Remote Sensing of Environment 230 (2019) 111193

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Earth observation and social media: Evaluating the spatiotemporal contribution of non-native trees to cultural ecosystem services

Ana Sofia Vaz[a,b,c,*], João F. Gonçalves[a], Paulo Pereira[a,d], Frederico Santarém[a,d], Joana R. Vicente[a,d,e], João P. Honrado[a,d]

[a] Research Network in Biodiversity and Evolutionary Biology, Research Centre in Biodiversity and Genetic Resources (InBIO-CIBIO), Campus Agrário de Vairão, Rua Padre Armando Quintas, PT4485-661 Vairão, Portugal

[b] Laboratorio de Ecología (iEcolab), Instituto Interuniversitario de Investigación del Sistema Tierra en Andalucía (IISTA-CEAMA), Universidad de Granada, Avenida del Mediterráneo s/n, 18006 Granada, Spain

[c] Departamento de Botanica, Universidad de Granada, Facultad de Ciencias, Campus Fuentenueva s/n, 18071 Granada, Spain

[d] Faculdade de Ciências, Universidade do Porto, Rua do Campo Alegre, s/n, PT4169-007 Porto, Portugal

[e] Laboratory of Applied Ecology, CITAB – Centre for the Research and Technology of Agro-Environment and Biological Sciences, University of Trás-os-Montes e Alto Douro, Vila Real, Portugal

ARTICLE INFO

Keywords:
Aesthetics
Plant invasion
Protected area
Remote sensing
Social media
Tourism

ABSTRACT

Understanding how non-material benefits from ecosystems, known as cultural services, are shaped by non-native biota is paramount to manage biological invasions and achieve the Sustainable Development Goals (SDGs). Despite recent advances, assessments of cultural services still lack an explicit temporal dimension, which is relevant for developing monitoring systems. Here, we evaluate the spatiotemporal contributions of non-native trees to landscape aesthetics and nature recreation in a National Park in Portugal. We use a multimodel framework to understand how those cultural services (evaluated from social media photos) relate to the environmental context (physical and visual accessibility, and wilderness; derived from ancillary GIS data) and landscape visual-sensory features (colour diversity, landscape heterogeneity, and vegetation functioning). The latter were computed from satellite imagery (MODIS and Sentinel-2 MSI sensors) for the four seasons of the year: Winter, Spring, Summer and Autumn. We found that, during Autumn, contributions of non-native trees prevailed mostly in landscapes with greater colour diversity (green-band, Sentinel 2). During Spring, their contributions prevailed in landscapes with lower wilderness and heterogeneous levels. In Winter, those contributions were less evident in more remote areas. As for Summer, no significant relations were found for those cultural contributions. These results are congruent with the phenology of dominant tree species: deciduous natives occurring with coniferous non-natives and evergreen invaders, leading to higher colour diversity in Autumn, versus the dominance of blooming invaders in accessible areas during Spring. Results also seem to match the seasonal dynamics of touristic demand in the National Park: the pursuit of wilder areas for ecotourism in Winter, versus the experience of popular recreational activities in Summer. We discuss the usefulness of Earth observations in the research of cultural services and, particularly, for supporting SDG targets 15.8 (on invasive species), 8.9 (touristic revenues) and 12.8 (nature awareness).

1. Introduction

1.1. Cultural ecosystem services and the Sustainable Development Goals

Nature contributes to human well-being by providing material benefits, recognised as provisioning (e.g. timber and food) and regulating (e.g. hazard mitigation and pollination) ecosystem services (MA, 2005). Ecosystems also offer non-material benefits, known as cultural ecosystem services, namely through touristic and aesthetic experiences (Fish et al., 2016). The ecosystem services framework is central to sustainable development, underpinning all dimensions of human, societal, cultural and economic well-being (Griggs et al., 2013; MA, 2005). However, there is a lack of explicit considerations of ecosystem services in the United Nations' Sustainable Development Goals

* Corresponding author at: Research Network in Biodiversity and Evolutionary Biology, Research Centre in Biodiversity and Genetic Resources (InBIO-CIBIO), Campus Agrário de Vairão, Rua Padre Armando Quintas, PT4485-661 Vairão, Portugal.

E-mail addresses: asofia.vaz@fc.up.pt (A.S. Vaz), p_pereira@cibio.up.pt (P. Pereira), fredericosantarem@cibio.up.pt (F. Santarém), jsvicente@fc.up.pt (J.R. Vicente), jhonrado@fc.up.pt (J.P. Honrado).

https://doi.org/10.1016/j.rse.2019.05.012
Received 23 June 2018; Received in revised form 23 April 2019; Accepted 10 May 2019
Available online 28 May 2019
0034-4257/

(SDGs) for 2030 (with a few exceptions, e.g. climate mitigation in SDG 13). Nevertheless, ecosystem services are embedded in most SDGs, considering that maintaining the integrity and function of ecosystems is essential to secure benefits and improve people's lives (UN, 2015).

Two of the proposed 17 SDGs are dedicated to protecting marine and terrestrial ecosystems and biodiversity (SDGs 14 and 15). To meet these (and other) SDGs, it is imperative to develop management efforts that protect ecosystems, while considering the sustainable supply and access to ecosystem services (Wood and DeClerck, 2015). Such efforts should be supported by informed assessments of ecosystem services and of their drivers (SDG 15, target 15.8). Despite increasing global focus, e.g. through the Intergovernmental Panel on Biodiversity and Ecosystem Services (IPBES), the assessment of ecosystem services has been particularly challenging for cultural ecosystem services (Blicharska et al., 2017).

Cultural services result from spiritual enrichment, cognitive development, recreational activities, and inspirational and aesthetic experiences (among others), which are co-produced by nature and people (Chan et al., 2011; Fish et al., 2016). Neglecting the cultural value of ecosystems can result, for instance, in losses of cultural identity and heritage, health quality, environmental education and opportunities for nature enjoyment (Soga and Gaston, 2016), often resulting in lower social support for nature conservation (Infield, 2001; Nuñez and Simberloff, 2005). Therefore, cultural services are not only relevant to reach many targets under the SDGs 13, 14 and 15, but also to advance many others, e.g. poverty alleviation in target 1.1, touristic revenues in target 8.9, cultural and natural heritage in target 11.4, and awareness about harmony with nature in target 12.8 (Geijzendorffer et al., 2017; Wood et al., 2018).

1.2. Remote sensing of cultural ecosystem services

Analysing cultural services is still a challenging task, mostly due to difficulties in capturing their subjectivity and utilitarian value (Chan et al., 2011; Fish et al., 2016). Traditional assessments of the utilitarian value of cultural services include the use of public polls, which are often expensive and have limited spatial and temporal coverage (Wood et al., 2013); monetary appraisals, for which economic assumptions may fail (Chan et al., 2011); and biodiversity mapping, that tends to merely focus on the potential supply of cultural services (Spangenberg et al., 2014).

In the "information age", the use of big data from social media has become a promising approach to monitor cultural preferences and perceptions towards nature, namely through the assessment of photographs shared by the public in online platforms (Figueroa-Alfaro and Tang, 2017; Nahuelhual et al., 2013; Vaz et al., 2018a). The participatory sensing of environment, through the sharing of georeferenced photos, has been useful for characterising the biophysical space, e.g. by means of land cover and terrain mapping (Antoniou et al., 2016; Chippendale et al., 2009; Foody and Boyd, 2013). Photo content analysis has become popular because it allows the identification and mapping of physical, visual and sensory features of landscapes underpinning the supply of cultural services (Figueroa-Alfaro and Tang, 2017; Oteros-Rozas et al., 2018; Richards and Friess, 2015).

Though participatory sensing helps to identify aspects of cultural appreciation of landscapes, cultural services also depend on the biophysical context in which they are supplied or accessed (van Zanten et al., 2016). The use of GIS and remote sensing can be particularly useful to describe and analyse the biophysical context in which georeferenced photos are taken, as already shown for the assessment and monitoring of forestry systems (Ferster and Coops, 2016; Molinier et al., 2016; Schepaschenko et al., 2015). In the particular context of cultural services, examples of remote sensing and GIS applications include the use of DMSP-OLS nighttime stable lights series to identify recreational hiking trails (Braun et al., 2018), the use of multi-date NDVI as a continuous measure of overall ecosystem services (Krishnaswamy et al., 2009) and viewshed analysis to model landscape aesthetics (Schirpke et al., 2016; Swetnam et al., 2016).

Combining georeferenced photos from social media with remote sensing data is an opportunity to advance our understanding of cultural services (Tenerelli et al., 2016; van Berkel et al., 2018). For instance, grounded on a set of geospatial variables (related with topography, specifically proximity to rivers) and Flickr photoseries, Tenerelli et al. (2016) revealed social preferences for several cultural services. Also, Yoshimura and Hiura (2017) modelled the aesthetic value of landscapes based on Flickr pictures and geospatial data on wilderness and landscape diversity. Furthermore, van Berkel et al. (2018) assessed landscape qualities associated to cultural recreation, by using Panoramio photos and a digital surface model obtained from high-resolution LiDAR (Light Detection and Ranging).

Nevertheless, the potentialities of satellite remote sensing to support the assessment of cultural services are far from being completely explored (Cord et al., 2017). Among those potentialities is the ability of satellite data to capture other visual-sensory attributes, which are relevant for landscape aesthetics and recreation (e.g. colours, grandness, land cover complexity; Tveit et al., 2006), in a more straightforward way compared to traditional GIS approaches (Swetnam et al., 2016; van Berkel et al., 2018). Another potentiality of remote sensing relates with its capacity to provide temporal data on the biophysical structure of ecosystems (Braun et al., 2018; Krishnaswamy et al., 2009). For instance, freely-available imagery from satellite sensors (e.g. MODIS and Sentinel-2 MSI) can capture landscape patterns and attributes that sustain the provision of cultural services (de Araujo Barbosa et al., 2015; van Berkel et al., 2018). This data can be acquired for different seasons according to plant phenology, particularly when using open access platforms with high processing ability (e.g. Google Earth Engine; Gorelick et al., 2017; Kwok, 2018).

However, the few approaches combining georeferenced photos from social media and remote sensing data in the context of cultural services still lack an explicit temporal dimension (e.g. Tenerelli et al., 2016; van Berkel et al., 2018; Yoshimura and Hiura, 2017). Recognising such a spatio-temporal dimension is important for developing indicators and monitoring systems of cultural services and design management strategies relevant for reaching several of the SDGs and targets (e.g. goal 15, targets 1.1, 8.9, 11.4, and 12.8; Geijzendorffer et al., 2017; Wood et al., 2018).

1.3. Social media and remote sensing of cultural services: insights from non-native trees

Monitoring systems can be particularly useful to understand how cultural services are shaped by fingerprints of the Anthropocene, such as non-native tree species (i.e. trees that were introduced by humans to new geographic areas; Richardson et al., 2011). Non-native trees have been introduced to obtain a variety of resources worldwide (e.g. wood and ornamental features; Brundu and Richardson, 2015; Vaz et al., 2018a). Yet, tree species are within the most challenging non-native biota, particularly when spreading and becoming invasive in introduced regions, often disrupting the supply of provisioning and regulating services (e.g. water supply or nutrient cycles; Brundu and Richardson, 2015; Vaz et al., 2017). However, how non-native trees contribute to cultural services is still a matter which requires attention (Kueffer and Kull, 2017; Vaz et al., 2018a).

Non-native trees can change visual-sensory landscape qualities, thereby influencing people's perception of cultural services (e.g. "*a beautiful tree*" or "*an ugly tree*"; Shackleton et al., 2019; Vaz et al., 2017). For instance, non-native trees can contribute to landscape homogeneity (e.g. large plantations or invasions), colour (e.g. through their unusual and colourful flowers or leaves) and productivity (e.g. fast-growing species; Kueffer and Kull, 2017). Also, the environmental context (e.g. topography, wilderness) determines people's accessibility to non-native trees and, hence, people's perceptions of the visual-sensory changes triggered by them (Shackleton et al., 2019). These changes further depend on the traits and phenology of tree species (Kueffer and Kull, 2017; Shackleton et al., 2019), thus differing in space (e.g. confined or widespread trees) and between time seasons (e.g. deciduous or evergreen trees).

Although the contribution of non-native trees to cultural services (e.g. aesthetics, cultural heritage or recreation) has been discussed across space (Dickie et al., 2014; Kull et al., 2011; Nuñez and Simberloff, 2005; Vaz et al., 2018a), seasonal assessments are lacking. Combining social media and remote sensing data through time can be very useful in this regard (Krishnaswamy et al., 2009; van Berkel et al., 2018; Vaz et al., 2018b). Evaluating this seasonal contribution can aid decision-makers and managers in understanding people's tolerances, perceptions and preferences for non-native trees (Dickie et al., 2014; Shackleton et al., 2019). The latter can influence societal support (or disapproval) towards policy and management efforts "*to prevent the introduction and significantly reduce the impact of invasive alien species on land and water ecosystems and control or eradicate the priority species*" (SDG 15, target 15.8).

1.4. Research goals and rationale

This study aims to advance the assessment of cultural services through Earth observations, thereby contributing to the monitoring of several SDGs and targets. Our goal is to evaluate the spatiotemporal contributions of non-native trees to cultural services, mostly related with landscape aesthetics and nature recreation. We use a multimodel inference framework to understand how cultural ecosystem services (evaluated from social media photographs) relate to their environmental context (i.e. physical and visual accessibility and wilderness; derived from ancillary GIS data) and visual-sensory features of the landscape (i.e. seasonal diversity, colour, and functioning; analysed from satellite data). We take advantage of satellite imagery from MODIS and Sentinel-2 MSI to obtain information on the visual-sensory features of the landscape across the four meteorological seasons of the year: Winter, Spring, Summer and Autumn. Our approach is tested in a National Park in Portugal ("Peneda-Gerês"), where informed management regarding non-native trees is needed to safeguard nature values and promote cultural benefits. We discuss the contributions of our results for advancing on the SDGs and targets, particularly 15.8 (management of non-native invasive species), but also on the targets 8.9 (touristic revenues) and 12.8 (awareness of harmony with nature). Finally, we outline opportunities for the research of cultural ecosystem services through Earth observations.

2. Methods

2.1. Test area

The test area (950 km^2) is located in northwest Portugal (41° 41′ N, 8° 25′ W; Fig. 1). It includes the only National Park in the country, "Peneda-Gerês" (established in 1971), and also a Special Protected Area (SPA) and a Site of Community Importance (SIC; Natura 2000 network). The climate is Temperate Atlantic to sub-Mediterranean, with mean annual temperature between 13 and 15 °C and total annual rainfall usually over 2000 mm. Altitude ranges between 100 and 1548 m and the prevailing bedrock type is granite. The area comprises biodiversity-rich mountain landscapes with native scrublands, grasslands and *Quercus* woodlands (Honrado, 2003). During the 19th century, and before its establishment as a protected area, many non-native trees were introduced, including currently widespread and invasive *Acacia* species (Fernandes, 2008). The area holds a rich archaeological (e.g. megalithic monuments and signs of Roman occupation) and historical heritage (e.g. traditional celebrations and land-use practices; Santarém et al., 2015). However, since the decrease of agro-pastoral and forestry activities due to rural abandonment, recreational and touristic activities with high socio-economic potential have been promoted (Kastenholz and de Almeida, 2008; Santarém et al., 2015). Thus, management actions in the test area need to be guided by solid strategies that safeguard both native biodiversity and socio-cultural benefits.

2.2. Methodological framework

Our approach included three main steps: (A) data collection and processing, (B) spatiotemporal analysis, and (C) multimodel inference (Fig. 2). Firstly, we compiled a georeferenced dataset of in-field photographs for our test area, from social media, and computed a set of predictors potentially explaining the contribution of non-native trees to cultural services, from satellite Earth observation and ancillary GIS data (see Section 2.3). Afterwards, the photographic dataset was analysed to evaluate the spatiotemporal contributions of non-native trees to cultural services in the test area, across the four meteorological seasons: Winter (December–February), Spring (March–May), Summer (June–August) and Autumn (September–November; Section 2.4.1). Finally, non-native tree contributions were used as response variables in a multimodel inference framework intended to evaluate the explanatory power of the set of predictors (related to environmental context, landscape visual-sensory, or both; Section 2.4.2).

2.3. Data collection and processing

2.3.1. Predictors

Based on previous research (Section 1.2) and data availability, we considered 75 variables as candidate predictors of the contribution of non-native trees to cultural services (see Table 1 for a synthesis and Supplementary Material for the full list of candidate predictors). Variables were arranged into two broad groups, according to the data type: (1) GIS data, related to environmental context (including data on visual and physical accessibility, and wilderness; following e.g. Nahuelhual et al., 2013; Schirpke et al., 2016; Tenerelli et al., 2016; Yoshimura and Hiura, 2017) and (2) satellite remote sensing data, related with landscape visual-sensory attributes (including information on landscape spectral heterogeneity, colour diversity and functioning for each meteorological season; following e.g. Braun et al., 2018; Krishnaswamy et al., 2009; Tveit et al., 2006; van Berkel et al., 2018). The variables were tested for pair-wise correlations (Pearson correlation) and multicollinearity (VIF: variance inflation factors). Variables with correlations > 0.6 and VIFs > 4 were discarded (Fox and Weisberg, 2011).

2.3.2. Collection and processing of satellite remote sensing data

Satellite remote sensing data was used to compute predictors expressing landscape visual-sensory attributes, namely regarding colour diversity, landscape heterogeneity and vegetation functioning, for each of the four meteorological seasons of the year. Information on colour diversity and landscape heterogeneity was obtained from Sentinel-2a/b L1C images. Vegetation functioning was evaluated from the MODerate Resolution Imaging Spectroradiometer (MODIS)MOD13Q1 product (Table 2).

2.3.2.1. Colour diversity. For describing seasonal landscape colour diversity with an emphasis on the visible part of the electromagnetic spectrum (relevant to human perception of landscape aesthetics; Tveit et al., 2006), we used Sentinel-2a/b L1C images available through Google Earth Engine (GEE; Gorelick et al., 2017). In GEE, we started by developing multi-annual cloud-free seasonal composites (one for each meteorological season) by applying a median reducer to all scenes within each season with < 30% of cloud cover and between 2015 and 2017 (comprising all the available data in GEE for Sentinel-2a/b; see Supplementary Material for the full list of images used). Seasonal composites were obtained by aggregating the visible bands B2, B3 and B4 (respectively the blue, green and red bands) through the median for all available images for Winter ($n = 33$), Spring ($n = 29$), Summer

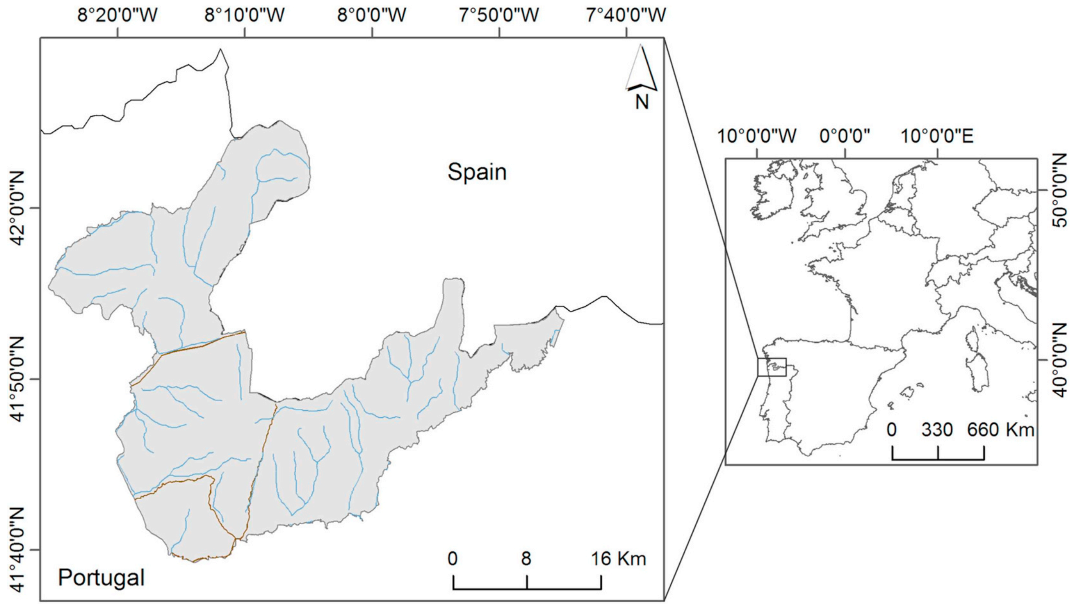

Fig. 1. Location of the test area, which includes the National Park "Peneda-Gerês" (on the left), in northwest Portugal (southwestern Europe; on the right). The figure on the left also shows the location of the main roads (brown) and rivers (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(n = 106) and Autumn (n = 81 images). Using this data, and with the purpose of portraying spectral and colour heterogeneity in a continuous fashion, we calculated the spatial standard-deviation and the average of reflectance values for the three bands, aggregating pixel values from the original spatial resolution (10 m) to 1000 m (our grid cell size).

2.3.2.2. Landscape heterogeneity. To characterize landscape heterogeneity, we performed a k-means unsupervised classification per meteorological season using each one of the previously generated multi-temporal cloud-free seasonal composites. We set the k-means algorithm (GEE function *ee.Clusterer.wekaKMeans*) to obtain a total of 20 clusters based on a sample of 30,000 pixels. No accuracy assessment was considered since seasonally clustered data was intended to reduce data dimensionality and to discretize areas with similar spectral and colour properties (not necessarily with the same land cover/use category). Based on the classified data for each seasonal composite, we then calculated the following diversity metrics for the 1000 m grid cells: (1) number of clusters, (2) Shannon diversity index, (3) the reciprocal Simpson diversity index and (4) the inverse Simpson diversity index (following e.g. Yoshimura and Hiura, 2017).

2.3.2.3. Vegetation functioning. We used the Enhanced Vegetation Index (EVI), available from MOD13Q1 product (version 6), for informing on seasonal vegetation functioning (Cabello et al., 2012; Ganguly et al., 2010). EVI was selected for its improved sensitivity over high-biomass regions and greater vegetation monitoring ability through the decoupling of the canopy background signal and a reduction in atmosphere influences (Didan et al., 2015; Huete et al., 2002). The EVI time-series comprised images from December 2011 to February 2017 (n = 121 images; see Supplementary Material for the list of images) to coincide with the years with greater availability of social media photos.

Data was downloaded from the *EarthData* platform (at: https://search.earthdata.nasa.gov/) and was then mosaicked, subset and re-projected to WGS 1984, UTM 29N coordinate system using MODIS Reprojection Tool (MRT release 4.1, 2011, at: https://lpdaac.usgs.gov/tools/modis_reprojection_tool). For improving outliers or spurious values, two procedures were performed sequentially: (1) Hampel outlier filtering (Davies and Gather, 1993; Hampel, 1974) and (2) time series smoothing using the Whittaker-Henderson algorithm (Eilers, 2003) with upper envelope weighting. From these series, we computed two measures to characterize vegetation functioning dynamics in each meteorological season based on the statistical properties of annual Vegetation Index (VI) curves (Cabello et al., 2012). These measures were the seasonal average (as a proxy related to vegetation amount and productivity) and the seasonal amplitude/range (describing vegetation seasonal variation). To depict the spatial heterogeneity at the landscape level we used the standard-deviation and the mean to aggregate values from MODIS original spatial resolution (250 m) to 1000 m (our grid cell size). All analytical procedures were performed in *R* software v3.4.0 (R Development Core Team, 2017).

2.3.3. Social media data on cultural ecosystem services

Cultural services were evaluated through the screening of photographs from two popular social media platforms: Flickr and Wikiloc (following Figueroa-Alfaro and Tang, 2017; Nahuelhual et al., 2013; Vaz et al., 2018a). We collected georeferenced photographs prior to 2018 and within the borders of the test area. Flickr data was collected using the application programming interface together with data collection tools which we developed with Python 3.5 (see Supplementary Material for descriptions on the collection tools). Wikiloc data was extracted from Google Earth (at: https://www.google.com/earth/). We registered the spatial location (latitude and longitude) and date (month and year) of each photograph. We then classified each photograph manually, through the visual identification of the dominant non-native or native tree species (following Vaz et al., 2018a), and based on the main focus of the photograph (see Table 3; following Hausmann et al., 2017; Oteros-Rozas et al., 2018). Details on tree taxonomy (i.e. genera or species name) and traits (e.g. bloomed tree) were recorded. Photographs with irrelevant subjects (e.g. advertisements, pamphlets and drawings) were excluded and photographs protected by users' privacy were neither downloaded nor analysed.

2.4. Data analyses

2.4.1. Evaluating non-native tree contributions to cultural services

Prior to analysing the contribution of non-native trees to cultural services, chi-square tests were considered to evaluate the significance of

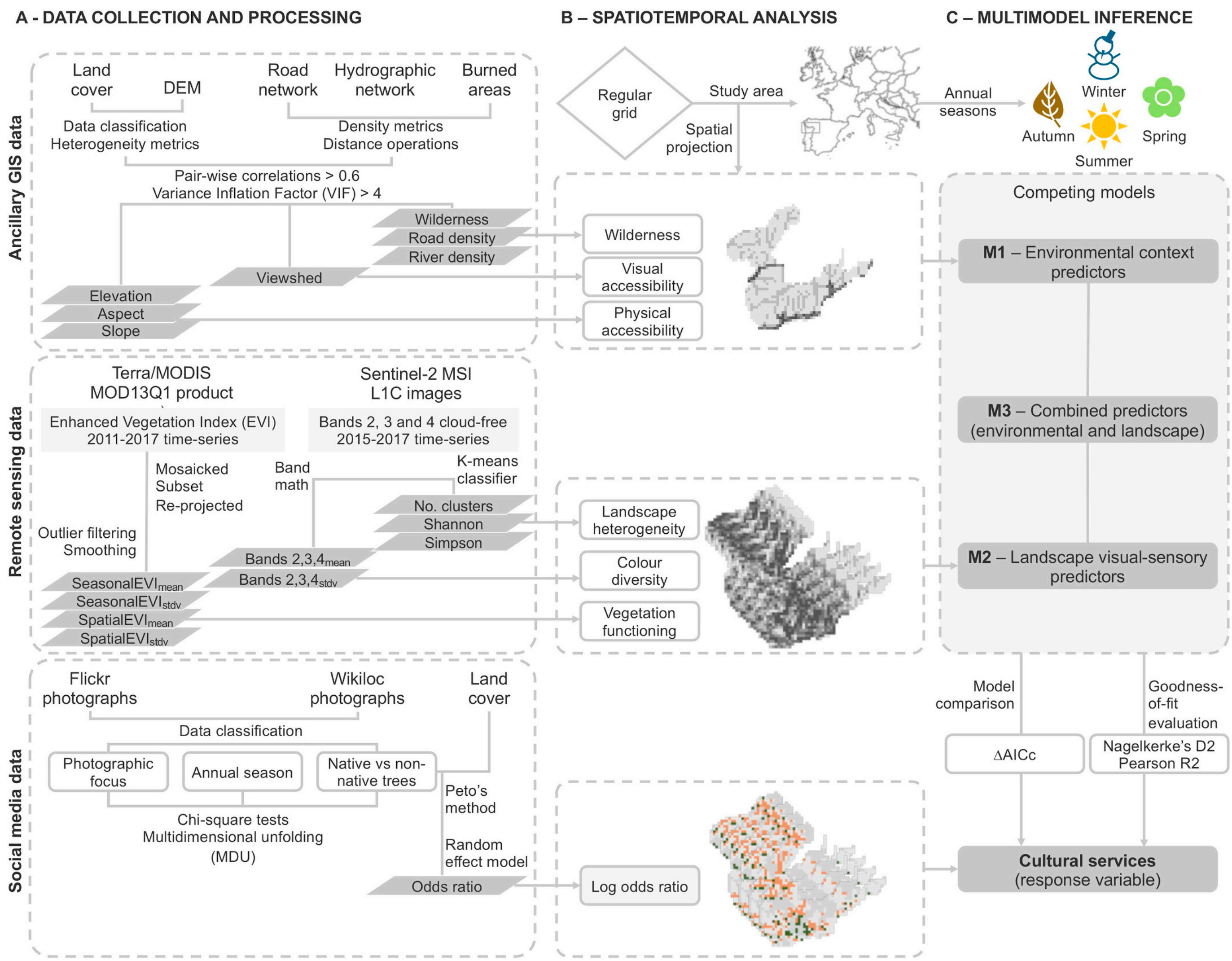

Fig. 2. Flowchart illustrating the methodological framework considered to assess the contribution of non-native trees to cultural services: (A) collection of social media photographs, and computation of Earth observation predictors; (B) calculation of the contribution of non-native trees to cultural services in the test area and across meteorological seasons; (C) multimodel inference, testing which set of predictors best explained the spatiotemporal contributions of non-native trees to cultural services.

associations among the date (year and season), focus (Table 3), and type of dominant tree (non-native or native) across photographs. To visualise the associations among the previous categories, we applied a multidimensional unfolding (MDU) based on matrices of preference data (see Supplementary Material for details).

Non-native tree contributions were evaluated through the odds ratio (Borenstein et al., 2009). The odds ratio was computed as the number of photographs dominated by non-native or native trees (i.e. observed contribution of non-natives in the photograph) per meteorological season, weighted by the proportion of cover area of non-native and native trees in a regular grid (i.e. the expected contribution of non-natives and natives in the area). We applied a regular grid of 1 km^2 to the test area, and for each grid cell we collected information on the cover area of non-native and native trees (based on Honrado, 2003; Vaz et al., 2018a). Cover areas were obtained from the most detailed and freely available national Land Cover Map (COS 2007; at http://mapas.

Table 1
Groups of variables considered as candidate predictors and respective input data. The table shows only the variables with correlations < 0.6 (Supplementary Material shows the full list of variables).

Groups of variables	Variables (related to…)	Input data
Environmental context (ancillary GIS data)		
Visual accessibility	Viewshed dimension	Digital elevation model
Physical accessibility	Elevation; slope	
Wilderness	Wilderness index; road density; river density	Local road and hydrographic networks
Landscape visual-sensory (satellite remote sensing data)		
Colour diversity	Mean and standard-deviation of reflectance values for bands 2, 3 and 4, per season	Sentinel-2 MSI L1C images
Landscape heterogeneity	Number of clusters; Shannon and Simpson diversity of clusters per season (Winter, Spring, Summer, Autumn)	
Vegetation functioning	Mean annual and spatial EVI; seasonal variability and spatial heterogeneity of EVI per season	MODIS MOD13Q1 product

Table 2
Details on satellite remote sensing information considered to evaluate landscape visual-sensory attributes.

Platform	Sentinel 2a/b	Terra
Sensor	MSI	MODIS
Number of images (N)	249	121
Start-end image dates	28/06/2015–24/12/2017	03/12/2011–18/02/2017
Temporal resolution (days)	05–10	16
Spatial resolution (m)	10	250
Spectral bands: bandwidths (nm)	B2 (Blue): 458–523 B3 (Green): 543–578 B4 (Red): 650–680	B1 (Red): 620–670 B2 (NIR): 841–876 B3 (Blue): 459–479

Table 3
Categories considered to classify each photograph according to its main focus.

Category	Description
Posing	People looking at the camera, with recognisable faces
Landscape	Pictures showing wide views of an area, with visible horizon
Species	Trees or parts of trees (e.g. flowers or leaves) as main subject
Human structures	Pictures showing human infrastructures (e.g. houses or monuments)
Human activities	People engaged in recreational activities (e.g. hiking and biking), including related objects (e.g. canoes and bicycles)

dgterritorio.pt/), complemented with information from the most recent National Forest Inventory (at http://www2.icnf.pt/portal/florestas/ifn/ifn6; see Supplementary Material for details on the mapping procedure). We calculated the weighted odds ratio (wOR) using the Peto's method and a DerSimonian-Laird random effects model, under non-parametric permutation tests with 1000 iterations (following Borenstein et al., 2009; Vaz et al., 2018a). Positive weighted odd ratios indicate that non-native trees had higher contributions to cultural service than native trees. Negative weighted odd ratios express lower contributions of non-native trees to cultural services, compared to native trees. Odds ratios equal to zero indicate similar contributions between non-native and native trees, and thus no preference for non-native (or native) trees (Vaz et al., 2018a; see Supplementary Material for computation details).

2.4.2. Explaining non-native tree contributions to cultural services from Earth observation

Three competing models (M1- M3) were considered in a multimodel inference framework (Burnham and Anderson, 2003) to test whether the contribution of non-native trees to cultural services was mostly explained by: M1 – predictors expressing the environmental context, calculated from ancillary GIS data; M2 – predictors expressing seasonal visual-sensory landscape features, obtained through satellite remote sensing data; or M3 – a combination of both types of predictors.

Given the meta-analytical nature of our response variable (expressed by the odds ratio), we implemented random-effect meta-regression models, using the maximum likelihood estimation, in *R* software (*glmulti* package; Calcagno, 2013). For model comparison, we calculated the Akaike Information Criterion difference (ΔAICc), as ΔAICc = AICc initial - AICc minimum (where AICc initial is the second-order AICc of the competing model and AICc minimum is the second-order AIC of the best model in the set). We further considered the weight (w_i) of each competing model, that represents the proportion of evidence from a competing model in relation to the total evidence from all models (ranging between 0 and 1). We used the Nagelkerke's deviance D2 (based on null-model testing) and Pearson correlation R2 (between predicted and observed values) as goodness-of-fit measures (Burnham and Anderson, 2003; Dormann et al., 2018).

3. Results

3.1. Non-native tree species contributions to cultural services

A total of 7227 photographs (from 2003 to 2017) were retrieved

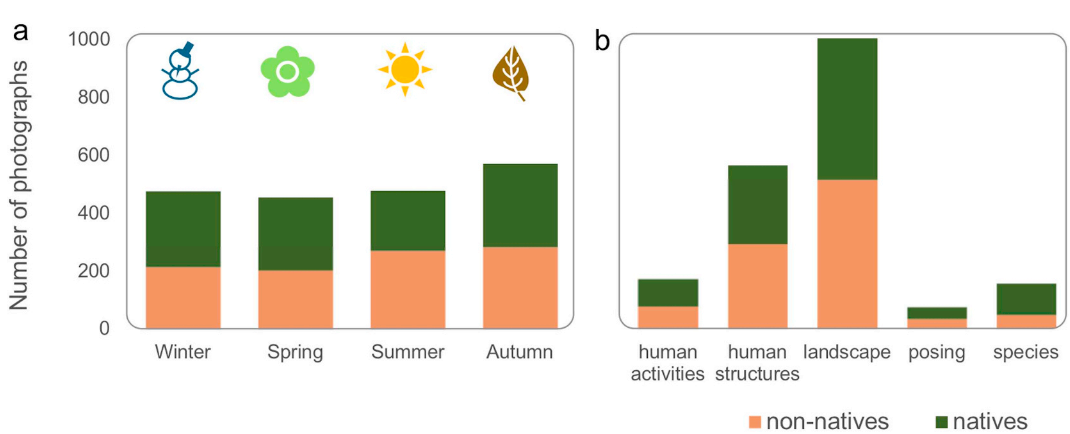

Fig. 3. Distribution of the number of photographs dominated by non-native and native trees, across meteorological seasons (a) and in relation to the photograph focus (b).

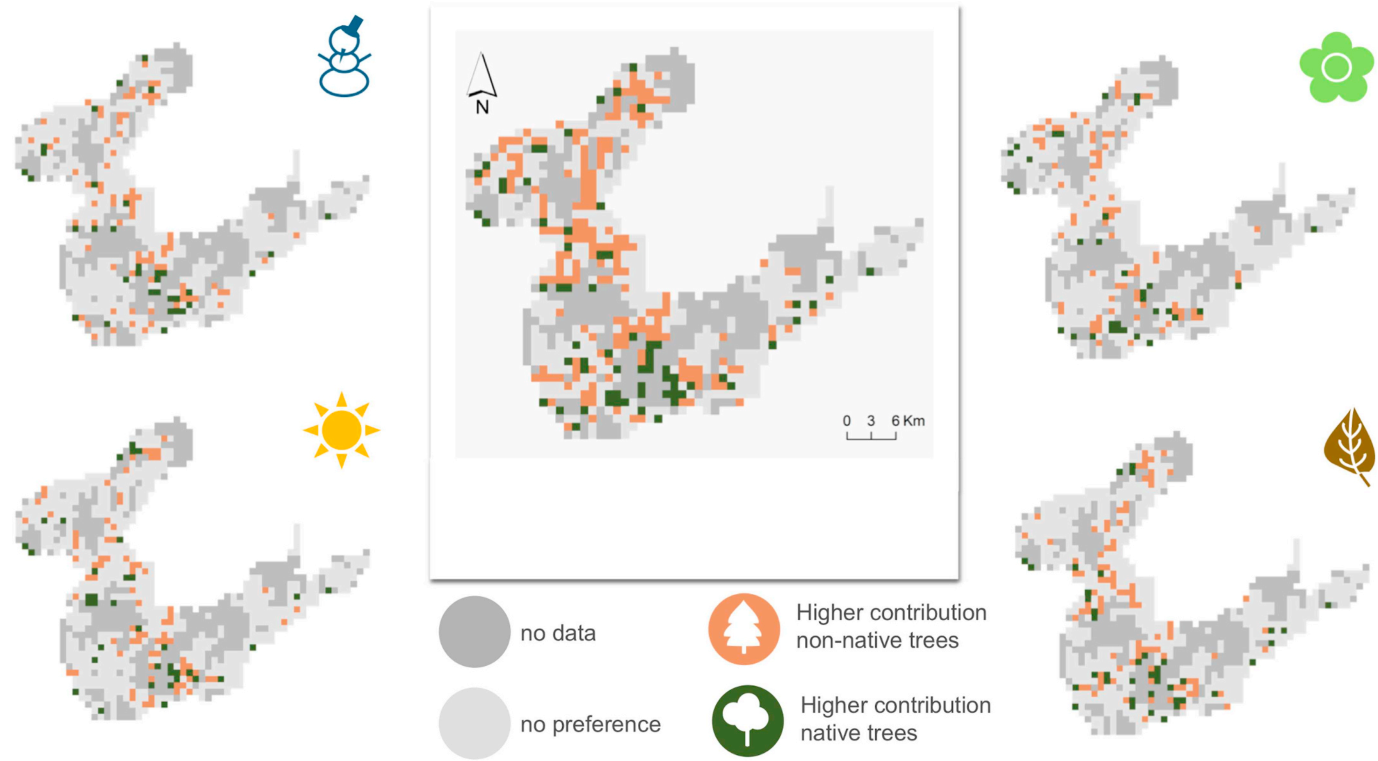

Fig. 4. Spatial representation of the contribution of non-native and native trees to cultural ecosystem services, in general (centre) and for each meteorological season: Winter (upper-left), Spring (upper-right), Summer (bottom-left) and Autumn (bottom-right). No data refers to the absence of photographs.

from Flickr (44% of all photos) and Wikiloc (66%), from which 1748 photographs were subsequently considered. Most photographs focused on landscapes (50.96%), followed by human structures (28.66%) and activities (8.68%), species (7.92%) and finally posing (3.79%; Fig. 3).

Pinus pinaster (53.23% of all photos), *Pseudotsuga menziesii* (8.48%), *Chamaecyparis lawsoniana* (8.13%), *Acacia dealbata* (7.51%), *A. melanoxylon* (6.98%) and *Eucalyptus globulus* (4.33%) were the most photographed non-native tree species (see Supplementary Material for details on tree proportions).

3.1.1. Spatial contributions of non-native trees to cultural ecosystem services

Overall, non-native trees held slightly higher contributions to cultural services than native trees, with 20% and 18% of all grid cells respectively showing positive and negative odds ratio values. The weighted odds ratio was significant and positive (wOR = 0.58; $p < 0.001$). The spatial projection of odds ratios showed the prevalence of positive values (i.e. preference for non-native trees) in western and central parts of the test area, whereas negative values (i.e. preference for native trees) prevailed in eastern and southern areas (Fig. 4).

3.1.2. Seasonal contributions of non-native trees to cultural ecosystem services

The number of photographs dominated by native or non-native trees was fairly similar across seasons: Winter (24.02%), Summer (24.17%), Spring (22.96%) and Autumn (28.86%; Fig. 3). Chi-square tests revealed significant associations between the dominant tree (non-native or native) and the meteorological season (chi = 25.812; df = 6; $p < 0.001$). No significant associations were found with the year (chi = 30.59; df = 22; $p > 0.10$) nor with the photograph focus (chi = 70.99; df = 8; $p > 0.05$). The MDU (stress = 0.63) also did not show an evident pattern regarding the association among the former (see Supplementary Material for full results). Nevertheless, we found significant and positive wOR values (i.e. preference for non-natives) for Autumn (wOR = 0.23; $p < 0.01$) and Spring (wOR = 0.19; $p < 0.01$), but negative wOR values (i.e. preference for natives) for Winter (OR = −0.19, $p < 0.001$). For Summer, the wOR was non-significant (wOR = 0.02, $p > 0.5$; see Supplementary Material for details on wOR results).

3.2. Explaining the contribution of non-native trees to cultural services

The contribution of non-native trees to cultural services (expressed by wOR values) was explained by predictors expressing both the environmental context (i.e. based on ancillary GIS data) and landscape visual-sensory features (i.e. based on satellite remote sensing data), depending on the meteorological season of the year.

3.2.1. Effects of environmental context predictors derived from ancillary GIS

Environmental context predictors (competing model: M1) retrieved from ancillary GIS data, were able to significantly explain the contribution of non-native trees to cultural services in Autumn, Spring and Winter (Table 4). Specifically, in Autumn (M1: $p = 0.02$) contributions of non-native trees were positively related to elevation (R2 = 0.35, $p = 0.01$), and negatively to river density (R2 = −0.10, $p = 0.01$). In Spring (M2: $p = 0.02$), non-native tree contribution was negatively associated to the wilderness index (R2 = −0.09; $p < 0.01$) and positively related with road density (R2 = 0.11; $p < 0.04$). In Winter (M1: $p = 0.01$), road density (R2 = −0.10; $p = 0.05$) also explained most of the contribution of non-native trees (negative relation), together with elevation (positive relation: R2 = 0.24; $p = 0.05$). No statistically significant relations were reported for the Summer dataset.

3.2.2. Effects of landscape visual-sensory attributes derived from satellite remote sensing

Predictors expressing landscape visual-sensory attributes, derived from satellite remote sensing (competing model M2), also explained the contributions of non-native trees to cultural services in most

Table 4
Summary of results from the multimodel framework: M1 – environmental context, M2 – landscape visual-sensory, M3 – combined environmental and visual-sensory model. Models are presented from the best to the least fit hypothesis, based on the Akaike Information Criterion difference (ΔAICc) and weight (w_i). D2: deviance; VIF: variance inflation factor; stdv.: standard deviation; div.: diversity; QM: heterogeneity of the explained response variable (tested by means of the Q statistics). Next to each predictor, we indicate whether the predictor was positively (+) or negatively (−) related to the contribution of non-native trees (Supplementary Material shows full results).

Model	ΔAICc	w_i	D2	VIF	QM	Predictors	Variable group
Autumn							
M3	0.00	0.62	0.54	1.27	5.84	River density (−)	Wilderness
						Stdv. reflectance B3 (+)	Colour diversity
M1	0.07	0.30	0.43	1.49	4.93	River density (−)	Wilderness
						Elevation (+)	Physical accessibility
M2	1.10	0.08	0.34	1.21	3.84	Number of clusters (−)	Landscape heterogeneity
						Stdv. reflectance B3 (+)	Colour diversity
Spring							
M3	0.00	0.68	0.59	1.23	4.08	Shannon div. Clusters (−)	Landscape heterogeneity
						Road density (+)	Wilderness
M2	0.10	0.23	0.36	1.08	3.63	Shannon div. Clusters (−)	Landscape heterogeneity
						Mean reflectance B2 (+)	Colour diversity
M1	1.26	0.09	0.32	1.26	3.30	Wilderness index (−)	Wilderness
						Road density (+)	Wilderness
Summer							
M3	0.00	0.47	0.25	1.24	2.57	Road density (+)	Wilderness
						Stdv. reflectance B3 (−)	Colour diversity
M1	0.10	0.34	0.15	–	1.57	Road density (+)	Wilderness
M2	0.77	0.19	0.08	–	0.81	Stdv. reflectance B3 (−)	Colour diversity
Winter							
M1	0.00	0.73	0.67	1.49	3.13	Elevation (+)	Physical accessibility
						Road density (−)	Wilderness
M3	0.10	0.21	0.40	1.54	4.71	Road density (−)	Wilderness
						Stdv. reflectance B3 (+)	Colour diversity
						Elevation (+)	Physical accessibility
M2	1.32	0.06	0.11	1.49	1.34	Stdv. reflectance B3 (+)	Colour diversity

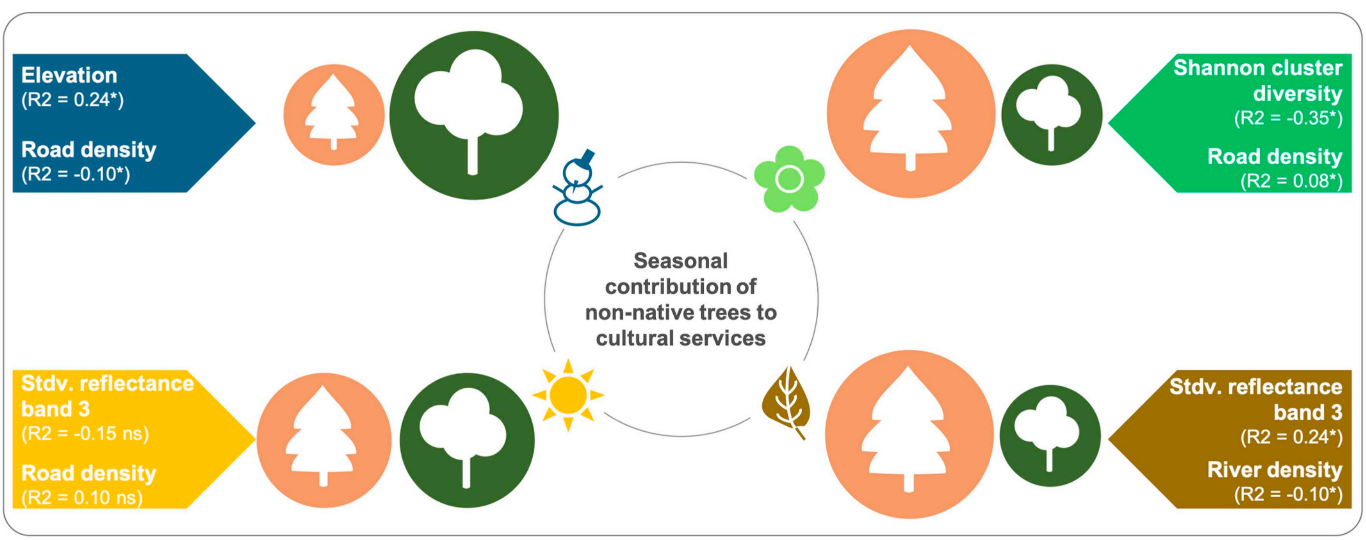

Fig. 5. Synthesis of results showing higher (bigger circles) or lower (smaller circles) contribution from non-native trees (orange circles) to cultural services, compared to native trees (green circles). The figure also shows the correlation and significance of predictors from the best competing model for each meteorological season (arrows): Winter (M1: based on environmental context), Spring, Summer and Autumn (M3: based on both environmental and landscape visual-sensory information). Significance: *$p < 0.05$, ns: non-significant. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

meteorological seasons. In Autumn (M2: $p = 0.02$), those contributions related mostly with the number of landscape clusters (negative relation: R2 = −0.06; $p = 0.01$), and with the standard deviation (stdv.) of Sentinel band 3 reflectance (positive relation: R2 = 0.22; $p = 0.01$). In Spring (M2: $p = 0.02$), a negative relation was found with the Shannon diversity of landscape clusters (R2 = −0.36; $p = 0.01$), while a positive relation was observed with the mean of Sentinel band 2 reflectance (R2 = 0.21; $p = 0.01$). In Winter (M2: $p = 0.05$), the contribution of non-native trees was significantly explained by the stdv. of band 3 reflectance (R2 = 0.16; $p = 0.05$).

3.2.3. Ranking of competing models based on ancillary GIS and satellite remote sensing

Values of ΔAICc for the three competing models (M1-M3) ranged from 0.00 to 1.32 (see Supplementary Material for details on resulting models). Table 4 shows the ranking of models based on AICc and w_i

values, for each the four seasons.

The models based on both ancillary GIS and satellite remote sensing predictors (M3) showed to perform the best, especially for Autumn (M3: $w_i = 0.62$; $QM = 5.84$; $p = 0.01$) and Spring (M3: $w_i = 0.68$; $QM = 4.08$; $p = 0.01$). In Autumn, contributions to cultural services increased with the wilderness level (river density: $R2 = -0.10$; $p = 0.01$) and with colour diversity (stdv. of band 3 reflectance: $R2 = 0.24$; $p = 0.04$). In Spring, however, contributions related negatively with the wilderness level (road density: $R2 = 0.08$; $p = 0.04$) and colour diversity (Shannon diversity of landscape clusters: $R2 = -0.35$; $p = 0.02$). For Summer, the model based on both types of predictors was also the most parsimonious (M3: $w_i = 0.47$; $QM = 2.57$), however, it was not statistically significant ($p > 0.05$). Finally, for Winter, the best model was based on predictors related to accessibility (M1: $w_i = 0.73$; $QM = 3.13$; $p = 0.01$). Road density ($R2 = -0.10$; $p = 0.04$) explained most of the contribution of non-native trees (negative relation), together with elevation, which hold a positive relation ($R2 = 0.24$; $p = 0.04$; Fig. 5).

4. Discussion

In this study we described an approach to assess the contributions of non-native trees to cultural services, mostly related with landscape aesthetics and nature recreation, considering information from social media and Earth observation in a multimodel inference framework. Our approach was tested in a National Park in Portugal, and allowed: (1) the mapping of the cultural contribution of non-native trees and the evaluation of its spatiotemporal variations; (2) the identification of the key environmental and landscape visual-sensory determinants of those contributions; (3) the provision of insights for advancing Sustainable Development Goals (SDG) and targets related with the contribution of non-native trees to cultural services; and (4) the discussion of opportunities for the research of cultural ecosystem services through Earth observations.

4.1. Spatiotemporal contributions of non-native trees to cultural ecosystem services

From the analysis of social media photographs, no significant association between the type of tree species and the focus of photograph is observed (Fig. 3), suggesting no influence of species nativeness when photographing nature (in agreement to Oteros-Rozas et al., 2018; Vaz et al., 2018a). Nevertheless, the mapping of the odds ratio in the test area reveals the highest contributions from non-native trees to cultural services in the western and central parts of the National Park, corresponding to more recreational-focused areas (Fig. 4; see Section 3.1.1). Contrastingly, non-native trees contribute the least to cultural services in areas of highest conservation value. These patterns match the known prevalence of non-native trees such as evergreen conifers, wattles (invasive *Acacia* spp.) and eucalypts (*Eucalyptus* spp.), and of native oak trees (specifically, old-growth *Quercus* forests) in the protected area (Honrado, 2003; Fernandes, 2008; Vicente et al., 2016).

Our results also indicate that the contribution from non-native trees to cultural services differs across meteorological seasons (Fig. 4; see Section 3.1.2). Specifically, non-native tree species show the highest contributions to cultural services in Autumn and Spring. This may be explained by the visual dominance of evergreen non-native trees during Autumn, when deciduous natives are already shedding their leaves, and by the emergence of attractive "exotic" features (e.g. acacia's yellow flowers and pine's cones) in Spring, which can make native trees less conspicuous (Martínez Pastur et al., 2016; Kueffer and Kull, 2017).

4.2. Explaining the contribution of non-native trees to cultural services based on Earth observation

Our study reveals that the predictors of contributions of non-native trees to cultural services relate to both the environmental context and visual-sensory features of the landscape (Table 4). Those contributions are significantly related to predictors of wilderness (i.e. river and road density) and physical access (i.e. elevation), computed from ancillary GIS data (see Section 3.2.1). These results are congruent with previous studies showing a relevant role of accessibility and wilderness (e.g. elevation and proximity to roads) in explaining landscape aesthetics (Schirpke et al., 2016; Swetnam et al., 2016) and recreation (Braun et al., 2018; Tenerelli et al., 2016) services. Still, no significant relation is found with visual accessibility (i.e., viewshed dimension), suggesting that this variable may not be useful to inform on the cultural services from non-native trees in our test area, in contrast to other studies (e.g. Schirpke et al., 2016; van Berkel et al., 2018).

Also, significant relations are found with the seasonality of colour diversity (i.e. standard deviation of green-band) and of landscape heterogeneity (Shannon diversity of landscape clusters), as evaluated from satellite imagery (Sentinel-2; see Section 3.2.2). These results highlight the importance of considering visual-sensory attributes, related with landscape colour and texture, in the evaluation of ecosystem aesthetics (Swetnam et al., 2016; Tveit et al., 2006; Yoshimura and Hiura, 2017). However, despite the potentialities of vegetation functioning dynamics for the supply of ecosystem services (Krishnaswamy et al., 2009), no significant relation between cultural contributions of non-native trees are found with EVI (retrieved from MODIS imagery).

The results from multimodel inference suggest different determinants of non-native tree contributions, according to the meteorological season of the year (Fig. 5; see Section 3.2.3). In Autumn those contributions are more evident in colourful landscapes (i.e. higher spectral diversity in the Sentinel-2 green-band) with higher wilderness levels, likely due to the intermix between deciduous (native), conifer and evergreen (non-native) trees in more remote areas (Martínez Pastur et al., 2016; Vicente et al., 2016). Conversely, in Spring, cultural contributions from non-native trees prevail in monotonous areas (i.e. low diversity of clusters) and with low wilderness levels (i.e. near roads), converging with the areas where invasive *Acacia* tree species prevail (Fernandes, 2008; Vicente et al., 2016). In Winter, non-native tree contributions are less evident in more remote and wilder areas, whereas in Summer none of the considered predictors exhibits significant explanatory power. These results seem to match the seasonal dynamics in tourism trends within the National Park, with a preference for eco- and nature-tourism in wilder and native areas, during Winter, and a preference for general recreational experiences (e.g. entertainment facilities), during Summer (Ceauşu et al., 2015; Kastenholz and de Almeida, 2008; Santarém et al., 2015).

4.3. Implications for the sustainable development goals and targets

Considering our results, we outline some guidelines towards the achievement of the Sustainable Development Goals and targets, particularly target 15.8 (management of non-native invasive species) but also targets 8.9 (touristic revenues) and 12.8 (awareness on harmony with nature) (https://sustainabledevelopment.un.org; Wood et al., 2018). Specifically, we recommend biosecurity efforts to prevent and mitigate non-native species' effects on natural and cultural heritage (including ecotourism) in the National Park (target 15.8). Biosecurity efforts should include preventive actions through environmental education and awareness (target 12.8) and in situ eradication and control of non-native trees (Marchante and Marchante, 2016; Reimer and Walter, 2013). Those efforts should prioritise landscapes closer to areas with the highest occurrence and cultural preference for non-native trees (also more prone to recreational tourism). Biosecurity efforts would have no considerable impact on tourism revenues (target 8.9), as no public preferences were shown during the peak season (i.e. Summer). Instead, they would be relevant for promoting people's engagement with nature (target 12.8), by controlling widespread invasives (e.g. *Acacia dealbata* and *A. melanoxylon*), as well as for preventing the naturalisation and invasion by other non-natives (e.g. *Pseudotsuga menziesii* and *Robinia pseudoacacia*). Nevertheless, these efforts should consider the contributions that non-native trees might have on other ecosystem services (Vaz et al., 2017). Failure to do so will likely hamper attempts to ensure that bundles of ecosystem services are included in current and future land planning and management.

4.4. Methodological considerations and future advances

We have shown that the combination of social media photographs and Earth observation data can be useful for the research of cultural ecosystem services and their determinants. Still, some methodological considerations are recognised. The spatial reference precision of social media photographs can bias the geolocation of collected data (Figueroa-Alfaro and Tang, 2017). Also, there may be some impact of using satellite imagery at distinct spatial resolutions, i.e. 10 m (Sentinel 2 MSI) versus 250 m (MODIS). Still, this bias was likely insignificant in our study, due to the aggregation of photographs (and predictors) at 1 km^2 spatial resolution. We also considered distinct time intervals across the datasets: social media photoseries (2003–2017), Sentinel-2 imagery (2015–2017) and MODIS product (2011–2017). This was due to limitations in data availability (e.g. short time-span of the data of the Sentinel-2 platform). Moreover, despite the advantages linked to image processing in GEE, some improvements to our image processing pipeline could also be made if this platform continues to evolve, namely the inclusion of Sentinel-2 L2A (atmospherically corrected) imagery and the possibility to perform time-series smoothing (both features not currently available). Yet, we are confident that remote sensing information was able to characterize the main patterns of colour diversity, landscape heterogeneity, and vegetation functioning dynamics in the test area.

Furthermore, in a multi-model framework, the predictive ability of a competing model is evaluated in relation to the other models, not necessarily meaning that the best model is able to explain the full range of variations. Nonetheless, we applied two independent evaluation measures (D2 and R2) to overcome this issue. In fact, the process of cultural evaluation of ecosystems may differ across social-ecological contexts and (groups of) individuals (Kull et al., 2011; Shackleton et al., 2019; Vaz et al., 2018a). Therefore, in order to further understand cultural preferences towards non-native trees, future research should examine the motivations underlying the choices and the perceptions (Shackleton et al., 2019) in relation to other (social) determinants (e.g. socio-demography, economy; Tenerelli et al., 2016; van Zanten et al., 2016; Vaz et al., 2018a). As social data platforms evolve and high-resolution satellite information becomes more available, the inclusion of these different types and sources of complementary information should be encouraged (Oteros-Rozas et al., 2018). However, the use of some types of publicly available data may be ethically sensitive, increasing scientific responsibility on the interpretation and communication of social patterns (Van Berkel et al., 2018). This was the main reason why we did not compile, nor analyse, data which was protected by users' privacy.

Nevertheless, our study considered the most relevant available data to assess the spatial and seasonal contributions of non-native trees to cultural ecosystem services. Our results suggest that the contribution of non-native trees to cultural services in the test area is defined by the local abundance and phenology of these species. Approaches based on Earth observation time-series can help to detect these species alongside their effects on recipient ecosystems (Ganguly et al., 2010; Pasquarella et al., 2018; Wulder et al., 2012). The cultural value of a natural feature also depends on people's accessibility to that feature (Ceaușu et al., 2015; Figueroa-Alfaro and Tang, 2017; Reimer and Walter, 2013). For instance, road sides are prone to the occurrence of non-natives but also to the movement of people, improving the chance of a given non-native tree being culturally valued. In this sense, Earth observation data is useful to feed modelling frameworks that can predict the spatial patterns of these species, e.g. along dispersal corridors. Also, the cultural value of nature depends on visually-attractive characteristics which succeed in capturing human attention (van Berkel et al., 2018). This is particularly relevant for non-native trees, which often exhibit higher growth performance and unusual phenological traits, particularly when natives are leafless and less conspicuous (Shackleton et al., 2019; Vaz et al., 2018a). Satellite data can aid in these assessments, capturing information on ecosystem functioning and biodiversity attributes, e.g. related to landscape seasonality and phenology (Ganguly et al., 2010; Pasquarella et al., 2018). Concurrently, satellite remote sensing provides temporal information on the prevalence of, and accessibility to, visual and sensorial characteristics of ecosystems.

Besides the availability of high-resolution Earth observation data (e.g. Sentinel-2), there is also investment in user-friendly platforms with easy to open access Earth observation data and with an increasing processing capacity (e.g. Google Earth Engine; Kwok, 2018). Furthermore, when associated to computational approaches in social sciences, namely through the evaluation of social and cultural information, remote sensing constitutes a revolutionary way to compile and analyse people's experiences and interactions with ecosystems (Lazer et al., 2009). In fact, encouraging citizen participation and making use of participatory data (besides social media) can be a way forward for advancing knowledge about nature's cultural benefits to people, and hence support the development of indicator-based monitoring systems for cultural services supported by objective, quantifiable and spatio-temporal measurements (Antoniou et al., 2016; Chippendale et al., 2009).

5. Conclusions

Cultural ecosystem services underpin many dimensions of human well-being which are essential to reach the United Nations' Sustainable Development Goals (SDG) for 2030. Developing indicators and monitoring systems for cultural services can be particularly useful to understand how these services are shaped by fingerprints of the Anthropocene, such as the occurrence of non-native tree species. Nevertheless, methodological approaches focused on cultural services still lack an explicit temporal dimension. Here, we combined Earth observations and social media data in a multimodel framework to assess the spatiotemporal contributions of non-native trees to cultural ecosystem services in a National Park in Portugal. Contributions of non-native trees to landscape aesthetics and recreation could be explained by physical accessibility, wilderness context, spatial heterogeneity and colour diversity of landscapes in the test area. The importance of the environmental context and of (remotely sensed) landscape visual-sensory features for those contributions also changed across meteorological seasons (i.e. Winter, Spring, Summer, and Autumn). Our results are congruent with the phenology of dominant vegetation and match differences in the seasonality of touristic demand. The proposed approach can be replicable worldwide, supporting decision-making on biosecurity efforts on invasive trees (target 15.8) and awareness strategies on natural capital (target 12.8) to safeguard biodiversity and recreational values (target 8.9) in protected areas.

Acknowledgements

The authors thank Joaquim Alonso and Carlos Guerra for providing access to predictors data, as well as Helena Santos for English revision and proofreading. Thanks also go to the anonymous reviewers for their stimulating suggestions that improved the paper. This work contributes to the GEOBON Working Group on Ecosystem Services. Funding: Vaz [grant PD/BD/52600/2014], Pereira [PD/BD/128492/2017], Santarém [PD/BD/132407/2017], and Vicente [SFRH/BPD/84044/2012] were supported by the Portuguese Foundation for Science and Technology (FCT). This work was also supported by FPS COST Action FP1403 NNEXT: *Non-native tree species for European forests – experiences, risks and opportunities*. Funding sources had no involvement in study

design, data collection, analysis and interpretation, article writing, and submission decisions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2019.05.012.

References

Antoniou, V., Fonte, C., See, L., Estima, J., Arsanjani, J., Lupia, F., Minghini, M., Foody, G., Fritz, S., 2016. Investigating the feasibility of geo-tagged photographs as sources of land cover input data. ISPRS Int. J. Geo.-Inf. 5, 64.

Blicharska, M., Smithers, R.J., Hedblom, M., Hedenås, H., Mikusiński, G., Pedersen, E., Sandström, P., Svensson, J., 2017. Shades of grey challenge practical application of the cultural ecosystem services concept. Ecos. Serv. 23, 55–70.

Borenstein, M., Hedges, L.V., Higgins, J.P.T., Rothstein, H.R., 2009. Introduction to Meta-Analysis. John Wiley & Sons, West Sussex.

Braun, D., Damm, A., Hein, L., Petchey, O.L., Schaepman, M.E., 2018. Spatio-temporal trends and trade-offs in ecosystem services: an Earth observation based assessment for Switzerland between 2004 and 2014. Ecol. Indic. 89, 828–839.

Brundu, G., Richardson, D.M., 2015. Code of Conduct on Plantation Forestry and Invasive Alien Trees. First Draft-T-PVS/Inf (2015) 1. Council of Europe, Strasbourg.

Burnham, K.P., Anderson, D.R., 2003. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. Springer-Verlag, New York.

Cabello, J., Fernández, N., Alcaraz-Segura, D., Oyonarte, C., Piñeiro, G., Altesor, A., Delibes, M., Paruelo, J., 2012. The ecosystem functioning dimension in conservation: insights from remote sensing. Biodivers. Conserv. 21, 3287–3305.

Calcagno, V., 2013. Glmulti: Model Selection and Multimodel Inference Made Easy. R Package Version, 1(7).

Ceaușu, S., Gomes, I., Pereira, H.M., 2015. Conservation planning for biodiversity and wilderness: a real-world example. Environ. Manag. 55, 1168–1180.

Chan, K.M.A., Goldstein, J., Satterfield, T., Hannahs, N., Kikiloi, K., Naidoo, R., Vadeboncoeur, N., Woodside, U., 2011. Cultural services and non-use values. In: Kareiva, P., Tallis, H., Rickets, T.H., Daily, G.C., Polaksy, S. (Eds.), Natural Capital: Theory and Practice of Mapping Ecosystem Services. Oxford University Press, Oxford, pp. 206–228.

Chippendale, P., Zanin, M., Andreatta, C., 2009. Re-photography and environment monitoring using a social sensor network. In: International Conference on Image Analysis and Processing, pp. 34–42.

Cord, A.F., Brauman, K.A., Chaplin-Kramer, R., Huth, A., Ziv, G., Seppelt, R., 2017. Priorities to advance monitoring of ecosystem services using earth observation. Trends Ecol. Evol. 32, 416–428.

Davies, L., Gather, U., 1993. The identification of multiple outliers. J. Am. Stat. Assoc. 88, 782–792.

de Araujo Barbosa, C.C., Atkinson, P.M., Dearing, J.A., 2015. Remote sensing of ecosystem services: a systematic review. Ecol. Indic. 52, 430–443.

Dickie, I., Bennett, B., Burrows, L., Nuñez, M., Peltzer, D., Porté, A., Richardson, D., Rejmánek, M., Rundel, P., van Wilgen, B., 2014. Conflicting values: ecosystem services and invasive tree management. Biol. Invas. 16, 705–719.

Didan, K., Munoz, A.B., Solano, R., Huete, A., 2015. MODIS Vegetation Index User's Guide (MOD13 Series) - Version 3.00. University of Arizona, Vegetation Index and Phenology Lab.

Dormann, C.F., Calabrese, J.M., Guillera-Arroita, G., Matechou, E., Bahn, V., Bartoń, K.A., Beale, C.M., Ciuti, S., Elith, J., Gerstner, K., 2018. Model averaging in ecology: a review of Bayesian, information-theoretic and tactical approaches. Ecol. Monogr. Doi: doi.org/https://doi.org/10.1002/ecm.1309.

Eilers, P.H.C., 2003. A perfect smoother. Anal. Chem. 75, 3631–3636.

Fernandes, M.M., 2008. Recuperação ecológica de áreas Invadidas Por *Acacia dealbata* Link no Vale Do Rio Gerês: Um Trabalho sísifo? (Ecological Restoration of Invaded Areas by *Acacia dealbata* Link in the Valley of Gerês River: A Hard Work?). Master thesis presented to the. University Trás-os-Montes e Alto Douro, Portugal (*In Portuguese*).

Ferster, C.J., Coops, N.C., 2016. Integrating volunteered smartphone data with multispectral remote sensing to estimate forest fuels. Int. J. Digit. Earth. 9, 171–196.

Figueroa-Alfaro, R.W., Tang, Z., 2017. Evaluating the aesthetic value of cultural ecosystem services by mapping geo-tagged photographs from social media data on Panoramio and Flickr. J. Environ. Plann. Man. 60, 266–281.

Fish, R., Church, A., Winter, M., 2016. Conceptualising cultural ecosystem services: a novel framework for research and critical engagement. Ecosyst. Serv. 21, 208–217.

Foody, G.M., Boyd, D.S., 2013. Using volunteered data in land cover map validation: mapping west African forests. IEEE J. Sel. Top. Appl. 6, 1305–1312.

Fox, J., Weisberg, S., 2011. An R Companion to Applied Regression. Sage Publications, California.

Ganguly, S., Friedl, M.A., Tan, B., Zhang, X., Verma, M., 2010. Land surface phenology from MODIS: characterization of the collection 5 global land cover dynamics product. Remote Sens. Environ. 114, 1805–1816.

Geijzendorffer, I.R., Cohen-Shacham, E., Cord, A.F., Cramer, W., Guerra, C., Martín-López, B., 2017. Ecosystem services in global sustainability policies. Environ. Sci. Pol. 74, 40–48.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27.

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M.C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., Noble, I., 2013. Policy: sustainable development goals for people and planet. Nature 495, 305.

Hampel, F.R., 1974. The influence curve and its role in robust estimation. J. Am. Stat. Assoc. 69, 383–393.

Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V., Di Minin, E., 2017. Social media data can be used to understand tourists' preferences for nature-based experiences in protected areas. Conserv. Let. 11, e12343.

Honrado, J., 2003. Flora e vegetação do Parque Nacional da Peneda-Gerês (Flora and vegetation from the National Park Penesa-Gerês). PhD thesis presented to the. Faculty of Sciences of the University of Porto, Portugal (*In Portuguese*).

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gaoa, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83, 195–213.

Infield, M., 2001. Cultural values: a forgotten strategy for building community support for protected areas in Africa. Conserv. Biol. 15, 800–802.

Kastenholz, E., de Almeida, A.L., 2008. Seasonality in rural tourism – the case of North Portugal. Tourism Rev 63, 5–15.

Krishnaswamy, J., Bawa, K.S., Ganeshaiah, K.N., Kiran, M.C., 2009. Quantifying and mapping biodiversity and ecosystem services: utility of a multi-season NDVI based Mahalanobis distance surrogate. Remote Sens. Environ. 113, 857–867.

Kueffer, C., Kull, C., 2017. Non-native species and the aesthetics of nature. In: Hulme, P., Vilà, M., Ruiz, G. (Eds.), Impact of Biological Invasions on Ecosystem Services. Springer, Cham, pp. 311–324.

Kull, C.A., Shackleton, C.M., Cunningham, P.J., Ducatillon, C., Dufour-Dror, J.-M., Esler, K.J., Friday, J.B., Gouveia, A.C., Griffin, A.R., Marchante, E., Midgley, S.J., Pauchard, A., Rangan, H., Richardson, D.M., Rinaudo, T., Tassin, J., Urgenson, L.S., von Maltitz, G.P., Zenni, R.D., Zylstra, M.J., 2011. Adoption, use and perception of Australian acacias around the world. Divers. Distrib. 17, 822–836.

Kwok, R., 2018. Ecology's remote-sensing revolution. Nature 556, 137–138.

Lazer, D., Pentland, A.S., Adamic, L., Aral, S., Barabasi, A.L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., 2009. Life in the network: the coming age of computational social science. Science 323, 721–723.

MA, Millennium Ecosystem Assessment, 2005. Ecosystems & Human Well-Being: Synthesis. Island Press, Washington, DC.

Marchante, E., Marchante, H., 2016. Engaging society to fight invasive alien plants in Portugal - one of the main threats to biodiversity. In: Castro, P., Azeiteiro, U.M., Bacelar-Nicolau, P., Filho, W.L., Azul, A.M. (Eds.), Biodiversity and Education for Sustainable Development. Springer International Publishing, Switzerland, pp. 107–122.

Martínez Pastur, G., Peri, P.L., Lencinas, M.V., García-Llorente, M., Martín-López, B., 2016. Spatial patterns of cultural ecosystem services provision in southern Patagonia. Landsc. Ecol. 31, 383–399.

Molinier, M., López-Sánchez, C., Toivanen, T., Korpela, I., Corral-Rivas, J., Tergujeff, R., Häme, T., 2016. Relasphone—Mobile and participative in situ forest biomass measurements supporting satellite image mapping. Remote Sens. 8, 869.

Nahuelhual, L., Carmona, A., Lozada, P., Jaramillo, A., Aguayo, M., 2013. Mapping recreation and ecotourism as a cultural ecosystem service: an application at the local level in Southern Chile. Appl. Geogr. 40, 71–82.

Nuñez, M.A., Simberloff, D., 2005. Invasive species and the cultural keystone species concept. Ecol. Soc. 10, r4.

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., Plieninger, T., 2018. Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. Ecol. Indic. https://doi.org/10.1016/j.ecolind.2017.02.009.

Pasquarella, V.J., Holden, C.E., Woodcock, C.E., 2018. Improved mapping of forest type using spectral-temporal Landsat features. Remote Sens. Environ. 210, 193–207.

R Development Core Team, 2017. R: A Language and Environment for Statistical Computing. URL: https://www.R-project.org/R Foundation for Statistical Computing, Vienna, Austria.

Reimer, J.K., Walter, P., 2013. How do you know it when you see it? Community-based ecotourism in the Cardamom Mountains of southwestern Cambodia. Tourism Manag 34, 122–132.

Richards, D.R., Friess, D.A., 2015. A rapid indicator of cultural ecosystem service usage at a fine spatial scale: content analysis of social media photographs. Ecol. Indic. 53, 187–195.

Richardson, D.M., Pyšek, P., Carlton, J.T., 2011. A compendium of essential concepts and terminology in invasion ecology. In: Richardson, D.M. (Ed.), Fifty Years of Invasion Ecology: The Legacy of Charles Elton. John Wiley & Sons, West Sussex, pp. 409–420.

Santarém, F., Silva, R., Santos, P., 2015. Assessing ecotourism potential of hiking trails: a framework to incorporate ecological and cultural features and seasonality. Tourism Manage. Pers. 16, 190–206.

Schepaschenko, D., See, L., Lesiv, M., McCallum, I., Fritz, S., Salk, C., Moltchanova, E., Perger, C., Shchepashchenko, M., Shvidenko, A., 2015. Development of a global hybrid forest mask through the synergy of remote sensing, crowdsourcing and FAO statistics. Remote Sens. Environ. 162, 208–220.

Schirpke, U., Timmermann, F., Tappeiner, U., Tasser, E., 2016. Cultural ecosystem services of mountain regions: modelling the aesthetic value. Ecol. Indic. 69, 78–90.

Shackleton, R.T., Richardson, D.M., Shackleton, C.M., Bennett, B., Crowley, S.L., Dehnen-Schmutz, K., Estévez, R.A., Fischer, A., Kueffer, C., Kull, C.A., Marchante, E., Novoa, A., Potgieter, L.J., Vaas, J., Vaz, A.S., Larson, B.M.H., 2019. Explaining people's perceptions of invasive alien species: a conceptual framework. J. Environ. Manag. 229, 10–26.

Soga, M., Gaston, K.J., 2016. Extinction of experience: the loss of human–nature interactions. Front. Ecol. Environ. 14, 94–101.

Spangenberg, J.H., von Haaren, C., Settele, J., 2014. The ecosystem service cascade:

further developing the metaphor. Integrating societal processes to accommodate social processes and planning, and the case of bioenergy. Ecol. Econ. 104, 22–32.
Swetnam, R.D., Harrison-Curran, S.K., Smith, G.R., 2016. Quantifying visual landscape quality in rural Wales: a GIS-enabled method for extensive monitoring of a valued cultural ecosystem service. Ecos. Serv. 26, 451–464.
Tenerelli, P., Demšar, U., Luque, S., 2016. Crowdsourcing indicators for cultural ecosystem services: a geographically weighted approach for mountain landscapes. Ecol. Indic. 64, 237–248.
Tveit, M., Ode, Å., Fry, G., 2006. Key concepts in a framework for analysing visual landscape character. Landsc. Res. 31, 229–255.
UN, United Nations, 2015. Transforming our World: The 2030 Agenda for Sustainable Development. A/RES/70/1. Division for Sustainable Development Goals: New York, NY, USA.
van Berkel, D.B., Tabrizian, P., Dorning, M.A., Smart, L., Newcomb, D., Mehaffey, M., Neale, A., Meentemeyer, R.K., 2018. Quantifying the visual-sensory landscape qualities that contribute to cultural ecosystem services using social media and LiDAR. Ecosyst. Serv. Doi: doi.org/https://doi.org/10.1016/j.ecoser.2018.03.022.
van Zanten, B.T., Van Berkel, D.B., Meentemeyer, R.K., Smith, J.W., Tieskens, K.F., Verburg, P.H., 2016. Continental-scale quantification of landscape values using social media data. PNAS 113, 12974–12979.
Vaz, A.S., Kueffer, C., Kull, C.A., Richardson, D.M., Vicente, J.R., Kühn, I., Schröter, M., Hauck, J., Bonn, A., Honrado, J.P., 2017. Integrating ecosystem services and disservices: insights from plant invasions. Ecosyst. Serv. 23, 94–107.
Vaz, A.S., Castro-Díez, P., Godoy, O., Alonso, Á., Vilà, M., Saldaña, A., Marchante, H., Bayón, Á., Silva, J.S., Vicente, J.R., Honrado, J.H., 2018a. An indicator-based approach to analyse the effects of non-native tree species on multiple cultural ecosystem services. Ecol. Indic. 85, 48–56.
Vaz, A.S., Alcaraz-Segura, D., Campos, J.C., icente, J.R., Honrado, J.P., 2018b. Managing plant invasions through the lens of remote sensing: a review of progress and the way forward. Sci. Total Environ. 642, 1328–1339.
Vicente, J.R., Alagador, D., Guerra, C., Alonso, J.M., Kueffer, C., Vaz, A.S., Fernandes, R.F., Cabral, J.A., Araújo, M.B., Honrado, J.P., 2016. Cost-effective monitoring of biological invasions under global change: a model-based framework. J. Appl. Ecol. 53, 1317–1329.
Wood, S.L., DeClerck, F., 2015. Ecosystems and human well-being in the sustainable development goals. Front. Ecol. Environ. 13, 123.
Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. Sci. Rep. 3, 2976.
Wood, S.L., Jones, S.K., Johnson, J.A., Brauman, K.A., Chaplin-Kramer, R., Fremier, A., Girvetz, E., Gordon, L.J., Kappel, C.V., Mandle, L., 2018. Distilling the role of ecosystem services in the sustainable development goals. Ecosyst. Serv. 29, 70–82.
Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2012. Opening the archive: how free data has enabled the science and monitoring promise of Landsat. Remote Sens. Environ. 122, 2–10.
Yoshimura, N., Hiura, T., 2017. Demand and supply of cultural ecosystem services: use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. Ecosyst. Serv. 24, 68–78.