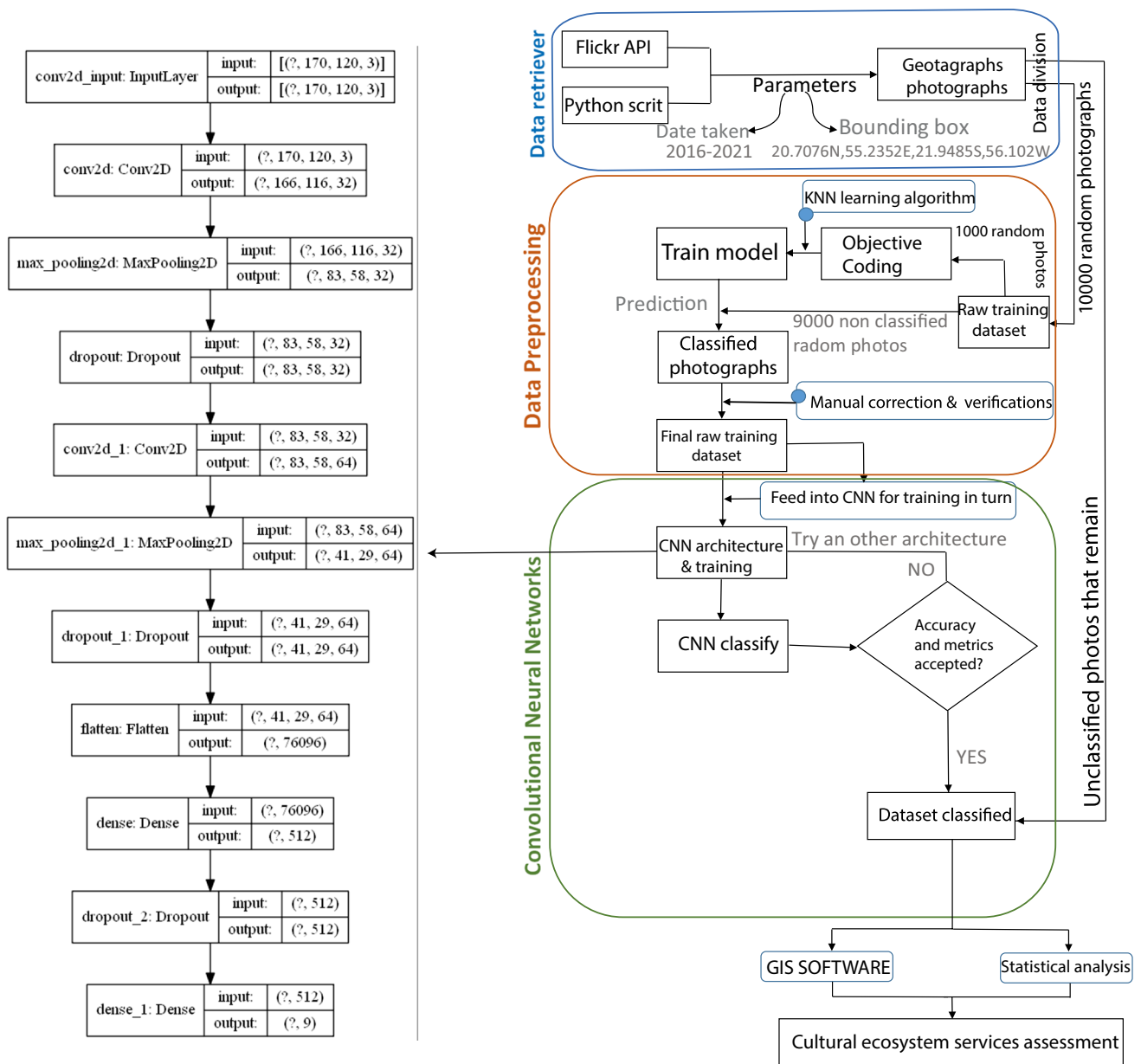
**Fig. 2** Hierarchical Structure of the coastal CES model

difficult in applied machine learning, but it is particularly difficult for unbalanced classification problems. First, because most of the standard measures that are widely used assume a balanced class distribution such as accuracy. In this regard, we added AUC (Area under the ROC Curve), precision, and recall as metrics to measure performance. In (Figs. 3 and 4) the performances are presented for each epoch of training and testing data.

**Training Performance**  As already mentioned, we trained the CNN architecture using the loss functions as a supervised metric for the early stopping process in addition to the performance metrics mentioned above.

As shown in (Fig. 3), we notice that the loss function curve decreases from 3.5 to 2 in the first epoch, although the noisy movements from epochs 1 to 4 seem to flatten when it reaches 21 epochs. Continued training of a good fit will likely lead to an over fit; as a result, the training stopped at epoch 29. In this context, we noticed that the performance metrics stopped improving after epoch 25, scoring, respectively, 99.16%, 99.98%, 99.16%, and 98.54% in accuracy, AUC, precision, and recall.

**Table 2** Convolutional image classification model architecture

| Layer (type) | Output Shape | Param # |
| --- | --- | --- |
| conv2d (Conv2D) | (None, 166, 116, 32) | 2432 |
| max_pooling2d_1 (Max-Pooling2D) | (None, 83, 58, 32) | 0 |
| Dropout (Dropout) | (None, 83, 58, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 83, 58, 64) | 51264 |
| max_pooling2d_1 (Max-Pooling2D) | (None, 41, 29, 64) | 0 |
| Dropout_1 (Dropout) | (None, 41, 29, 64) | 0 |
| flatten (Flatten) | (None, 76,096) | 0 |
| Dense (Dense) | (None, 512) | 38961664 |
| Dropout_2 (Dropout) | (None, 512) | 0 |
| Dense_1 (Dense) | (None, 9) | 4617 |

**Testing Performance** In order to evaluate our model's performance, we used a new dataset to validate the progress of the algorithm's training and optimized it for improved results.

As shown in (Fig. 4), we perceived that the testing data performance was almost the same as that of the training data, which ensured that our model was generalized. The accuracy and precision metrics scored 99.01%, whereas the recall attained 98.13%.

**Confusion Matrix** To evaluate each class's performance, we opted to use the confusion matrix (Fig. 5). A confusion matrix is an NxN matrix that is used to evaluate the

performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by the machine learning model.

We can see that the classification was done well, even though the data are not balanced. The error margin is not as big as it might be. When we look at some classes such as landscape appreciation, nature appreciation, and social recreation we see that there is a lot to be confused about. This could be because there is a certain similarity between the characteristics of the other classes, such as the presence of the landscape. On the other hand, the other class is a point of confusion when compared to most other classes, because it could have some features in common with other classes.

## Data Analysis

After setting up the CNN model for the image classification, all the photographs extracted from the Flickr database were grouped into the classes above (data categorization section). The data analysis provided a summary of the overall number of images and users for each CES, as well as the percentage representation of each category. Then, in order to define the distribution of the images within the research region, we conducted a temporal and spatial analysis (Fig. 2) using the date each photograph was taken and the corresponding geographical coordinates. ArcGIS 10 for Desktop was used to conduct
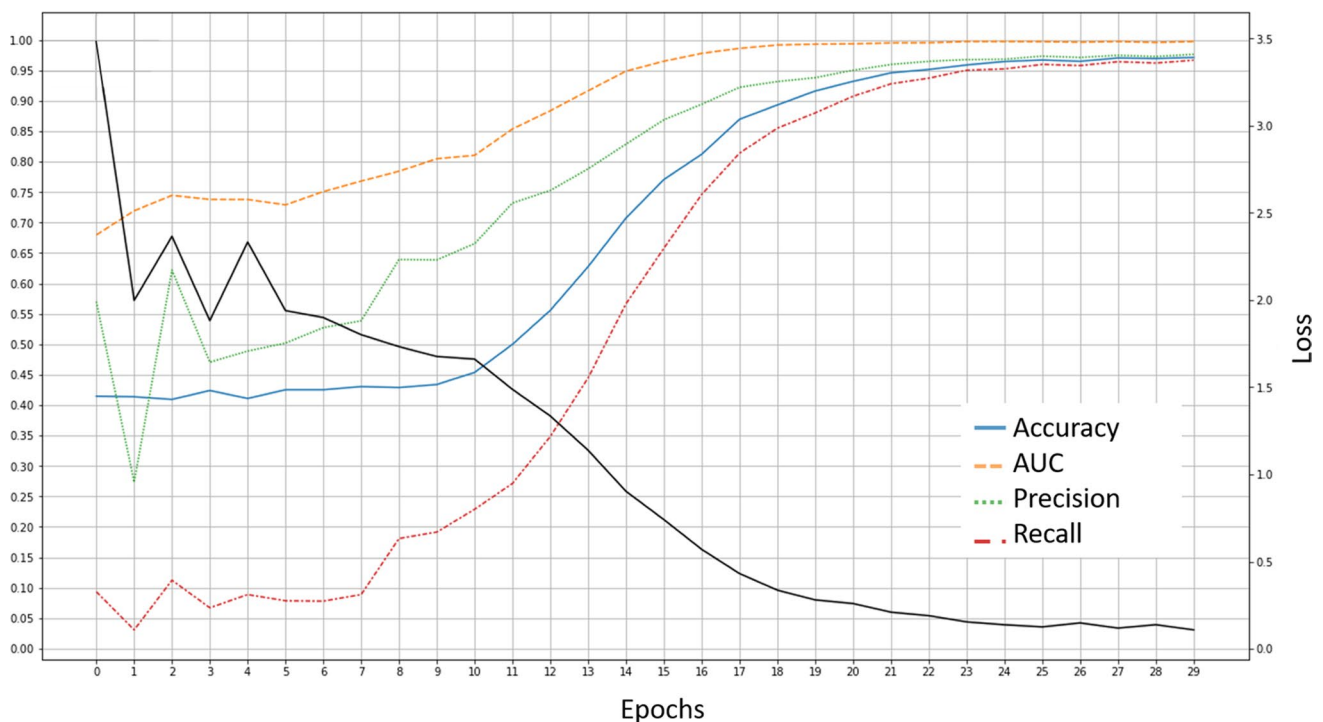


**Fig. 3** Training data history of 29 epochs' iterations of CNN. The blue curve is the classification accuracy of the training data. The black curve is the loss function
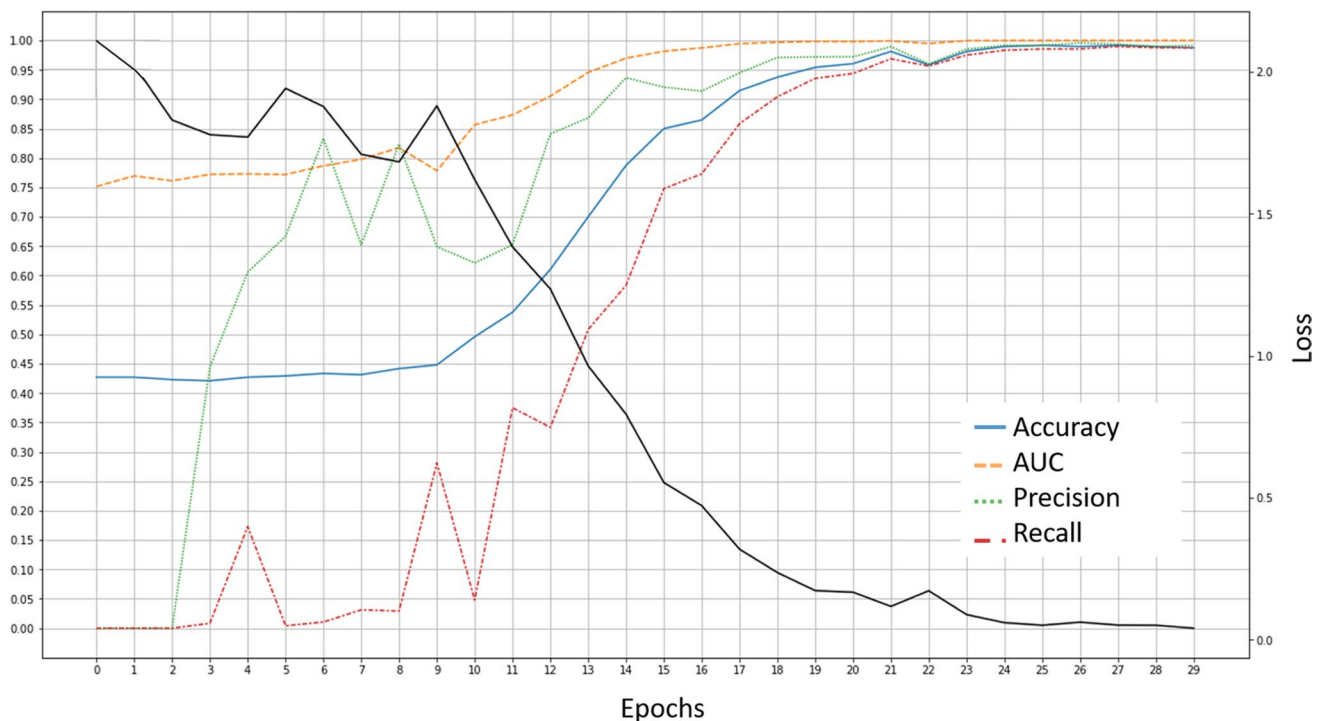
**Fig. 4** Testing data history of 29 epochs' iterations of CNN. The blue curve is the classification accuracy of the training data. The black curve is the loss function

the spatial studies (ESRI, 2011). The proportion of the total images captured according to year and month was evaluated in the temporal analysis. The spatial evaluations were conducted in order to better understand the general distribution of the cultural ecosystem services. This was accomplished by calculating the density of the images inside the Lithuanian coastal zone and mapping the total number of photographs per square kilometer using output cell sizes of 1 km$^2$ and a radius of 2,500 m. Pearson's correlation coefficient was also used to assess the geographical relationship between the distinct CES. Finally, a k-means cluster analysis of Flickr users was performed in order to further contextualize the kinds and associations of CES involvement at the user level for study area visits. This study was carried out using the proportions of images taken by each user in each of the four most represented CES categories, as well as the percentage of photographs in the other CES categories. The principal component analysis was used to estimate the appropriate number of clusters.

## Results

Between 2017 and 2021, 29,000 photographs published by 2,456 users were collected and analyzed. Only 27,807 photographs indicated participation in the CES; these were

published by just 147 individual users, who were also part of the initial number of users.

The majority of users shared photographs representing landscape appreciation (68.7%, n = 101) and social recreation (44.9%, n = 66). Over a quarter of all the users (36.7%, n = 54) took photographs depicting their specific encounters with biodiversity "Nature Appreciation Class" (Table 3).

According to the CES criteria used in this study, 27,807 photographs that indicated CES involvement were classified. The most common CES category was landscape appreciation, to which 37.5% of the photographs were assigned. Nature appreciation, historical monuments, and social recreation were also commonly represented, with 28.50%, 14.47%, and 7%, respectively, which also represented 50% of the total number of photographs. Less than 3% of the photos in the CES were about religious and spiritual expressions, as well as artistic or cultural expressions and appreciation.

### Spatial Distribution of CES

The photographs illustrating CES engagement are evenly distributed along the Lithuanian coast. The densest photo concentrations were observed in the coastal cities on the mainland and the Curonian Spit (Palanga, Šventoji, Klaipėda, Juodkrantė, and Nida), while the smallest accumulations were found on the outskirts of the coastal cities or in small
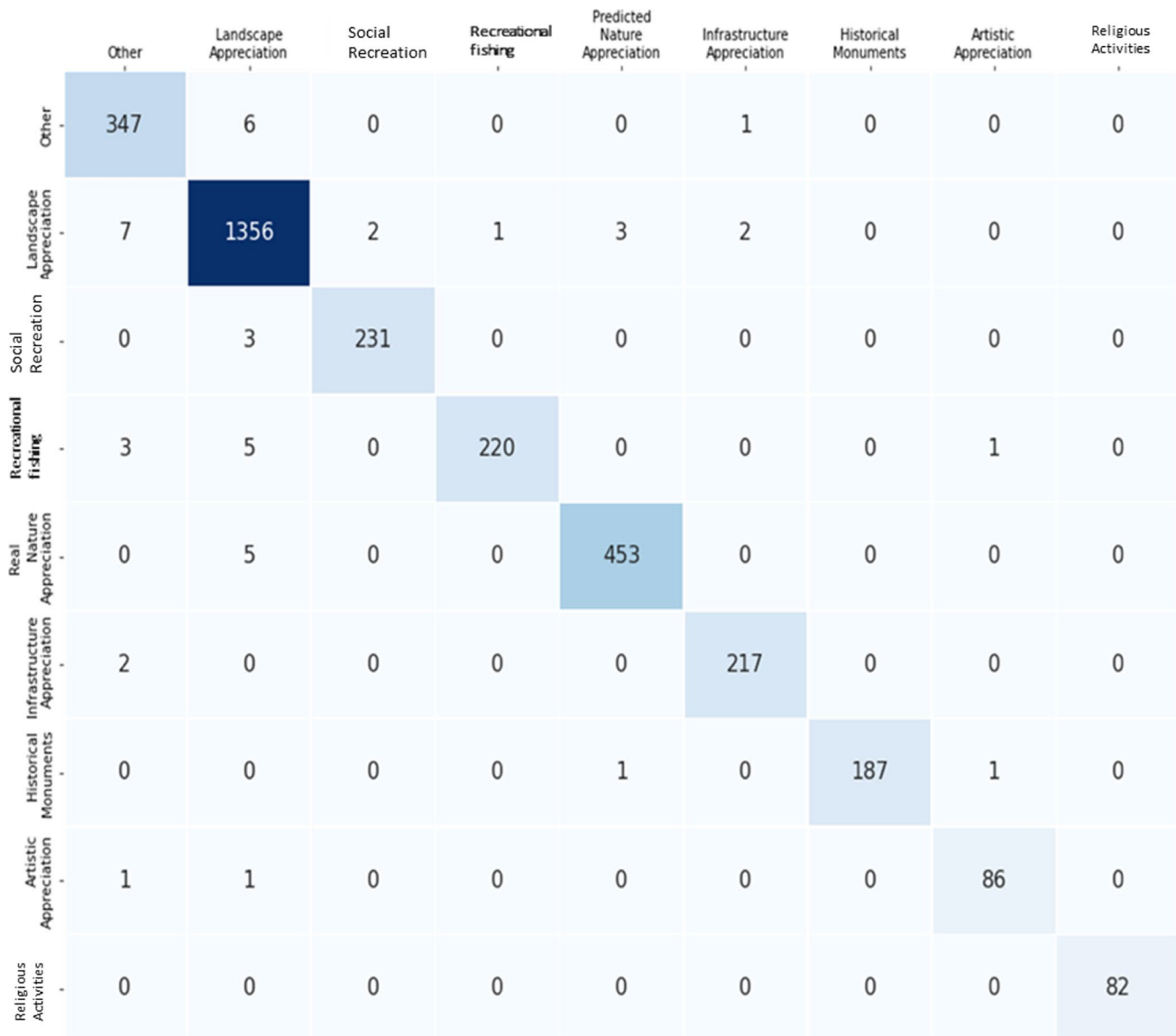
| | Other | Landscape Appreciation | Social Recreation | Recreational fishing | Predicted Nature Appreciation | Infrastructure Appreciation | Historical Monuments | Artistic Appreciation | Religious Activities |
|---|---|---|---|---|---|---|---|---|---|
| Other | 347 | 6 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Landscape Appreciation | 7 | 1356 | 2 | 1 | 3 | 2 | 0 | 0 | 0 |
| Social Recreation | 0 | 3 | 231 | 0 | 0 | 0 | 0 | 0 | 0 |
| Recreational fishing | 3 | 5 | 0 | 220 | 0 | 0 | 0 | 1 | 0 |
| Real Nature Appreciation | 0 | 5 | 0 | 0 | 453 | 0 | 0 | 0 | 0 |
| Infrastructure Appreciation | 2 | 0 | 0 | 0 | 0 | 217 | 0 | 0 | 0 |
| Historical Monuments | 0 | 0 | 0 | 0 | 1 | 0 | 187 | 1 | 0 |
| Artistic Appreciation | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 86 | 0 |
| Religious Activities | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 82 |

**Fig. 5** Confusion matrix

**Table 3** Number of photographs illustrating CES engagements on the Lithuanian coast. Note that individual users may have engaged with more than one category of CES. Total number of distinct users = 147

| CES categories | Number of Photographs | Percentage of Photographs | Number of Users | Percentage of Users |
|---|---|---|---|---|
| Landscape Appreciation | 10871 | 37.49% | 101 | 68.71% |
| Nature Appreciation | 8263 | 28.50% | 54 | 36.73% |
| Historical Monuments | 4196 | 14.47% | 21 | 14.29% |
| Social Recreation | 2031 | 7.00% | 66 | 44.90% |
| Infrastructure Appreciation | 891 | 3.07% | 42 | 28.57% |
| Recreational Fishing | 876 | 3.02% | 45 | 30.61% |
| Religious, Spiritual, or Ceremonial Activities and Monuments | 408 | 1.41% | 14 | 9.52% |
| Artistic or Cultural Expressions and Appreciation | 271 | 0.93% | 20 | 13.61% |

settlements (Karklė, Monciškės, Šventoji, and Būtingė) (Fig. 6).

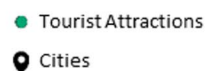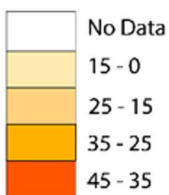A dense concentration of photographs in a particular area indicates a popular destination or hotspot. The study area was gridded with output cells measuring 2 km² to locate the hotspots and the quantification was determined using a measure of photo users per day (PUD). Five hotspots along the Lithuanian coast were identified, indicating a significant

**Fig. 6** Map of the Lithuanian coast, representing the numbers of photos per 2 km.²
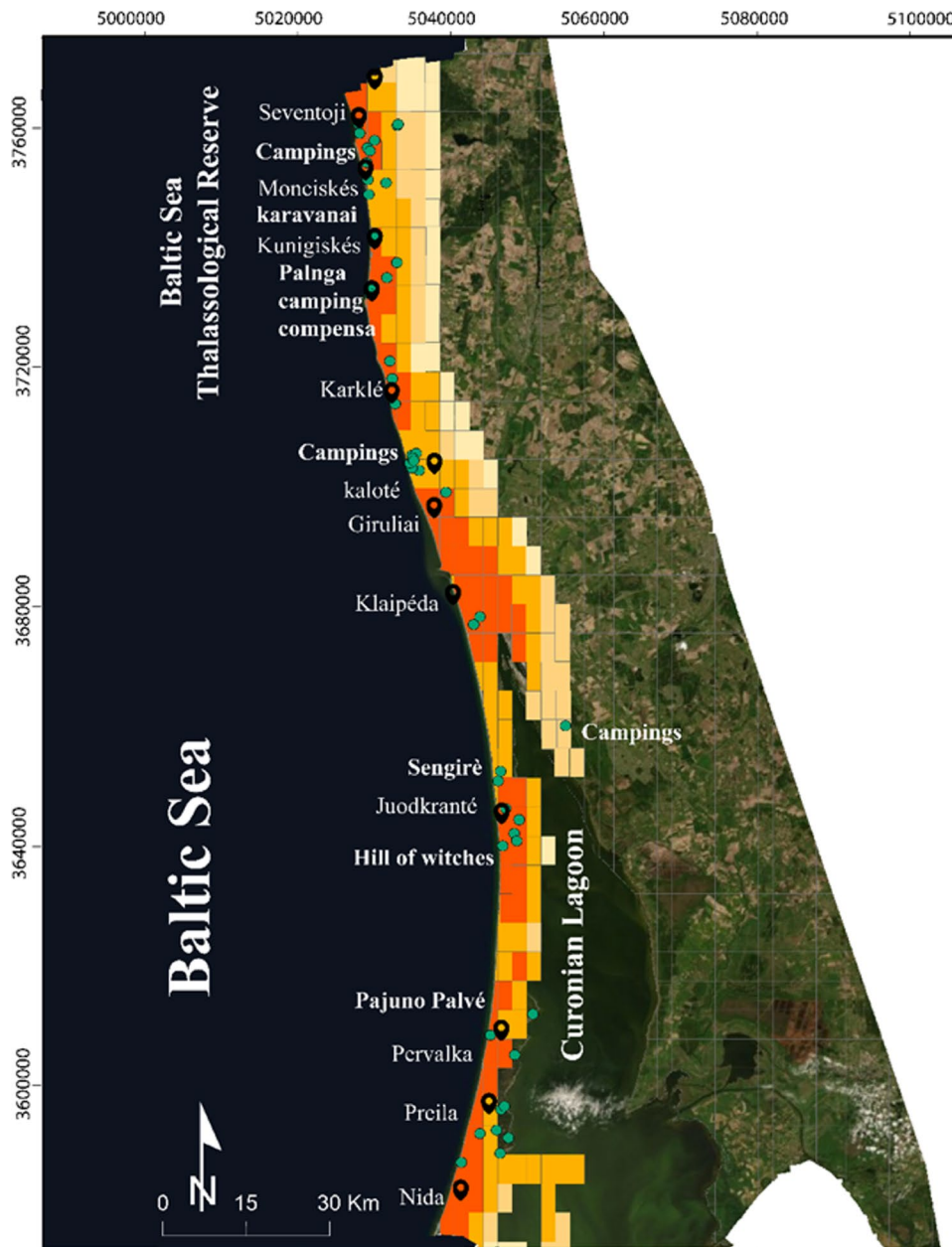
concentration of photographs. The first two hotspots are located on the mainland coast, specifically near the cities of Šventoji, Palanga, and Karklė, with 1013 PUD and 3552 PUD, respectively. The third and fourth hotspots are located in the central part of the coast near Klaipėda and Juodkrantė). with a very high number of photographs (4161 PUD and 8619 PUD). The final hotspot is located in the southern part of the coast (Pervalka, Preila, and Nida settlements) with a concentration of 8400 PUD. The analysis indicated that the number of photographs taken decreases in an easterly direction, where the distance from the coastal line increases (Fig. 6).

We used kernel density analysis to locate the CES engagements and to gain a better understanding of the

relationship between their location and the locations of the photographs. The kernel density analysis of the research region revealed that photographs of the most abundant category, landscape appreciation, are distributed along the entire coastal area and form several hot spots on the Curonian Spit (Nida, Pervalka, Juodkrantė, Smiltynė) and mainland coast (Palanga, Šventoji, Karklė, Klaipėda) (Fig. 7a). The densest concentration of photos were detected near environmental heritage objects such as the Parnidis and Naglis dunes located on the Curonian Spit, while an object of great interest on the mainland coast was the Oldando kepurė cliff. Pierses, embankments, small ports, and public beaches of coastal settlements were also recognized as
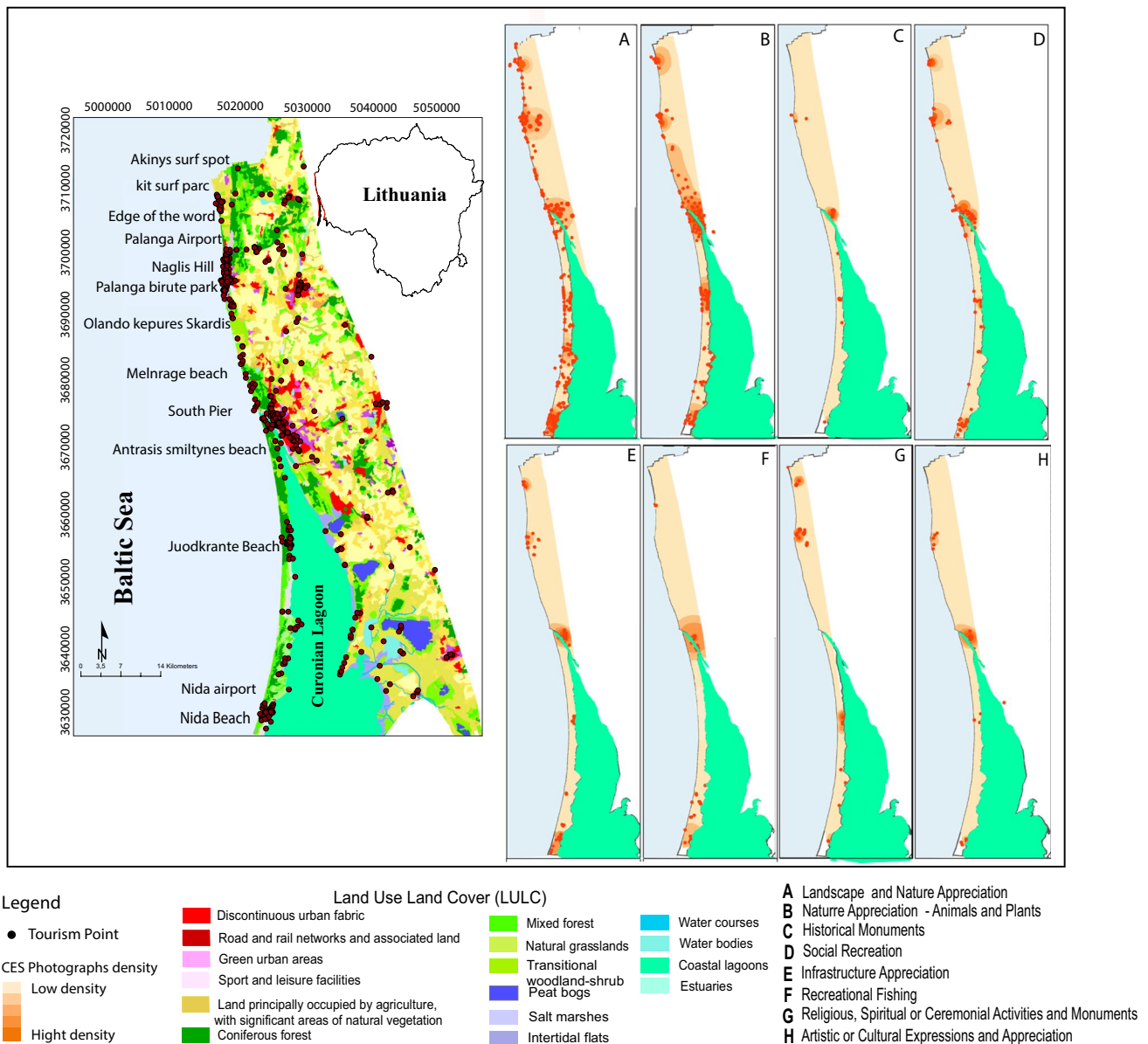


**Fig. 7** Maps of the density of photographs depicting engagements with different CES types

objects of great interest. Dense concentrations of the natural appreciation category were detected in the surroundings of Juodkrantė, Nida, and Palanga in forest areas or near bodies of water (Fig. 7b). Photos of historical monuments created hot spots in the biggest coastal cities of Klaipėda and Palanga (Fig. 7c). Nonetheless, other CES classifications were very densely concentrated in the previously mentioned locations, with the exception of recreational fishing and artistic or cultural appreciation, which were mostly concentrated around specific locations. Since the density ratio is influenced by the area of the study regions, these values identified the main coastal cities and natural reserves as the most attractive places to visit, according to the social media data obtained. In addition, we can say that these places are more attractive than others because of their established status as tourist areas. Consequently, there is a greater probability that they will be selected by people.

The Pearson's correlation coefficient revealed a significant spatial correlation between the CES classes (Table 4). Most of the CES classes had a strong positive correlation. Nature appreciation was positively correlated with landscape appreciation (Pearson's $r = 0.67$); social recreation was also closely and positively correlated with fishing recreation, artistic or cultural expression, and infrastructure appreciation, with $r = 0.77$, $r = 0.75$, and $r = 0.77$, respectively; and infrastructure appreciation was closely and positively correlated with artistic or cultural expressions and appreciation, with an R coefficient of 0.78.

## Temporal Distribution of CES

An analysis of the annual numbers of photographs showed that this study period experienced an increase in the numbers of photographs with a spike in 2019 ($n = 9502$), followed by a considerable decrease in 2020 ($n = 5812$), and a slight increase in 2021 ($n = 7188$).

A monthly analysis of the photographs illustrating engagements with CES showed that August, September, and October had the highest numbers of photographs compared to the other months of the year, with ($n = 12,038$, $n = 7206$,

and $n = 4437$, respectively), whereas March, April, and November had the fewest photographs with ($n = 49$, $n = 84$, and $n = 27$, respectively). Otherwise, the other months of the year had an average monthly number of photographs, ranging from $n = 132$ (December) to $n = 2009$ (July) (Fig. 8).

## Classification Analysis of CES User Engagements

To deal with the correlated CES classes and to visualize the data in a two-dimensional space, we used Principal Components Analysis (PCA). The first two axes of the PCA captured a large proportion (67%) of the user-level variance in the CES engagements in the Lithuanian coastal zone. These axes were then used to determine the primary types of Lithuanian coastal visitors based on their CES engagement practices (Fig. 9). Four main user clusters were identified. Cluster 1 was strongly associated with landscape appreciation and cluster 2 was mostly associated with nature appreciation. Clusters 3 and 4 comprised users who most often visited historical monuments and engaged in social recreation in the study area. The four main primary types of Lithuanian coastal visitors based on their CES engagement practices are landscape appreciation, nature appreciation, historical monuments, and social recreation.

## Discussion

Previous CES studies that have used photographs from social media have treated them as homogenous indicators of cultural interest. The CES framework emphasizes the need to identify beneficiaries as well as visitors in order to create non-homogenized recreation maps. Photograph content analysis enables a variety of cultural purposes to be identified. Flickr data analysis demonstrated spatial and temporal visitation patterns of distinct groups of users, which could contribute to a better identification of CES beneficiaries. An applied approach for mapping the spatial distribution of CES on the Lithuanian coast has two advantages: 1) neutrality in terms of place, group, and season and 2) cost and effort

**Table 4** Pearson's correlation coefficient ($\rho$) between the categories of photographs that fell within the grid cells that intersected the Lithuanian coast.** The correlation is significant at the 0.01 level (bilateral) (** $p < 0.01$)

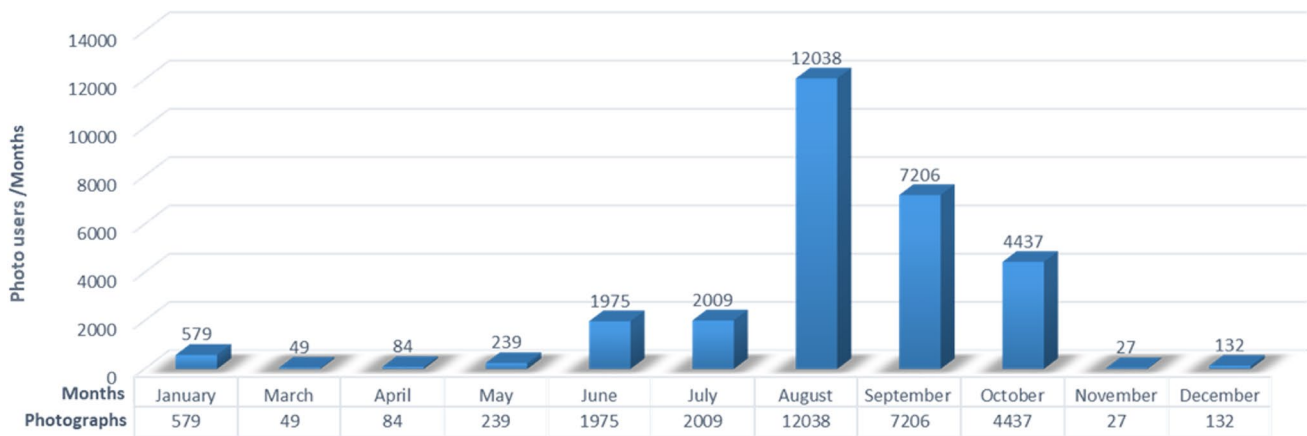|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. Nature Appreciation | 1 |  |  |  |  |  |  |  |
| 2. Landscape Appreciation | ,679** | 1 |  |  |  |  |  |  |
| 3. Social Recreation | 0,356 | 0,297 | 1 |  |  |  |  |  |
| 4. Recreational Fishing | 0,123 | 0,165 | ,774** | 1 |  |  |  |  |
| 5. Historical Monuments | 0,202 | -0,058 | 0,008 | 0,166 | 1 |  |  |  |
| 6. Artistic or Cultural Expression | 0,105 | 0,041 | ,759** | ,889** | 0,008 | 1 |  |  |
| 7. Infrastructure Appreciation | 0,329 | 0,34 | ,776** | ,917** | 0,19 | ,784** | 1 |  |
| 8. Religious and Spiritual | -0,069 | 0,122 | -0,116 | -0,032 | 0,061 | 0,002 | 0,066 | 1 |

**Fig. 8** The numbers of monthly photographs representing the CES engagements by each user

**Fig. 9** Classification analysis of users illustrating the different types of users and their preferred engagements with CES on the Lithuanian coast. Four main user clusters were identified; landscape appreciation, nature appreciation, social recreation, and historical monuments
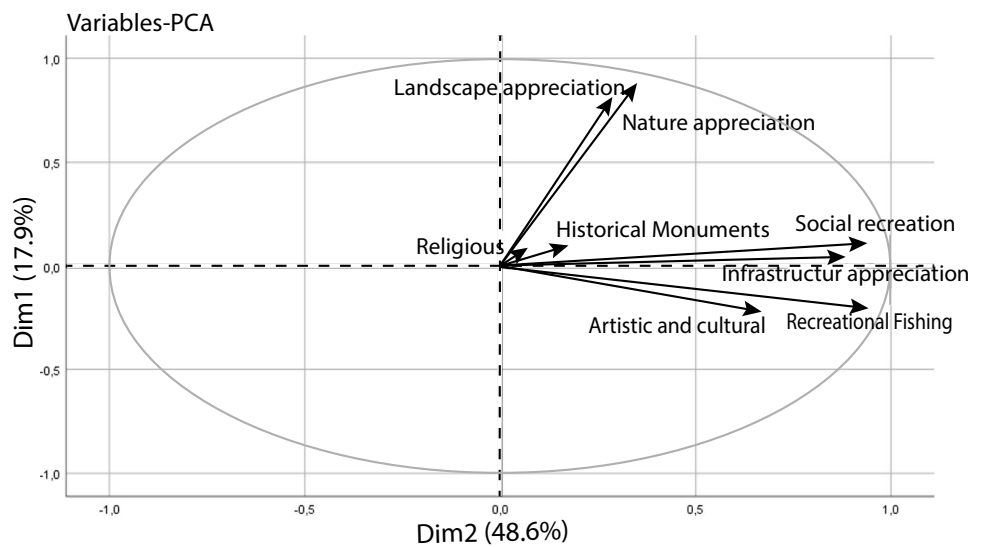


effectiveness. These levels of spatial detail are compatible with the scale of a lot of environmental management, which commonly considers several single sites (Peh et al. 2020).

Our sample of photographs showing CES engagements in the study area is likely to provide a good overview of CES engagement dynamics in Lithuanian coastal areas. Compared to previous studies, the number of photographs sampled in our research is considered robust (Richards and Friess 2015; Tenkanen et al. 2017). Other coastal studies that used crowdsourced photographs all specified a maximum of two thousand photographs per area. The high number of photographs collected in our research is remarkable given the limited area of land and likely reflects the coastal zone's importance for tourism, since the number of photographs taken inside an area is known to correlate with the number of visitors. This is also evident from the temporal distribution of photographs, with user activity concentrated during the peak tourist months of the summer season, especially around popular travel holidays, summer holidays, and specific celebrations or events. While we recognize that care should be taken when interpreting temporal trends and visitor dynamics from social media data, these results were generally expected and reaffirm the potential of social media data analysis to provide insights into visitation patterns to coastal areas (Tenkanen et al. 2017; Wood et al. 2013).

The photographs were distributed along the entire coast of Lithuania, with spots identified in the major cities such as Klaipėda, Palanga, Nida, and Juodkrantė that clearly emerged as the most important hotspots. This can be explained by the development of tourist and urban areas along the coast, with some of the main tourist attractions. This trend is likely to be partly driven by convenience and proximity to hotels, campsites, beaches, tourist sites, and historical monuments. Another relevant factor may be the

presence of well-developed infrastructure for visitors in these areas: road networks, walking paths, and parking places. A lot of tourist activities take place in these areas; in Klaipeda, for example, tourist boat trips to the Curonian Spit or Curonian Lagoon are available for visitors. This supports other recent studies that show an association between visitor infrastructure and photograph density (Ghermandi 2016; Richards and Friess 2015).

It is also crucial to keep in mind that the usability of social media data as an indicator of visitation depends on temporal granularity. To this end, the hotspots identified in the results of this study are located in urban environments. Most of the photographs in these clusters were taken by combining three elements that affect trends. The first crucial element that is repeated at the same level in all the clusters is the presence of accessible views of specific landscapes (beaches and dunes); this forms the basis for larger clusters, with high numbers of contributors. These places are characterized by concentrations of photographs that resemble environmental observations. Finally, there is the recreational element, where photographs show the presence of recreational facilities, for example, public parks and recreational infrastructure. Therefore, people's interest in natural features and open spaces is not limited to nature reserves and other designated areas but is supported by the accessibility and organization of cultural practices. A similar trend includes historical monuments whose cultural value is characterized by a higher degree of accessibility. Photographs of this cultural activity are taken where the Lithuanian Sea Museum and Dolphinarium is located and on the Hill of Witches. These two areas, in particular, are of obvious historical interest to the study area.

Birds and nature are predominant attractions in the northern part of the study area where the Baltic Sea Thalassological Reserve is located, which explains the dense concentrations of photographs showing birds and plants. Other studies have confirmed that bird watching is a fast-growing recreational activity and has been described as a new variant of niche tourism, attracting often unsuspecting tourists (Connell 2009). Appreciation of landscape, which is an important aspect, made up the largest percentage of photography (68.7%), followed by social recreation, where meeting friends and family, leisure, visiting tourist attractions, and general social activities are the most important (44.9%). Identifying and attracting these tourists can be beneficial to local economies. For example, approximately 98 million adults engage in activities such as bird watching, wildlife photography, hunting, and fishing, and spend $59.5 billion a year in the United States alone (Özcan et al. 2009).

Our analysis has successfully captured the overlapping spatial dynamics of natural engagements and social recreation (Fig. 7). The clear spatial association of the different types of CES engagements is not surprising given that many types of CES are clustered throughout the study area (Ament et al. 2017; Plieninger et al. 2013; Raudsepp-hearne et al. 2010). A CES analysis of bundles could potentially be used as an effective way to inform the local management of opportunities to improve CES commitments or to manage potential conflicts due to their spatial overlap. This information can be used to plan and keep track of ways to control visitor flow, such as by building infrastructure assets (Jepson et al. 2017) or by putting spatial and temporal restrictions in place for better management.

Regional attractions are also important for visitors (Chazée and Valat 2016). This study also contains a comparative process between the numbers of photographs taken annually, and the numbers of annual visitors to Lithuania. Both graphs (Fig. 10) show an assimilable trendline. The numbers of visitors, as well as the numbers of photographs taken, increased between 2016 and 2019. The tourist economy was hit hard by the Coronavirus pandemic and by the measures that were adopted to limit the spread of the virus, which also impacted the numbers of visitors. This shock led the international tourist economy to contract by between 60 and 80% in 2020, which explained the huge drop in the numbers of visitors as well as the numbers of photographs taken annually. The curve resumed its growth in 2021. This rise can be explained by the decision to lift the closure measures on recreational areas for leisure and relaxation, beaches and tourist attractions.

## Supporting Protected Area Management with Social Media Data

Our findings suggest that data collected from social media may be used to better understand and monitor the extent to which CES involvement occurs in coastal regions across geographical and temporal dimensions. Additionally, this data may be used to determine which biophysical assets are associated with CES delivery (Retka et al. 2019). This is particularly true for services that do not correlate well with any other CES. Managers may use this data to determine the non-substitutability of CES (Valck et al. 2016), and to integrate this information into more effective management strategies (Tenerelli et al. 2016). According to (Daniel et al. 2012), promoting value-generating practices linked to unique CES can help people connect more with nature, which in turn can help them support biodiversity conservation and sustainable natural and coastal resource management in the long-term.

The numbers of photographs taken in our study area are known to be associated with the numbers of visitors. These results were generally expected and reaffirm the potential of social media data analysis to provide information on

**Fig. 10** Numbers of photographs representing CES engagements per year (green bars), B- Tourist arrivals in the coastal municipalities of Lithuania (orange line) from 2016 to 2021
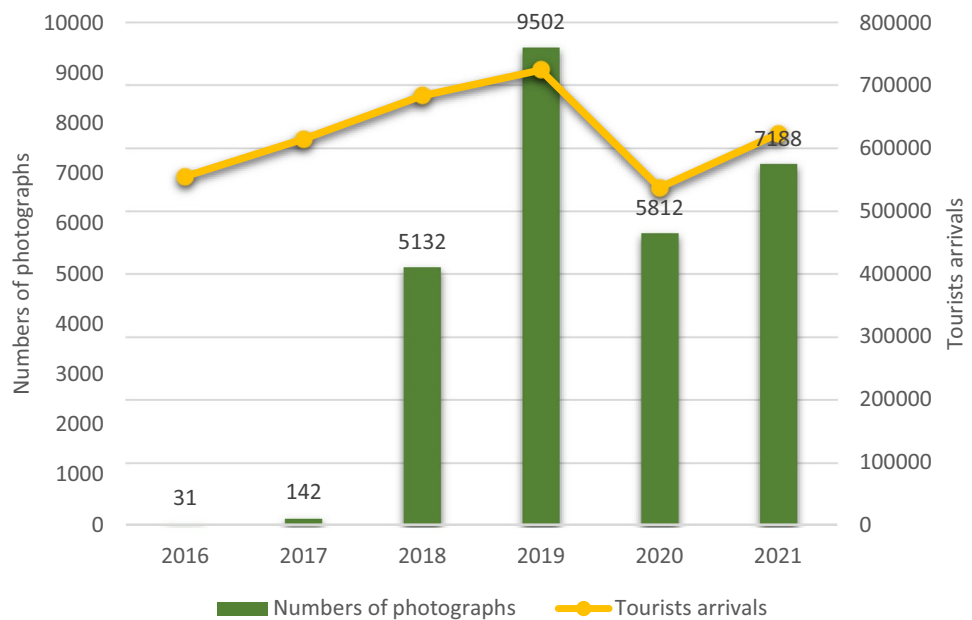


visitation patterns to protected areas and coastal zones. Social media data is also available across national boundaries and could inform global conservation. For example, it could help estimate global visitation patterns in coastal zones in a manner similar to that done by Balmford et al. using visitation statistics. In addition, social media data can be used to assess the intensity of human activities on a global scale to inform the spatial prioritization of wetland conservation under pressure.

The long-term viability of coastal regions is highly reliant on community support. Identifying the synergy between societal values and environmental aims may help managers develop effective communication methods that result in beneficial conservation results (Whitehead et al. 2014). In this context, social media data could be an additional tool to communicate the beneficial impacts of management actions and stimulate communication and interaction with coastal area staff to enhance relationships with community members. Additionally, it may be beneficial to monitor community-based initiatives to restore biodiversity, which often result in the provision of CES such as educational and recreational opportunities (Krasny et al. 2014).

Another area where social media data can potentially benefit coastal and protected area management is through the analysis of non-compliant or illegal activities (Retka et al. 2019). It has been argued that the Internet and social media offer new opportunities for the fight against illegal trade in wildlife and rare species (Lavorgna 2014). Further, there is evidence that other forms of illegal activities, such as hunting, are also documented online (El Bizri et al. 2015; Retka et al. 2019) and there are results identifying some cases of illegal activities.

Recent years have seen significant developments in the use of social media data to monitor illegal wildlife trade, particularly through the application of machine learning algorithms (Di Minin et al. 2021). The possibilities offered by these methods, if they can be extended to monitor other forms of illegal activities, have the potential to revolutionize the monitoring and management of illegal wildlife activities on coastlines and in protected areas.

## Model Limitation

The Flickr analysis enabled distinct actor groups to be identified that are important for coastal managers; nevertheless, it must be emphasized that particular actors were not as numerous as other CES groups. Several CES categories were underrepresented in the current study, including natural objects and monuments, religious activities, and fishing. This is unlikely to reflect the true value of the Lithuanian coast for these types of CES, given that the fishery and aquaculture sectors (which are primarily derived from processing activities) account for less than 0.5 percent of Lithuania's GDP and that the majority of Lithuania's fishing ports are located in coastal cities (Klaipėda, Nida, and Šventoji). Fishing activities, as well as natural buildings and monuments, are unlikely to be documented by Flickr, since neither the participants nor any passers-by may believe they are worth recording. A similar problem may occur with religious/spiritual emotions and appreciation, since photographing and sharing religious moments or devotional behaviors on public social media accounts may be seen as disrespectful. Another constraint associated with wetland environments is that users may not want to register directly in watery environments to

avoid getting moisture on their smart devices. Instead, they may choose to register on shorelines or in more developed areas due to weak phone signals, which could indicate an unrecognized bias between location and cultural activity.

In this regard, social media data should be seen as a complement to (rather than a substitute for) more conventional social survey methods. Recent work has tried to establish approaches for incorporating diverse data sources (Vieira et al. 2018) in order to allow other social groups to be included in CES analyses, although further work in this area is certainly required. Finally, as mentioned before, the quality and endurance of photographic data collected through the Internet may be compromised as a result of changes to user privacy settings or platform modifications, such as Application Programming Interfaces (Ladle et al. 2016). Despite the enormous potential for social media data to contribute to coastal area management and monitoring, Flickr data is biased by variables that are always changing, such as the platform's popularity, user demographics, and location (Sessions et al. 2016). Flickr is widely used in the United States and Western Europe (Noam et al. 2012), hence it was an appropriate choice for our research. There are other popular photo-sharing social media platforms, including Flickr, Panoramio, and Instagram (Gibbons 2015). Instagram currently has the largest user base and seems to be the most accurate representation of visitor numbers (Tenkanen et al. 2017). However, subsequent changes to the Instagram API and Terms of Service have restricted researchers' access to photographs, which will likely limit the platform's usability for comparable future studies. Similar adjustments and limits apply to other sites, further restricting researchers' access to publicly published pictures. This is likely to bias samples toward privileged actors and engagements of a certain sort (Hirons et al. 2016). For instance, the Lithuanian coast receives hundreds of thousands of visits each year, but only a few hundred were included in our sample, which was presumably driven in part by variables related to technology availability and adoption. Additionally, some kinds of interactions with natural environments are more prevalent on particular social media platforms than on others (Hausmann et al. 2018), implying that a thorough evaluation of CES engagements may need a cross-platform study.

## Conclusion

In summary, in this study we demonstrated that deep learning approaches using freely available platforms can be used for identifying and classifying CES-relevant natural and human elements from social media photographs taken in natural areas. If cautiously interpreted and when combined with other social-cultural approaches, this data has the potential to help researchers to unravel the human-nature interactions that drive CES distributions, benefits, and values. We were able to model the spatial and temporal patterns of the actual use of CES, to monitor and analyze actual CES usage, and to explore the impacts of environmental attributes, social attributes, and facilities on the spatial and temporal distributions of CES. The application of our approach to the Lithuanian coast showed a preference for landscape appreciation and nature appreciation, which can provide meaningful insights into visitors' preferences, as well as being very useful for the management of these protected and natural areas. Using photographic data from social media to quantify the cultural values and traits of coastal areas has some limitations, including inherent biases associated with capturing certain activities or events, as well as uncontrolled changes in data availability and quality over time. Nonetheless, social media data on CES significantly expands the types of information that may be extracted from standard survey methodologies, most notably the volume and size of the data. Indeed, although we applied our technique to a coastal region, there were no intrinsic or practical limitations to the geographical size of study, and, unlike social surveys, it is readily replicable on a regional, national, or even global scale. This worldwide expansion may need more investment in the automated (or semi-automatic) content categorization of photographs using machine learning.

## Declarations

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