Classifying and mapping cultural ecosystem service using artificial intelligence and social media data

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Abstract

For managers of coastal areas, data and statistics on the usage and appreciation of nature are important. Utilization of social media platforms, such as the photo-sharing website Flickr, is a potential trend. We propose a unique strategy based on machine learning (image analysis) and convolutional neural network (CNN) for assessing cultural ecosystem services (CES) by collecting, and interpreting 29,000 photographs from the Lithuanian costal area. The most often represented CES categories were landscape appreciation and social recreation, which reflects the evident benefits. Similarly, historical monuments and environmental enjoyment were well represented. Engagements with CES followed distinct geographical and temporal patterns that were related to user behavior and reflected the infrastructure features of various places along the Lithuanian coast. Due to the data's extensive spatial coverage and high spatio-temporal resolution, this technique is suitable for finding CES hotspots/cold spots and, despite limits, holds promising potential for monitoring the impact of management actions on CES provision. Our study demonstrates how analyzing large amounts of digital photographs expands the analytical toolbox available to researchers and allows the quantification and mapping of CES at large geographical scales.

1. Introduction

For decades, the concept of ecosystem services (ES) has been used to known as the « usefulness » of nature for people and society(Paracchini et al. 2014)(Retka et al. 2019). ES and natural capital were considered necessary elements of sustainable development in the concept of 1990s(Braat and de Groot 2012), thus, the ES concept began to gain popularity with the scientific community (Retka et al. 2019). ES were identified as natural support systems that sustain human life and were formalized during this time with the Millennium Ecosystem Assessment (MEA) in 2005(Millennium Ecosystem Assessment 2005). In policy discussions, ES has maintained a prominent position.

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

Due to the intangible and subjective nature, CES has been underestimated in the academic research(Hernández-Morcillo, Plieninger, and Bieling 2013). The assessment of CES depends on a trade-off between the spatial level and the time required to carry out. Traditional approaches commonly used 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, Plieninger, and Bieling 2013). For the 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). In comparison 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). It has been the subject of collaborative action in recent years. 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, Preis and Moat (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 analyses in the context of CES rely on the manual classification of photos or texts shared by social media users (Cheng et al. 2019), with 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, Kutz, and Brunton 2018)) are especially promising because they can learn to recognize similarities in the information content of an image in a way like that of 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, Roy, and August 2020) camera traps (Ferreira et al. 2020) However, to date CNN tools used to analyse CES represented in crowdsourced social media data are not freely available in their full version(Egarter Vigl et al. 2021; Gosal et al. 2019a), restricting its 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. 2019b).We provide a unique way to merge social media, machine learning, and deep learning image recognition using the Lithuanian coast as a case study. This method is applicable to various coastlines and protected regions. This study should use of emerging big data technologies that infer human worth and emotion toward the environment through digital representations of photographs, as well as artificial intelligence(Gibbons 2015; Sherren et al. 2017). These techniques are regarded as a cost-effective strategy since they enable quick mapping of CES with high spatial precision in the geographic region and may be used in conjunction with or in place of older methodologies. The existing photograph density may be utilized to do large-scale evaluations of coastal CES, as well as 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. The content analysis of images on social networks enables the identification of social preferences and the mapping of geographical patterns. Our specific goals for this paper were to i) assess CES provision along the Lithuanian coast using georeferenced social media photographs; ii) examine the spatial distributions and temporal trends of cultural ecosystem services along the Lithuanian coast; and iii) discuss the utility of georeferenced photographs in managing the coastal zone in particular and protected areas in general.

2. Material And Methods

2.1 Study area

Lithuania, located in the southeastern part of the Baltic Sea, covers an area of 65,300 km² and has a population of 2,8 million inhabitants. The Lithuanian coast being the one of the most significant objects of recreation and tourist attraction in Lithuania, has the shortest coastline (90,6 km in length) among the all Baltic Sea countries (Fig. 1). The Bounding Box of 20.71 N, 55.231 E, 21.95 S, 56.10 W is affiliated to our study area. Lithuanian climate is semi-continental, with cold winters and mild, moderately rainy summers, hence favorable weather conditions is the crucial factor for tourism and outdoor activities. The mean annual air temperature reach 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 this coast into two sections, a 51.03 km long compartment on the Curonian Spit and a 38.49 km long mainland section (Jarmalavičius *et al.* 2012). The mainland coast is relatively highly populated (228,384 inhabitants, approx. 8% of the total population of Lithuania) comparing to the Curonian Spit (3,782 inhabitants) (Lithuanian Census data 2021). There are approximately 54% of agricultural area, 28% of forests, and 1,5% of wetlands in the coastal municipalities (EEA, 2018). The Lithuanian marine coastal area is managed by four coastal municipalities. Seaport Klaipeda is the northernmost ice–free port on the Eastern coast of the Baltic Sea. It is the most important and biggest Lithuanian transport hub, connecting sea, land and railway routes from East to West and it serves for freight transport as well as cruise ships besides it is the third most populated city in Lithuania where resides 148,348 inhabitants (Lithuanian Census data 2021). The coastal town Palanga is the leading resort in Lithuania and its municipality account for 63 thousand beds in the official accommodation establishments (17.8% of total Lithuania bed places). Approximately 369,8 thousand tourists (16,6% of the total tourist arrivals of country’s total) arrived to visit the municipality of Palanga in 2021, it is also the most popular destination for domestic tourists (Lithuanian census in 2021). Palanga resort provide rehabilitative sanatorium treatment, health and beauty services entire year. Respectively Neringa municipality provide 13 thousand beds (3.6% of total Lithuania bed places) and meet approximately 75 thousand tourists (3,4% of the total tourist arrivals of country's total) annually (Lithuanian Census data 2021). Since Curonian spit is included into the list of the UNESCO World Heritage sites and its terrestrial and nearshore parts are designated by several protection statuses (reserves, parks, Natura 2000) development of the spit is limited what impact population growth. Likewise, accessibility of Curonian Spit only by ferry and entrance fee to Curonian Spit National park significaly control tourist flows. All coastal municipalities have approximately 780 objects of archaeological, architectural and art heritage (most of them concentrated in Klaipėda) as well 30 objects of environmental heritage (springs, hills, dunes, moraine cliffs, stones) that serve as major attraction sites for tourists. As well area is designated to three strict reserves, 24 reserves and two national and regional parks.

Lithuanian coast is a typical example of micro-tidal low-lying coast formed of Quaternary deposits and belongs to the accumulative-abrasive coastal type (Bitinas et al., 2005; Jarmalavicius et al., 2012). Sandy sediments (optionally containing a certain amount of gravel, pebble, and boulders) prevail on the mainland coast, while glacial (moraine) deposits are exposed in abrasional cliffs in the central part which serves as attraction points to visitors (Bitinas et al. 2005 Jarmalavičius et al. 2012). The overall continuity of the sandy coast is interrupted by several river outlets. Several sections of the mainland coast suffer from serious sediment deficit that occurs mainly due to hydrotechnical constructions intercepting the nearshore sediment transport. Beach nourishment has been applied as coastal protection method since 2006 in Palanga coastal area. Contrary to the mainland coast the largest amount of fine sediment is found on the Curonian Spit. The predominant accumulation processes in the Lithuanian section of the spit are reflected via the presence of wide beaches and well developed foredunes (Gudelis 1998).

The Lithuanian coastal zone was chosen as a research location because of its complicated linkages between local resource extraction, recreation, and the environmental values present in the region, as a result of its sustainable use designation.

2.2 Retrieve of Flicker data

Wood (Gosal et al. 2019b)describe Flickr as a popular photo-sharing service with more than 70 million members and 200 million photos shared globally. It is not clear how many Flickr users are based in or have visited the study area, but the website is likely to have a reasonable market share in the country when compared to its most similar competitors, such as Photobucket and Panoramio. Instagram looks to be considerably more popular than Facebook, but it cannot be used since the application-programming interface (API) prohibits automated data processing without user authorization (Instagram, 2014). We develop Python scripts as a first step to retrieve the data that the Flickr web site hosts. We have developed a script in the Python environment with Flickr's Application Programming Interface (API) to facilitate repeatable requests to the Flickr API. The functions of this approach make a call to the Flickr

API and return both the raw photographs and the additional metadata stored in a CSV table. The feature of this Python script is that it provides a reproducible way to access geolocated photographs via search queries, making it possible to provide useful datasets for a range of ecological analyses. The script feature allows users to define a set of search criteria that are then queried against the Flickr database. A block of data containing the metadata of the photographs corresponding to the search criteria is then returned. The ability to refine search parameters allows a more targeted approach to using Flickr's geolocated photographs by returning only those that are relevant to the research. The package also includes features for uploading photos (link URL S, URL O, URL SQ...) and collecting user information. In our case study, we used Bounding BOX coordinates 20.7076 N, 55.2352 E, 21.9485 S, 56.102 W. The images were downloaded with associated metadata, including longitude and latitude, the date and time the photograph was taken, and the user ID of the photographer. A total of 29,000 images uploaded by 2456 users between 2017 and 2021 were downloaded. The limitations of the package created in the Python environment usually turn to the level of photo searches via the Flickr API, which will return only 4,000 unique results per search criterion, which will limit the 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 (min date taken and max 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 next 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 having only the metadata of the first 4,000 unique images repeated several times.

2.3 Data categorization

The data was divided into three parts. An objective coding technique based on prior CES research and tailored to the Lithuania coast environment was used to show and classify the 1000 contents of each photograph. 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). The authors visited the Lithuanian coastal zone to get a feel of the area's physical, environmental, and cultural aspects to assist in the contextualization and categorization of CES. A total of 8 categories were used to classify each photograph once the CES kinds had been established (Table 1).

Table 1
Classification categories of cultural ecosystem services.

CES category	Description
Artistic or Cultural Expressions and Appreciation	Photographs representing people in artistic activities (e.g. painter, sculptor), cultural activities (e.g. artisanal fisheries, folk dancing) or their products (e.g. painting, pottery)
Historical Monuments	Photographs depicting historical infrastructure (e.g. historical buildings, ruins)
Landscape Appreciation	Photographs for which the main focus is a wide and large-scale view of the landscape
Nature Appreciation	Photographs focusing on animals, plants or other living organisms
Religious, Spiritual or Ceremonial Activities and Monuments	Photographs representing religious or spiritual monuments or activities (e.g. church, indigenous ritual)
Social Recreation	Photographs that represent groups of people in an informal or non-dedicated recreative (i.e. not sport) social environment
Infrastructure appreciation	Photographs that primarily depicted aspects of the built
Fishing recreation	Photographs that depicted people engaged in fishing
Other	Photographs that do not fit any of the above criteria

2.4 Training data labelling

The 29000 photos were randomly split into three sections. The first segment includes 1000 photos with technical objective coding annotations. This technique was made 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 will allow us to annotate a large number of images which constitute the training data. K-nearest neighbors (KNN) algorithm is a supervised machine-learning algorithm that belongs to the class of simple and easy-to-implement learning algorithms. It can be used to solve classification and regression problems. In our case study, we used the KNN algorithm as an automatic annotator which receives a set of corresponding output with values, which are the 1000 images already annotated on which it will be able to train and define the prediction model. The KNN algorithm prediction was carried out with some manual annotation corrections to perform an annotation with the best possible precision (Fig. 2). The algorithm uses the similarity of longitude and latitude features to predict the CES classes of a set of photographs (9000 photographs), which further means that new photographs will be annotated based on how close they are to CES classes in the training set (1000 images). 80% of the annotated data was devoted to training and 20% to testing, mindful that the training set size of all images is 10000 Photographs.

2.5 Convolutional neural networks (CNNs)

Deep learning algorithms are mostly based on artificial neural network architectures with more hidden layers, so they are called "deep neural networks." Deep learning algorithms” are part of a larger group of machine learning algorithms. They can make machines "learn" based on their past experiences to do the job they were given, which makes them better at the task. It works well with a large dataset and can extract the features on its own. They don't usually require human intervention in this process. Deep learning algorithms require highly configured machines, normally GPUs, as they require a long time to be trained. Among the three main architectures used to create deep learning models, the convolution Neural Network (CNN).

A deep convolutional neural network is one of the most widespread deep neural network models. It possesses the capability of learning features automatically from input data. CNN basically uses neural network architecture and mostly applied for image classification as it eliminates manual feature extraction process. It is capable of performing an entire task like classification of images without manual intervention. It requires a huge set of labeled data for training as it is a supervised learning method. The Convolutional layer is made up of a series of filters that are applied to the input image and then the resulting data is given to the Pooling layer. At each convolution layer, feature maps are created. It is generated by calculating convolutions between local patches and weight vectors, which are often referred to as filters. The features are then mapped to the predicted outputs in the final learning step. Finally, completely linked layers’ function as a conventional neural network.

2.5.1 Convolutional image classification model

- **Training**:

After carrying out several CNN architecture and transfer learning Approaches such as VGG and AlexNet, we proposed a new convolutional architecture for classifying images. As illustrated in (Table 2), it takes as input RGB images of a size (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 Convolution and the dense layers.

Table 2
Convolutional image classification model architecture

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 166, 116, 32)	2432
max_pooling2d_1 (MaxPooling2D)	(None, 83, 58, 32)	0
Dropout (Dropout)	(None, 83, 58, 32)	0
conv2d_1 (Conv2D)	(None, 83, 58, 64)	51264
max_pooling2d_1 (MaxPooling2D)	(None, 41, 29, 64)	0
Dropout_1 (Dropout)	(None, 41, 29, 64)	0
flatten (Flatten)	(None, 76096)	0
Dense (Dense)	(None, 512)	38961664
Dropout_2 (Dropout)	(None, 512)	0
Dense_1 (Dense)	(None, 9)	4617

Convolution. The first convolution layer used to extract the various feature maps from the input images. A mathematical operation of convolution is performed in this layer between the input image, a filter of a size 32 and a kernel of 5x5. By sliding the filter over the input image using a stride of 1x1, the dot product is taken between the filter and the parts of the input image. Then, the convolutional layer applies 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.

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

1

Max-Pooling. Besides convolution layers, CNN often uses max pooling layers. It is used primarily to reduce the size of the tensor in order to speed up calculations. This layer selects the maximum value from each region of a size (2x2) and transfers them to the next layer.

$$h_{xy}^{L} = max_i = 0, \ldots, s, j = 0, \ldots, sh_{(x+i)\ (y+j)}^{L-1}$$

2

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

Dense. Dense Layer is a simple layer of neurons in which 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 9 classes in the output layer. As an optimizer, we used NADAM, which is another variation of Adam, resulting in a little faster training time than Adam. The parameters used in Nadam optimizer are, (learning rate = 0.001, beta 1 = 0.9, beta 2 = 0.999, epsilon = 1e-07). Since we deal with 9 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 9, once the chosen performance measure stops improving. However, the model at the end of training may not be the model with best performance on the validation dataset. In this regard, we managed to use Model Checkpoint, which monitors the training based on in order to keep the model that has achieved the best performance.

- **Testing**:

In order to measure the performance of the trained model, we relied on the testing phase in which we used 20% of the data. Choosing an appropriate measure is generally difficult in applied machine learning, but is particularly difficult for unbalanced classification problems. First, because most standard measures that are widely used assume a balanced class distribution such as accuracy. In this regard, we added AUC, precision, and recall. In (Figs. 3 and 4), the performances are presented for each epoch concerning training data and testing data.

2.5.2 Image classification model results

- **Training**:

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 is decreasing from 3.5 to 2 in the first epoch, although the noisy movements from epoch 1 to 4 seem to flatten when it reaches 21 epochs. A 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 notice 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.

- **Testing**:

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

As shown in (Fig. 4), we perceive that the testing data performance is almost the same as that of the training data, which ensures that our model is generalized. The accuracy and precision metrics scored

99.01%, whereas the recall attained 98.13%.

- **Confusion Matrix**

To evaluate the performance of each class, we opted for the use of the confusion matrix (Fig. 5). A confusion matrix is an NxN matrix 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 isn't as big as it might be. When we look at some classes like landscape appreciation, nature appreciation, and social leisure 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 class other is a point of confusion when compared to most other classes, because it could have some features in common with other classes.

2.6 Data analysis

After setting up the CNN model for image classification, all the photographs extracted from the Flickr database have been 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 images within the research region, we conducted a temporal and spatial analysis (Fig. 2) using the date of each photograph taken and the corresponding geographical coordinates. ArcGIS 10 for Desktop was used to conduct spatial studies (ESRI,2011). The proportion of total images captured by year and month was evaluated in temporal analysis. Spatial evaluations were conducted in order to better understand the general distribution of cultural ecosystem services. This was accomplished by calculating the density of images inside the Lithuanian coastal zone and mapping the total number of photographs per square kilometer using output cell sizes of 1 km2 and a radius of 2500 m. Pearson's correlation coefficient was also used to assess the geographical relationship between 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 other CES categories, and the 'principal component analysis was used to estimate the appropriate number of clusters.

3. Results

Total of 29000 photographs were identified and analyzed between 2017 and 2021. Among them, 147 individual users shared photographs illustrating the CES's participation, with significant differences in the number of users participating in various CES categories. The majority of users shared photographs that represented landscape appreciation (68.7%, n = 101) and social recreation (44.9%, n = 66). Over a quarter of all users (36.7% percent, n = 54) took photographs illustrating their specific encounters with biodiversity “Nature appreciation class” (Table 3).

Table 3
Number of photographs illustrating CES engagements within 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%
Fishing recreation	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%

Total of the 27807 collected images indicated CES involvement and were classified using the CES criteria used in this study. The most common CES category was landscape appreciation, which 37.5% photographs were assigned. Nature appreciation, historical monuments, and social recreation were also highly represented, with 50% of total photographs. Religious and spiritual expressions, as well as artistic or cultural expressions and appreciation, had the fewest pictures less than 3% in the CES.

3.1 Spatial analysis of CES

3.1.1 Photo kilometers per square kilometer

The photographs illustrating CES engagements are evenly distributed along the Lithuanian coast. The highest photo concentrations were observed in coastal cities of mainland and Curonian spit (Palanga, Šventoji, Klaipėda, Juodkrantė, and Nida), while the smallest accumulations were found on the outskirts of the coastal cities or at small settlements (Karklė, Monciškės, Šventoji, and Būtingė) (Fig. 6).

A high concentration of photographs in a particular area indicates a popular destination, or hotspot. The study area was gridded with output cells measuring 2 km^2 to locate the hotspots and the quantification was determined using a measure of photo users per day (PUD). Five hotspots along the Lithuanian coast have been identified, indicating a significant concentration of photographs. The first two hotspots are located in 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 in the area of 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 concentration of 8400 PUD. The analysis indicates that the number of taken photographs decreases to the eastern direction, where distance from the coastal line is increasing (Fig. 6).

3.1.2 Density maps

We use a kernel density to locate CES engagements and gain a better understanding of the relationship between their location and the location of photographs. The kernel density analysis of the research region revealed that photos of the most abundant category landscape appreciation distributed along the entire coastal area and forms several hot spots in Curonian spit (Nida, Pervalka, Juodkrantė, Smiltynė) and mainland coast (Palanga, Šventoji, Karklė, Klaipėda) (Fig. 7a). The highest concentration of photos detected close to environmental heritage objects such as Parnidis and Naglis dunes located in Curonian Spit, while the object of high interest in the mainland coast was Oldando kepurė cliff. Pierses, embankments, small ports and public beaches of coastal settlements recognized as objects of high interest as well. High density spots of natural appreciation category detected in surrounding of Juodkrantė, Nida and Palanga in forest area or close to water bodies (Fig. 7b). Photos of historical monuments creates hot spots in the biggest coastal cities Klaipėda and Palanga. (Fig. 7c). Nonetheless, other CES classifications demonstrated a high density in the previously mentioned locations, with the exception of fishing recreation, and artistic or cultural appreciation that were mostly concentrated around specific locations. Since the density ratio is influenced by the area of the study regions, these values identify 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 establishment as tourist areas. Consequently, they have a higher probability of being selected by people.

Table 4

Pearson correlation coefficient (ρ) between categories of photographs that fall within 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. Fishing recreation	0,123	0,165	,774**	1				
5. Historical Monuments	0,202	-0,058	0,008	0,166	1			
6. Artistic or Cultural Expressions	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

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

3.2 Temporal analysis of CES

The annual photograph number analysis showed that the period subject to this study experienced a photograph number upward evolution with a spike in 2019 (n = 9502), followed by a considerable decrease in 2020 (n = 5812), with a slight improvement in 2021 (n = 7188)

A monthly analysis of photographs illustrating engagements with CES showed that August, September, and October had the greatest photographs number comparing to the other months of the year, with (n = 12038, n = 7206, and n = 4437, respectively), whereas the month of March, April, and November had the least photographs with (n = 49, n = 84 and n = 27, respectively). Otherwise, the other months of the year had an average monthly photograph number, ranging from n = 132 (December) to n = 2009 (July) (Fig. 8).

3.3 Classification analysis of CES user engagements

To deal with correlated CES classes and to visualize data in a two-dimensional space, we used the principal analysis component (PCA). A large proportion (67%) of the user-level variance in CES engagements in the Lithuania coastal zone was captured by the first two axes of the Principal Components Analysis. These axes were then used to determine the primary types of Lithuanian coast visitors based on 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. Cluster 3 and 4 encapsulated users that most often engaged with historical monuments and social recreation in the study area. The four main primary types of the Lithuanian coast visitors based on CES engagement practices are, landscape appreciation, nature appreciation, historical monuments and social recreation.

4. 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 for identifying beneficiaries, as well as identifying visitors in order to create non-homogenized recreation maps. Photograph content analysis enables the identification of a variety of cultural purposes. Flickr data analysis demonstrated spatial and temporal visitation patterns of distinct groups of users, which could contribute to better identification of CES beneficiaries. Applied approach for mapping the spatial distribution of CES on the Lithuanian coast has two advantages: 1) neutrality in terms of place, groups, and seasons and 2) cost and effort effectiveness. These levels of spatial detail are compatible with the scale of much 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 the Lithuanian coastal part. 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 land's strip 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(Hausmann et al. 2018) (Tenkanen et al. 2017; Wood et al. 2013).This is also evident from the temporal distribution of photographs, with user activity concentrated in the months of heavy tourism during 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 analyses to provide insights on visitation patterns to coastal areas(Tenkanen et al. 2017; Wood et al. 2013).

Photographs have been distributed along the entire coast of Lithuania, with spots that have been identified in the major cities such as Klaipėda, Palanga, Nida and Juodkrantė that clearly emerge 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 net, walking paths, parking places Several activities for tourist have taken place in these areas; specifically, in Klaipeda, for example, tourist boat trips to the Curonian Spit or Curonian lagoon are available for visitors. This supports other recent studies showing an association between visitor infrastructure and photograph density(Ghermandi 2016; Richards and Friess 2015).

Birds and nature are predominant attractions in the northern part of the study area where the Baltic Sea Thalassologic Reserve is located, which explains the high concentration of photographs illustrating 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). The appreciation of landscape, being an important aspect, marked the largest percentage of photography (68.7%), followed by social recreation, where meeting with friends and family, leisure, visiting tourist places, and general social activities are the most important (44.9%). Identifying and attracting these tourists can be beneficial to the local economy. For example, about 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 leisure (Fig. 7). The clear spatial association of the different types of CES engagements is not surprising given that many types of CES are clustered along the study area(Ament et al. 2017; Plieninger et al. 2013; Raudsepp-hearne, Peterson, and Bennett 2010). CES analysis of bundles could potentially be used as an effective way to inform local management of opportunities to improve CES commitments or manage potential conflicts due to their spatial overlap. This information can be used to plan and keep track of ways to control visitor flow, like 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). The study also contains a comparative process between the number of photographs taken annually, and the number of annual visitors to Lithuania. Both graphs (Fig. 10) showed an assimilable trendline. The number of visitors, as well as the number of photographs taken, has grown from 2016 to 2019. The tourism economy has been hit hard by the coronavirus pandemic and by the measures that have been adopted to limit the spread of the virus, which has also impacted the number of visitors. This shock has led the international tourism economy to contract by 60–80% in 2020, which explains the huge drop in the number of visitors as well as the number of photographs taken annually. The curve resumed its growth in 2021. This rise is explained by the decision to lift the closure measures on recreational areas for leisure and relaxation, beaches and tourist attractions.

4.1 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, such data may be utilized 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 utilize this data to determine the non-substitutability of CES(Valck et al. 2016), and integrate this information into more effective management strategies(Tenerelli, Demšar, and Luque 2016). According to(Daniel et al. 2012) promoting value-generating practices linked to unique CES can help people connect more deeply with nature, which could help them support biodiversity conservation and sustainable natural and coastal resource management in the long-term.

The long-term viability of coastal regions is highly reliant on community support. Identifying 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).

4.2 Model Limitation

The Flickr analysis enabled the identification of distinct actor groups 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 fisheries 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 passing viewers may believe they are worthy of 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 disrespectful. 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 the inclusion of other social groups 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 in 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 Levin,Salit Kark n.d.), and hence was an appropriate choice for our research. There are other popular photo-sharing social media platforms, including Flickr, Panoramio, and Instagram(Gibbons 2015), however Instagram presently has the greatest 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, restricting researchers' access to publicly published pictures. This is likely to bias samples toward privileged actors and engagements of a certain sort(Hirons, Comberti, and Dunford 2016). For instance, the Lithuanian coast receives hundreds of thousands of visits each year, but only a few hundreds of them were included in our sample, which is 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 cross-platform study.

5. Conclusion

The content analysis of social media photographs enables large-scale studies of human-nature interactions and the generation of novel insights for the conservation and management of ecosystems and their services. We were able to effectively combine a classification of photographic content with a study of the temporal and geographical distributions of CES in order to demonstrate the distinctive characteristics of Lithuania's coastline region. Utilizing photographic data from social media to quantify the cultural values and traits of coastal places has limitations, including inherent biases associated with capturing certain activities or publics, 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 data. Indeed, although we applied our technique to a coastal region, there are no intrinsic or practical limitations on the geographic size of study, and, unlike social surveys, it is readily replicable at regional, national, or even global scales. This worldwide expansion may need more investments in the automated (or semi-automatic) content categorization of photographs using machine learning.

Declarations

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Conflicts of interest/Competing interests The authors declare that they have no conflict of interest and no competing interests.

Ethics approval Not applicable.

Consent for publication Not applicable.

Consent for publication Not applicable.

Availability of data and material All data generated or analysed during this study are included in this published article and its supplementary information files.

Code availability Not applicable.

Authors' contributions All authors contributed to the study conception. Material preparation, data collection and analysis, were performed by IM, MeM and IB.IM, ME, MM and MeM verified the analytical methods. The first draft of the manuscript was written by IM, MeM IB and All authors commented on previous versions of the manuscript. All authors discussed the results and approved the final manuscript.

References

1. Ament, Judith M, Christine A Moore, Marna Herbst, and Graeme S Cumming. 2017. “Cultural Ecosystem Services in Protected Areas: Understanding Bundles , Trade-Offs , and Synergies.” 10(August): 440–50.
2. Braat, Leon C., and Rudolf de Groot. 2012. “The Ecosystem Services Agenda:Bridging the Worlds of Natural Science and Economics, Conservation and Development, and Public and Private Policy.” *Ecosystem Services* 1(1): 4–15. http://dx.doi.org/10.1016/j.ecoser.2012.07.011.
3. Chazée, Laurent, and Tour Valat. 2016. “Monitoring Recreational and Educational Services Provided by Mediterranean Wetlands: How Natural Capital Impact Human and Social Capital?” (2014): 2014–17.
4. Cheng, Xin, Sylvie Van Damme, Luyuan Li, and Pieter Uyttenhove. 2019. “Evaluation of Cultural Ecosystem Services: A Review of Methods.” *Ecosystem Services* 37(June 2018): 100925. https://doi.org/10.1016/j.ecoser.2019.100925.
5. Connell, John. 2009. “Birdwatching , Twitching and Tourism: Towards an Australian Perspective Birdwatching , Twitching and Tourism: Towards an Australian Perspective.” (January 2015): 37–41.
6. Daniel, Terry C et al. 2012. “Services Agenda.” 109(23).
7. Egarter Vigl, Lukas et al. 2021. “Harnessing Artificial Intelligence Technology and Social Media Data to Support Cultural Ecosystem Service Assessments.” *People and Nature* 3(3): 673–85.
8. Ferreira, André C. et al. 2020. “Deep Learning-Based Methods for Individual Recognition in Small Birds.” *Methods in Ecology and Evolution* 11(9): 1072–85.
9. Ghermandi, Andrea. 2016. “Analysis of Intensity and Spatial Patterns of Public Use in Natural Treatment Systems Using Geotagged Photos from Social Media.” *Water Research* 105: 297–304. http://dx.doi.org/10.1016/j.watres.2016.09.009.
10. Gibbons, James Michael. 2015. “Prospects and Challenges for Social.” 3(September): 1–6.
11. Gomes, Eduardo et al. 2021. “Future Scenarios Impact on Land Use Change and Habitat Quality in Lithuania.” 197(February).
12. Gosal, Arjan S. et al. 2019a. “Using Social Media, Machine Learning and Natural Language Processing to Map Multiple Recreational Beneficiaries.” *Ecosystem Services* 38(June 2018): 100958.

https://doi.org/10.1016/j.ecoser.2019.100958.

13. Gosal, Arjan S et al. 2019b. “Using Social Media , Machine Learning and Natural Language Processing to Map Multiple Recreational Beneficiaries.” *Ecosystem Services* 38(June 2018): 100958. https://doi.org/10.1016/j.ecoser.2019.100958.
14. Guerrero, Paulina, Maja Steen Møller, Anton Stahl Olafsson, and Bernhard Snizek. 2016. “Revealing Cultural Ecosystem Services through Instagram Images : The Potential of Social Media Volunteered Geographic Information for Urban Green Infrastructure Planning and Governance.” 1(2): 1–17.
15. Hausmann, Anna et al. 2018. “Social Media Data Can Be Used to Understand Tourists’ Preferences for Nature-Based Experiences in Protected Areas.” *Conservation Letters* 11(1): 1–10.
16. Havinga, Ilan et al. 2021. “Social Media and Deep Learning Capture the Aesthetic Quality of the Landscape.” *Scientific Reports* 11(1): 1–11. https://doi.org/10.1038/s41598-021-99282-0.
17. Hernández-Morcillo, Mónica, Tobias Plieninger, and Claudia Bieling. 2013. “An Empirical Review of Cultural Ecosystem Service Indicators.” *Ecological Indicators* 29: 434–44. http://dx.doi.org/10.1016/j.ecolind.2013.01.013.
18. Hirons, Mark, Claudia Comberti, and Robert Dunford. 2016. “Valuing Cultural Ecosystem Services.”
19. Jepson, Paul R et al. 2017. “Protected Area Asset Stewardship.” *Biological Conservation* 212(September 2016): 183–90. http://dx.doi.org/10.1016/j.biocon.2017.03.032.
20. Kitchin, Rob. 2014. “Big Data, New Epistemologies and Paradigm Shifts.” *Big Data and Society* 1(1): 1–12.
21. Krasny, Marianne E, Alex Russ, Keith G Tidball, and Thomas Elmqvist. 2014. “Civic Ecology Practices : Participatory Approaches to Generating and Measuring Ecosystem Services in Cities.” *Ecosystem Services* 7: 177–86. http://dx.doi.org/10.1016/j.ecoser.2013.11.002.
22. Ladle, Richard J et al. 2016. “Conservation Culturomics.”
23. Lusch, Bethany, J. Nathan Kutz, and Steven L. Brunton. 2018. “Deep Learning for Universal Linear Embeddings of Nonlinear Dynamics.” *Nature Communications* 9(1).
24. Millennium Ecosystem Assessment. 2005. Current *Ecosystems and Human Well-Being : Current State and Trends , Volume 1*.
25. “Ministério Do Meio Ambiente Instituto Chico Mendes de Conservação Da Biodiversidade.” 2016.
26. Noam Levin,Salit Kark, David Crandall. “Where Have All the People Gone? Enhancing Global Conservation Using Night Lights and Social Media.”
27. Özcan, Hasan et al. 2009. “Ecotourism Potential and Management of Kavak Delta (Northwest Turkey) Ecotourism Potential and Management of Kavak Delta (Northwest Turkey).” (253): 781–87.
28. Paracchini, Maria Luisa et al. 2014. “Mapping Cultural Ecosystem Services: A Framework to Assess the Potential for Outdoor Recreation across the EU.” *Ecological Indicators* 45(2014): 371–85. http://dx.doi.org/10.1016/j.ecolind.2014.04.018.
29. Peh, Kelvin S et al. 2020. “Short Communication TESSA : A Toolkit for Rapid Assessment of Ecosystem Services at Sites of Biodiversity Conservation Importance.” 5(2013): 51–57.

30. Pleasant, Mary M. et al. 2014. "Managing Cultural Ecosystem Services." *Ecosystem Services* 8: 141–47. http://dx.doi.org/10.1016/j.ecoser.2014.03.006.
31. Plieninger, Tobias, Sebastian Dijks, Elisa Oteros-rozas, and Claudia Bieling. 2013. "Land Use Policy Assessing , Mapping , and Quantifying Cultural Ecosystem Services at Community Level." *Land Use Policy* 33: 118–29. http://dx.doi.org/10.1016/j.landusepol.2012.12.013.
32. Raudsepp-hearne, C, G D Peterson, and E M Bennett. 2010. "Ecosystem Service Bundles for Analyzing Tradeoffs in Diverse Landscapes."
33. Retka, Jared et al. 2019. "Assessing Cultural Ecosystem Services of a Large Marine Protected Area through Social Media Photographs." *Ocean and Coastal Management* 176(July 2018): 40–48. https://doi.org/10.1016/j.ocecoaman.2019.04.018.
34. Richards, Daniel R. et al. 2021. "Harnessing Artificial Intelligence Technology and Social Media Data to Support Cultural Ecosystem Service Assessments." *People and Nature* 3(3): 673–85. https://doi.org/10.1016/j.ecoser.2017.09.004.
35. Richards, Daniel R., and Daniel A. Friess. 2015. "A Rapid Indicator of Cultural Ecosystem Service Usage at a Fine Spatial Scale: Content Analysis of Social Media Photographs." *Ecological Indicators* 53: 187–95. http://dx.doi.org/10.1016/j.ecolind.2015.01.034.
36. Seresinhe, Chanuki Illushka et al. "Using Deep Learning to Quantify the Beauty of Outdoor Places Supplementary Material."
37. Sessions, Carrie, Spencer A. Wood, Sergey Rabotyagov, and David M. Fisher. 2016. "Measuring Recreational Visitation at U.S. National Parks with Crowd-Sourced Photographs." *Journal of Environmental Management* 183: 703–11. http://dx.doi.org/10.1016/j.jenvman.2016.09.018.
38. Sherren, Kate et al. 2017. "Digital Archives , Big Data and Image-Based Culturomics for Social Impact Assessment : Opportunities and Challenges." *Environmental Impact Assessment Review* 67(July): 23–30. http://dx.doi.org/10.1016/j.eiar.2017.08.002.
39. Tenerelli, Patrizia, Urška Demšar, and Sandra Luque. 2016. "Crowdsourcing Indicators for Cultural Ecosystem Services: A Geographically Weighted Approach for Mountain Landscapes." *Ecological Indicators* 64: 237–48.
40. Tenkanen, Henrikki et al. 2017. "Instagram , Flickr , or Twitter : Assessing the Usability of Social Media Data for Visitor Monitoring in Protected Areas." *Scientific Reports* (July): 1–11. http://dx.doi.org/10.1038/s41598-017-18007-4.
41. Terry, J. Christopher D., Helen E. Roy, and Tom A. August. 2020. "Thinking like a Naturalist: Enhancing Computer Vision of Citizen Science Images by Harnessing Contextual Data." *Methods in Ecology and Evolution* 11(2): 303–15.
42. Valck, Jeremy De et al. 2016. "Landscape and Urban Planning Contrasting Collective Preferences for Outdoor Recreation and Substitutability of Nature Areas Using Hot Spot Mapping." *Landscape and Urban Planning* 151: 64–78. http://dx.doi.org/10.1016/j.landurbplan.2016.03.008.
43. Weinstein, Ben G. 2018. "Scene-Specific Convolutional Neural Networks for Video-Based Biodiversity Detection." *Methods in Ecology and Evolution* 9(6): 1435–41.

44. Whitehead, A M Y L et al. 2014. “Integrating Biological and Social Values When Prioritizing Places for Biodiversity Conservation.” 00(0): 1–12.
45. Wood, Spencer A., Anne D. Guerry, Jessica M. Silver, and Martin Lacayo. 2013. “Using Social Media to Quantify Nature-Based Tourism and Recreation.” *Scientific Reports* 3.
46. Zoderer, Brenda Maria et al. 2016. “Identifying and Mapping the Tourists’ Perception of Cultural Ecosystem Services: A Case Study from an Alpine Region.” *Land Use Policy* 56: 251–61. http://dx.doi.org/10.1016/j.landusepol.2016.05.004.

Figures

Figure 1

Location of the study area with locations of Flicker’s photographs.

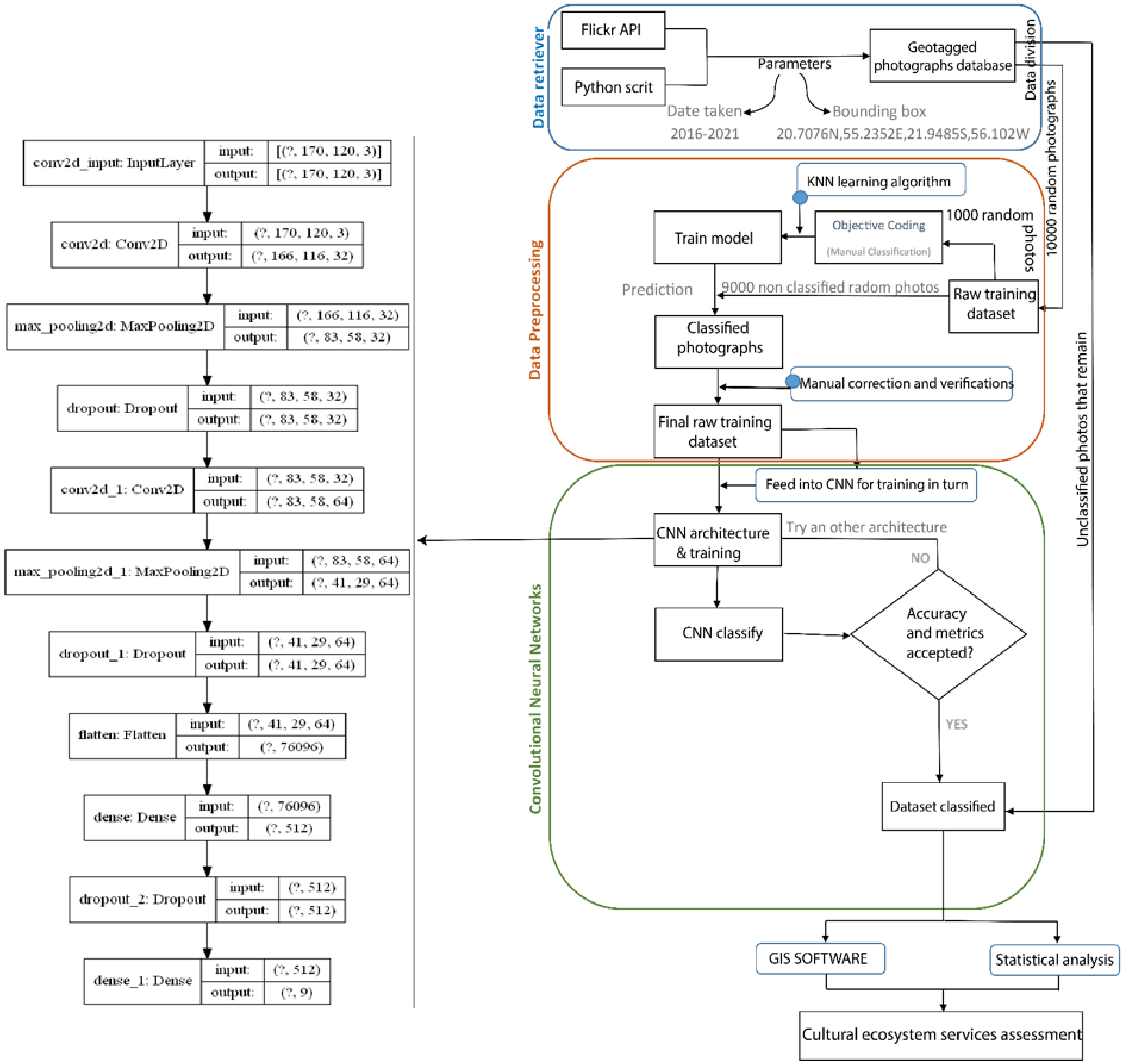

Figure 2

Flowchart showing the process followed and developed to access CES

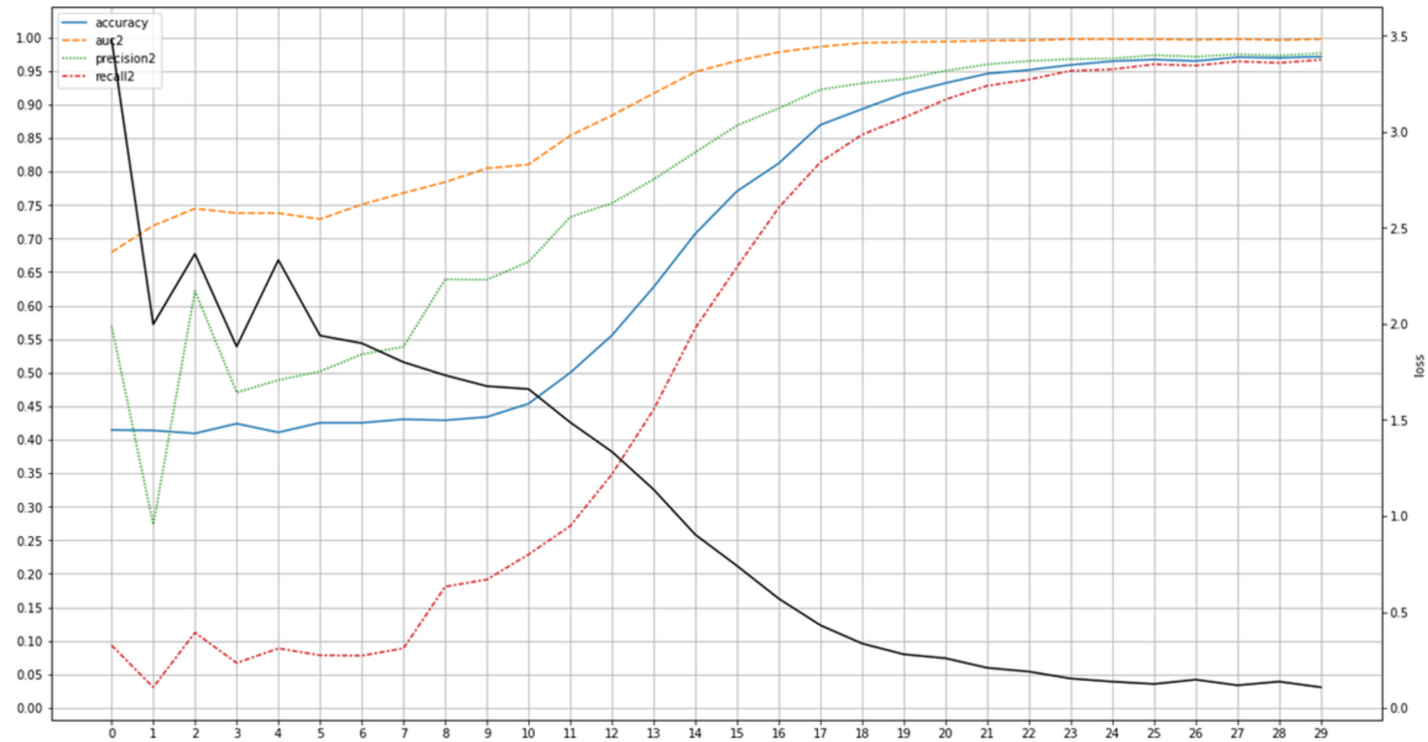

Figure 3

Training data history of 29 epoch’s iteration of CNN. The blue curve is the classification accuracy of the training data. The Black curve is the loss function.

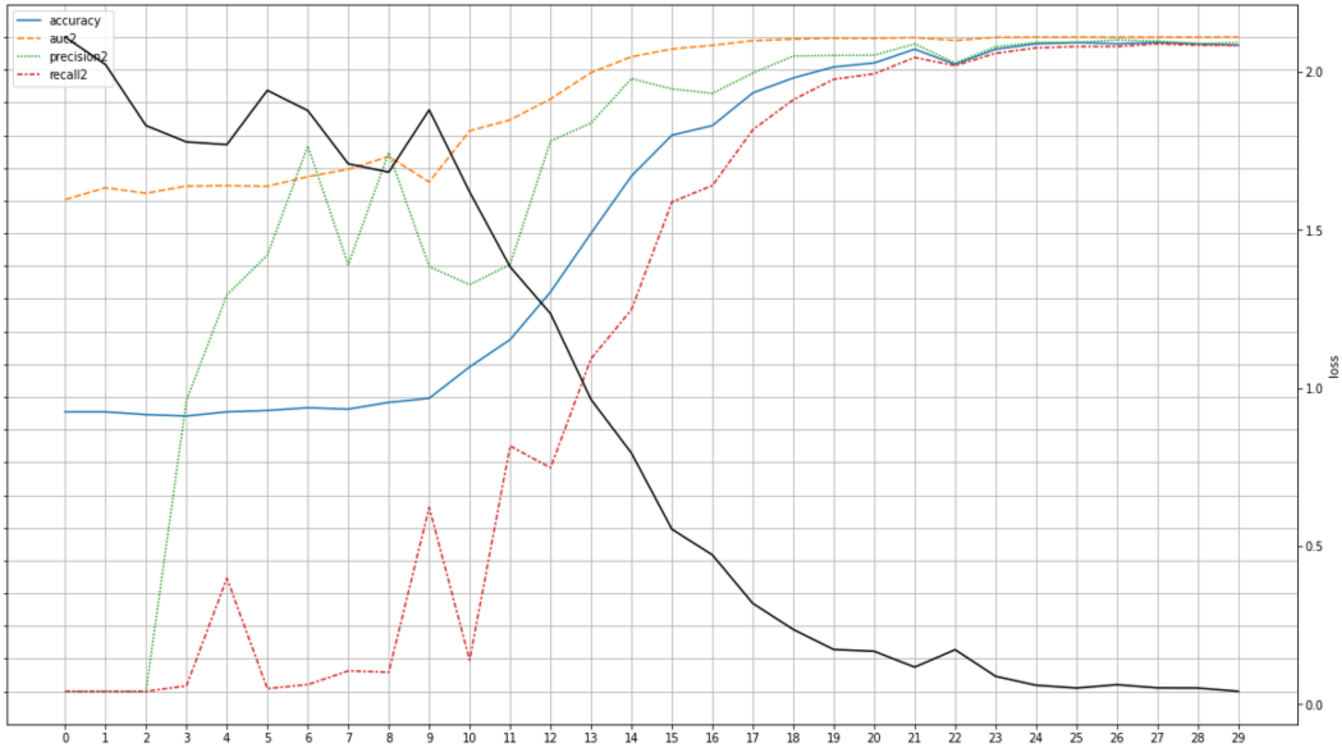

Figure 4

Testing data history of 29 epoch’s iteration of CNN. The blue curve is the classification accuracy of the training data. The Black curve is the loss function.

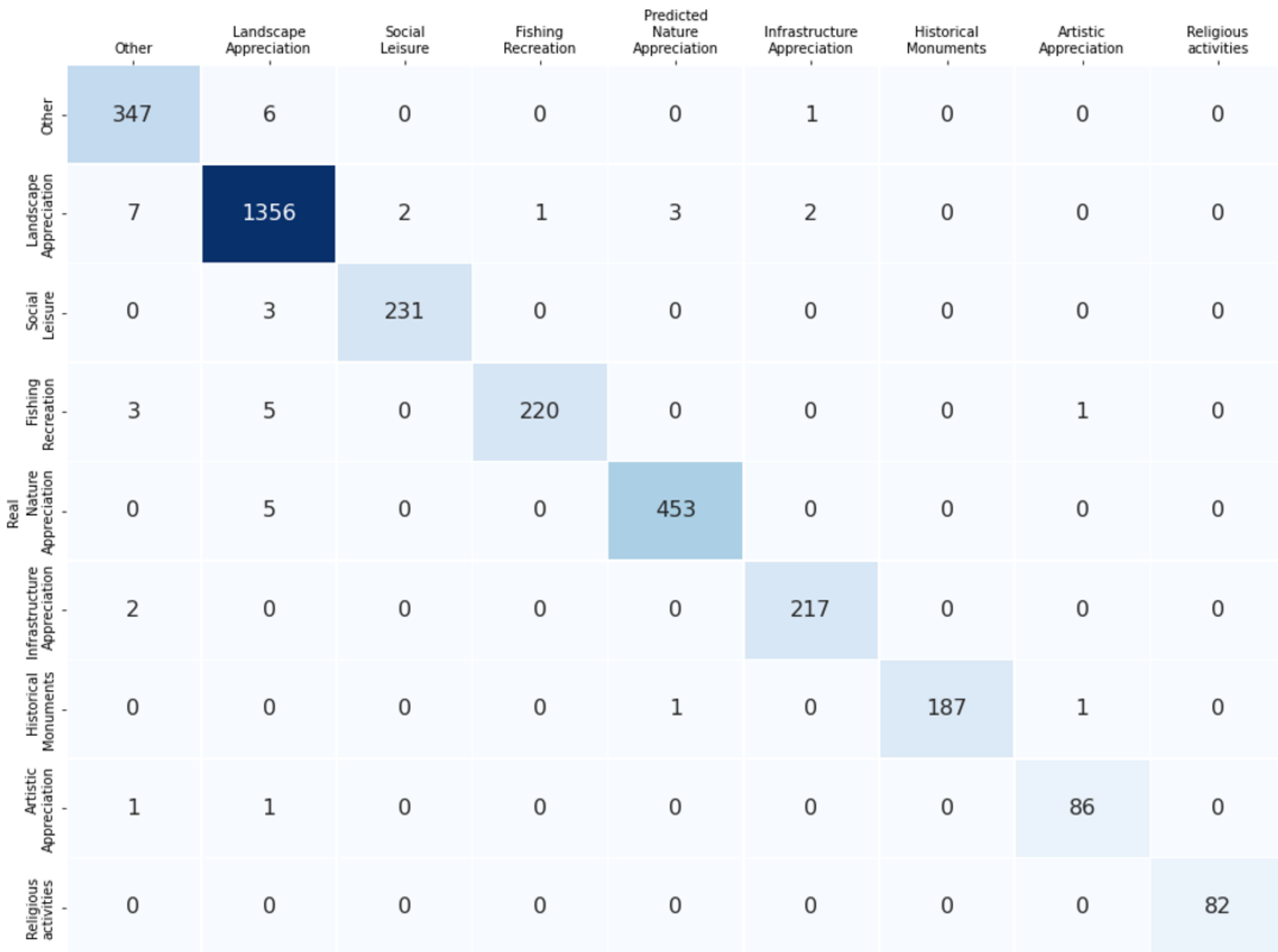

Figure 5

Confusion matrix

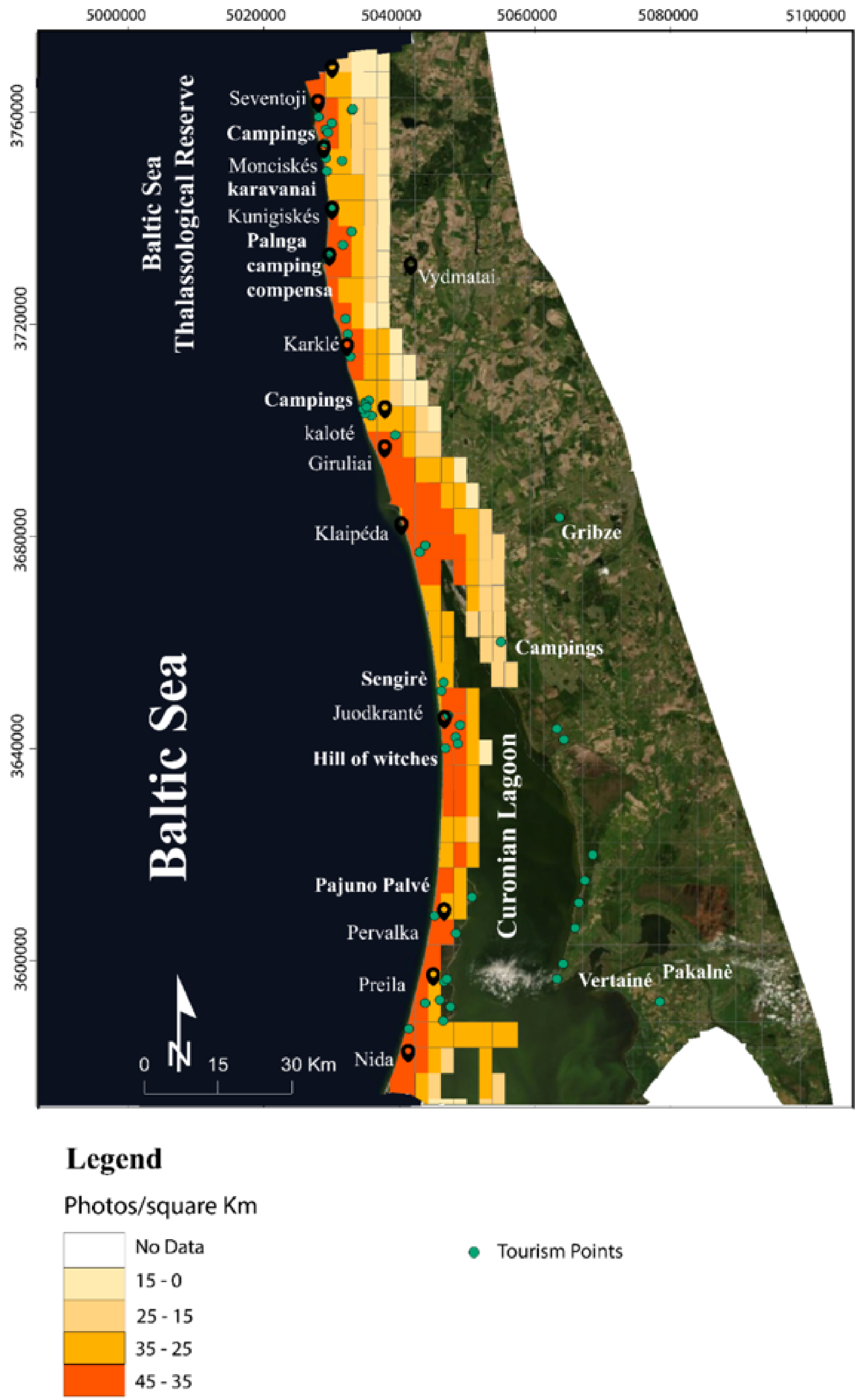

Figure 6

Map of the Lithuanian coast, representing number of photos per 2 square kilometer.

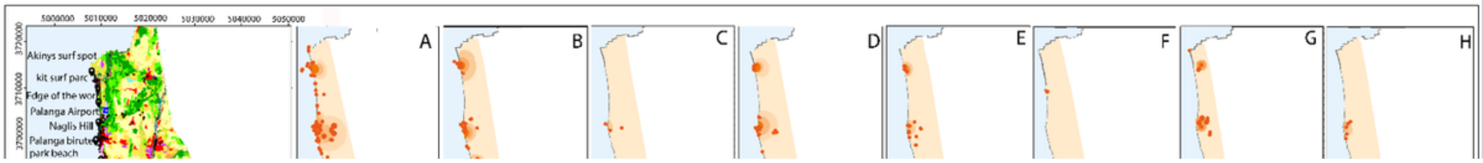

Figure 7

Maps of the density of photographs depicting engagements with different CES type

Figure 8

Number of monthly photographs representing CES engagements taken by each user.

Figure 9

Classification analysis of users illustrating the different types of users and their preferential engagements with CES in the Lithuanian coast. four main user clusters were identified; landscape appreciation, nature appreciation, social recreation and historical monuments

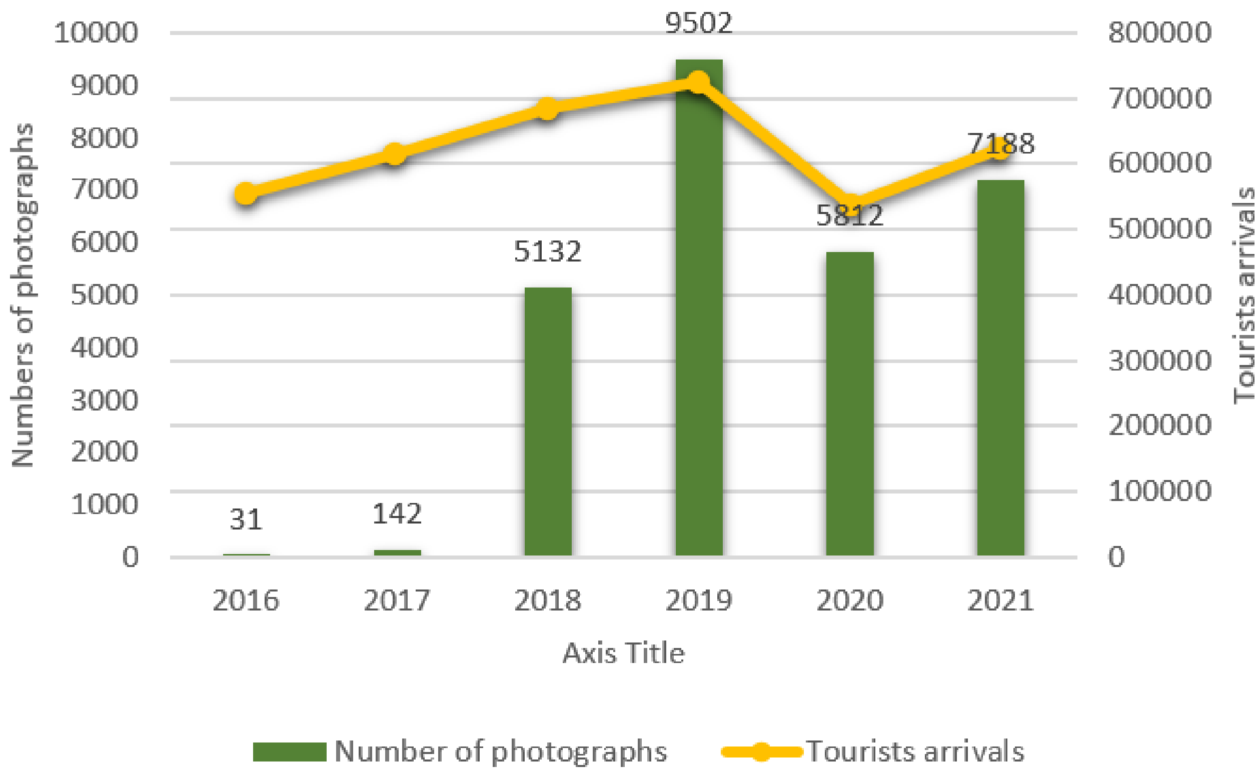

Figure 10

Number of photographs representing CES engagements per year (Green bars), B- Tourists arrivals in coastal municipalities of Lithuania (orange line) from 2016 to 2021.