1. Introduction

Cultural ecosystem services (CES) are, in the words of Chan et al. (2012; 2016), everywhere and nowhere at once. Due to their unique intangible character, CES have always been standing out among other ecosystem services. Since the first pivotal papers (Costanza et al., 1997; Daily, 1997) and Millennium Ecosystem Assessment (MAE, 2005), CES operationalisation has progressed across several comprehensive assessment frameworks (TEEB, 2010; SEEA EEA, 2012; UK-NEAFO, 2014; IPBES, 2019; Maes et al., 2020). Notwithstanding the numerous examples of spatially explicit CES assessment, authors report a systematic overlooking of the relational values of nature, underlying CES, in environmental decision-making compared to its instrumental and intrinsic values (Klain et al., 2017; Blahna et al., 2020). In practice, this means that even in the most recent EU-wide report, a spatially explicit CES assessment remains limited to a single CES (i.e. nature-based recreation) that is assessed simply by visitation numbers – in contrast to material ES that were assessed with a much higher level of details (Maes et al., 2020). Therefore, research is needed to develop a cost-effective, replicable and regular CES assessment methodology that works over large areas.

To address this issue, the use of quantitative models of CES supply has become a central topic in CES assessment studies since the (e)valuation of the state of the environment is needed for assessing global progress towards achieving United Nations' Sustainable Development Goals by 2030, including Goals 11 and 15. Therefore, CES assessment benefits from including the spatial dimension (Potschin and Haines-Young, 2011; Burkhard and Maes, 2017) relying on environmental indicators and map-based methodologies (Richards and Friess, 2015; Hermes et al., 2018; Albert et al., 2019).

Up to date, there is a solid body of knowledge on how landscape morphology shapes landscape experience, values and preferences, underlying CES use (Tveit et al., 2006, 2018; Fry et al., 2009; Potschin and Haines-Young, 2011; Zandersen et al., 2017). Despite the crucial importance of remote sensing information about environmental conditions and landscape morphology (Rose et al., 2015; Pettorelli et al., 2018; Kugler et al., 2019; Ramirez-Reyes et al., 2019), the spatially explicit models of CES supply often do not realise the full potential of remote sensing methods (Vaz and Santos, 2018). Remote sensing data used in CES research are often limited to categorical models such as land cover maps or basic vegetation indices. For example, a systematic review of urban ecosystem services revealed that "the most cited methodology was the LULC (75%) [*LULC refers to land use/land cover – our note*], followed by the normalized difference vegetation index (NDVI) with 15.91%" (Tavares et al., 2019).

Publicly available social media data (such as geotagged photographs and metadata, text posts) contain a wealth of information on the whereabouts of millions of Flickr, Twitter, VK.com and other applications' users. They provide a proxy to assess the people-nature interactions and landscape experience (Calcagni et al., 2019; Ghermandi and Sinclair, 2019; Zhang et al., 2020). Social media data have been widely used as evidence for CES use, primarily for detecting all kinds of outdoor activities and landscape appreciation (Richards and Tunçer, 2018; Ghermandi et al., 2020; Havinga et al., 2020; Muñoz et al., 2020). Social media provide evidence of CES use in areas where insufficient, unsystematic or sporadic statistical data are available (Ilieva and McPhearson, 2018; Toivonen et al., 2019; Moreno-Llorca et al., 2020).

As evidenced from social media, the presence of particular CES use can be explained by using spatial remote sensing-based indicators of landscape conditions and attributes in statistical modelling frameworks (Vaz et al., 2020; Alemu et al., 2021). In this way, remote sensing provides a unique opportunity to quantify demanded landscape conditions, supplying valuable landscape experience (Ayad, 2005; Ozkan, 2014; Karasov et al., 2018; Chmielewski et al., 2020; Sowińska-Świerkosz and Michalik-Śniezek, 2020) yet unknown in the context of CES supply-demand relationships.

Since social media data are a growing and comprehensive, but still incomplete source of data on people-nature interactions (Muñoz et al., 2020), we operationalise selected CES under several assumptions:

1) the presence of geotagged photographs, collected from open social media sites, is a proxy for *CES flows*, or actual CES use events (Langemeyer et al., 2018); the total number of photographs, representing CES use events within some area, combined with the remoteness of the respective geolocations relative to populated areas was considered as a proxy for *CES demand* (Wolff et al., 2015);

2) *CES supply* can be measured using the environmental suitability model for taking photographs, representing CES demand (Peña et al., 2015; Vallecillo et al., 2019); and

3) some CES beneficiaries living within the areas of lower opportunities for CES use (Ala-Hulkko et al., 2016; Bing et al., 2021) have, respectively, also less equitable CES access (Burkhard and Maes, 2017; Vallecillo et al., 2019).

This research aims to demonstrate the feasibility of diverse remote sensing-based techniques for the country-wide analysis of landscape pattern suitability and distributional justice for three selected CES: (i) landscape watching, (ii) wildlife watching, and (iii) active outdoor recreation. For this purpose, we explore the demand for the selected CES through the social media photographs representing cases of respective CES use. We also analyse the accessibility of the demanded locations from the populated areas and estimate CES opportunities for populated areas related to population density.

Using this framework for the territory of Estonia, we aimed at answering the following questions:

i) What are the locations of higher CES demand, as evident from social media data?
ii) How can remote sensing data be used to provide a spatially explicit and area-covering assessment of CES supply?
iii) What is the accessibility of CES use in Estonia?

2. Data and Methods

2.1. Study area

We demonstrated the supply-demand CES mapping framework in Estonia, located in Northern Europe. The Baltic Sea influences its temperate climatic conditions. Postglacial landforms, abundant lakes, wetlands, coastlines, and forests make Estonian landscapes picturesque and unique. Due to its low population density, many relatively untouched natural areas have become popular among local and international tourists (Saluveer et al., 2020). In addition, Estonia has a high Internet penetration rate, and 57% of Estonians are active users of various social media sites (Kemp and Kepios Team, 2019), thus rendering it a good case study.

2.2. CES demand mapping

We reused the existing dataset on CES flows in Estonia for CES analysis, based on combined non-private Flickr and VK.com geolocated user-generated photographs from 2015 to 2018 (Karasov et al., 2020a). Flickr is the US-based repository for photographs, launched in 2004, and VK.com is the Russia-based social network, launched in 2006 and popular among the Slavic communities. Flickr and VK.com photographs were collected via respective automated programming interfaces. We removed all the Flickr and VK.com photographs located inside buildings according to OpenStreetMap (OpenStreetMap contributors, 2021), i.e., spatially indoor photographs. Then, this pre-processed social media dataset (21,242 photographs) was processed via the Clarifai platform (Clarifai Inc., Wilmington, DE, U.S) for image content recognition. Each photograph from the dataset was automatically tagged according to its content (up to 20 tags with prediction confidence score >90%), and photographs with non-relevant tags (fashion, architecture, indoors, etc.) were removed. The resulting 9,983 photographs were then automatically classified – using the Latent Dirichlet Allocation algorithm, implemented in Orange software (Demšar et al., 2013) into three categories: landscape watching, outdoor recreation, and wildlife watching (Figure S1).

Landscape watching photographs depict outdoor scenes with no or minor people's presence in the shot frame. Outdoor recreation photographs explicitly represent people. Wildlife watching photographs depict biodiversity at organism and community levels: plants, animals, and mushrooms. The final dataset contains 6,153 geotagged photos for landscape watching, 2,345 for outdoor recreation, and 1,484 for wildlife watching (Figure S1) from 1,120 unique users. We used all the photographs per user to predict all CES events' occurrence regardless of visitation.

For the CES use, we assumed that locations more distant from populated areas (Figure 1A) require more significant efforts for visiting (Paracchini et al., 2014), while frequently photographed areas indicate a higher number of CES experiences (Yoshimura and Hiura, 2017; Bing et al., 2021). The populated areas were identified based on population density per km^2) (Statistics Estonia, 2020). We aggregated photographs representing CES demand within 10-km grid cells (Figure 2). We used 10-km grid cells as optimal for generalising local photographing variability and the most visually plausible for the country scale of analysis compared to 1- and 5-km cells upon initial testing. For these grid cells, we calculated the median travelling distance from centroids of the population density grid cells via roads using the OpenStreetMap road network and Iso-Area as Interpolation algorithm implemented in QNEAT3 QGIS plugin (Raffler, 2021).

2.3. CES supply modelling

To model CES supply, we used remote sensing and other spatial data from several sources:

- Cloudless summertime Landsat 8 mosaic (original spatial resolution 30 m, surface reflectance, compiled using Google Earth Engine (Gorelick et al., 2017), Figure 1B) for 2018 to coincide with the social media dataset for the 2015–2018 period;
- A radar-based Digital Elevation Model NASA SRTM Digital Elevation 30m, provided by NASA / USGS / JPL-Caltech, original spatial resolution 30 m (Google Earth Engine image "USGS/SRTMGL1_003");
- A radar-based Digital Surface Model ALOS DSM: Global 30m provided by the JAXA Earth Observation Research Center, original spatial resolution 30 m (Google Earth Engine image collection "JAXA/ALOS/AW3D30/V3_2");
- Land Cover Model of Europe 2017 from the project "S2GLC", original spatial resolution 10 m (Figure 1C) (Malinowski et al., 2020).

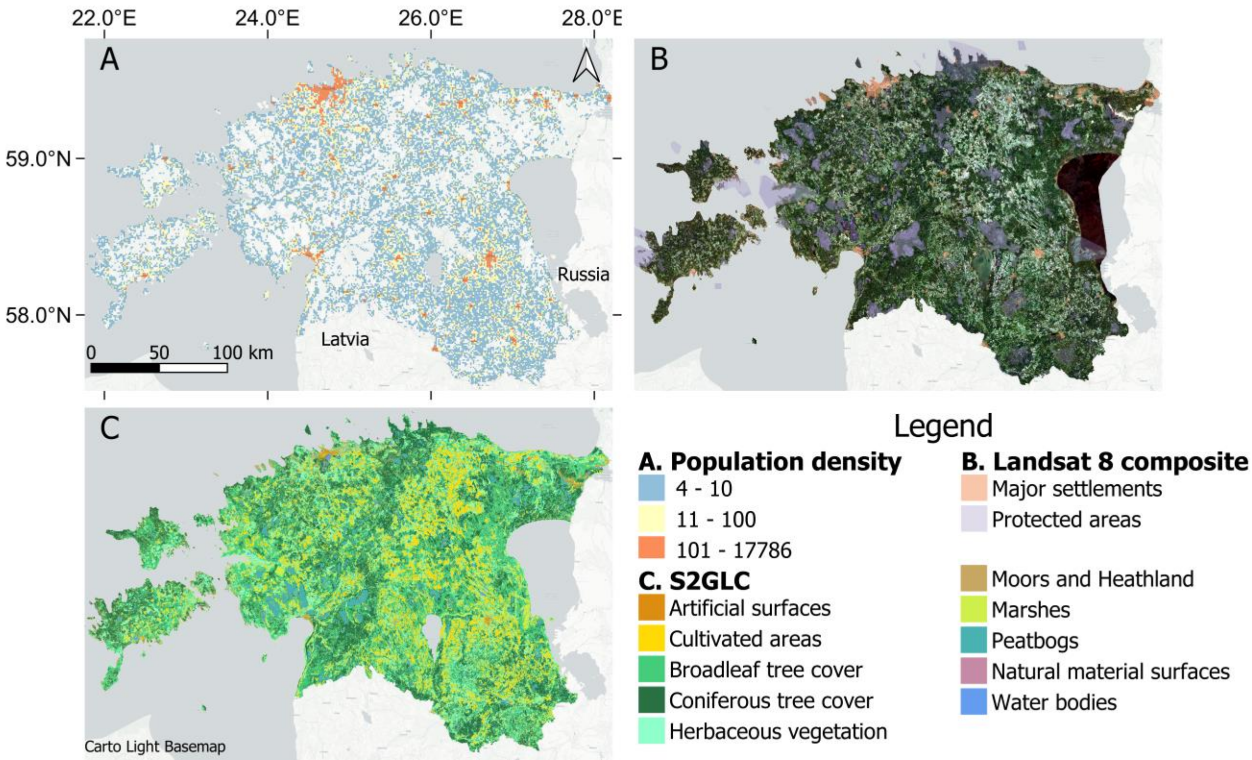

Figure 1. Selected data used for mapping CES demand and supply: population density, people per square km in 2018 (A); cloudless summertime year 2018 Landsat 8 mosaic, surface reflectance, RGB composite (B), the Land Cover Map of Europe 2017 from S2GLC project (Malinowski et al., 2020) (C). Panel (B) also shows the major protected areas (UNEP-WCMC and IUCN, 2020) and cities (Estonian Land Board, 2020).

We utilised the set variables measuring the spatial landscape pattern in Estonia to predict the probability of taking CES-related social media photographs. We calculated a set of 526 predictor variables (Table S1, Supplementary materials) based on previous studies (Ozkan, 2014; Vukomanovic and Orr, 2014; Van Berkel et al., 2018; Sottini et al., 2019; Karasov et al., 2020b; Vaz et al., 2020) and expert knowledge. All the co-occurrence and occurrence indices were calculated using the square kernels of 7 and 21 pixels, following Hall-Beyer (2017) to detect the optimal landscape representation for textural metrics across scales. All the calculations except for three patch shape indices from WhiteboxTools (Lindsay, 2019) were performed via the Google Earth Engine platform to ensure reproducibility of the analysis.

To model the CES supply, we applied the statistical models implemented in USGS Software for Assisted Habitat Modeling–SAHM version 2.0.1 (Morisette et al., 2013), a part of VisTrails software (Freire et al., 2006). In total, 21 (out of 526) uncorrelated spatial predictors were selected: 10 the best predictors for each CES class (Table 1, Figures S2 and S3). Using the change in Area Under Curve (AUC) when each predictor is permuted, we estimated the relative importance of each used predictor for the CES supply models (Figure S2). Further, only variables with Pearson, Spearman, or Kendall correlation coefficients ≤ 0.70 were retained using a pairwise approach. We used the percent deviances explained from a univariate generalized additive model, provided in the Covariate Correlation and Model Selection SAHM module and expert knowledge on plausible environmental settings to decide which highly collinear variables should be removed.

Table 1. Description of 21 remote sensing-based indicators of CES, selected for CES supply modelling. GLCM stands for Grey Level Co-Occurrence Matrix. In indicator aliases, l8 refers to Landsat 8, s2glc – to S2GLC land cover model, s1 – to Sentinel-1, alos – to ALOS digital surface model, 7 and 21 – to the kernels of 7 and 21 pixels

Indicator	Model	Description. GLCM stands for Gray Level Co-Occurrence Matrix	Landscape attribute interpretation	Formula reference
l8tcap_brightness_gearys_7	Landscape watching, outdoor recreation	Local Geary's C index of spatial autocorrelation of the Tasseled Cap Brightness	Local dissimilarity of the soil brightness intensities in landscape	(Anselin, 1995)
l8sat_dent_7	Landscape watching, outdoor recreation, wildlife watching	GLCM-based difference entropy of the colour saturation	The randomness of land cover colour intensities	(Haralick et al., 1973)
l8nir_mean_21	Landscape watching	Mean focal statistics for the near-infrared band	Mean vegetation biomass	(Haralick et al., 1973)
s2glc_prom_21	Landscape watching	GLCM-based cluster prominence of land cover classes	Uniformity of land cover classes	(Conners et al., 1984)
l8lumi_prom_21	Landscape watching, outdoor recreation, wildlife watching	GLCM-based cluster prominence of the luminance (a grayscale derivative of RGB band combination)	Uniformity of land cover reflectance intensities	(Conners et al., 1984)
s2glc_corr_21	Landscape watching	GLCM-based correlation of land cover designations	Spatial autocorrelation of land cover patches	(Haralick et al., 1973)
s1ratio_prom_21	Landscape watching, outdoor recreation, wildlife watching	GLCM-based cluster prominence of VV and VH backscatter ratio	Uniformity of vegetation types and built structures	(Conners et al., 1984)
l8nir_sd_7	Landscape watching	Standard deviation focal statistics for near-infrared band	Dispersion of NIR pixel intensities indicates patch edges in the landscape	

s1ratio_dent_7	Landscape watching, outdoor recreation	GLCM-based difference entropy of VV and VH backscatter ratio	The randomness of vegetation types and built structures	(Haralick et al., 1973)
s2glc_contrast_7	Landscape watching, outdoor recreation	GLCM-based contrast of land cover classes	Drastic land cover changes	(Haralick et al., 1973)
l8ndvi_dvar_21	Outdoor recreation	GLCM-based difference variance of NDVI	Indicates patch edges in the landscape	(Haralick et al., 1973)
l8tcap_greenness_mean_21	Outdoor recreation	Mean focal statistics of Tasseled Cap Greenness	Smoothed greenness of vegetation and interior of vegetated patches	
l8hue_ent_7	Outdoor recreation	GLCM-based entropy of landscape hues	The randomness of landscape hues	(Haralick et al., 1973)
l8tcap_brightness_sd_21	Outdoor recreation	Standard deviation focal statistics for Tasseled Cap Brightness	Dispersion of soil brightness intensities in landscape	
s2glc_contrast_21	Wildlife watching	GLCM-based contrast of land cover classes	Drastic land cover changes	(Haralick et al., 1973)
s2glc_prom_7	Wildlife watching	GLCM-based cluster prominence of land cover classes	Uniformity of land cover classes	(Conners et al., 1984)
alos_imcorr1_7	Wildlife watching	GLCM-based information measure of correlation 1 calculated for heights of the digital surface model	Indicates wetlands and water bodies in the landscape	(Haralick et al., 1973)
s2glc_dent_7	Wildlife watching	GLCM-based difference entropy of land cover designations	The randomness of land cover classes in landscape	(Haralick et al., 1973)
l8nir_gearys_7	Wildlife watching	Local Geary's C index of spatial autocorrelation of the near-infrared band	Local dissimilarity of vegetation and edges of landscape patches	(Anselin, 1995)

l8swir1_gearys_7	Wildlife watching	Local Geary's C index of spatial autocorrelation of the shortwave infrared band	Local dissimilarity of moisture conditions and edges of landscape patches	(Anselin, 1995)
l8tcap_brightness_sd_7	Wildlife watching	Standard deviation focal statistics for the Tasseled Cap Brightness	Dispersion of soil brightness intensities and edges of landscape patches	

Using different statistical models, we used the 21 retained covariates to model the probability of taking CES-related social media photographs as a proxy for the CES flows. Boosted Regression Trees (Elith et al., 2008), Generalized Linear Model (Hosmer and Lemeshow, 2000), Multivariate Adaptive Regression Spline (Elith and Leathwick, 2007), Maximum entropy—Maxent (Phillips et al., 2004), and Random Forest (Breiman, 2001) models were executed as common in environmental niche modelling (West et al., 2017; Young et al., 2020). We applied default SAHM settings (Talbert and Talbert, 2012) for geolocations of CES-related photographs as presence data and randomly generated 10,000 geolocations as pseudo-absence data. We used 10-fold cross-validation to compare the performance of the models (Table S2, Supplementary materials). Since different modelling algorithms demonstrated discrepancies in their outputs (Figure S4, Supplementary materials), we combined the model outputs for each CES (with AUC>0.7) into an ensemble model of relative environmental suitability to reduce individual model errors (West et al., 2016).

2.4. CES accessibility mapping

To estimate the availability of CES supply for the Estonian population, we detected spatial aggregation of median values of modelled CES supply per population density cell using Getis-Ord Gi* statistics with the Optimized Hot Spot Analysis ArcGIS 10.6 tool. Hot spots encompass the cells of the population density grid of high CES supply, surrounded by similarly high values. Cold spots, by contrast, correspond to the cells of the population grid of lower CES supply, surrounded by similarly low values, which decrease the accessibility of CES supply. Based on the confidence scores provided, we distinguished between CES hot spots as those populated areas with ≥95% confidence in hot spot determination and cold spots as the populated areas with ≥95% confidence in cold spot determination.

Also, we modelled the distance between CES-related social media photographs using the Iso-Area as Interpolation algorithm implemented in the QNEAT3 QGIS plugin (Raffler, 2021) and calculated the median distance within the population density grid cells. QNEAT3 algorithm produces the interpolated distance raster for the point dataset of locations via road network, using QgsTinInterpolator interpolation method, available in QGIS3. Then we identified cold and hot spots (high accessibility and low accessibility) of CES use proximity using the same Getis-Ord Gi* statistics with the Optimized Hot Spot Analysis ArcGIS 10.6 tool.

3. Results

3.1. CES demand mapping

Figure 2 suggests that Southern Estonia, the coastal areas of Northern Estonia and remote parts of the Estonian islands of Saaremaa and Hiiumaa are the most demanded CES-related destinations. These regions have higher concentrations of photographs, and social media users visited these areas despite higher travel efforts and expenses. These regions are well-known "anchor points" with natural monuments (cliffs, hills, valleys, peninsulas), historical monuments (manor houses) and vacation sites (beaches, ski and hiking tracks).

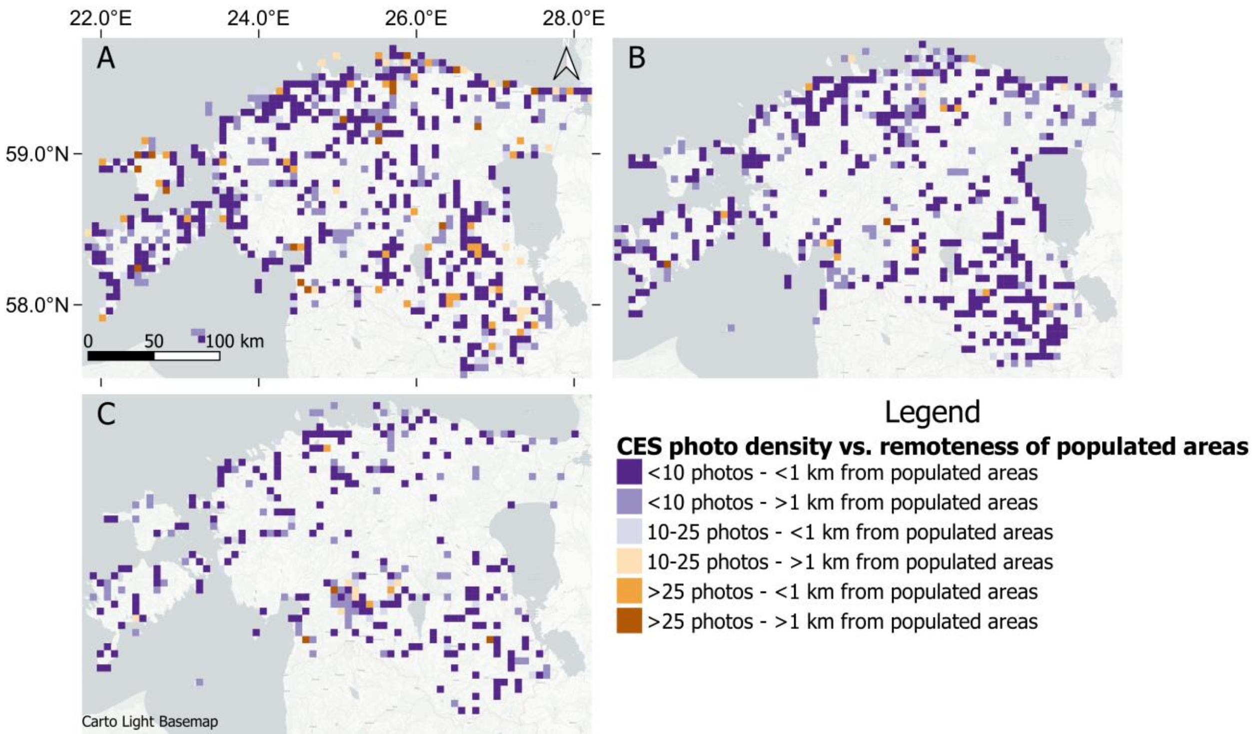

Figure 2. CES demand detected in Flickr and VK.com photographs: landscape watching (A), outdoor recreation (B), wildlife watching (C). The number of photographs is aggregated within 10-km grid cells and median distance to the urban areas. Increasing distance to the urban areas corresponds to increasing travel efforts; photo counts indicate the density of CES experiences

3.2. CES supply modelling with remote sensing data

According to table S2 (Supplementary materials), the single environmental niche models generated for landscape watching photographs prior to stacking to ensemble have the best performance (AUC for Random Forest cross-validation models >0.9). Overall, Random Forest and Boosted Regression Trees algorithms perform better than Maxent in most cases; notably, Random Forest also has a lower ΔAUC value (up to 0.003 among train and validation data split). The most important predictors of landscape watching represent the randomness of landscape colour intensities and green vegetation (l8sat_dent7 and l8nir_mean_21). The most important variable for outdoor recreation also indicates randomness of colour intensity (l8sat_dent7), followed by randomness and uniformity of vegetation types (s1ratio_dent_7 and s1ratio_prom_21). The most important explanatory variables for wildlife watching relate to land cover diversity (s2glc_dent_7 and s2glc_contrast_21).

The diversity of colour saturation (l8sat_dent_7) showed a positive relationship with the landscape watching, meaning that landscapes with varying colours are preferred for this CES (Figure S3A). At the same time, the uniformity of landscape structure (l8lumi_prom_21, s1ratio_prom_21) suggests that less fragmented landscapes composed of large patch clusters are more often photographed. Also, the importance of landscape diversity (s2glc_contrast_7) indicates that landscapes with larger spatial variability in land cover are preferred. In contrast, densely vegetated (l8nir_mean_21) areas of the highest biomass classes are less preferred for landscape watching. Spatial autocorrelation metrics (s2glc_corr_21, l8tcap_brightness_gearys_7) show non-uniform relationships with landscape watching.

Outdoor recreation demand is also positively associated with higher colouristic diversity (l8sat_dent_7, l8hue_ent_7, Figure S3B). This finding is also supported by the dissimilarity of soil brightness values (l8tcap_brightness_gearys_7) and a land cover diversity (s2glc_contrast_7), which positively affect outdoor recreation. By contrast, landscapes composed of high biomass production (l8tcap_greenness_mean_21) negatively affect outdoor recreation, suggesting that large homogeneous vegetated areas are less suitable for recreational purposes.

The diversity of land cover (s2glc_dent_7 and s2glc_contrast_21) is positively related to wildlife watching occurrence (Figure S3C). Moreover, fragmented landscapes with a high edge density (l8swir1_gearys_7), clear clusters of vegetation and built structures (s1ratio_prom_21, l8lumi_prom_21), and the presence of water bodies (alos_imcorr1_7) support higher environmental suitability for wildlife watching.

Figure 3 represents the ensemble map of environmental suitability for CES classes as the indicator of CES supply. Spatial patterns of high CES supply are similar among CES classes: they encompass lakes and seashore areas, river valleys, cities, hilly areas in Southern Estonia, post-industrial mining landscapes of Northern-Eastern Estonia.

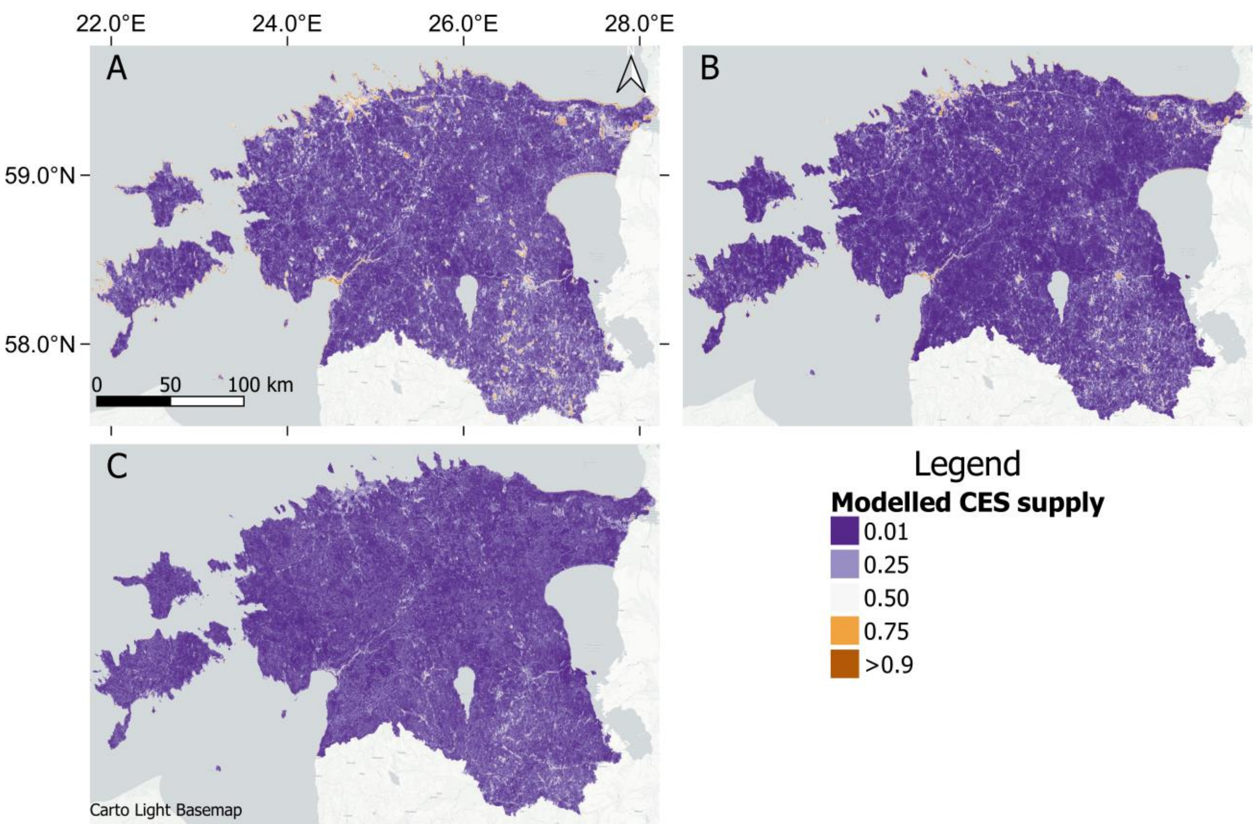

Figure 3. Modelled CES supply based on ensemble environmental suitability (unitless): landscape watching (A), outdoor recreation (B), and wildlife watching (C). High CES supply is detected in Southern Estonia, coastal areas and major cities.

3.3. CES accessibility mapping

Maps in Figure 4 represent the spatially aggregated areas of high (hot spots) and low (cold spots) median CES supply values per 1 square km (cells of population grid) using the Getis-Ord Gi* statistics. These maps rank populated places in Estonia according to their CES supply. Landscape watching, outdoor recreation, and wildlife watching supply demonstrate rather similar spatial distribution patterns: hot spots occur in the largest cities (Tallinn, Tartu, Pärnu, Narva, Viljandi, etc.) and settlements spread along the coastlines of the Baltic Sea and Lake Peipus suggesting a good match between CES supply and population density in these areas. In contrast, settlements in the cold spot zones are predominantly concentrated in the inner areas of Estonia. According to the spatial statistics on population density in Estonia, the total Estonian population is 1,35 million people. Our analysis showed that most Estonians reside in the CES supply hot spots. More specifically, 69.4% reside in landscape watching hot spots (95% confidence), and 5.5% of the population reside in landscape watching cold spots. These numbers are 70.4% and 3.1% for outdoor recreation and 67.1% and 7.3% for wildlife watching, respectively.

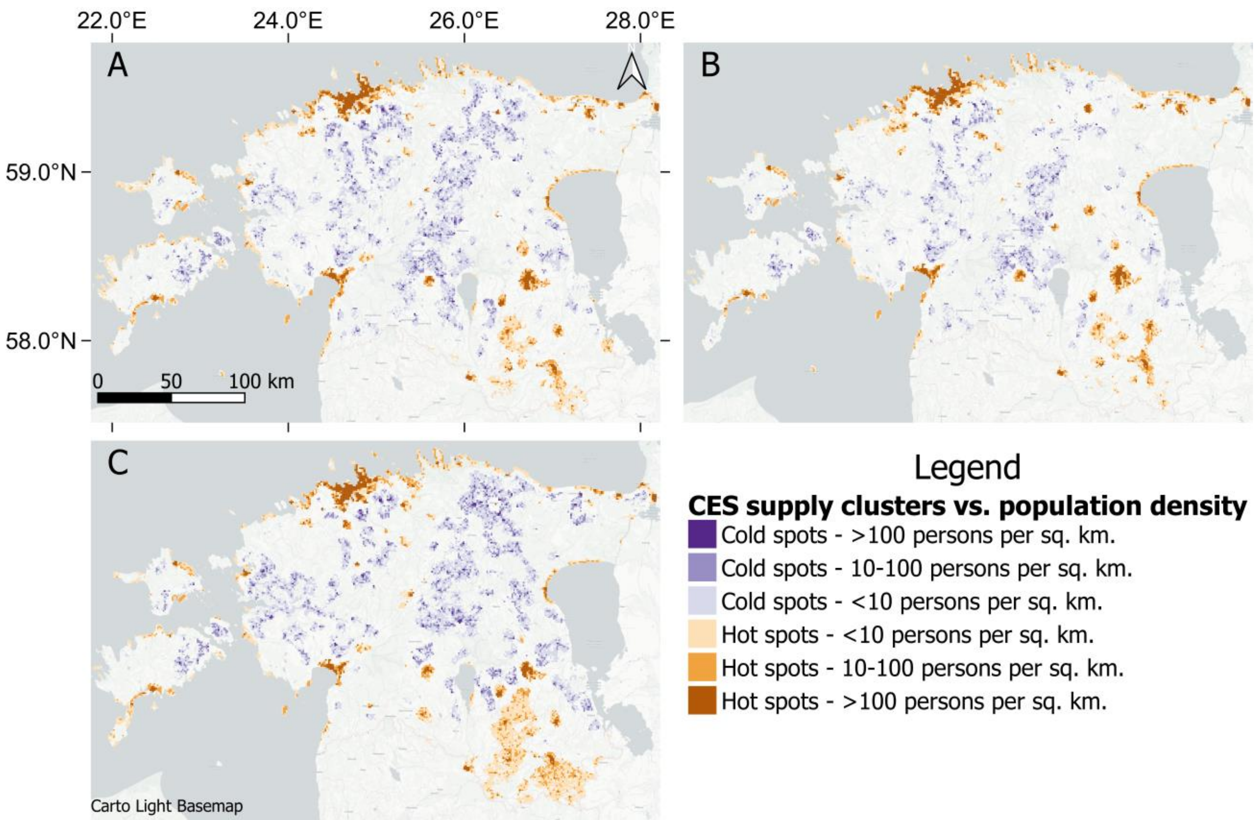

Figure 4. Spatial clusters of median CES supply within populated areas in Estonia: landscape watching (A), outdoor recreation (B), wildlife watching (C). Areas of higher CES supply occur predominantly in the main cities, Southern Estonia and along the coastlines; areas of lower CES supply tend to concentrate in

the central parts of continental Estonia and islands. Darker purple colours indicate an increasing mismatch between CES supply and population density

The spatial pattern of relationships between CES supply and population density (Figure 4) is similar to relationships between transport accessibility of CES use and population density (Figure 5). Highly populated urban centres and suburban zones, coastal areas, border areas are also close to the demanded geolocations. At the same time, many inner settlements seem to have low opportunities for CES use. In contrast to CES supply accessibility, CES accessibility via road network shows larger discrepancies with local population density: 50.3% of the population resides in the spatial clusters of high proximity of landscape watching events. In comparison, 15.0% of the population resides in the spatial clusters of remote access to landscape watching (about 2 km and further, corresponding to approximately 30 min of walking). These percentages are 46.6% and 21.1% for outdoor recreation, and 24.9% and 18.7% for wildlife watching, respectively.

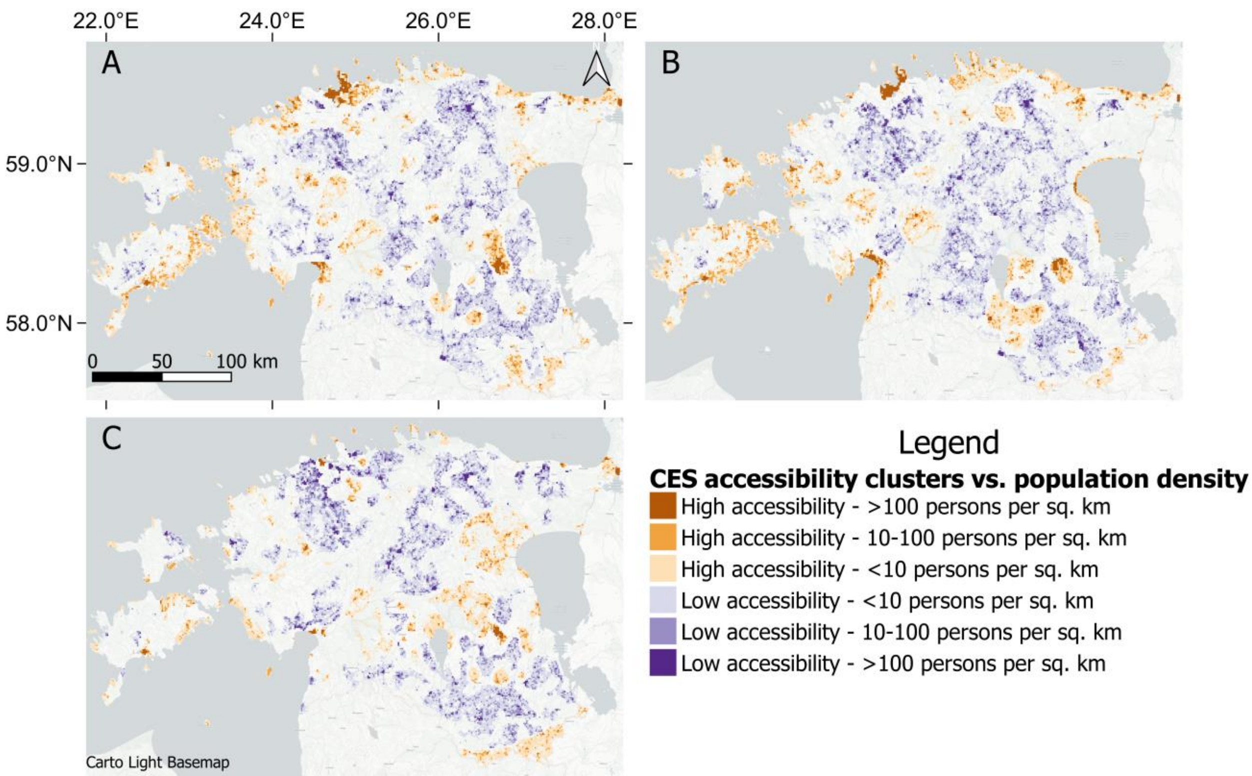

Figure 5. Spatial clusters of the median distance between CES-representing social media photographs via the transport network taken within the populated areas: from highly populated areas and proximity of CES use cases (high opportunity of CES use, reddish colours) to highly populated areas and remoteness of CES use (purple colours). Panel A shows the accessibility of landscape watching; B – outdoor recreation; C – wildlife watching

4. Discussion

4.1. Landscape context

This study demonstrated the importance of different remote sensing and social media data for CES assessment from complementary bird's-eye and horizontal landscape perspectives (Antrop and Van

Eetvelde, 2017). In short, CES-related photographs tend to prevail in locations of diverse colours and complex land cover composition and clusters of small landscape patches with the presence of water bodies or wetlands. These landscape characteristics are plausible and align with the existing body of literature on valuable landscape attributes (Tveit et al., 2006; Fry et al., 2009; Ode and Miller, 2011; Bell, 2012; Dronova, 2017; Swetnam et al., 2017). People are more likely to recreate in diverse areas, promising more high-quality views (Ode and Miller, 2011; Tveit et al., 2018). However, landscape diversity should have optimum values for the highest quality of landscape experience (Kaplan and Kaplan, 1989; U.S. Forest Service, 1995; Bell, 2012), and usage of spatial indicators of landscape diversity may result in non-uniform relationships with landscape preferences (Uuemaa et al., 2013). This finding is coherent with the compactness of patches as a factor of more diverse and, therefore, preferable landscapes (Rieb and Bennett, 2020).

Our country-wide results significantly extend the paradigmatic shift in CES supply modelling with remote sensing data, initiated by Vaz et al. for the protected areas in Portugal and Spain (Vaz and Santos, 2018; Vaz et al., 2019, 2020). Complementing these papers, we would like to lay a foundation for a high-resolution and further long-term (Landsat 5–8 archives date back to 1984, Sentinel 2 archives – to 2015) CES supply monitoring across scales. For these purposes, we identified the most relevant remote sensing-based indicators. In addition to LULC-based indicators of diversity, we unexpectedly revealed that colouristic diversity (namely variations in saturation of colours, not in their hues or lightness) is the strongest predictor for landscape watching demand. This finding reinforces the evidence about the role of colour in landscape preferences (Arriaza et al., 2004; Schirpke et al., 2013; Vaz et al., 2020). However, the extent of greenness, indicated by NDVI and other vegetation indices in our study, displayed a negative relationship with CES use, contrary to the findings of other studies (Vukomanovic et al., 2018; Alemu et al., 2021). In line with previous studies, our results highlight the presence of water bodies (Tieskens et al., 2018; Gosal and Ziv, 2020) and urban areas (Langemeyer et al., 2018) as a positive factor of CES supply.

In the context of distributional justice, our findings enrich previous results on the accessibility of public green spaces. We provided a piece of replicable and objective evidence on the existence of relationships between nature and people in the form of three CES flows. Our results can be used to mitigate the shortening supply of high-quality outdoor landscapes in Estonian cities (Lõhmus, 2020; Orru et al., 2020; Sepp and Lõhmus, 2020) with blue and green infrastructure interventions. We suggest that the areas of high CES supply, derived from our study, can be considered to expand protected areas further and correct their delineation based on CES use (Rose et al., 2015).

4.2. Methodological constraints and advancements

Our results provide a marked novelty to CES supply modelling, which until now predominantly relied either on land cover-driven GIS-analysis (Langemeyer et al., 2018; Vallecillo et al., 2019) or Maxent models (Richards and Friess, 2015; Yoshimura and Hiura, 2017; Sottini et al., 2019; Alemu et al., 2021). In particular, we revealed that Maxent models of CES supply might not be the most accurate models for CES supply assessments. Maxent modelling may need to be complemented or replaced by other environmental niche models, such as Boosted Regression Trees or Random Forest, which are robust to non-linear relationships. However, the quality of the resulting models primarily depends on the quality of the input data. For example, the low modelled CES supply in some regions does not necessarily indicate a low landscape quality. It means that no sufficient evidence of CES flow is found in social media materials due to sampling bias or the lack of evidence of visitation. Therefore, our social media-based research should be treated with caution.

The joint usage of social media and remote sensing data is not free from biases and methodological constraints. First of all, we recognize a population representation bias as not all age, sex, national and cultural groups are equally represented in the social media user community (Karasov et al., 2020a). Moreover, the spatial accuracy of our analysis might be limited by the relatively low reference precision of GPS receivers embedded in modern smartphones, and the moderate resolution of remote sensing data increase the spatial uncertainties. We addressed this accuracy bias by analysing photographs within the grid cells. We conducted this research in compliance with EU General Data Protection Regulation requirements to avoid deanonymisation of the social media users.

Notwithstanding these limitations, the remote sensing data combined with social data have significant strengths, such as the potential for frequent updates, which enables the operative assessment of CES in rapidly changing environments (Vaz et al., 2019, 2020; Alemu et al., 2021). Remote sensing has already significantly boosted the assessment of landscape aesthetics (Ayad, 2005; Ozkan, 2014), but remote sensing applications in the CES domain are in their infancy (Rose et al., 2015; Vaz and Santos, 2018). Complementary usage of time-series of remote sensing and social media data opens the possibility of nearly global monitoring of status and trends in CES budgets (Liu et al., 2015).

5. Conclusions

In this study, we proposed a novel integrated mapping of the CES (landscape watching, outdoor recreation, and wildlife watching) supply-demand relationships based on remote sensing (Landsat 8 optical data) and social media data (Flickr, VK.com) in Estonia. We obtained good performance of remote sensing-based indicators for mapping the relative environmental suitability for the flow of three selected CES types. Also, we mapped those areas where many people live but where access to CES remains limited. We recommend prioritising these areas for a more in-depth CES supply valuation and potential land management actions: green and blue infrastructure development, promoting local tourism, analysis of synergies and trade-offs with other ecosystem services.

We conclude that the synergy of remote sensing- and social media-based approaches are highly relevant for a spatially explicit assessment of CES supply and demand with a sufficient level of accuracy at the national level. Further research should be focused on social media datasets of higher quantity and quality: from social media beyond Flickr and VK.com; this would also include Twitter, Strava, and Instagram data, where possible. The impact of landscape dynamics (e.g., land cover transitions) on the diversity and quality of CES flows was beyond the scope of this study and should be addressed in future studies. In addition, there is a high potential of this methodology being used to identify the impact of landscape development and modifications on CES supply.

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The Google Earth Engine code scripts for retrieval of remote sensing data, SAHM VisTrails workflow file, and code files for the environmental niche modelling are available via the GitHub repository: https://github.com/oleksandrkarasov/ES_2021

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