Eesti Maaülikool
Estonian University of Life Sciences

LANDSCAPE METRICS AND CULTURAL ECOSYSTEM SERVICES: AN INTEGRATIVE RESOURCE-DRIVEN MAPPING APPROACH FOR LANDSCAPE HARMONY

MAASTIKUMEETRIKA JA ÖKOSÜSTEEMI KULTUURITEENUSED – RESSURSIPÕHINE INTEGREERIV LÄHENEMINE MAASTIKUHARMOONIA KAARDISTAMISELE

OLEKSANDR KARASOV

A Thesis
for applying for the degree of Doctor of Philosophy in Environmental Protection

Väitekiri
filosoofiadoktori kraadi taotlemiseks keskkonnakaitse erialal

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CONTENTS

LIST OF ORIGINAL PUBLICATIONS

The thesis is a synthesis of the following papers, which are referred to in the text by their Roman numerals.

I. **Karasov, O.**, Külvik, M., & Burdun, I. (2019). Deconstructing landscape pattern: applications of remote sensing to physiognomic landscape mapping. *GeoJournal*, 1-27.

II. **Karasov, O.**, Külvik, M., Chervanyov, I., & Priadka, K. (2019). Mapping the extent of land cover colour harmony based on satellite Earth observation data. *GeoJournal*, *84*(4), 1057-1072.

III. **Karasov, O.**, Vieira, A. A. B., Külvik, M., & Chervanyov, I. (2020). Landscape coherence revisited: GIS-based mapping in relation to scenic values and preferences estimated with geolocated social media data. *Ecological Indicators*, *111*, 105973.

IV. **Karasov, O.**, Heremans, S., Külvik, M., Domnich, A., & Chervanyov, I. (2020). On how crowdsourced data and landscape organisation metrics can facilitate the mapping of cultural ecosystem services: an Estonian case study. *Land*, 9, 158.

The contributions of the author of this thesis and other scientists to the publications were the following:

	I	**II**	**III**	**IV**
Original idea	OK	OK	OK, IC, MK	OK, IC, MK
Study design	OK	OK, MK, IC, KP	OK, AV	OK, SH
Data collection	OK	OK	OK, AV	OK, AD
Data analysis	OK	OK	OK, MK	OK, SH
Manuscript preparation	OK, MK, IB	OK, MK	OK, AV, MK	OK, SH, MK

MK – Mart Külvik, IC – Igor Chervanyov, AV – Antonio Vieira, SH – Stien Heremans, IB – Iuliia Burdun, KP – Kostiantyn Priadka, AD – Artem Domnich, **OK – Oleksandr Karasov**

ACRONYMS AND ABBREVIATIONS

CES – cultural ecosystem services
GIS – geographic information system
CICES – common international classification of ecosystem services
GDP – gross domestic product
VGI – volunteered geographic information
DLM – digital landscape model
DEM – digital elevation model
DSM – digital surface model
TPI – topographic position index
LU/LC – land use / land cover
CHI – colour harmony index
LCI – landscape coherence index
LBSM – location-based social media
NCP – nature’s contributions to people

1. INTRODUCTION

My research work originated in 2012 within the framework of bachelor's studies at the V. N. Karazin Kharkiv National University (Ukraine). I began researching the so-called "intangible nature use", which describes the non-material component of people-nature relationship. The intangible nature use encompasses a wide range of *intangible natural resources* (i.e. those natural materials, bodies and processes, the use of which does not cause any extraction or transformation of substance or energy, while profitable and valuable). These natural phenomena and their properties become intangible assets, being recognised and used by economic actors as elements of natural capital and sources of economic rent or left behind the quantitative assessment as positive *externalities* (Bourassa 1992; Dronova 2019).

We are witnessing now a paradigm shift in environmental science and related disciplines towards rethinking the complexity of people-nature relationships, including non-material interactions (Díaz et al. 2018; Dronova 2019). A major direction of this shift has gained increasing attention over past decades because of the concept of (cultural) *ecosystem services* (Daily 1997; Millennium Ecosystem Assessment 2005). In parallel, the concept of *environmental resources* was introduced to capture also the cultural values related to nature (Mather and Chapman 1995). Since that time, the concept of environmental resources was frequently being used in combination with natural resources, adding essential matters of cultural and regulating ecosystem services to the common discourse of natural resources (Saastamoinen 2016). However, both semantic and practical issues continued to exist: all the mentioned approaches suffer from a lack of generalisation. More recently, a new concept of *nature's contributions to people* (NCP) was introduced (Díaz et al. 2015). Classification of NCP includes already non-material contributions, moving towards more universal and adequate conceptualisation (Pires et al. 2020). At the same time, cultural ecosystem services also become discussed as those which have "no material benefits" (Small et al. 2017) or informational (De Groot et al. 2002; Bukvareva et al. 2019). Bukvareva et al. define informational ecosystem services simply as "all kinds of information that is contained in natural ecosystems and can be used by people" (2019) and this logic appears to be the most fruitful for the approach, used in this thesis (while still limited with biological notion of ecosystem and also service itself). We argue that the concept of service is applicable to the fact of non-material people-nature interaction (landscape watching, doing sports outdoors, recreational activities, etc) but not to the particulars of environment as provider of the services. This opinion is enshrined in the well-known cascade model of ecosystem services (Potschin and Haines-Young 2011; Small et al. 2017), but authors writing on the topic of the visual landscape quality (main environmental characteristics, responsible for the arousal of aesthetic and recreational values) rarely put it in the context of resources. One of a few examples of such resource-driven approach is a psychophysical methodology of visual resources inventory, which is quite widespread in the USA (BLM 1986).

This thesis aims to examine the visual environment using quantitative geographic tools to increase awareness on the visual environment as a provider of cultural ecosystem services and, more generally, NCP. For this purpose, the concept of intangible (non-material) natural resources will be used. It emerged within the local Ukrainian school of environmental geography (Prof. Bagrov and Prof. Bokov (V.I. Vernadsky Taurida National University), Prof. I. Chervanyov (V. N. Karazin Kharkiv National University)). Noteworthy is that the considered problematics is elaborated primarily using economic discourse, since much of environmental economics is concerned with a scarcity of natural resources, and intangible natural resources, being non-material and, therefore almost inexhaustible (given that factors of their formation are persistent), provide a source of hypothetically endless economic gain. Based on previous assumptions, we suggest the following definition of intangible natural resources: conditions of outdoor environment (with a significant part of natural or semi-natural origin, possibly managed or designed but not purely artificial) that positively influence people's quality of life, well-being and health and enable cultural ecosystem services and NCP use; it also is applicable to the management of associated natural resource rents.

The objective organisation of visual environment—physical (abiotic), ecological (biotised), and cultural (anthropised)—is a typical subject of mapping and monitoring by means of remote sensing, complementing the field research. The objective environment acts as a source of three types of information [Weizsäcker (1974) as described by Naveh and Lieberman (1984)]: syntactic (arrangement of signs, pattern), semantic (meaning, symbolic), and pragmatic (related to active use by receiver), affecting the behaviour of receivers. People act as receivers of information, interpreting it as landscape conditions (intangible natural resources) for various outdoor activities (cultural ecosystem services or non-material NCP), assessable by means of social media analysis and various kinds of crowdsourcing. Semantic information supports the intrinsic values, while syntactic and pragmatic information are responsible for relational ones, important for sustainable decision-making for purposes of nature conservation, landscape design and management. Figure 1 presents the logical chain of research: how natural conditions (expressed visually as physiognomic attributes) become conceptualised as natural capital (by means of intangible natural resources). It is easily seen that remote sensing and GIS can be used for quantification of intangible natural resources, but such quantification should be validated with people-generated subjective data, such as coming from social media.

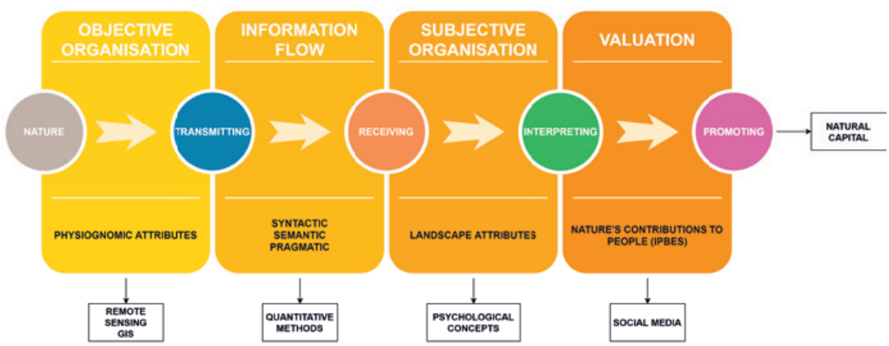

Fig. 1. "Logical chain" of the research; intangible natural resources are covered here by the concept of natural capital. Inspired by the ecosystem services delivery chain (Haines-Young and Potschin 2010), but with a focus on natural organisation and theory of information.

We will discuss further the selected visual intangible natural resources for landscapes within the study areas in Estonia and Portugal, namely, the extent of landscape coherence and colour harmony of land cover in relation to outdoor photographing preferences. Chapter 2 presents the literature review, substituting the relevance and methods, used further. Chapter 3 describes aims, research questions and hypotheses, while the following chapters follow common Methods-Results-Discussion scheme, and Chapter 7 finalises the thesis with conclusions. Methods, results and discussion are the compilation of the methods, results, and discussion from the manuscripts that were published (paper I covers the theoretical topic of remote sensing applicability for landscape pattern mapping; papers II and III propose the colour harmony and landscape coherence indices respectively; and paper IV examines the proposed indices in Estonia). However, the introduction, literature review and conclusions are completely original providing a wide context for interpretation of the published or submitted results.

2. REVIEW OF THE LITERATURE

2.1. Economic relevance: justification of intangible natural resources

The basic anthropocentric idea behind the economic value of landscape has been extensively implemented in form of CES studies; this common purely economic perspective on CES even becomes the reason for their criticism (Chan et al. 2012; Díaz et al. 2018; Pires et al. 2020). In contrast, the economic value of particular landscape features and attributes was directly synthesised, with minor references to the ecosystem services concept, just in a few major undertakings (Price 2013; Price 2017), supporting the integration of landscape ecology and landscape economics (Tagliafierro et al. 2013; Tagliafierro et al. 2016). This thesis does not apply any monetary evaluations of landscape; however, it can facilitate the task of such integration, considering the landscape attributes as intangible natural resources. The problem is that a high level of uncertainty associated with subjective landscape attributes may prevent them from substantial economic analysis (van der Heide and Heijman 2013). Standard metrics of visual landscape quality may help to internalise landscape into the body of economics; for example, a GIS-based landscape appreciation model in the Netherlands is reported to be useful for economic analysis (Sitjsma et al. 2013).

The notion of intangible natural resources benefits from the thesis of Peruvian economist Hernando de Soto from his well-known book, "The Mystery of Capital: Why Capitalism Triumphs in the West and Fails Everywhere Else," highlighting the importance of property rights and recognition of all kinds of economic activities for economic development (De Soto 2000). He argues that the prosperity of countries depends on the ability of economic actors to internalise natural resources into legal economic domain, turning them into natural assets and capital rather than on just presence of such resources (hence, resource curse). Indeed, despite the fact that from ancient times natural resources were typically discussed as a basement for wealth of countries, the second half of the 20th century saw the beginning of the economic value of natural resources complementing other ascending problematic concepts: externalities (1920; 1958), tragedy of commons (1833; 1968), Dutch disease (1977), and resource curse (1993). Even though there is still no single formula for economic success, economists began preferring other factors, such as the institutional capacity and services sector, human capital, and a "green economy" share in the whole economy of states. In other words, democratisation and growth of economic transparency leads to the increasing wealth of countries, and vice versa, hidden or unrecognised economic activities tend to retard the economic progress; in this way, availability of natural resources is closely linked to the quality of adopted management practices (Durnev and Guriev 2007; Guriev and Sonin 2008).

Because of the reasons mentioned above and also as a result of the Green Revolution (or Third Agricultural Revolution in the 1960s), and the boom of green innovations that we are witnessing today the economies of the most developed countries are becoming less dependent on traditional non-renewable natural resources, such as oil products or soil fertility (Fücks 2013). The main aim of the ongoing green revolution and numerous start-ups is to prove that the trend towards the environmental sustainability does not inhibit economic growth. In contrast, economic sustainability can be supported by environmental initiatives. Thereby, a process of the economic internalisation is going on, from the wider utilisation of available renewable resources (such as sunlight or wind) to commoditisation of intangible properties of nature, supporting travel and tourism industry, which created about 10% of the global GDP in 2017 (UNWTO 2017). The ultimate goal of such efforts is to operationalise those economically profitable natural bodies and phenomena that may support economic growth *without losing environmental quality* on Earth. Despite the fact that such commoditisation may not seem ethically correct, we argue that turning an environmental quality (ecosystem or landscape quality, first of all) into an economic asset is a rational way to sustain it (Turner et al. 2019). Therefore, our "mission" in economic domain is to contribute to the articulation and operationalisation of those intangible conditions of nature, which have actual or potential benefits for human well-being and quality of life, by means of more accurate objective assessment with novel methods (remote sensing and social media).

We argue that environmental science and nature protection will benefit from deeper incorporation of economic concepts, discussing favourable environmental conditions as non-material natural resources within the inter- and cross-disciplinary studies. Given the fact that sustainability is usually discussed as based on three equally important pillars—environmental, economic and social—this logic complements some attempts to recognise landscape ability to provide services (including cultural) within landscape sustainability approach (Musacchio 2013; Wu 2013). To sum up the economic relevance, we argue that the quality of environmental management affects economic growth and vice versa; therefore, because of the absence of the CES market and underestimation of ecosystem/landscape conditions responsible for human well-being, outdoor recreation, leisure activities, and nature-based tourism, those ecosystem/landscape conditions should be assessed as valuable intangible natural resources that are a source of economic gain and basis for cultural ecosystem services (non-material people-nature interactions). Remote sensing and GIS can advance non-monetary (and further integrated to monetary) assessment of these conditions in combination with ground-based social media data and public surveys.

2.2. Environmental relevance: Can non-material values be connected to objective natural patterns and processes?

Several years ago, the conceptual possibility of linking non-material values to the objective structures of environment within the ecosystem services framework was debated by Daniel at al. (2012) and Kirchhoff (2012). One of the key arguments by Kirchhoff, who was against such linking, was “the sense of a poem results from a meaningful arrangement of words and not from a pattern of ink on the paper” (Kirchhoff 2012). This distinction continues the sound discussions on the topic of quantitative landscape evaluation, dating back to 1960s and choosing between a more ”holistic” and subjective assessment of environment on the one hand and a component-based objective approach (Lothian 1999; Price 2013) on the other. Still these two opposite directions of landscape research co-exist, mutually complementing each other. The European Landscape Convention (2000) attempts to combine them in the broad definition of landscape: “Landscape means an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors”. However, the vast majority of landscape-related studies still utilise either objective (often GIS-based) models of landscape deconstruction, such as “patch-corridor-matrix” (Forman 1995), with various spatial and functional pattern models (Bell 2012; Antrop and Van Eetvelde 2017a), or subjective deliberative and participatory methods, such as in-depth interviews, sociological surveying, focus group workshops, polls and debates (Waterton 2019).

Following to some extent Marc Antrop and Veerle Van Eetvelde (2017b), we argue that the notion of landscape should play rather integrating role, bridging opposite intellectual traditions. According to Granö (1997; Antrop 2013), a pivotal status of visual perception of distant environment compared to multisensory perception of its closer parts, differs landscape from so-called "proximity". Therefore, landscape researchers deal with patterns of distant visual environment. Quantification of the landscape pattern for purposes of its visual and functional understanding traditionally occurs by means of information theory (Nowosad and Stepinski 2019). Information, as Figure 1 illustrates, can be interpreted within three main categories (Naveh and Lieberman 1984): syntactic information (measured with classic formulas by Hartley and Shannon as function from some set of distinct elements), semantic information (meaning, subject of the dispute between Daniel and Kirchhoff in 2012), and pragmatic information (inducing receiver's actions). Semiotically interpreting landscape as a text (Lindström et al. 2019), landscape was frequently examined with syntactic information-based landscape metrics and indices (Uuemaa et al. 2013; Antrop and Van Eetvelde 2017c). Semantic and pragmatic information affecting intrinsic and operational nature-related values (Pascual et al. 2017) was neglected instead. We argue that completely information-based definition of landscape as a visual abiotic, biotised and anthropised environment, transmitting the syntactic, semantic, and pragmatic information to the human observer as a receiver, encompasses all the complexity of objective and subjective approaches to landscape conceptualisation. Those information concepts also resonate with theories of landscape preferences; the most widely adopted theory is currently so-called "information processing theory" by Rachel and Stephen Kaplan from the University of Michigan (Kaplan and Wendt 1972; Kaplan and Kaplan 1989; Kaymaz 2012). This theory focuses on organisation of visual environment as a driver for arousal of landscape appreciation; diversity, complexity and heterogeneity of landscapes (assessable by means of objective landscape metrics) are in a core of modern landscape assessment studies (Dronova 2017; Albert et al. 2019; Dronova 2019). Earlier, Berlyne's and Wohlwill's approaches to environmental aesthetics, the famous prospect-refuge theory, Gibson's theory of affordances, and even Gestalt principles, mentioned in this context as well (Kaymaz 2012; Bell 2012), are focused either on visual organisation of symbols, pragmatic information, or syntactic information—of course, indirectly, but all these theories can be described in terms of information processing.

From a geographic perspective, mapping of environmental conditions is a source of information about the visual environment, being connected in this way to the landscape problematics, intangible natural resources and cultural ecosystem services. Landscape attributes are becoming more assessible and monitorable with tracking status and trend of the land, water, soil, air and other processes, such as urbanisation or desertification, spatially and over time. The leading role in understanding and monitoring of environment belongs to the remote sensing of various spatiotemporal resolution. Globally available sources of data on environmental quality are pivotal for achievement of sustainable development goals (Espey 2019), thereby our primary task is to contribute to the conversion of the raw environmental data (such as satellite imagery or social media data) to the valuable information about visual quality of environment (Karasov et al. 2018; Karasov et al. 2020b). Remote sensing is a worldwide available data acquisition method, supporting sustainable development (Guo 2020). Passive crowdsourcing is a methodologically advanced method of collecting the information about environment and individual landscape experience, both in contexts of nature conservation (Ghermandi and Sinclair 2019; Toivonen et al. 2019) and urban planning (Ilieva and McPhearson 2018).

Supervised and unsupervised classifications are applied to create categorised maps of land use and land cover (LU/LC), which are the most commonly used for ecosystem services mapping compared to other remote sensing tools (Karasov et al. 2019; Tavares et al. 2019). It is interesting that those applications of remote sensing are highly dependent on perceptual and cognitive phenomena: LU/LC classifications reflect language-based distinctions between areas, while satellite imagery bands include also the visible spectrum (so-called "natural colours"), corresponding to the human perception of colours. In this way remote sensing can facilitate the monitoring of environmental conditions with the monitoring of visual quality of environment. Reliable objective quantitative indicators, based on remote sensing data and confirmed with in situ Earth observations, may create the basis for economic estimations of endowments of intangible natural resources. To sum up, the visual configuration (organisation) of environment, assessable and monitorable by means of remote sensing techniques, exposes visual stimuli to the observer, creating specific landscape experience and, arising as a result, non-material values.

2.3. Social relevance: how individual landscape experience turns into knowledge

Philippe Saint-Marc, a modern French philosopher, is among the first authors who recognised the importance of the nature as a public good, or commons (Saint-Marc 1971). He suggested the dichotomy of "to have" and "to be": to have some things or material goods, and to be healthy, happy, and satisfied. This fundamental distinction also highlights the importance of the topic of intangible natural resources as publicly available characteristics of environment, boosting its habitability for people and responsible for people's well-being and health. Especially, the problems of intangible environmental quality are recognised within the tourism and recreation (Sonter et al. 2016; Schirpke et al. 2019) and urban quality studies (Martínez Pastur et al. 2016; Chen and Xu 2016), since the vast majority of the world population lives in urbanised areas.

Article 5 of the European Landscape Convention obliges parties "to establish procedures for the participation of the general public, local and regional authorities, and other parties with an interest in the definition and implementation of the landscape policies", highlighting the importance of bottom-up approach and public engagement in decision-making. Indeed, environmental awareness and everyday environmentally friendly habits are gradually becoming increasingly popular. Alongside global environmental threats, such as climate change, bottom-up activities and local conflicts of interest on environmental basis are much more understandable and engaging for local communities (Suškevičs et al. 2019; Storie and Külvik 2019). Therefore, reliable estimations of visual quality of environment give an additional tool for resolving local conflicts through evidence-based decision-making, more informed publics, business and government. Another aspect, remote sensing and location-based social media (LBSM), can be used jointly in order to complement each other as top view and ground-based data; there are many of successful examples of citizen science and remote sensing interdisciplinary research (Fritz et al. 2017; Calcagni et al. 2019). In this way, local evidences on visual environmental quality can be explored globally, creating "a big picture" for large-scale analysis.

In the digital era, the social component of environmental research increasingly involves location-based social media (for ease, this umbrella term will be used to encompass all mobile applications, social networks and photo hostings for geolocated photographs). This approach seemed especially fruitful several years ago, when Flickr, Instagram and Panoramio could be jointly used to examine people's spatial behaviour and landscape values (Van Zanten et al. 2016). Unfortunately, when Facebook acquired Instagram in 2015 (and Camridge Analytica scandal in 2016) and Google stopped support of Panoramio in 2017, these major services were no longer available as open sources of geolocated photographs. Instead, Russian-based service VK.com is becoming more popular for such purposes (personal observation at the ESP 10 World conference in Hannover, Germany, 2019), and Flickr continues to be widely used.

Passively crowdsourced geotagged imagery from social media is highly applicable for urban studies due to the high population concentration (Ilieva and McPhearson 2018), but, of course, it also reflects the everyday interactions of people with their outdoor environment, tourism, leisure and recreation activities, aesthetical preferences and scenic values (Seresinhe et al. 2018). A passively crowdsourced digital footprint has been used for:

(i) the assessment of touristic place visitation rates (Wood et al. 2013; Sonter et al. 2016; Levin et al. 2017),

(ii) mapping landscape values across spatial scales (Thiagarajah et al. 2015; Van Zanten et al. 2016; Oteros-Rozas et al. 2018),

(iii) mapping landscape aesthetic flow (Tenerelli et al. 2017; Langemeyer et al. 2018; Tieskens et al. 2018; Bubalo et al. 2019),

(iv) flow, demand and supply of cultural ecosystem services (Fuchs et al. 2009; Casalegno et al. 2013; Tenerelli et al. 2016; Gliozzo et al. 2016; Figueroa-Alfaro and Tang 2017; Yoshimura and Hiura 2017; Richards and Tunçer 2018; Lee et al. 2019), and

(v) analysing landscape perception (Dunkel 2015; Hao et al. 2016).

Content analysis of the geolocated photograph for purposes of its further linking to landscape composition or mapping cultural ecosystem services is one of the most time- and labour-consuming processing issues, previously often solved manually (Richards and Friess 2015; Tieskens et al. 2018). However, advances in machine learning (image recognition models, based on neural networks), significantly simplify the content analysis (Richards and Tunçer 2018; Lee et al. 2019). More efficient computer vision methods, automatizing content analysis of images, allow the extraction of to-date knowledge about subjective parts of people-nature interactions, complementing traditional forms of offline people engagements (surveys, workshops, interviews, etc). Obviously, use of VGI is not free from difficulties, because researchers in most cases cannot analyse personal information about a landscape observer or recreant, such as age, gender, or cultural and education background, etc. Instead, VGI may overcome traditional issues of offline surveys, such as intrusiveness, reproducibility, representativeness because of the usually small number of participants, continual temporal and spatial coverage. Moreover, as it will be shown further, VGI can be integrated to the remote sensing studies as a proxy of people-environment interactions, allowing for mapping of comparatively large areas, up to the size of a country as in our case, or even up to continent (Van Zanten et al. 2016). To sum up, GIS- and remote sensing-enabled tools represent a positivistic approach to the explanation of landscape values, and the social media approach is substituting a phenomenological, or subjective approach to landscape valuation. The only problem is to establish the mutual points of interests between these opposite intellectual traditions; we argue that the solution lies in attributes of landscape character.

2.4. Visual landscape quality assessment

Landscape character attributes serve as an interface between map-based and visual environmental characteristics for purposes of visual landscape quality assessment (Fry et al. 2009; Martín et al. 2016; Swetnam et al. 2017). Daniel and Vining (1983) classified the variety of approaches to the landscape quality assessment into the five main models, ranging from purely objectivistic to absolutely subjectivistic (Tveit et al. 2018). The ecological model does not imply any subjective landscape experience, excluding people from analysis or considering them just as a part of landscape (Angelstam et al. 2013). Within this approach, the most basic landscape attributes, such as a degree of landscape naturalness or even wilderness (Daniel and Vining 1983) and heterogeneity (Balling and Falk 1982; Dronova 2017), are examined. The formal aesthetics model is based on visual primitives of environment: points, lines, shapes, density and variety, colours, textures and volumes. It is therefore not surprising that this model appears to be the most commonly used by landscape architects or in formal visual resources examination adopted in the United States (BLM 1986; U.S. Forest Service 1995; Bell 2004; O'Connor 2010; Bell 2012). The psychophysical model takes the best from both paradigms and integrates geographical knowledge on the environment with its subjective valuation (Arriaza et al. 2004; de la Fuente de Val et al. 2006; Ode et al. 2008; Ozkan 2014; Vukomanovic et al. 2018; Tieskens et al. 2018; Oteros-Rozas et al. 2018). In this study we use formal aesthetics principles (papers II and IV), as well as psychophysical approach (papers III and IV).

Landscape coherence is quite a mainstream term, which is predominantly used within two contexts: ecological and psychological. Ecological landscape coherence itself is of a little interest within the framework of our psychophysical research (Karasov et al. 2020a), because it is based on extent of ecological connectivity (in sense of species' migration) or, vice versa, landscape division and fragmentation. However, this particular approach has resulted in many GIS-based applications with spatial autocorrelation (Mander et al. 2010) or connectedness and fragmentation indices (Jaeger 2000; Saura and Pascual-Hortal 2007; Nowak and Grunewald 2018). In contrast, there had been no attempts to apply GIS-based approach to mapping subjective landscape coherence until recently, except for borrowing traditional GIS-based metrics from ecological studies (Ode et al. 2008; Martín et al. 2016).

Thus, mapping of subjective landscape coherence seems a challenging and novel task. Difficulties in its quantitative assessment emerge because of the large number of definitions and connotations. Many authors connect landscape coherence to quite a philosophical and, therefore, rarely used concept of landscape harmony (U.S. Forest Service 1995; Tveit et al. 2006; Sowiſska-ſwierkosz 2016). Here we limit ourselves with the notion of landscape coherence only, but harmony should be mentioned here to understand the overall unity of the thesis. So, according to Kaplan and Kaplan (1989), who made this concept mainstream, coherence differs complex landscapes from messy ones. References to organisation and order are the most frequent among the classic and contemporary attempts to describe landscape coherence (U.S. Forest Service 1995; Rosley et al. 2013; Pazhouhanfar and Mustafa Kamal 2014; Kuper 2017).

Objective landscape coherence is referred to the vertical, horizontal or temporal relationships among landscape components (van Mansvelt 1997; Kuiper 1998). Antrop and Van Eetvelde tend to comprehend both objective and subjective approaches to the landscape coherence within the holistic paradigm (2017a), "Coherence expresses the strength of the relations between landscape elements and components… Coherence stimulates legibility of the landscape". Moreover, "Order expresses the degree of certainty that is experienced in a landscape, as opposed to the uncertainty associated with disorder or chaos. It is often expressed and measured by the information entropy. The order relates to many other indicators such as heterogeneity, complexity, coherence, harmony, predictability, legibility and disturbance" and "We perceive and experience this coherence as order" (Antrop and Van Eetvelde 2017a). Another definition describes landscape coherence as "… an ordered structure that we can understand and where the comprehension of the whole is more significant than the individual parts" (Bell 2012). Noteworthy is the connection between the coherence and information theory, as well as with system properties, or emergence (comparison of the whole and its individual parts).

Landscape coherence, measured in a subjective way, was reported as having an uneven positive association with landscape preferences, ranging from rather weak (Sevenant and Antrop 2009; van der Jagt et al. 2014; Kuper 2017), to medium and strong (Kaplan and Kaplan 1989; Herzog and Bosley 1992; Stamps 2004; Herzog and Kropscott 2004; Herzog and Bryce 2007). Therefore, the topic of landscape coherence seems to be understudied, and the overall feasibility of GIS-based approach is not obvious, while studies generally support validity of the preference matrix by Kaplans. Both the conceptual diversity and weak GIS- and remote sensing-based elaboration of its mapping with subjective principles in mind make it highly relevant for further research. To avoid any semantic misconceptions, we consider landscape coherence as a key component of the landscape harmony, along with colour harmony.

Colour harmony of landscape is another big topic that conceptually complements the notion of coherence, because of the conceptual unity of the concepts of coherence and harmony (U.S. Forest Service 1995; Tveit et al. 2006; Sowiſska-ſwierkosz 2016), and also because all the elements of environment can be physically described with colours, which are inherent spectral properties of real world. In this way, harmony of colours is to a significant extent a component of the overall landscape harmony, responsible for the visual landscape quality (Sullivan and Meyer 2016). At the same time, authors tend to examine just colour diversity or discuss specific natural colours in the context of visual landscape quality and preferences instead of proceeding to their harmony (de la Fuente de Val et al. 2006; Acar and Sakıcı 2008; Lengen 2015; Swetnam et al. 2017; Dronova 2017; Kuper 2018). No studies assessing and mapping the extent of colour harmony of landscape over the large areas using remote sensing data were found. We argue that landscape studies will benefit from wider implications of the theory of colour harmony, well-developed in art, design and, more importantly, experimental psychology.

Colour harmony depends on "how strongly an observer experiences the colours in the combination as going or belonging together, regardless of whether the observer likes the combination or not" (Schloss and Palmer 2011). Chamaret (2016) distinguishes three categories of colour harmony models:

- geometrical (based on classical assumptions regarding the mutual locations of the colours under consideration on the colour wheel), for example, Itten's (1973) well-known theory (Westland et al. 2012),

- more recent numerical models, making colour harmony quantifiable with remote sensing (Caivano 1998; Ou and Luo 2006; Schloss and Palmer 2011; Nemcsics 2012), and,

- a conceptual contingent model suggested by Zena O'Connor (2010).

The numerical models differ in terms of the detected aesthetical regularities (not least because of the evolution of the concept of colour harmony and preferences-caused bias), but recently some universal principles for colour harmony were agreed upon among the several the most cited researchers in the field (Ou et al. 2018). Borrowing psychological regularities from the literature, we can attempt to adapt them for landscape evaluation applications with remote sensing as a formal aesthetics study.

3. STUDY OBJECTIVES AND HYPOTHESES

This study was guided by two general objectives and hypotheses:

1. To retrieve landscape harmony information from GIS data and satellite imagery (**hypothesis**: satellite imagery is applicable for mapping of the valuable landscape attributes, including colour harmony of land cover and landscape coherence), and

2. To extract evidence of CES use from location-based social media (**hypothesis**: the combination of automated image processing and topic modelling facilitates CES use mapping with passively crowdsourced geolocated photographs).

Particular matters of the research process are described as follows, using the set or research questions (RQ) and sub-question (SQ). The first challenge was to investigate with literature which attributes of visual landscape are explorable and assessable by means of remote sensing techniques. The aim was to identify the perceptual and cognitive attributes of visual landscape and explain the remote sensing applicability for tasks of their mapping. The first research question was established:

RQ1: How can visual landscape studies benefit from usually biophysically oriented remote sensing (Paper I)? We intuitively extracted from literature the perceptual and cognitive landscape attributes (our distinction) and explored the papers, in which they are somehow mapped or measured with remote sensing.

Based on the results of literature review, two cognitive landscape attributes of high research interest were revealed: colour harmony of land cover and landscape coherence. The second key challenge was to explore the spatial variation (pattern) of extent of colour harmony of land cover within the Vooremaa Landscape Protection Area in Estonia. The aim was to develop a new interdisciplinary method of colour harmony mapping for land cover with remotely sensed products. Hence, the second research question is formulated as follows:

RQ2: How can colour harmony of land cover as an essential component of aesthetic and cultural landscape values be quantified (Paper II)? To answer the second research question, we formulated a bunch of the following related sub-questions:

SQ2.1. How consistent are the maps of the extent of colour harmony produced within the different frameworks? This sub-question addresses the variety of colour harmony estimation approaches and which methods are appropriate to be applied for satellite imagery. Should we use the colour wheel or empirical psychological results from the literature? What kind of colour space instead of RGB is suitable?

SQ2.2. How does the mean colour harmony index vary for different land cover classes? Here we explore which land cover classes are the most responsible for higher colour harmony of land cover. Does colour harmony extent decrease with increasing cultural modification of land cover classes?

SQ2.3. Which geographic attributes explain the distribution of colour harmony values? The third sub-question aims to identify the environmental variables, explaining the spatial pattern of colour harmony. Does it change with increasing distance from the main roads, or temperature of land cover, or modelled wetness? Understanding of relationships between these variables and colour harmony makes it manageable.

SQ2.4. How does remotely assessed colour harmony extent correspond to actual scenery alongside the roads? The most challenging sub-question links estimations of colour harmony from top view perspective with ground-based photographs, taken along the transect (road). How do actual roadscape photographs reflect modelled colour harmony extent?

The third main challenge for landscape pattern examination was to convert the psychological notion of landscape coherence, reported to be predominantly positively correlated to landscape values and preferences, to the GIS-based indicator. The aim was to understand the landscape coherence with theory of information, namely utilize Hartley entropy to estimate the relationship between the terrain and land cover as one holistic entity (system). The geographic extent of the study was the

Peneda-Gerês National Park in Portugal. The third research question is the following:

RQ3: How can the landscape coherence be quantified objectively, but at the same time based on the subjective landscape coherence notion (Paper III)? Respectively, another set of sub-questions was established:

SQ3.1. How does the GIS-based model represent the objective landscape organisation, utilising the landscape coherence concept? Landscape coherence has many implications in GIS using ecological connotations. How can the psychological notions of landscape coherence and GIS-based methods, based on concepts of organisation and emergence be linked?

SQ3.2. How does the landscape coherence indicator relate to the uneven spatial pattern of photographs taking frequency evidenced from the location-based social media? As an indicator of landscape values and preferences, landscape coherence extent should be hypothetically reflected in the photographing preferences. Do people prefer to take photographs of the places of more coherent landscape?

SQ3.3. How is the suggested indicator applicable to landscape management and planning? We assumed that, as landscape is a subject of management (Council of Europe 2000), landscape coherence pattern among the parametric landscape classes based on TPI landform classification and CORINE land cover will become a suitable for management, being linked to particular known spatial units. Which landscape classes are less and more coherent?

The last, but not least, challenge was to proceed from landscape pattern-based studies to deeper understanding of the content of geolocated photographs. The geographic coverage was the entire territory of Estonia (excluding built-up areas to filter indoor photographs) and data sources were publicly available VK.com and Flickr outdoor photographs. The aim was to identify various groups of CES demand in the sample of photographs, map the spatial concentrations of particular CES, and relate CES use to the landscape coherence and colour harmony, mapped based on previous findings. Hence, the research question is the following:

RQ4. How may the photo-series and textual analysis be used to reveal CES use within Estonia (Paper IV)?

SQ4.1. What are the main groups of CES, evidenced from social media in Estonia? Since the complete variety of cultural ecosystem services is hardly detectable with location-based social media (LBSM), and there is a significant volume of non-relevant content, we classified all the relevant photographs to one of three main categories.

SQ4.2. What is the association between the landscape coherence and colour harmony of land cover, and CES? Do people in Estonia take photographs with consideration for landscape coherence or colour harmony during their outdoor activities? This knowledge would contribute into a deeper understanding of landscape aesthetics, values and preferences.

The basic assumptions, used when working on the thesis materials, were:

- Psychological notions of colour harmony and landscape coherence can be quantitatively assessed with objective indicators;

- The pixel of GIS-based model or remote sensing imagery (scene or mosaics) is an elementary unit of top perspective landscape research;

- A geolocated photograph in open access, uploaded to the social media, is an elementary unit of ground-based landscape research; and

- Remote sensing- and ground-based landscape research are combined by means of viewshed analysis, outlining the visibility area for each geolocated photograph.

4. MATERIALS AND METHODS

Our research aimed at comprehending the approaches to landscape evaluation, such as formal aesthetics and the psychophysical model, with quantitative geographical tools: remote sensing and GIS (geomatics), integrating with in situ photographs from location-based social media as pictorial landscape and CES representations. In particular, we used spectral and textural remote sensing analysis, supervised classification of land cover, overlay and neighbourhood GIS analysis, statistical exploratory analysis and modelling to find correlations between the variables and identify mechanisms of relationships in some cases.

4.1. Remote sensing feasibility for visual landscape deconstruction (Paper I)

As suggested in our paper I, Figure 2 (made with Tableau Public 10.5 software; Seattle, Washington, USA) provides evidence of the growing interest in visual landscape examination with remote sensing techniques. Developing this figure, we aimed to find in Scopus and Web of Science the papers using cognitive concepts such as "harmony", "diversity", "similarity", as well as features of visual landscapes (points, lines, surfaces, colours, and textures) within the remote sensing framework to examine the current state in this interdisciplinary field. Figure 2 illustrates that naturalness and diversity are the most commonly occurring concepts among the recent remote sensing studies and naturalness primarily relates to land cover classifications and transitions between relatively natural and artificial land cover classes. The interesting finding from this literature review suggests that visual landscape evaluation topic occurs in remote studies rather indirectly (as a side product of other tasks) and dedicated mainly to the ecological model of landscape quality. Rarely, remote sensing papers also utilize the harmony concept to describe the dynamic balance between the natural and artificial land cover, as well as nature-friendly land use (Cao et al. 2013; Fujiki et al. 2018), or proceed to the formal aesthetics (Karasov et al. 2018) and psychophysical models (Ayad 2005; Ozkan 2014; Vukomanovic et al. 2018; Karasov et al. 2020a).

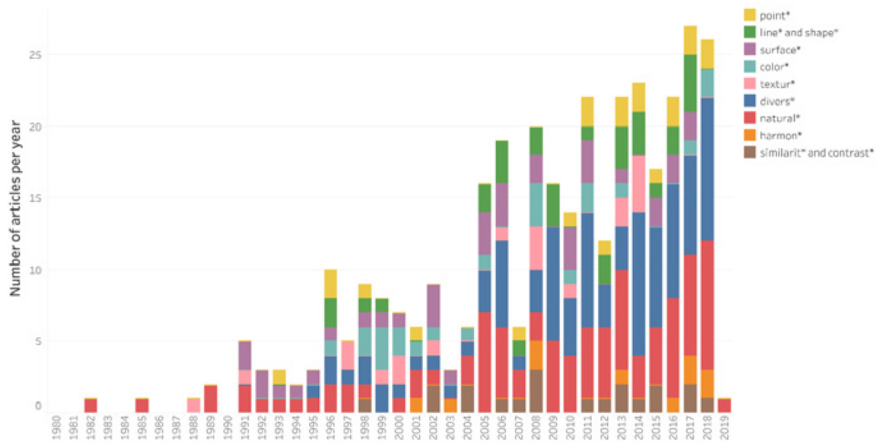

Fig. 2. Growing number of articles in per-reviewed journals as of the beginning of 2019 (indexed by the Web of Science Core Collection indices and Scopus per year) operationalising some spatial landscape attributes with remote sensing (Paper I). The key queries reflecting landscape attributes were searched in conjunction with the remote sensing terms ("remote sensing", "satellite", "earth observation", "UAV", "drone") as well as with the landscape queries (physiognom*, scenic, landscap*). Asterisk (*) means the word ending, intentionally neglected to facilitate the search. Notably, diversity- and naturalness-related topics (ecological model of landscape visual quality) have become the most popular and well-studied recently.

The methodological basement for application of remote sensing models is clear from Figure 3, representing DEM, DSM and aerial orthophoto for the example area in Estonia and borrowed from Paper I. Active remote sensing is used to detect the surface of bare ground (land relief) and also canopy and built-up areas surface, while passive remote sensing is responsible for multi- and hyperspectral caption of colours and textures. Remote sensing-based models are applicable for both ecological (naturalness and diversity), formal aesthetics (points, lines, colours, textures, shapes, to some extent volumes), psychophysical (spectral and textural indices, other indicators in conjunction with subjective evaluations from psychological or phenomenological studies) approaches to visual landscape quality evaluation. For simplicity, we have drawn the distinction between the perceptual landscape attributes, directly detectable with remote sensing (geometrical primitives: points, lines, areas, colours) and cognitive landscape attributes, requiring mathematical equations or mind operations to be mapped (naturalness and diversity, harmony and fragmentation, similarity and contrast, temporal variability).

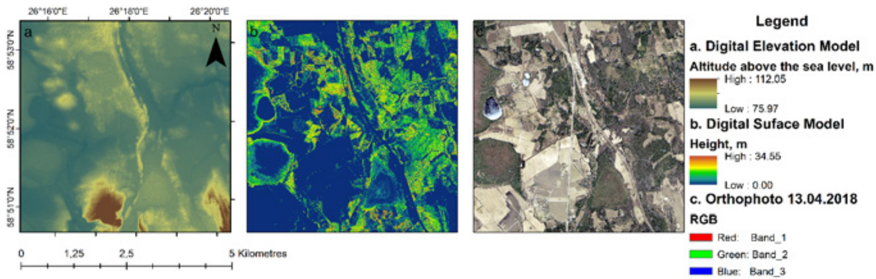

Fig. 3. Remotely sensed data for an area in Eastern Estonia (panel a – LiDAR-based digital elevation model, panel b – LiDAR-based normalised digital surface model, panel c – multispectral orthophotograph captured 13.04.2018, natural colours band combination), which are commonly used to deconstruct the physiognomic landscape (Paper I). There are easily recognisable linear patterns, as well as various textures typical for different land cover classes (water bodies, crop fields, forest), orthophotograph reflects the perceivable colours of land cover, DEM and DSM represent surfaces of perceived environment. Pixels assigned with spectral or elevation values are in relationships of similarity and contrast, diversity, colours and land cover classes may be in harmony (Data credit: Estonian Land Board, Maa-amet).

4.2. Mapping colour harmony of land cover with remote sensing in relation to environmental characteristics (Paper II)

For purposes of colour harmony mapping, we have decided to use HSV transformation, remarkably often used in remote sensing for the wide range of operations (Marcelino et al. 2009; Baykan and Yilmaz 2010; Pekel et al. 2011; Pekel et al. 2014; d'Andrimont and Defourny 2018). Chroma and lightness in the further text correspond to Saturation and Value dimensions in HSV colour space. It should be noted that various colour spaces are used in colour harmony research; they differ mathematically but are very similar conceptually (hue as a marker of colour itself, saturation as amount of grey [colour purity], and lightness as amount of white). Correspondingly, our methodology with HSV colour space is the approximation of existing experience rather than exact replication of regularities.

4.2.1. Study area

The study area is described in Paper II; we chose one in Eastern Estonia. This hilly area is a specimen of a postglacial landscape, full of elongated moraine lakes (the biggest one is Saadjärv lake), wetlands, forests, agricultural, rural and urban areas, including Tartu, which is the second largest city in Estonia. We chose this territory of complex landscape pattern, composed of diverse land cover types and landforms, because we intended to explore the spatial variability of colour harmony as aesthetic landscape category. In addition, there are several protected areas, such as the Vooremaa Landscape Protection Area and the Alam-Pedja Nature Reserve (partially). This fact allowed us to check whether the colour harmony within the protected areas is higher than outside (in other words, whether the considered protected areas have higher aesthetic value in general).

4.2.2. Research data

Particulars of the data gathering and pre-processing are described in Paper II. In brief, we used a cloud-free part of the Landsat-8 image as of 17 June 2017 (Figure 4) of its original spatial resolution. As auxiliary GIS data, the EU-DEM 1.1. digital elevation model (DEM) and the CORINE 2012 land cover model (downloaded via the Copernicus Land Monitoring Service) and the LiDAR-based digital surface model (DSM, Estonian Land Board) were used. We also extracted a sample of

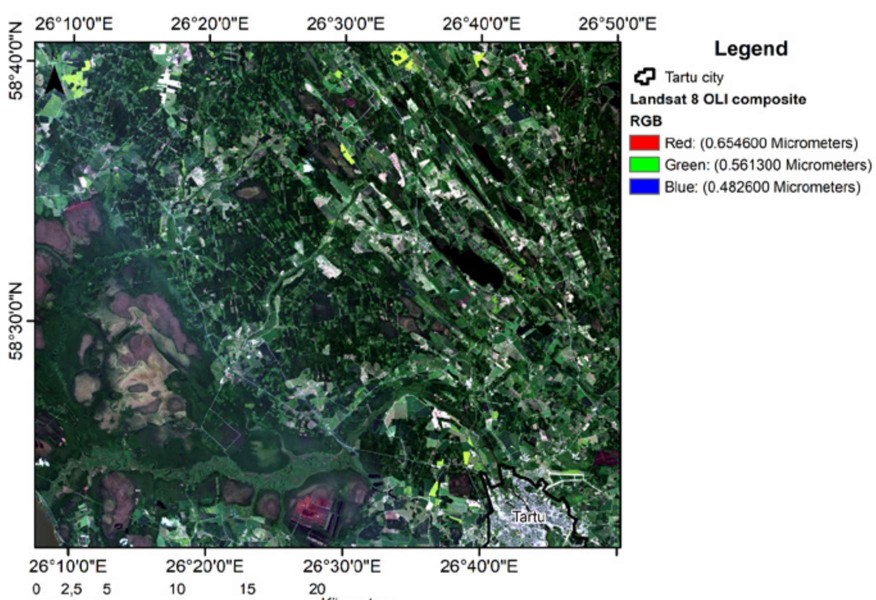

Fig. 4. Pre-processed Landsat 8 OLI scene (dated 17-06-2017, RGB composite), further converted to HSV colour space to measure the extent of colour harmony (Paper II).

five landscape pictures (taken 23 June 2017) from the freely available crowdsourced imagery, provided by Mapillary service (each 150th within the Vooremaa Landscape Protection Area) to explore the variability of visual landscape in relation to the colour harmony estimates. Both satellite and ground-based images were chosen due to their temporal proximity and summertime period of the high vegetation vigour, as well as relatively good atmospheric conditions.

4.2.3. Colour harmony estimation

As indicated in Paper II, Caivano (after Janello) argues (1998), that colour harmony implicates constancy (or similarity, homogeneity) of Hue or Saturation or Lightness scores of the colours under the comparisons. Ou and Luo (2006) generalise several principles of two-colour harmony, including "(a) Equal-hue and equal-chroma; (b) High lightness; (c) Unequal lightness values". These findings are confirmed more recently (Szabó et al. 2010). Schloss and Palmer, in contrast, suggest hue similarity, low saturation and low lightness contrast as colour harmony factors (Schloss and Palmer 2011). Finally, Nemcsics argues that "the most highly ordered colours, according to their saturation and lightness, have the highest harmonious content" (2012). Noticeable that concepts of similarity, difference and orderliness can be covered for pixel pairs (two-colour combinations) with second-order Haralick's textural metrics (Haralick et al. 1973; Hall-Beyer 2017a) – see Table 1 for equations.

Table 1. GLCM-based Haralick's texture metrics and their equations (Paper II).

Pixel-based GLCM texture metrics	Equation
Homogeneity (GLCMH)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{1}{1+(i-j)^2}P(i,j)$
Contrast (GLCMC)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}P(i,j)(i-j)^2$
Second moment (GLCMSM)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\{P(i,j)\}^2$

P(i,j) – the probability of co-occurrence of pixel values *i* and *j*. N_g – the number of distinct grey levels in the quantised image (64 in our case).

Thereby, we converted pre-processed Landsat 8 scene (Figure 4) to HSV space and applied indices from Table 1 to the resulting Hue, Saturation, or Value space according to the colour harmony principles from the literature above. Then the indices of colour harmony were summarised to create the joint Summarised Colour Harmony Index (CHI). The overall GIS-based procedure is illustrated in Figure 5.

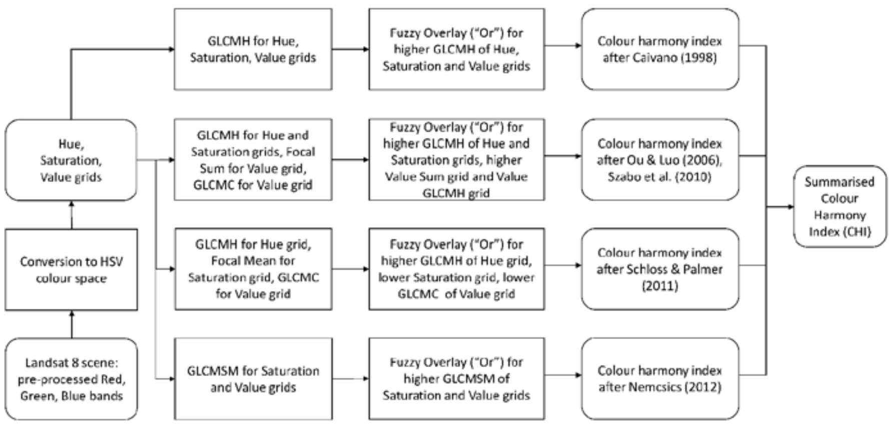

Fig. 5. General GIS-procedure for summarised Colour Harmony Index computation (Paper II). Rectangles correspond to the GIS operations, and rectangles with rounded corners correspond to the raster grids (maps). See the abbreviations explanation in Table 1.

Also, according to the details of the research framework, available in paper II, a LiDAR-based DSM (spatial resolution of 8 m, provided by the Estonian Land Board) of the Vooremaa Landscape Protection Area and surroundings was used in Viewshed analysis using the respective QGIS plug-in, performed for five samples of the Mapillary viewpoints with the observer height of 1.0 m and a 90° maximum horizontal view angle in order to map the area visible from each Mapillary viewpoint. Next, the mean CHI for each viewshed was calculated and visually compared to the content of the Mapillary photographs. In addition, average colour harmony after each author for CHI mapping was compared between the CORINE land cover classes.

4.2.4. Explaining the extent of colour harmony

To understand the factors, underlying spatial changes in CHI, we modelled Box-Cox transformed (to meet the assumptions of the regression model)

CHI as a variable, dependable on the distance cost from roads (Terrain Ruggedness Index as a cost surface, code name Costd_roads), values of the SAGA Wetness Index (SAGA TWI), the brightness temperature (BT) and albedo index (Albedo). Explanatory variables were chosen, using Random Forest algorithm. The Generalised Additive Model–GAM (Wood 2017), implemented in the mgcv R package (Wood 2011; R Core Team 2019), was used to model the relationships between the CHI and explanatory geographic attributes. Compared to the common regression models, GAM is reported to have some advantages, including ease in detection of non-linear effects and automated spline variation, avoiding overfitted models with penalties.

4.3. Landscape coherence as factor of photographing preferences (Paper III)

We understand landscape coherence as the extent to which the properties of digital landscape model (for example, diversity) exceed the properties of its components (Lammeren 2011). Since land relief and land cover are two essential components of landscape pattern (Antrop 2000), we assembled two digital landscape models (DLM), parametrically composed of landforms and land cover models: i) DLM of fine spatial resolution, based on elementary landforms (Minár and Evans 2008) and custom land cover classification based on SPOT and RapidEye satellite imagery; and ii) DLM of coarse spatial resolution, based on TPI (Topographic Position Index) landforms and CORINE land cover. Patches and classes of the DLM of coarse spatial resolution along with floating circle and hexagonal grid were used as the neighbourhood to calculate the landscape coherence index.

4.3.1. Study area

We chose the National Park Peneda-Gerês in northern Portugal as a study area (this part of the research was carried out in Portugal within the individual doctoral project). Peneda-Gerês is the only national park in Portugal; therefore, this territory is highly valuable in recreational and nature protection contexts. There is a rich landscape structure and configuration (Figure 6) due to the complex topographic conditions, climate specifics (strong Atlantic influence) and uneven distribution of the settlements along with agricultural fields in the mountain valleys. In particular, there are explicit vertical relationships between the spatial distribution of landforms and land cover within the park, which make it a highly suitable study area for assessment of landscape coherence (Paper III).

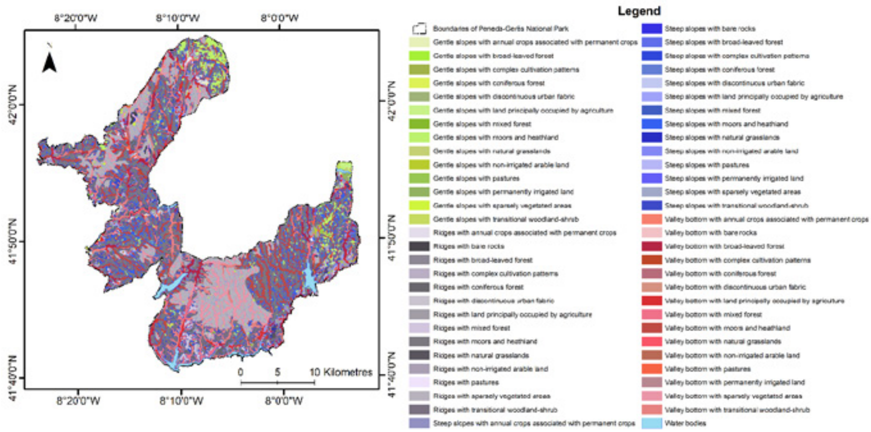

Fig. 6. Coarse-resolution digital landscape model of the study area: the physiognomic classification of Peneda-Gerês National Park (Paper III).

4.3.2. Research data

In paper III we used a digital elevation model of 10 m spatial resolution, created with Topo to Raster ArcGIS tool from the isohypses of topographic map; we designed elementary landforms as unique parametric combinations of the slope steepness, solar exposition, and general curvature (Table 2). We intended to use the landform classification, which is, on the one hand, ecologically meaningful and, on the other hand, applicable for *visual* landscape research. Therefore, we used the slope steepness classification for the mountainous regions, suggested by Zhuchkova and Rakovskaya (2004; Svidzinska 2014). This classification is intuitive and to a large extent oriented on the visual perception of steepness. Solar exposition (aspect in GIS-terms) was taken into account with Whittaker's ecological row due to its ability to bridge the heat supply and moisture conditions, influencing vegetation growth, depending on the slope orientation (Whittaker 1975). In addition, general curvature was used as geomorphometric variable, drawing the distinction between the concave and convex relief and regulating flows of erosion and accumulation of materials. Overall, combination of the mentioned geomorphometric parameters allows to generate a very detailed model of discrete landforms, applicable for the landscape coherence mapping.

Table 2. The categories of the main geomorphometric parameters for elementary landforms mapping (Paper III).

Slope steepness						
Author/criteria	Classes					
Zhuchkova and Rakovskaya (2004): increase in slope steepness	Gentle slopes: 4-10°	Rolling slopes: 10-20°	Moderately steep slopes: 20-30°	Steep slopes: 30-45°	Very steep slopes: 45-60°	Extremely steep slopes: >60°
Solar exposition						
Whittaker (1975): increase in dryness	Northeast to North	Northwest to East	West to Southeast	South to Southwest		
General (standard) curvature						
Curvature: directions of erosion and deposition	Concave: <0	Convex: >0				

Further, the author pre-processed (radiometrically calibrated and atmospherically corrected using ENVI 5.2) the high-resolution SPOT and RapidEye imagery for spring 2011, available at the Department of Geography of the University of Minho and combined them to the cloudless mosaics (Paper III). Applying GIS techniques, the author performed the supervised land cover classification, following the classes of land cover adopted in CORINE 2012 land cover model. In total, we mapped 11 land cover classes (Figure 7).

Also, we collected geolocated photographs from Flickr and Panoramio (currently unsupported) within the territory of the national park for the entire period of the activity of these services until 2015, using manual requests to Flickr and SAS.Planet software for Panoramio. Geolocated photographs were manually checked for non-relevant content; we deleted the photographs of explicit non-relevant content (i.e. taken indoors). Geographic coordinates of the geolocated photographs were further used for viewshed analysis, based on the digital surface model ALOS PRISM: DSM of spatial resolution 30 m and vertical error up to 5 m (EORC & JAXA 2017).

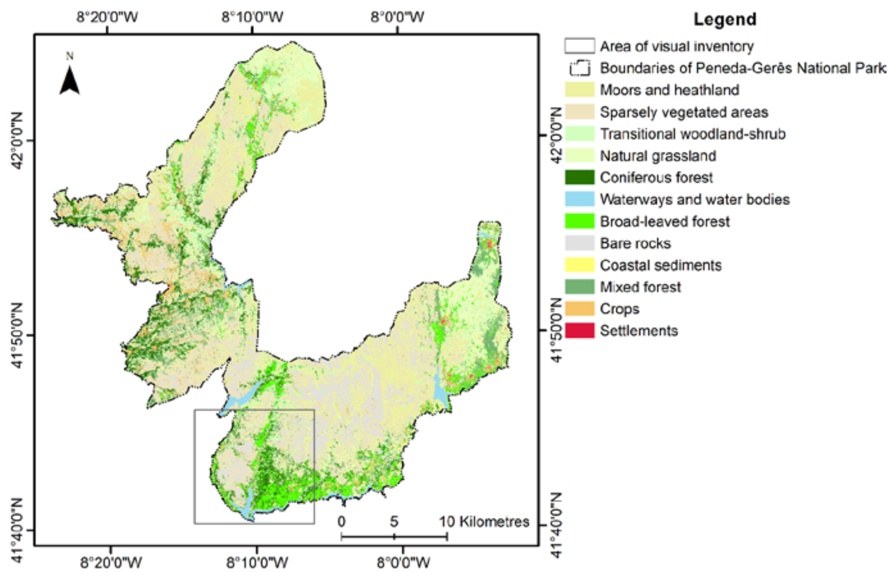

Fig. 7. Fine-resolution land cover model of the study area, composing with elementary landforms a digital landscape model for landscape coherence estimation and mapping (Paper III)

4.3.3. Landscape coherence mapping

The author applied the syntactic information notion to calculate landscape coherence (Naveh and Lieberman 1984). Shannon entropy, or Shannon-Weaver diversity index, is among the most frequently used landscape indices based on the information theory (Uuemaa et al. 2013; Nowosad and Stepinski 2019).

$$H = \sum_{i} p_i \, log_b p_i \tag{1}$$

H is Shannon entropy value, p_i is the probability of the observation (land facet/class *i*) appearing among other observations (landscape, composed of various land facets, classes).

Hartley's formula (Eq. 2) is a simple particular case of Shannon's formula (Eq. 1) for sets with equiprobable elements. We applied this formula to the raster datasets of landforms and land cover, as well as to their parametric combination (digital landscape model).

$$I = log_2 W = n log_2 m \tag{2}$$

I is the amount of information; *W* is a possible number of different land patches/facets/classes; *m* is all number of land patches/facets/classes; *n* is the number of land patches/facets/classes in the one part of a set.

According postulates for the sets E_N, E_M, E_{MN}, consisting of equiprobable N, M, MN elements:

$$I(E_{MN}) = I(E_N) + I(E_M) \tag{3}$$

$I(E_{MN})$ is the amount of information, $I(E_N)$ is the amount of information in the set E_N, $I(E_M)$ is the amount of information in the set E_M. It means that, "The sum of the pieces of information of two independent sets EN and EM is equal to the information of the union set EMN (all sets consist of elements occurring with equal probability)" (Arndt 2001). Therefore, we excluded the assumption of equiprobability for our datasets and assumed that Hartley's information for the digital landscape model will exceed the summarised Hartley's information amounts for landforms and land cover as system components in case they are NOT independent, and landscape demonstrates holistic properties. Consequently, there is a theoretical ground for landscape coherence assessment based on the emergent theory of information (Hartley's emergence coefficient), suggested by Lutsenko (2002). We propose the landscape coherence index (LCI), reflecting this additional system properties of landscape composite, differing it from the sum of its parts (Figure 8, Eq. 4).

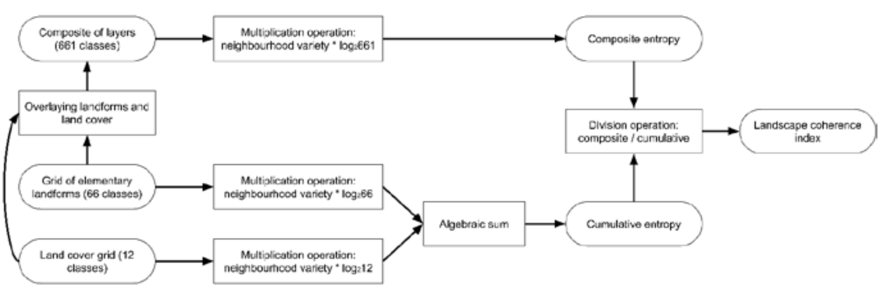

Fig. 8. General GIS-procedure for deriving the landscape coherence index for digital landscape model (Paper III). Raster grids are shown in the rounded rectangles, GIS-operations – in the rectangles

LCI can be calculated as follows:

$$\varphi = \frac{I_{landscape}}{I_{relief} + I_{land\ cover}} \tag{4}$$

φ is the landscape coherence index, $I_{landscape}$ is the amount of information in the digital landscape model, I_{relief} is the amount of information in the elementary landforms, $I_{land\ cover}$ is the amount of information in the land cover model.

To explore the spatial variation of landscape coherence, LCI was calculated within the following neighbourhoods:

- floating circle of 990 m,
- hexagonal grid of 1000 m,
- patches of coarse -resolution DLM (Figure 6),
- classes of coarse-resolution DLM.

Coarse-resolution DLM was used to find the relationships between the estimated LCI and photographing frequency based on Flickr and Panoramio geolocations. Coarse-resolution DLM classes have been ranged according to LCI values to make this index applicable for landscape management.

4.3.4. Landscape coherence in relation to photographing frequency

In Paper III, the particulars of analysis are described, and here we focus mainly on its purpose. Cumulative viewshed analysis is one of the techniques commonly used to quantify the photographing preferences and CES use (Kopperoinen et al. 2017; Lu et al. 2019) as number of DSM pixels, falling inside the viewsheds of geolocated photographs. Author applied the Viewshed Analysis QGIS plug-in with default settings for geolocations of Flickr and Panoramio photographs based on ALOS PRISM DSM (EORC & JAXA 2007). Non-photographed areas were excluded from analysis, and only the extent of photographic frequency was examined as a dependable variable. To meet the assumption of the regression, describing relationship between the cumulative photographic frequency and LCI as explanatory variable; photographic frequency within the study polygons was Box-Cox transformed.

4.4. Mapping cultural ecosystem services, represented in social media (Paper IV)

Content analysis of the location-based social media data has become a common approach to CES mapping, especially if authors are interested in CES assessment over the relatively large areas (Van Zanten et al. 2016; Calcagni et al. 2019). CES, among other ES, are a prerequisite for arousal of diverse values of nature (Potschin and Haines-Young 2011; Martín-López et al. 2016). Therefore, we aimed to contribute into more efficient methodology for content analysis of pictorial social media data, combining automated image recognition (image tagging) with natural language processing (topic modelling to classify tags). The other task was to find out, whether colour harmony of land cover and landscape coherence, as suggested in our previous publications (papers II-III) may influence photographic preferences.

4.4.1. Study area

To increase the research and managerial values of our research, we decided to use the entire territory of Estonia as a study area. Mapping and Assessment of Ecosystems and their Services (MAES) encompasses various international and country-wide projects throughout the European Union, such as OpenNESS and ESMERALDA (Burkhard et al. 2018; BISE 2020). Our results will contribute (of course, being continued and using reproducible tools) to the aims of the Estonian MAES-related project L180249PKKK (Töövõtuleping nr 4-5/18/40) "Ökosüsteemide ja nende teenuste baastasemete hindamine ja kaardistamine, sh metoodika väljatöötamine Keskkonnaagentuurile (19.12.2018−31.07.2020)", principal investigator Siiri Külm, Estonian University of Life Sciences (the topic can be roughly translated as "Assessment and mapping of basic levels of ecosystems and their services, including development of methodology for the Environmental Agency"). Also, it was interesting to test the colour harmony and landscape coherence mappings over the entire country area, complementing our previous research.

Since, according to DataReportal, 98% of Estonians are Internet users to some extent, and 57% are active users of social media (Kemp and

Kepios Team 2019), cultural ecosystem services, provided by Estonian landscapes are to a significant extent represented in social media, determining the study area choice. This high level of Internet penetration, taken with a well-developed touristic policy and infrastructure, as well as the quite huge share of the Russian-speaking minority in the total population (VK.com is based in Russia), render Estonia a good study area for social media and CES-related studies. What is more, the diverse environmental conditions and numerous protected areas in Estonia enable opportunities for analysis from geographic and nature conservation perspectives.

4.4.2. Research data

For Paper IV we used Flickr (one the most widely used providers of geolocated photographs in the location-based social media studies) and VK.com (the largest Europe-based social network, predominantly used by Russian-speaking minority and tourists in Estonia). We downloaded the photographs' metadata with manual requests to the Flickr and VK.com APIs, including user and photograph ID, longitude and latitude, and the time the photograph was taken and uploaded to the Flickr or VK.com, web-links. Those photographs, located inside the buildings according to the OSM data (OpenStreetMap contributors 2019), have been eliminated; only 21,242 geographically outdoor photographs were further processed and combined into a single Flickr-VK dataset. We did not aim to explore the differences between the CES use by Flickr and VK.com separately, focusing on geographic regularities of landscapes, enabling CES use rather than respective social factors.

4.4.3. Mapping of CES use

Paper IV is dedicated to the conjunctive use of automated image recognition, applied to the geolocated photographs, and natural language processing (topic modelling). We used API requests to Clarifai services (Clarifai Inc., New York), namely to its General model. Each photograph was labelled with tags, describing its content with more than 90% accuracy. Then the procedure of topic modelling, namely Latent Dirichlet Allocation, LDA (Blei et al. 2003) was applied to the tags to cluster them into the pre-defined number of categories with Orange data mining toolbox (Demšar et al. 2013). Tags were classified based on probabilistic approach: how likely they co-occur among the photographs.

Those photographs, sharing the same tags, were assumed to share the same "topic", or specific combination of tags. Photographs of irrelevant tags were excluded from analysis, and the rest of photographs (9,983 photographs out of 21,242) were further automatically classified according to CICES. We devised an *a priori* working hypothesis about the small number of relevant CES (about 3 to 5), according to the CICES classes (Haines-Young and Potschin 2018). The very first three LDA topics already represented the relevant CES croups: landscape watching, outdoor recreation, and wildlife watching.

In addition, we manually post-processed CES-related photographs with common visual content analysis to verify the performance and accuracy of the initiated approach. We transferred to the outdoor recreation category those photographs that were automatically selected for landscape watching if they contained minor presence of people or their equipment; since presence of pets was automatically interpreted as wildlife (the general machine learning model provided by Clarifai does not account specifically for this distinction), we also manually moved these photographs to the category for outdoor recreation. Photographs with a minor presence of wild animals classified as related to landscape watching were also manually transferred to the wildlife watching category. Landscape watching is the widest category of CES, represented in social media in Estonia, active outdoor recreation is the second widest, and wildlife watching is the least represented CES group.

4.4.4. Mapping of colour harmony and landscape coherence in relation to CES use

The last paper IV also describes how previously suggested landscape organisation indices, namely landscape coherence and colour harmony can be used to explain the distribution of CES groups within the territory of Estonia.

We calculated the landscape coherence index within a circular neighbourhood of seven pixels, using equation 4 for LU/LC data, and TPI-based landforms for DEM, provided by Estonian Land Board (2020). For purposes of colour harmony mapping we composed the cloudless satellite imagery mosaics with Landsat-8 OLI data (summertime, 2018). The bands of visible spectrum, namely red (B4), green (B3), blue (B2) were converted from RGB colour space to HSV, discussed above. Unlike in Paper II, completely dedicated to colour harmony mappings after different authors, this time we decided to use only the most general principles of colour harmony, namely Hue and Saturation similarity (for pixel pairs), recently also listed among the universal principles of colour harmony (Ou et al. 2018). We used the grey level co-occurrence matrix (GLCM) Homogeneity index (Haralick et al. 1973) to measure the similarity of image pixel pairs (Hall-Beyer 2017a). Thereby, we simplified our previous colour harmony mapping, choosing only two indicators.

To quantify whether people prefer locations of higher landscape coherence or colour harmony extent compared to the random choice in addition to the CES-related geolocations, we created the same number of randomly generated geolocations, serving as "pseudo-absence" data. 6,154 random geolocations were generated within the territory of Estonia (spatially excluding the OpenStreetMap-based building vector data) for comparison with landscape watching geolocated photographs; in the same way 2,345 randomly generated geolocations were used for comparison with the outdoor recreation photographs, and 1,484 random geolocations were used for comparison with wildlife watching photographs.

Then we calculated median values of LCI and colour harmony indices for the viewsheds of actual CES geolocations and random ones. For the viewshed analysis we used the PixScape software (Sahraoui et al. 2018) and the European Digital Elevation Model (EU-DEM), version 1.1 (Copernicus Land Monitoring Service 2016). We compared medians using the boxplot visualisation and the Wilcoxon's rank-sum test with continuity correction (see Appendix of Paper IV) implemented in the Exploratory software (Exploratory Inc., 2020). Based on the satellite mosaics, we calculated the median normalized difference vegetation index (NDVI) for each viewshed and then compared values of colour harmony and landscape coherence for rather vegetated (NDVI >0.1) and non-vegetated (NDVI <0.1) viewsheds.

The study areas and periods, as well as data used are summarised in Table 3.

Table 3. Summary of the materials, used in the thesis papers

Paper	Study area	Study period	Remote sensing and GIS data	Geolocated photographs
Paper II	Part of Eastern Estonia	June 2017	Landsat-8 image as of 17 June 2017	5 Mapillary photographs
Paper III	Peneda-Gerês National Park (Portugal)	Until 2015 (inclusive)	SPOT and RapidEye mosaics for spring 2011, DEM, Estonian Land Board DSM interpolated from topographic vector data, ALOS DSM	≈9,000 Panoramio and ≈9,000 Flickr photographs
Paper IV	Territory of Estonia and some buffer	2015-2018	Landsat-8 cloudless summertime mosaics (2018), EU-DEM 1.1, Estonian Land Board DEM	9,983 photographs (combined Flickr and VK.com)

5. RESULTS

5.1. Deconstructing landscape pattern: applications of remote sensing to physiognomic landscape mapping (Paper I)

The results from the paper I suggest that the question of remote sensing application to the landscape mapping and evaluation is highly dependent on the landscape notions and models of landscape evaluation and is discussed in the literature review. An ecological notion of landscape evaluation typical for the understanding of landscape as a natural territorial complex or ecological system is fruitful for remote sensing applications. Indeed, quantification and monitoring of vegetation or water quality, species habitat or urban sprawl are among the most common remote sensing tasks. However, treating the landscape as a product of perceptual-cognitive processes (and proceeding from the ecological model of landscape evaluation to formal aesthetics and psychological ones) results in accounting of the previously neglected landscape attributes. In this way, while common applications of remote sensing work with the biophysical indicators of environmental quality (Figure 9, indicators A), there is a need to promote also the complementary remote sensing-based indicators of the physiognomic quality (Figure 9, indicators B).

It is important to understand that visual landscape observation and evaluation involve a significant phenomenological component (Pellitero 2011; Wylie 2018). However, in its current form it is usually trivialised to the purely subjective landscape experience (Tveit et al. 2018), moving from the initial phenomenological approach, elaborated by Edmund Husserl. According to Husserl's theory, the physical world affects sensory system of the observer and, in this way, appears as a mental phenomenon (representation) in the human mind (Zahavi 2003). Modern authors usually refer to the second part of this so-called phenomenological reduction, when people attempt to extract the "mindscape" of the visual environment. In turn, we suggest focusing on another aspect of Husserlian phenomenology: focusing on *appearance* of physical environment in addition to its *cognition*. For example, we see vegetation greenness. The supporter of naturalistic reduction (in Husserlian terms) may think about it just as about indicator of the vegetation vigour and health, quality of plants. On the contrary, a phenomenologist will think about vegetation greenness *per se,* removing the physical reality behind of greenness "out of the equation". This distinction is based on the common difference between the humanities and so-called "hard" science. We argue, that Husserlian phenomenology is fruitful for visual landscape mapping with remote sensing in case the researcher focuses primarily on visual landscape variables, such as geometric primitives, colours, textures, shapes and volumes, and only after that — on their biophysical nature. Therefore, remote sensing can be used by both psychological and biophysical studies (Figures 9-10).

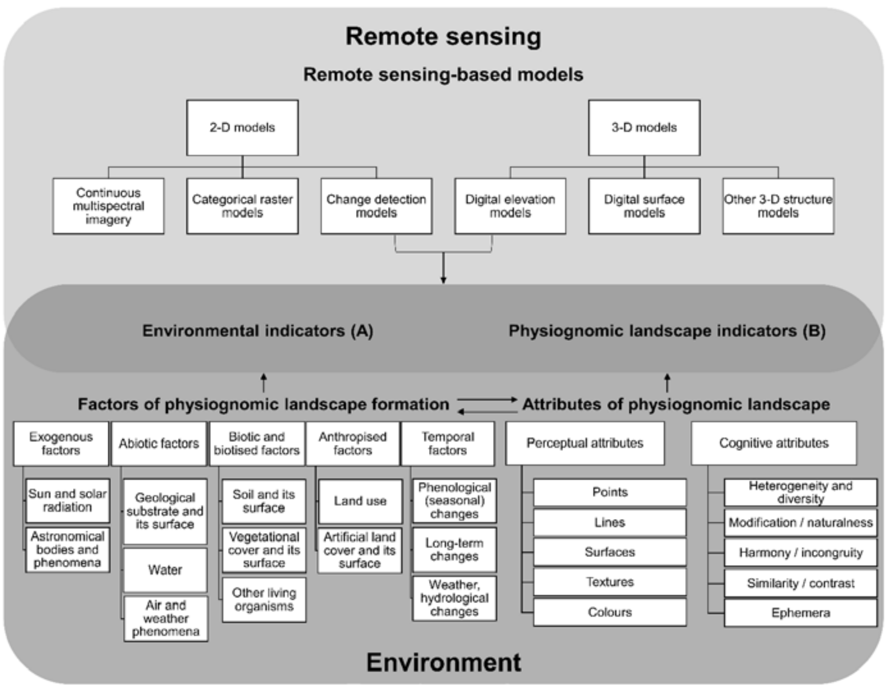

Fig. 9. Conceptual scheme of remote sensing applications to the perceived environment (Paper I). The physical environment, which is perceived visually, constitutes the respective physiognomic landscape (serving as a factor for the formation of different perceptual and cognitive phenomena). Remote sensing-based models are designed to deal with the physical environment mainly through its physiognomy from a top view perspective, and in this way, are used to examine the attributes of the physiognomic landscape, with the respective indicators. Environmental indicators describe the quality of the environment, while physiognomic landscape indicators refer to the quality of the visual environment.

In Figure 10 we attempted to illustrate the idea of remote sensing feasibility for purposes of visual landscape quality assessment. Remote sensing provides a unique opportunity to reduce the complexity of landscape patterns, textures and colours to just pixel relationships of multispectral satellite imagery (of course, other types of remote sensing data are also applicable). Pixel relationships capture landscape diversity and homogeneity, contrast and similarity, orderliness and entropy. Since many of those concepts are also discussed in the psychological and formal aesthetics studies on visual landscapes (see section 2), remote sensing comprehends the various problematics in this field and may be applied for an objective examination of both visual landscape situation and drivers of changes in landscape values.

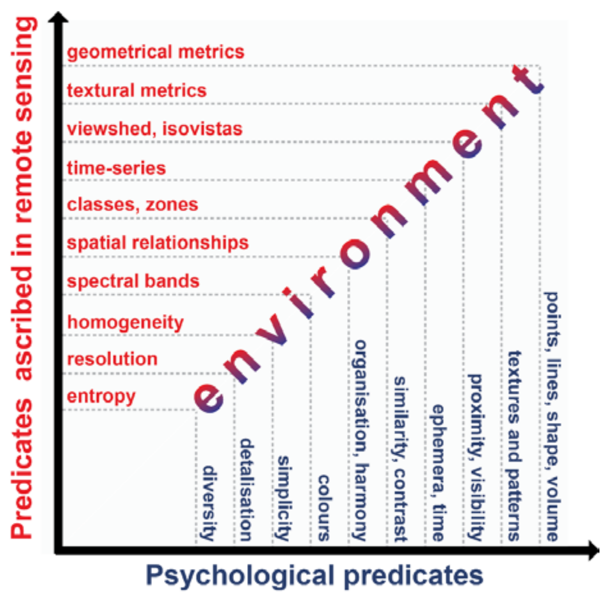

Fig. 10. Parallels between the predicates used in remote sensing, psychology and landscape science (Paper I). Entropy as mathematical function describes landscape diversity; spatiotemporal and spectral resolution of imagery corresponds to detailing (or generalisation) of landscape image; remote sensing-based calculations of homogeneity indicate simplicity of landscape; spectral bands of visible spectrum correspond to human vision of colours; spatial relationships between the pixels responsible for harmony and organisation mapping; classification of imagery is based on similarity inside the classes of land cover; time series of imagery describe feeling of time; viewshed analysis is based on landscape proximity concept; textural and geometrical metrics are based on human ability to extract patterns from visual images.

A literature review on the particular examples of remote sensing applications to the mapping or evaluation of the perceptual and cognitive landscape attributes is provided in publication I.

5.2. Mapping the extent of land cover colour harmony based on satellite Earth observation data (Paper II)

The purpose of the first experimental of the paper II was to test the applicability of remote sensing data, processed with Haralick's textural metrics, to the mapping of land cover colour harmony. To present the remote sensing feasibility for this task, Figure 11 illustrates the results of summarised Colour Harmony Index (CHI) mapping, whereas Figure 12 compares maps of colour harmony according to the principles and authors, mentioned in paragraph 4.2.3. Summarised CHI can be considered as the complex integrated indicator for colour harmony of land cover, resulting from overlay analysis of colour harmony indices after different authors.

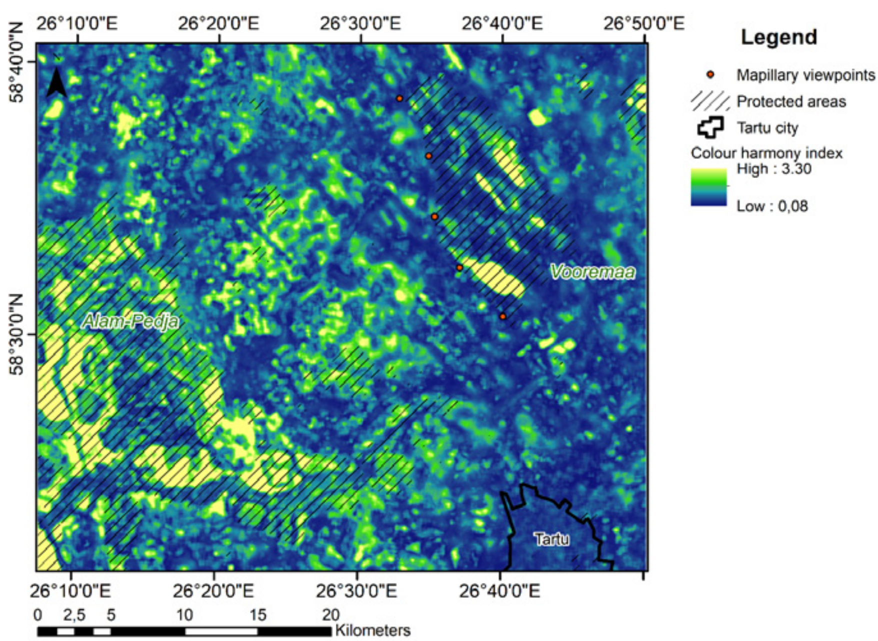

Fig. 11. Summarised Colour Harmony Index (CHI), generalising all the colour harmony maps (Paper II). Protected areas include land cover of high colour harmony, whereas urban (Tartu city) and rural areas have low colour harmony. See Mapillary scenes on Figure 16, labelled in the North-Western direction.

5.2.1. How consistent are the maps of the extent of colour harmony produced within the different frameworks?

Our findings suggest the agreement between the colour harmony mappings after different authors; despite some difference in transition zones, the maximum and minimum colour harmony zones are highly consistent (Paper II). Maps 12a and 12d, designed after Nemcsics (2012) and Caivano (1998) represent the least sensitive indicators for colour harmony. To smooth all the possible drawbacks, resulting in the final pattern, all the four maps have been summarised to the Colour Harmony Index map (Figure 11), generalising colour harmony pattern. It should be noticed that Haralick's textural indices, used for colour harmony mappings meet the assumptions of numerical colour harmony models, which usually refer to the two-colour combinations.

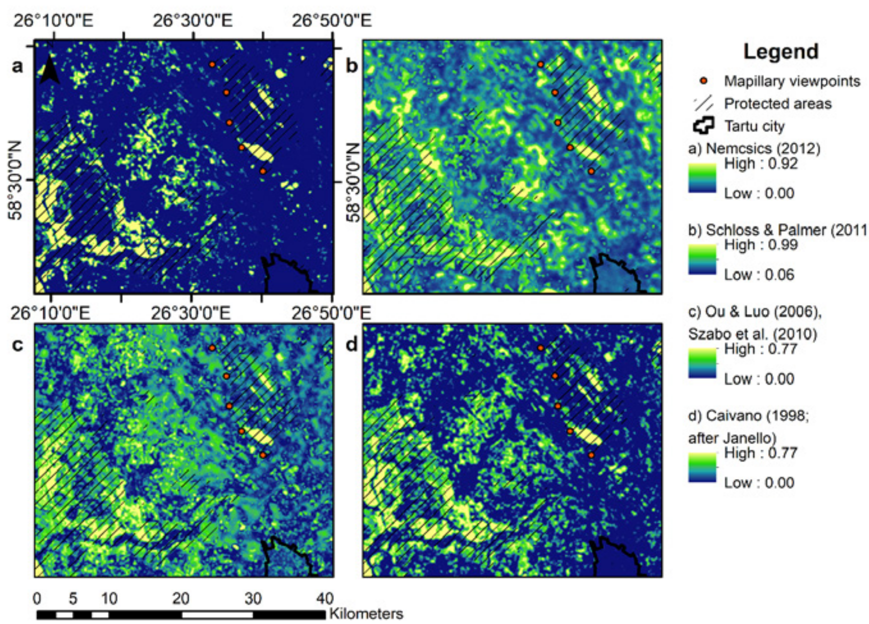

Fig. 12. Maps of colour harmony extent, created with different principles (according to the authors, mentioned in the legend): lighter areas correspond to higher land cover colour harmony, and darker areas correspond to lower colour harmony (Paper II). All the maps are different, though consistent. Protected areas include land cover of the highest colour harmony. Colour harmony estimates are presented without rounding.

5.2.2. How does the mean colour harmony index vary for different land cover classes?

The variation of mean colour harmony estimates among the CORINE 2012 land cover classes is illustrated in Figure 13 (made with Tableau Public 10.5 software; Seattle, Washington, USA). It is easy to see that the extent of cultural modification results in decrease in colour harmony. For instance, water bodies, various forest classes and wetlands have the highest colour harmony values. Such land covers, as arable land, pastures and other agricultural areas indicate lower colour harmony. Completely urban territories are the least colouristically harmonious; however, there are some minor exceptions. For example, areas associated with water courses have lower colour harmony than airports (likely due to the spatial resolution of the land cover model and satellite imagery).

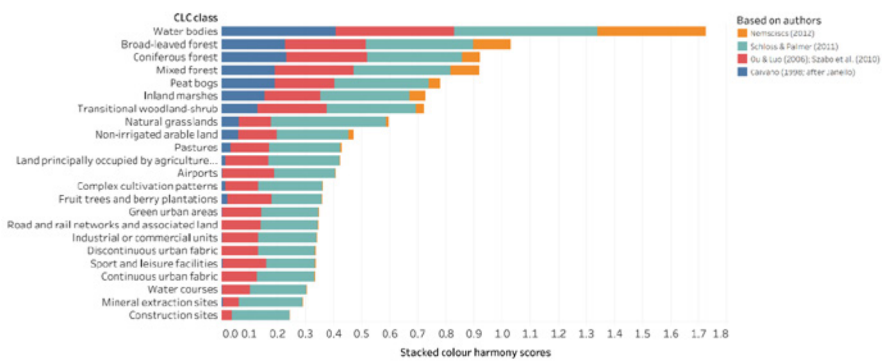

Fig. 13. Stacked mean colour harmony after each author for each CORINE land cover class, arranging land cover classes according to their inherent colour harmony (Paper II). The decrease in colour harmony extent is associated with man-made structures and culturally modified land cover.

5.2.3. Which geographic attributes explain the distribution of colour harmony values?

This stage of analysis aimed to examine the relationships between the Box-Cox transformed summarised CHI of land cover and selected geographic attributes, representing variables of man-made infrastructure, topography and surface energy balance using the GAM. Table 4 shows the results of CHI modelling according to changes of distance cost from roads (Costd_roads), values of the SAGA Wetness Index (SAGA TWI), the brightness temperature (BT) and albedo index (Albedo).

Table 4 (Paper II). Results of the GAM applied to summarised Colour Harmony Index (CHI)

Box-Cox transformed CHI				
	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.624442	0.006861	-91.01	<0.01
Approximate significance of smooth terms:				
	edf	Ref.df	F	p-value
Costd_roads	8.854	8.990	60.02	<0.01
SAGA TWI	1.000	1.001	494.55	<0.01
BT	8.397	8.895	82.27	<0.01
Albedo	7.961	8.576	183.12	<0.01
R-sq.(adj) = 0.54 Deviance explained = 54.3%				
GCV = 0.23648. Scale est. = 0.23519 n = 4996				

The GCV score is the minimised generalised cross-validation (GCV) score of the GAM fitted. F stands for the degrees of freedom matrix.

The main identified drivers of spatial colour harmony variation: albedo (reflective ability of landscape), brightness temperature (indicator of land surface temperature, affected by atmospheric conditions), SAGA Wetness Index (indicator of topographic wetness), and cost distance from roads (as roads are more densely distributed in cities and towns, which is the indicator of cultural modification and urbanisation of land cover along with transport accessibility) are represented in Figures 14 and 15. It appears, that albedo negatively relates to the CHI, while brightness temperature relates to the CHU unevenly; the respective relationship is rather U-shaped. CHI linearly increases, following the SAGA Wetness Index growth, and rather logarithmically positively responds to the increasing of the cost distance. Altogether these indicators explain up to 54% of CHI variation; therefore, some factors behind CHI remain unclear. However, we conclude that increasing wetness, cost distance from the roads (meaning more untouched nature), decreasing albedo (being the lowest for water bodies) and unevenly warm and cold areas (such as wetlands and water bodies) positively affect colour harmony of land cover.

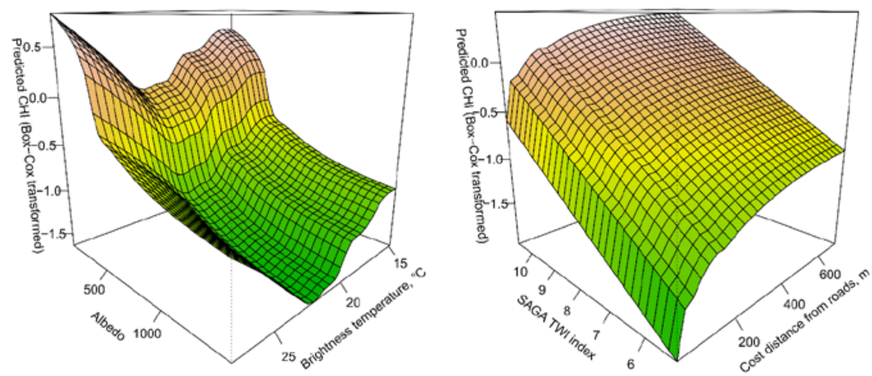

Fig. 14. Box-Cox transformed Colour Harmony Index, plotted against the albedo, brightness temperature, SAGA Wetness Index and cost distance from roads, explaining the spatial distribution of land cover colour harmony (Paper II).

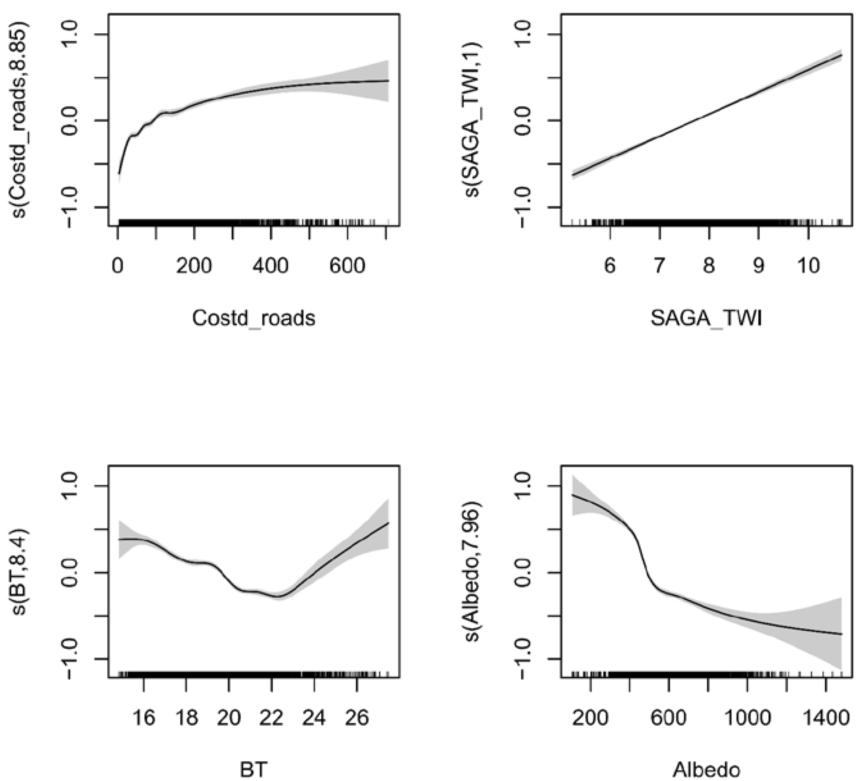

Fig. 15. Splines for the cost distance from roads, the SAGA Wetness Index, brightness temperature and albedo with 95% confidence intervals (Paper II). Only the topographic SAGA Wetness Index has a linear relation to the summarised Colour Harmony Index.

5.2.4. How does remotely assessed colour harmony extent correspond to actual scenery alongside the roads?

We found no obvious differences between the Mapillary scenes 16a-d, whereas scene 16e provides the presence of crop fields and settlements (Figure 16). As a logical consequence from Figures 14 and 15, signs of settlements and crop fields explain low mean CHI for the scene 16e. However, the lowest colour harmony score for the scene 16a is unclear and might be related to the landscape features outside the view. Moreover, Mappillary geolocated photographs are focused on the roadscape only; therefore, the opportunity to link the ground-based photographs with remotely sensed data is limited within this approach. We will return to this topic in paper IV.

Scene	Mapillary ID	Mean CHI
a	sRgQfpIqx_89WHmk0lKGmg	0.24
b	VOsOgZrSCBuwavp-D6rMzA	0.89
c	-rjsSf6q70yNrsfxM3H-8Q	0.50
d	y_Wpf8Pag8eJwdDjgc-bSA	0.45
e	kxW8yQ27owDnWpTC1f3D1g	0.31

Fig. 16. Mapillary scenes (crowdsourced street-level photographs), compared to the mean Colour Harmony Index for verifying the respective viewsheds (Paper II). Labelling the scenes in a North-Western direction (locations of the viewpoints see in Figures 11 and 12).

Together, our results in land cover colour harmony mapping suggest that the numerical models of colour harmony estimation developed in psychological studies are transferable to the environmental science with GIS and remote sensing techniques and provide meaningful information about the state of visual landscape quality. Regimes of moisture and heat supply, cultural modification and accessibility play the most important role in colour harmony support and, therefore, are responsible for management of colour harmony of land cover.

5.3. Landscape coherence revisited: GIS-based mapping in relation to scenic values and preferences estimated with geolocated social media data (Paper III)

We obtained the maps for landscape coherence index, using four principles for the neighbourhood (Figure 17): floating circle of 33 pixels (990 m wide), hexagonal grid (each cell is 1000 m wide), patches, and classes of coarse-resolution DLM (Figure 6). However, only LCI for patches and classes of coarse-resolution DLM were used for comparison with social media data (Figure 17).

5.3.1. How does the GIS-based model represent the objective landscape organisation, utilising the landscape coherence concept?

Landscape coherence mapping was done within the four different spatial frameworks: Figure 17 illustrates the landscape coherence index mappings using floating circle, hexagonal grid, landscape patches (facets), and classes (panels a, b, c, and d respectively). Figures 17a and 17b are presented for explorative purposes only; we assumed that nearly 1,000-m mapping zones are able to detect phenomena on landscape scale. Maps 17b and 17c were used in further analysis in comparison to the CES indicator.

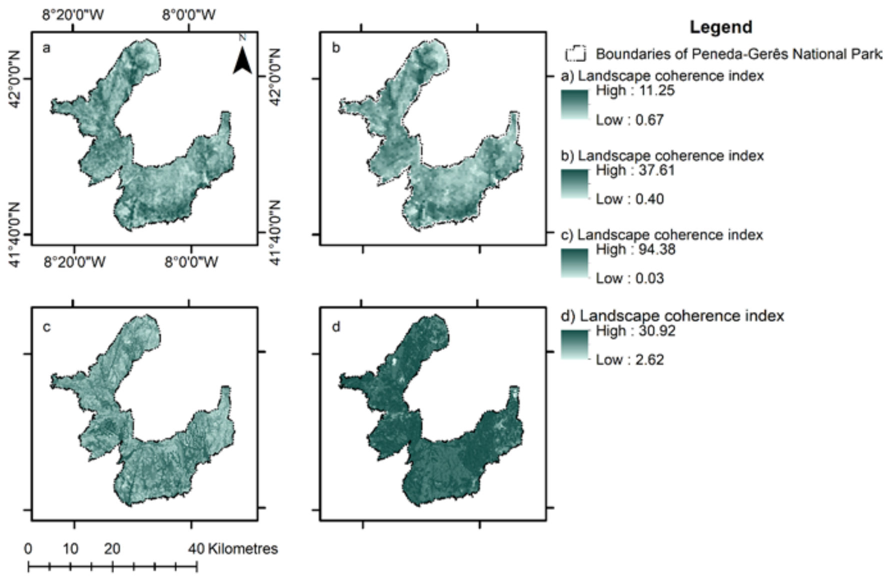

Fig. 17. Spatial pattern of landscape coherence index within the national park Peneda-Gerês: a) mapped within a kernel (moving circle) of 33 pixels in diameter (approximately corresponds to 990 m); b) mapped within a regular hexagonal grid (each cell is 1,000 metres wide); c) mapped within the physiognomic patches, parametrically composed of TPI landforms and CORINE land cover (i.e. on the chorological level); d) mapped within the physiognomic classes, parametrically composed of TPI landforms and CORINE land cover (i.e. on the typological level) (Paper III). Chorological and typological models (panels c and d) have been used in a further analysis to be linked to the spatial distribution of geolocated photographs.

5.3.2. How does the landscape coherence indicator relate to the uneven spatial pattern of photographs taking frequency evidenced from the location-based social media?

The most interesting finding from this stage of research is that there is a weak but positive relationship (Figure 18) between the LCI and cumulative photographing frequency when these variables are calculated within the landscape patches (chorological level). Calculation within the entire classes of landscape patches (typological level) enhances the strength of this relationship. Spearman's correlation on the chorological level varies from 0.41 for Flickr data to 0.47 to Panoramio data; on typological level, the same indicator varies from 0.86 to 0.87. As for the R-squared metric, indicating the predictive power of the regression line, it varies from 0.2 to 0.25 and from 0.58 to 0.62 respectively. Both Panoramio and Flickr data show similar behaviour in relation to LCI, but Panoramio's response to LCI changes is more explicit. All these results are statistically significant at the p-value < 0.05 level for both plots. Since there is a strong concordance between the land cover types (typological level) and LCI extent, this fact provides some opportunities for landscape management, which will be discussed further.

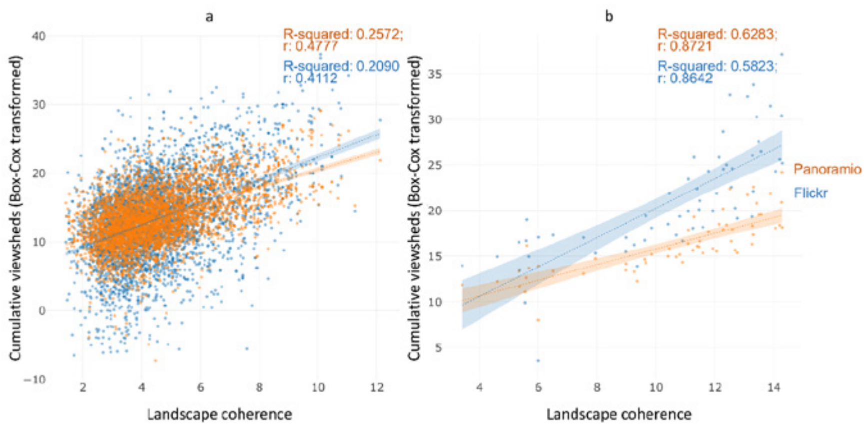

Fig. 18. Relationships between the Flickr- and Panoramio-based cumulative viewsheds and landscape coherence for the Peneda-Gerês National Park area (Paper III). Plots show Box-Cox-transformed response data (cumulative viewsheds) with corresponding regression line and 95% confidence intervals; r refers to Spearman's correlation. Panels show the relationships: a) between the Flickr- and Panoramio-based cumulative viewsheds and landscape coherence on the physiognomic patch (chorological) level; and b) between the Flickr- and Panoramio-based cumulative viewsheds and landscape coherence on the physiognomic class (typological) level.

5.3.3. How is the suggested indicator applicable to landscape management and planning?

Continuing the topic of uneven attractiveness of landscape classes for taking photographs, we ranged them according to the landscape coherence extent (Figure 19). All the DLM classes, containing water bodies as a land cover, have been combined to the same class of water bodies, regardless of landform. It was noticeable that the gentle slopes of various land cover usually have lower LCI, while valley bottoms and ridges and steep slopes show much higher coherence with land cover. Land cover of DLM classes with higher landscape coherence includes agricultural areas, forests and transitional types of vegetation. It is likely that the traditional agriculture, preserved in the Peneda-Gerês, does not reduce the visual landscape quality in part of its coherence.

Thus, landscape coherence is increasing with agricultural modification and is dependent on the density of geographic processes (the most explicitly expressed in the mountain valleys and steep slopes of diverse land cover). Instead, homogeneous areas, such as bare rocks, to a lesser extent are subject of geographical evolution and, therefore, less coherent. In this way, managing land cover and, to some extent, landforms, land managers and planners may expect the respective increase or decrease of landscape coherence, measuring it with the suggested index.

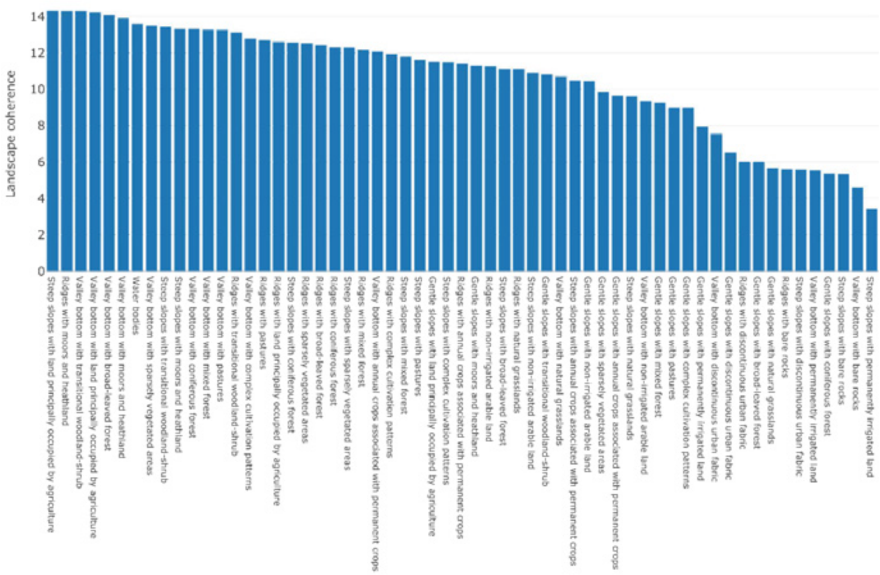

Fig. 19. Physiognomic classes (mapped on the Figure 6) ranged concerning the degree of landscape coherence (Paper III). The decrease in landscape coherence mostly corresponds to the urban fabric, bare rocks and irrigated land, as well as gentle slopes.

5.4. How crowdsourced data and landscape organisation metrics can facilitate the mapping of cultural ecosystem services: an Estonian case study (Paper IV)

The following topics, corresponding to the CES groups according to CICES 5.1 (Haines-Young and Potschin-Young 2018), have been distinguished:

1) Landscape watching: This consists of the following tags: nature, outdoors, landscape, tree, nobody, wood, sky, travel, water, and summer (6,154 photographs; 17 manually transferred from topic 3).

2) Active outdoor recreation: This consists of the following tags: people, recreation, adult, fun, man, leisure, outdoors, one, sport, and action (2,346 photographs: 770 manually transferred from topic 1, and 114 from topic 3).

3) Wildlife watching: This consists of the following tags: nature, outdoors, nobody, flora, leaf, wild, wildlife, season, animal, growth (1,485 photographs; 124 manually transferred from topic 1, and two from topic 2).

Photographs of landscape watching represent scenes without presence of people or their equipment for outdoor activities. Photographs of active outdoor recreation (further just outdoor recreation) contain signs of people's activities or the people themselves. Wildlife watching-related photographs focus on plants, animals and mushrooms (macro scale of landscape-related photographs, level of organisms or some communities).

5.4.1. What are the main groups of CES, evidenced from social media in Estonia?

The map of CES-related geolocations from social media: photographs, representing i) passive landscape watching, ii) active outdoor recreation; and iii) wildlife watching, is presented in the Figure 20. There are clear linear patterns alongside the roads and coastlines; photographs of CES use are concentrated in the national parks (such as Sooma, Vilsandi and Lahemaa), recreational areas near Otepää and suburban areas of the main cities (Tallinn, Tartu, Narva, etc.). Moreover, about 59% of all the photographs were taken within the protected areas, confirming their high relational landscape values. Also, 6,148 out of 6,153 landscape-watching photographs, 2,311 out of 2,345 outdoor recreation photographs, and 1,483 out of 1,484 wildlife-watching photographs have been taken no farther than 500 m from the roads and trails of all types, indicating the pivotal importance of transport accessibility for landscape experience and CES use.

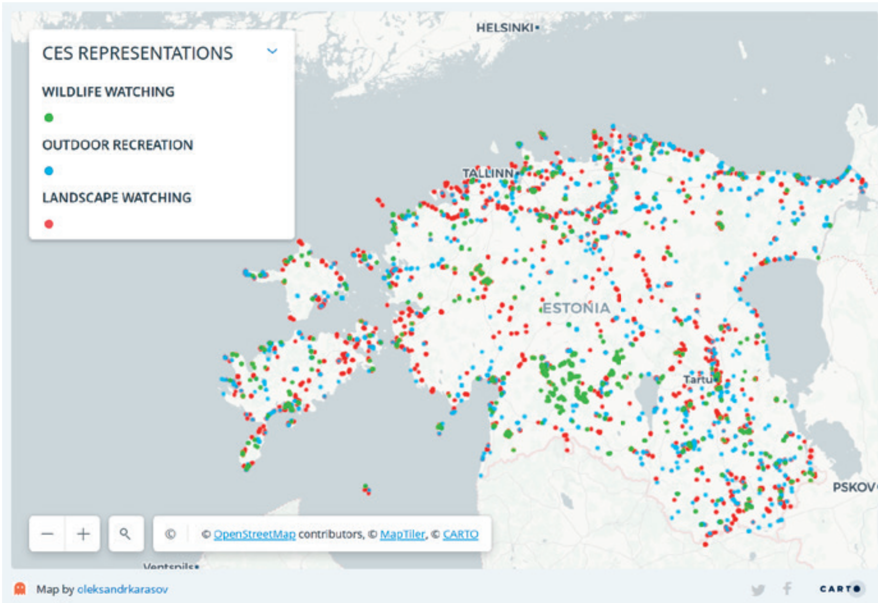

Fig. 20. Geotagged photographs representing actual use of three groups of CES in Estonia (2016-2018): landscape watching (passive recreation), outdoor recreation activities, and wildlife watching (Paper IV). The web map, designed in Carto, is available via the following link:
https://oleksandrkarasov.carto.com/builder/1e69e28a-9705-45a9-8276-471a330da2ff/embed.

As for the land cover influence (CLC 2018), Figure 21 provides the evidence that photographs were mainly taken in coniferous and mixed forests, agricultural areas and transitional woodland-shrub. Landscape watching is more represented also within the water bodies and courses, sea, peat bogs and marshes, as well as within the natural grasslands. Outdoor recreation is more concentrated within the complex cultivation patterns and green urban areas. Wildlife watching is well represented in broad-leaved forest and pastures.

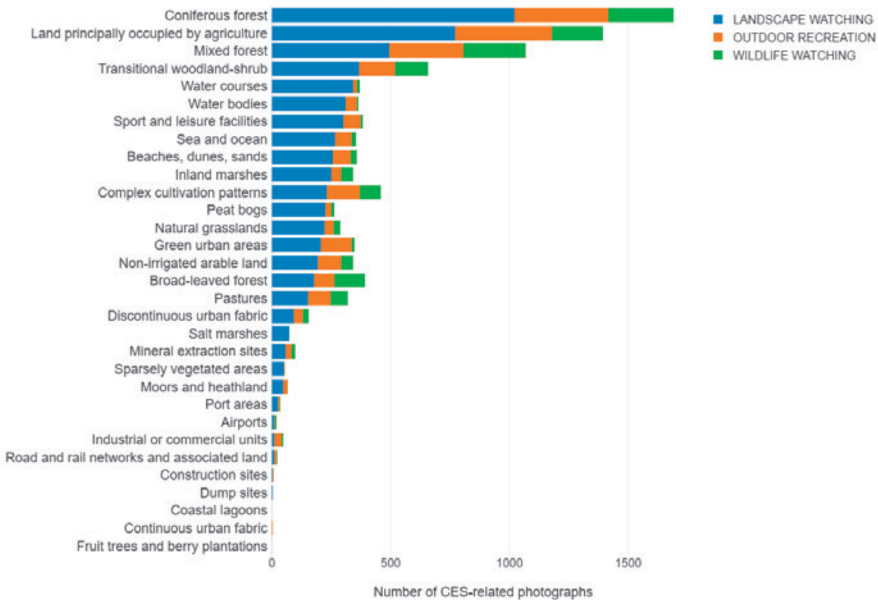

Fig. 21. CES use in Estonia encompasses predominantly natural and semi-natural land cover (CLC 2018, Paper IV). Land cover classes are ranked in order of decreasing number of landscape-watching photographs.

5.4.2. What is the association between the landscape coherence and colour harmony of land cover, and CES?

The comparison of the medians (Figure 22) shows that people take landscape watching- and recreation-related photographs with consideration for colour harmony of landscape (hue and saturation similarity). Medians of the respective indices are significantly higher (see the Wilcoxon test results in Appendix of Paper IV) for viewsheds of actual geolocated photographs than for pseudo-absence geolocations. LCI, in contrast, is better associated with wildlife watching photographs. Notably, that the respective associations in case of LCI are valid for rather vegetated areas (NDVI >0.1), while colour harmony indices describe rather non-vegetated areas (NDVI <0.1), such as water bodies (Appendix, Figure A1).

These results are also supported by the Wilcoxon non-parametric test, applied with no regard for the median NDVI values for each viewshed. The median values of colour harmony indicators tend to be higher for CES-related viewsheds in case of the landscape watching and outdoor

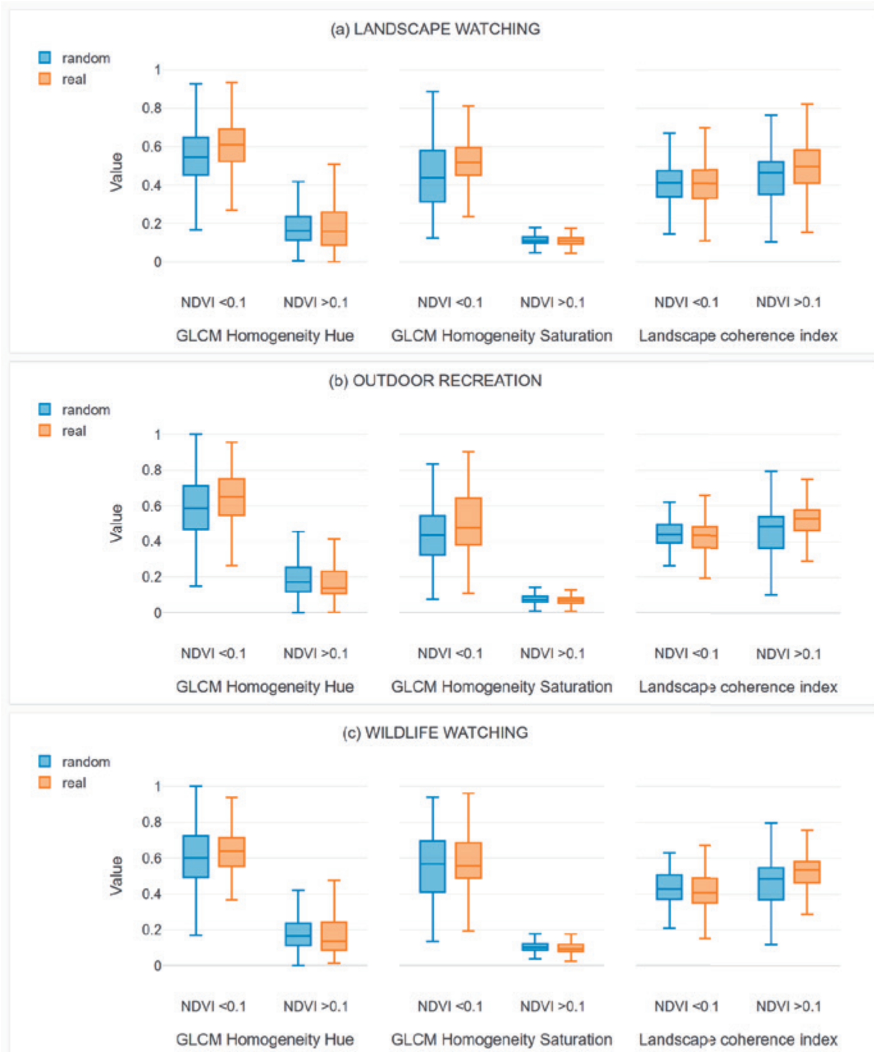

Fig. 22. Comparison of medians of landscape coherence and harmony-based visual quality indices for each group of CESs within viewshed areas for actual geotagged photographs ("real") and randomly simulated locations ("random"): (a) landscape watching; (b) outdoor recreation; and (c) wildlife watching. Boxplots are designed separately for median normalized difference vegetation (NDVI) index values for each viewshed being higher 0.1 and lower 0.1 to present the index performance for rather vegetated and non-vegetated area (mainly water bodies and streams). Colour harmony indices are higher for actual CES viewsheds in the case of non-vegetated areas, while landscape coherence index is higher for photographs of vegetated areas. The GLCM homogeneity index for the saturation of pixel pairs does not indicate wildlife watching in any case (Paper IV).

recreation. The density distribution of the median viewshed values of colour harmony indicators contains the part that exceeds the density distribution of the median values for randomly generated viewsheds (Figure 23ab). This difference in the density distribution is less expressive for landscape coherence index, which also shows some increase for all groups of CES compared to values within the random viewsheds (Figure 23c).

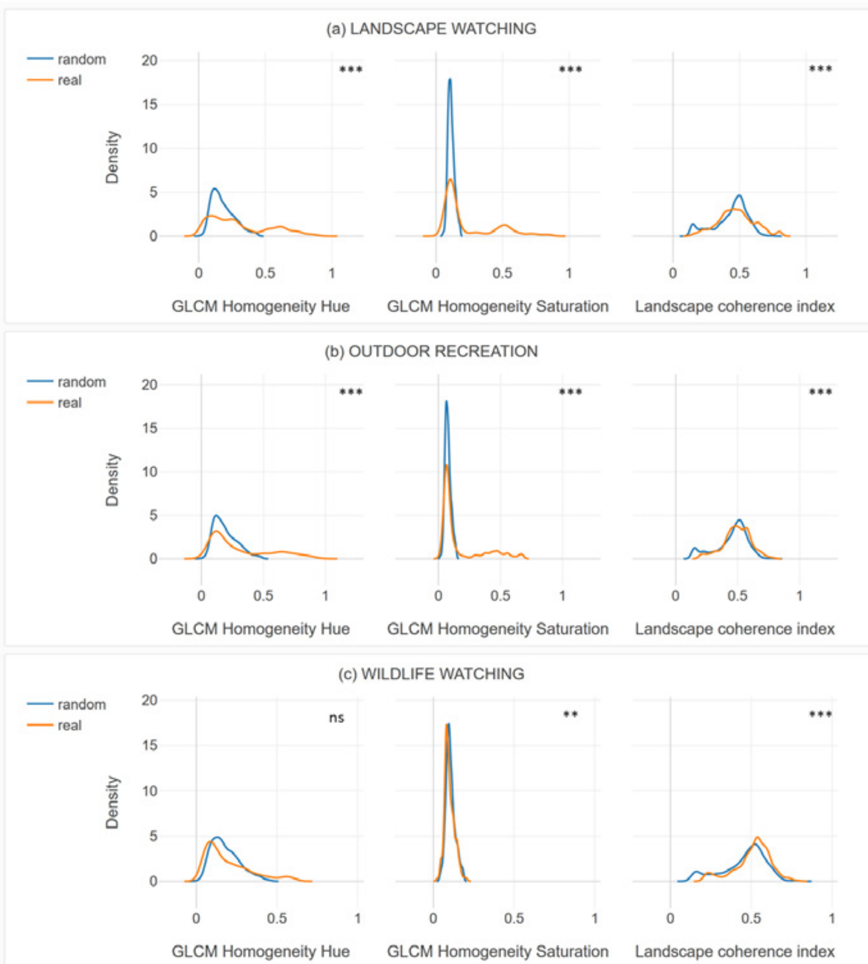

Fig. 23. Density plots representing the results of the Wilcoxon rank sum test with continuity correction, applied to the medians of landscape coherence and harmony-based visual quality indices for each group of CESs within viewshed areas for actual geotagged photographs ("real") and randomly simulated locations ("random"): (a) landscape watching; (b) outdoor recreation; (c) wildlife watching. Significance levels: *** p-value less than 0.001; ** p-value less than 0.01; ns—not significant. Alternative hypothesis: two-sided. Confidence level: 0.95 (Paper IV). See the complementary test data in Appendix of Paper IV.

This behaviour of the suggested indices corresponds to the land cover types. The landscape coherence increases for the culturally modified land cover, such as urban green areas and fabric, agricultural areas, and at the same time, colour harmony increases for more natural water bodies, forest and peat bogs (Figure 24). Colour harmony is not associated with wildlife watching. As a result, colour harmony indicators, being associated with a specific land cover, can be considered as its important attribute, influencing decisions to take landscape- and recreation-related photographs. Landscape coherence index also may be considered as such an important attribute, but to a lesser extent and predominantly for wildlife watching occurrence.

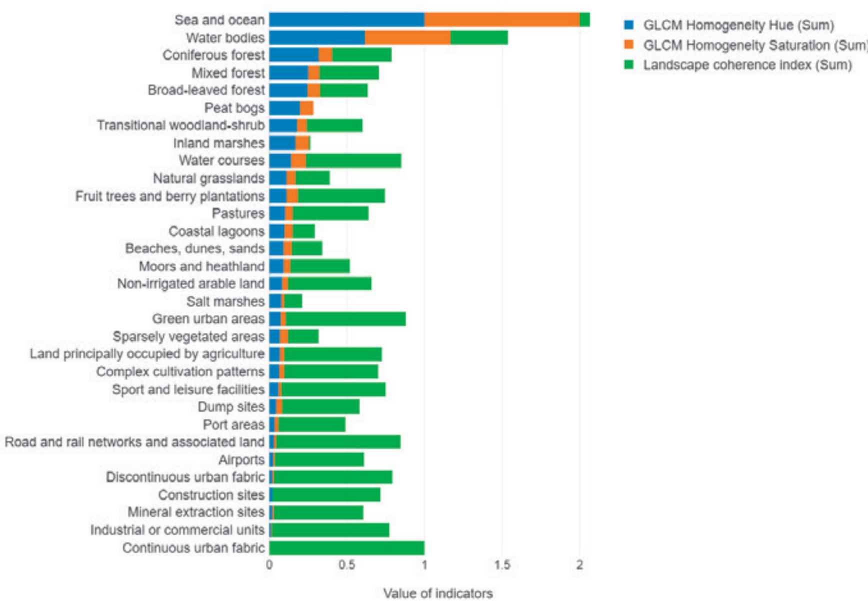

Fig. 24. CORINE 2018 land cover classes ranged in order of decrease in GLCM Homogeneity for Hue component of HSV colour space, indicating transition from water-related and natural land cover to urban-related areas. Landscape coherence generally increases in this direction (Paper IV).

6. DISCUSSION

In total, our results are meaningful in different regards. First of all, they extend the conceptual (Paper I) and experimental opportunities of remote sensing applications within the formal aesthetics (Paper II) and psychophysical (Paper III) approaches to landscape visual quality evaluation, which is important in context of evidence-based landscape planning and management, and CES assessment (Paper IV). Also, our results increase remote sensing applicability for purposes of nature conservation, namely for monitoring of the aesthetic properties of the environment and delineation of the protected areas, based on such properties and cultural ecosystem services provision. What is more important, the evolution of our research has resulted in deeper integration of geomatics with problematics of landscape experience, evidenced from location-based social media data. Policy targets concerning environmental quality and ecosystem services are deeply connected with the sustainable development goals (Wood et al. 2018), so our results are highly relevant to achieving these goals, while limited spatially and temporally. Analytical reduction of the extremely complex harmony-related environmental attributes to just a few GIS-based indicators is a nearly impossible task. In addition, people's decisions to take photographs are highly uncertain and unpredictable. However, our results contribute to the objective and evidence-based understanding of people-nature relationships, reducing the respective uncertainty for more informed decision-making. Discussion of particulars of the papers, included in the thesis, is provided as follows.

6.1. Remote sensing provides tools for operationalisation of intangible nature values (Paper I)

The main message of paper I was to explain, that the Earth observations from space and the ground do not conceptually differ, despite the different perspectives on landscape: top-view and oblique respectively. However, linkages to environmental psychology are rather absent in remote sensing studies of landscape, except for a few papers (Ayad 2005; Ozkan 2014; Vukomanovic et al. 2018), and vice versa, remote sensing is not widely implemented in environmental psychology. In our paper we articulate this problem and legitimate multidisciplinary studies, based on both regularities of landscape perception and remote sensing derivatives. Wider implementation of remotely sensed data in physiognomic landscape research would complement the ground-based assessment of visual landscape quality and enhance the inter-, multi- and cross-disciplinarity of the landscape studies. Human visual perception is always evaluative; therefore, visual landscape quality is an essential component of favourable habitability conditions, contributing to the overall well-being of billions of people and, respectively, to CES use. We argue that there is time to complement the landscape monitoring based on traditional components of landscape as a geosystem of air, water, geological substrate, soil, biota and human structures, with the monitoring of physiognomic landscape as appearance of environment.

Remote sensing applications for mapping landscape conditions, enabling CES use and arousal of relational intangible nature values (Small et al. 2017; Pascual et al. 2017; Bachi et al. 2020) are rather understudied. Thereby, our research contributes to bridging the opposite research traditions, so-called "hard" and "soft" landscape science (Miklós et al. 2019). Notably, remote sensing is highly relevant also to ecological habitat modelling and, in this way, can be applied also for modelling of locations, likely rich of CES use (Richards and Friess 2015; Yoshimura and Hiura 2017). Moreover, results obtained with a top perspective should be examined and verified with ground-based Earth observations within the frameworks, adopted in citizen science and data crowdsourcing (Fritz et al. 2017). For these purposes, street-level crowdsourced imagery, provided by Mapillary, as well as location-based social media data, provided by Flickr, VK.com, Strava, and Twitter can be used. This imagery is passively crowdsourced via the official APIs of these services and, in this way, provide much less intrusive and richer source of data on landscape perception and use, than traditional active crowdsourcing and surveys (even online-based ones). Moreover, nature protection initiatives will benefit from the reliable mappings of CES potential and visual landscape quality with remote sensing, complementing mentioned active engagements of people (Dramstad et al. 2006; Rose et al. 2015; Sullivan and Meyer 2016; Janečková Molnárová et al. 2017).

Moreover, assessment and monitoring of the visual landscape quality from space and ground over time would support environmental policies of various spatial scale. For instance, the global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development suggests integrating "ecosystem and biodiversity values into national and local planning, development processes, poverty reduction strategies and accounts" (UN General Assembly 2018). This logic continues ideas, enshrined in the European Landscape Convention, which oblige parties, including Estonia and Ukraine, "to assess the landscapes thus identified, taking into account the particular values assigned to them by the interested parties and the population concerned" (Council of Europe 2000). Therefore, despite the local legislation differences, many countries take responsibility for the preservation and possible enhancement of visual quality of environment (using, for example, target-based policy). Visual landscape quality is an intrinsic basement for GDP of countries with developed tourism and leisure industry, therefore, it should be operationalised and institutionalised within the natural capital assessments as a prerequisite for landscape, economic and social sustainability.

6.2. Problematics of colour harmony in landscape research (Paper II)

Colour harmony is among the landscape aesthetics principles, recognised in practises of visual resources assessment (BLM 1986), nature protection (Sullivan and Meyer 2016), landscape aesthetics and scenery management (U.S. Forest Service 1995), classics of landscape research (Granö et al. 1997; Bell 2012; Antrop and Van Eetvelde 2017a); landscape design and architecture (Bell 2004; O'Connor 2010) landscape ecology (Tveit et al. 2006; Sowiſska-ſwierkosz 2016). No works that mapped colour harmony with satellite imagery or orthophotographs from a top perspective were found. However, our results complement the first attempts to calculate scenic colour (dis)harmony for the landscape photographs (Sowiſska-ſwierkosz 2016) and previous attempts to examine the landscape colour diversity and composition (Arriaza et al. 2004; Lindemann-Matthies et al. 2010; Polat and Akay 2015; Zhang et al. 2017; Kuper 2018).

6.2.1. Data quality and processing

Here we note the drawbacks and limitations of the initiated colour harmony mapping approach. First of all, spatial and temporal resolution of satellite imagery, atmospheric conditions, quality of multispectral sensors, carried by satellites, affect the resulting estimations. For example, our mapping in Paper II was based on Landsat-8 OLI data of 30 m original spatial resolution for the one selected date, while future mappings may include multitemporal mapping of colour harmony for satellite imagery of higher spatial resolution (Sentinel 2 predominantly, other imagery based on availability, orthophotographs). Further, the scale of analysis depends also on the choice of floating circle (moving window, kernel) for pixel pairs examination: it should be optimal for scale of landscape features, balancing the capturing of minor details and large patches. Thirdly, Haralick's textural features are reported as often multicollinear (Hall-Beyer 2017b), and choice of the correct index for the most accurate estimation of pixel pairs in colour harmony context is a highly subjective, requiring further research. Noticeable, that Haralick's GLCM textural features were applied to derive the colour textures in emotional context (Machajdik and Hanbury 2010). Our research complements existing knowledge, presenting land cover colour harmony as a potential predictor for visual landscape quality mapping.

6.3. Issues of landscape coherence mapping (Paper III)

Landscape coherence is one of the most diverse and complicated concepts, used in our research; even colour harmony, which is also provoking discussion, is much more agreed upon among the researchers. In contrast, landscape coherence research in environmental psychology (Kaplan and Kaplan 1989; Hansson et al. 2012; Kuper 2018) is very different from the landscape coherence in landscape ecology studies (Kuiper 1998; Mander et al. 2010) and mainly refers to the structural landscape connectedness (Jongman et al. 2004). Some studies, combining both subjective and objective landscape evaluation approaches, simply borrow objective ecological notion of landscape coherence and apply it in subjective landscape evaluation (Martín et al. 2016). The backward process, implementing intuitive psychological concepts into the objective mappings is in its theoretical stage of development (Tveit et al. 2006; Ode et al. 2010; Bell 2012). Thereby, our approach for landscape coherence mapping based on intuitive basement of landscape systematicity, and emergence, first of all, contributes to the objectivization of subjective landscape coherence concept.

Moreover, objectivization of subjective landscape coherence serves to the purposes of linking objective factors of landscape appreciation to the metrics of landscape values and preferences (Langemeyer et al. 2018). Our results, revealing concordance between the extent of landscape organisation, legibility, and systematicity and cumulative photographing frequency for Flickr and Panoramio data, serve as a proxy for legitimation the GIS-based practises in such a highly subjective field, as landscape valuation. In addition, we confirm the link between the landscape heterogeneity and coherence: areas of higher diversity are also more coherent (van der Jagt et al. 2014; Martín et al. 2016; Kuper 2017). Notably, agricultural areas within the NP Peneda-Gerês obtained high scores of landscape coherence—we interpret this fact as supporting the idea that low intensive agriculture contributes to the landscape diversity (Mander et al. 1999).

Of course, landscape coherence as a fundamental aesthetic category should not be trivialised to any GIS mapping: "Beauty is in the eye of the beholder". Therefore, our suggested approach just indicates one aspect of visual landscape organisation, in addition to harmony, which is discussed as a concept, very similar to the notion of coherence (U.S. Forest Service 1995; Tveit et al. 2006). Further work in this direction of mapping the landscapes with metrics, uncovering their organisation and legibility for observer, can benefit from wider usage of information theory (Nowosad and Stepinski 2019).

6.3.1. Data quality and processing

In a similar way to landscape colour harmony mapping, estimation of the landscape coherence has inherent biases, related to the adequacy of initial landform and land cover models and neighbourhood choice. Substantiation of the optimal floating window size is shown in the discussion of Paper III. Here, we note that landscape metrics generally are very sensitive to data quality, and extremum values may significantly bias the results. For example, in our case, the floating circle approach resulted in unexpectedly linear pattern of landscape coherence values and Hartley information estimates, therefore we used strictly defined DLM patches and classes to reveal the relationship with photographic frequency as indicator of landscape values and avoid the problem of over-differentiated patterns. Also, quality of the viewshed analysis was influenced by the coarse resolution of DSM. The cumulative viewsheds also served as an indirect indicator of transport accessibility (Lu et al. 2019).

6.4. Assessment of CES with LBSM (Paper IV)

Our last study (paper IV) contributes to the quite wide niche of CES-related studies, linking spatial distribution of CES to the metrics of landscape organisation, assessible, among others, with remote sensing (Oteros-Rozas et al. 2018; Calcagni et al. 2019). Transport accessibility and naturalness are the most influential factors behind the spatial distribution of CES, which is in line with previous research (Van Zanten et al. 2016; Van Berkel et al. 2018). What is important is that photographs, representing different groups of CES in Estonia, tend to overlap spatially, creating basis for assessment of landscape multifunctionality (Mander et al. 2007). Landscape multifunctionality is important for emergence of intangible nature-related values and, therefore, our results can support the informed and evidence-based trade-off land use analysis in case of comparison with other ecosystem services and land use trajectories over time. Currently we have indicated the hotspots of CES, revealing cultural importance of landscape (Cao et al. 2013; Ghermandi and Sinclair 2019), and our results can be further extended for the cities (urban research and planning) and over time (to capture the seasonality and other temporal effects on CES use).

Nature protection is another important aspect that benefits from mapping the CES use in Estonia. Since the majority of photographs in this way or another was taken within the protected areas, our results allow to monitor the efficiency and efficacy of the nature protection policy, namely recreational use of the protected ecosystems and landscapes which contribute to the nature-based tourism (Kim et al. 2019). Thereby, the location-based social media data is a valuable source of information for nature conservation and tourism activities (Yoshimura and Hiura 2017; Tenkanen et al. 2017; Hausmann et al. 2018; Toivonen et al. 2019).

The landscape coherence index (LCI), suggested in Paper III, was additionally tested in relation to CES in Estonia. Within the framework of this study we found that increase in LCI estimates follows the increase of cultural modification of land cover; this is contrary to the colour harmony indices, increasing with higher naturalness of land cover (Figure 24). This fact is logical, because culturally modified landscapes should be more legible and ordered than natural landscapes. Estonian agricultural areas and cities for the most parts do not decrease landscape diversity, supporting high extent of the visual landscape quality. However, LCI does not indicate well neither landscape watching, nor outdoor recreation and cannot be considered as a stand-alone strong predictor of landscape values and preferences. However, as some photographed places have higher LCI, there is still some positive influence of anthropogenic modification signs (parks, suburban areas, agricultural landscapes, etc) on these CES, complementing naturalness value (Martínez Pastur et al. 2016). Our results suggest that people take wildlife watching-related photographs in places with higher LCI, meaning that they prefer to contact with biota in rather understandable zones near settlements—in agreement with previous reports (Mancini et al. 2018).

Colour harmony indices are more important indicators of visual landscape values (passive watching and outdoor recreation), because more natural land covers have higher colour harmony extent. Therefore, because of this strong association between the colour harmony extent and type of land cover, it is hard to distinguish the effect of colour harmony from the effect of land cover itself, as land cover usually has also powerful intrinsic values. What is more, people may choose landscapes to be photographed unconsciously, therefore our results should be treated with caution. They rather contribute to the general understanding of visual environment, than directly explain landscape preferences.

6.4.1. LBSM as a source of bias

LBSM data are provided by a limited sample of population, who are active users of Flickr and VK.com. Also, some users can produce many photographs, while other are just rarely active. To overcome this bias, we did not apply cumulative viewshed analysis as in Paper III (in this paper analysis was done for the national park only, therefore motivations of photographs' taking was much less diverse, than in case of entire Estonia with many outdoor events and activities).

Moreover, it is likely that elderly people and children are not well-represented users of LBSM. This drawback is being gradually smoothed by regular ageing of the overall population on the Earth: Flickr and VK.com were launched in 2004 and 2006, respectively, and have become popular among diverse people. Internet penetration in Estonia is also permanently growing (Statistics Estonia 2019). In the coming years (given the constant API access), LBSM will become even more useful for CES use assessment. Of course, the LBSM data provide very limited information about the individual's age, gender, cultural background, education and nationality. On the other hand, that may be an advantage, because the volume of the involved personal data is minor. What is more important, contrary to offline surveys, LBSM data is provided by much larger sample of people and the way of data collection is not intrusive. LBSM data do not suffer from the recollection (given the constantly open API access) and mind biases, which reduce the reliability and replicability of the traditional bottom-up people engagement practises (Dunkel 2015; Ilieva and McPhearson 2018; Ghermandi and Sinclair 2019).

7. CONCLUSIONS AND FURTHER WORK

Overall, the results from the published and submitted papers suggest that the visual quality of landscape can be assessed from the top perspective with remote sensing and GIS techniques by means of specifically developed indicators. We have developed measures for aesthetical attractiveness of landscapes, enhancing their recreational values. As this research was not experimental, we did not manipulate the landscape coherence or colour harmony of landscape; however, the proposed measures and partially explored (semi)natural regimes of environmental organisation can be applied for safeguarding and enhancing the visual quality of most European landscapes within the target-based landscape planning and management.

Some of the landscape conditions, enabling opportunities for landscape beauty appreciation and various outdoor activities, were assessed by means of joint use of remotely sensed and location-based social media data. In this way, our research promotes the more integrated use of globally available space- and ground-based Earth observations, as well as uncovering rather hidden potential of remote sensing in this field. We argue that by measuring and mapping visual landscape attributes, as well as detecting landscape use (as represented in social media,) we contribute to the assessment of intangible natural resources and, therefore, to the more accurate assessment of natural capital of the countries. Adequate decision-making in nature protection and landscape planning, based on more informed accounting for potential conflicts, synergies and trade-offs, and enhanced with the suggested methodologies, will be able to support also economic and, as a result, social and environmental sustainability through avoidance, mitigation and offsetting of nature use regimes that lead to land degradation or disturbance. Conjunctively used remote sensing and GIS techniques provide visualisations for the state of visual landscape quality and may facilitate communication with stakeholders: planners, administration, NGOs, citizens, business.

In particular, our results indicate that:

a. Colour harmony of land cover and landscape coherence are important aesthetic landscape attributes, assessable and mappable by means of remote sensing; and

b. Methodological combination of automated image recognition and topic modelling facilitated CES use mapping based on LBSM data.

Despite the methodological diversity of approaches to the quantification of colour harmony and land cover and landscape coherence, it was possible to identify the major regularities from literature that appear consistent enough. Colour harmony of land cover is linked to land cover classes, decreasing with their cultural modification. In contrast, landscape coherence which is confirmed as a positive but rather weak indicator of landscape preferences (as represented in selected social media) increases, following cultural modification. The landscape coherence index is especially high for low intensity agricultural areas in the study area in Portugal, and urbanised areas in Estonia. GIS-based mapping of landscape coherence should be further improved with more robust and powerful mathematical functions from information theory behind.

The following aspects covered with the thesis materials can be considered as scientific contributions:

- landscape harmony is discussed as accountable intangible natural resource—in particular, we attempted to substantiate the methodology for objective inventory of the selected visual resources;

- recognition of landscape as a provider of cultural ecosystem services was promoted;

- information theory was shown to be useful for landscape harmony mapping in addition to diversity;

- linkages between the theory of information, environmental psychology, formal aesthetics, social media, GIS and remote sensing were demonstrated; and

- methodology for complementary CES use mapping with social media data was suggested.

Our research reports predominantly correlations between the measurable properties of visual landscape (colour harmony and coherence) and some people-generated digital footprint in a similar way to many other psychophysical studies. Instead, directions for further work should be focused more on the causal mechanisms of landscape use and appreciation. Using modelling techniques, it will be possible, first of all, to comprehend these causal relationships more deeply and create maps of the potentially available intangible natural resources and CES supply. For such purposes, automated image recognition for LBSM content used in combination with natural language is confirmed as a promising alternative to the traditional offline CES assessments and manual content analysis.

Finally, the presented results are just preliminary for the full implementation of regular RS- and LBSM-based mapping of visual landscape quality and cultural ecosystem services use over the regions, countries and continents on the permanent basis. Further work will continue the issue of their integration, using comparative and exploratory analysis of photograph-based quantitative indices of visual landscape quality, and the respective map-based indices. What is more, content-analysis of location-based social media data may be further complemented with more accurate web-based individual reports of users on the visual landscape and recreation quality.

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APPENDIX

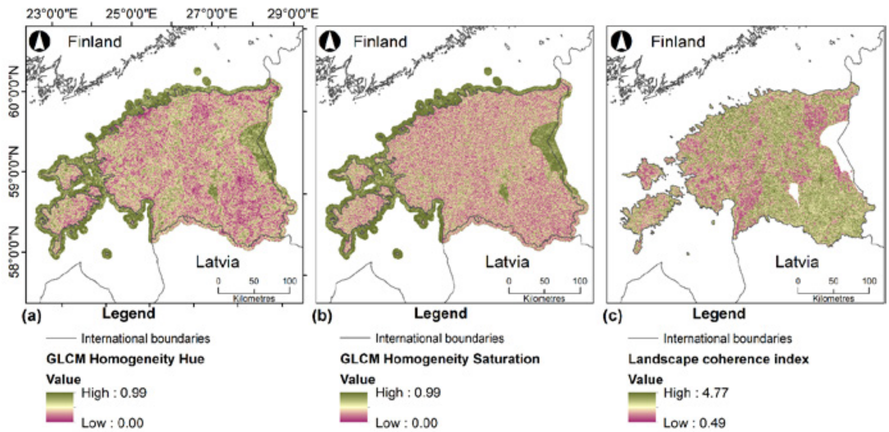

Fig. A1. Colour harmony (panels a and b) and landscape coherence (panel c) patterns within Estonia

KOKKUVÕTE

MAASTIKUMEETRIKA JA ÖKOSÜSTEEMI KULTUURITEENUSED – RESSURSIPÕHINE INTEGREERIV LÄHENEMINE MAASTIKUHARMOONIA KAARDISTAMISELE

Sissejuhatus

Kultuuriliste ökosüsteemiteenuste kontseptsiooniga arvestatakse erinevates inimese ja looduse mittemateriaalselt vastastikust toimet käsitlevates teadusvaldkondades, eriti majandus- ja keskkonnateadustes, järjest enam. Üks peamisi kultuuriliste ökosüsteemiteenuste kasutamist ja maastikukogemust mõjutavaid keskkonnafaktoreid on maastiku visuaalne kvaliteet. Probleem seisneb selles, et nii kultuurilised ökosüsteemiteenused kui ka maastiku visuaalne kvaliteet on nende mittemateriaalse iseloomu tõttu raskesti kvantifitseeritavad ja kaardistatavad. Maastiku kogemine on infoprotsess, mis ei põhjusta materiaalseid või energeetilisi üleminekuid, kuid loob majanduslikke stiimuleid looduskaitses. Seetõttu pakume välja, et maastiku visuaalse kvaliteedi määra võiks tõlgendada mittemateriaalse loodusvarana, mida tuleks sarnaselt teiste keskkonnaressurssidega kasutada mõistlikult. Suurem osa maastikku ja kultuurilisi ökosüsteemiteenuseid seostavaid uuringuid jätavad tähelepanuta kaugseire ja geograafiliste infosüsteemide (GIS) võimalused, kasutades vaid GIS-põhist maastiku mitmekesisuse või maastikuelementide kauguse ja spektraalsete taimkatteindeksite analüüse. Uuringud kasutavad ka rohkelt passiivsete kohtseotud fotode põhist kultuuriliste ökosüsteemiteenuste kaardistamist, kuid tehes seda ilma ajamahuka visuaalse sisuanalüüsi või külastus- või pildistusmäära arvestuseta. Käesolev uuring seadis eesmärgiks arendada edasi kultuuriliste ökosüsteemiteenuste kaardistamist, täiendades sotsiaalmeedia andmete *temaatilise modelleerimise* protseduuri ning maastiku visuaalse kvaliteedi kahe aspekti – *maakatte värviharmoonia* ja *maastikukooskõla* – GIS-põhiste indeksitega kaardistamist. Värviharmooniana võib määratleda kahe või enama värvi omavahel hästi sobivat kombinatsiooni, sõltumata sellest, kas vaatlejale kombinatsioon meeldib või mitte. Maastikukooskõla (ka: -koherentsuse) mõiste hõlmab keskkonnapsühholoogias maastiku harmoonia ja süsteemsuse määra.

Väitekirja eesmärk oli testida geograafilisel infosüsteemil põhinevate maakatte värviharmoonia ja maastikukooskõla indikaatorite suutlikkust tuvastada ökosüsteemi kultuuriteenuseid ja maastiku visuaalset kvaliteeti.

Uurimistöö ülesanded

Väitekirja eesmärgi saavutamiseks seati järgmised uurimisülesanded.

1. Sünteesida seniseid kaugseire rakenduste uuringutulemusi, mis käsitlevad valitud maastikutunnuste kaardistamist. Esimeses uurimisartiklis oli meie eesmärgiks vastata küsimusele – mida saaks maastiku visuaalsete aspektide uuringutel kasutada tavapäraselt biofüüsikalistele omadustele keskendunud kaugseirest?

2. Hinnata satelliitkujutiste abil maakatte värviharmoonia väärtusi. Teises uurimisartiklis oli eesmärgiks selgitada, kuidas kvantifitseerida maakatte värviharmooniat kui maastiku esteetilise väärtuse koostiosa, kasutades Landsat-8 andmete pilvitut fragmenti Eestist.

3. Hinnata subjektiivsetel eeldustel, kuid maastiku GIS digimudelil põhineva maastikukooskõla määra. Kolmandas uurimisartiklis testisime selliselt hinnatud maastikukooskõla määra maastikufotodega (Flickr ja Panoramio) Peneda-Gerês rahvuspargis (Portugal).

4. Testida sotsiaalmeediapõhise kultuuriliste ökosüsteemiteenuste kaardistamisega maastikukooskõla ja värviharmoonia indekseid Eestis. Neljandas uurimisartiklis kombineerisime automatiseeritud pildituvastust teemamodelleerimisega, et esile tuua kolm kultuuriliste ökosüsteemiteenuste tüüpi üle kogu Eesti territooriumi.

Materjal ja metoodika

Töö teoreetilise interdistsiplinaarse lähtekomponendina kaardistati ja analüüsiti kaugseire kontekstis teaduskirjanduses esindatud kognitiivseid kontseptsioone, nagu harmoonia, mitmekesisus ja sarnasus ning maastike visuaalseid tunnuseid, nagu punktid, jooned, pinnad, värvid ja tekstuurid.

Seejärel selgitati välja, et psühholoogias arendatud numbrilised värviharmoonia mudelid toetuvad kahe värvi kombinatsioonide toonide, küllastuse ja heleduse väärtuste sarnasusele, kontrastile ja reeglipärasusele.

Sellele teadmisele tuginedes kasutati Landsat-8 andmete pilvitut osa (suvi 2017, Lõuna-Eesti), et arvutada katsealal värviharmoonia määrad tooni-küllastuse-väärtuse (HSV-värvimudel) värvimudeli ja Haralicki teksturaalmeetrika abil, mis kirjeldab pikslipaaride seoseid. Värviharmoonia ruumilise muutlikkuse selgitamiseks ja reaalse maastiku visuaalse aspektiga sidumiseks kasutati valitud geograafilisi muutujaid ning Mapillary fotosid.

Maastikukooskõla (-koherents) määratleti Peneda-Gerês rahvuspargi (Portugal) katsealal komponentide suhtena: a) Hartley valemiga arvutatud infohulga digitaalsel maastikumudelil (sisaldades maakatte ja elementaarsed reljeefimudelid) ning b) erinevate digitaalse maastikumudeli komponentide jaoks arvutatud summeeritud Hartley infohulkade vahel. Pakutud indeksit kontrolliti kultuuriliste ökosüsteemiteenuste kasutust iseloomustava kumulatiivse pildistussagedusega, põhinedes Panoramio ja Flickr kohtseotud fotodel ja vaatevälja analüüsil.

Neljas uuringueesmärk oli seotud Eesti sotsiaalmeedias esindatud põhiliste kultuuriliste ökosüsteemiteenuste kasutusklasside eristamisega. Flickr ja VK.com kohtseotud fotode maastikuvaadete põhjal kaardistati ökosüsteemide kultuuriteenuseid (katsealaks kogu Eesti territoorium) Clarifai automaatse pildituvastusega ja tekstitöötlustehnoloogiaga. Eelnevates uuringuetappides selgitatud maastikukooskõla ja värviharmoonia indikaatoreid testiti ökosüsteemide kultuuriteenuste suhtes, kasutades vaatevälja sisu analüüsi; ökosüsteemiteenuseid kujutavate kohtseotud fotode ja juhuslikult genereeritud geograafiliste asukohtade jaoks kasutati Wilcoxon-i mitteparameetrilist testi.

Tulemuste kokkuvõte ja järeldused

Tavapäraselt biofüüsikalistele omadustele keskendunud kaugseire pakub võimalust taandada maastiku mustrite, tekstuuride ja värvide komplekssust satelliitpildi pikslite vahelistele seostele, hõlmates sel moel maakatte mitmekesisuse ja ühtlikkuse, kontrastsuse ja sarnasuse, korrastatuse ja entroopia. Kuna neid mõisteid on käsitletud ka psühholoogia ja formaalse esteetika valdkonna teadusuuringutes, siis saab kaugseiret kasutada nii maastike visuaalsete aspektide objektiivsel hindamisel kui ka maastiku väärtuste muutuste algpõhjuste selgitamisel (artikkel I).

Eri autorite värviharmoonia printsiipidest lähtuvalt loodud maakatte satelliitkujutiste värviharmoonia kaarte analüüsiti eraldi ning seejärel kombineeriti lähtpunkte ühildava nn värviharmoonia indeksi kaardina. Sellistel kaartidel saab jälgida värviharmoonia ruumilist jaotumist. Näiteks antropogeensed maastikumõjutused vähendavad värviharmooniat, looduslikud veekogud, erinevad metsakooslused ja märgalad omavad suurimat värviharmoonia väärtust. Valitud geograafilised muutujad selgitavad kuni 54% värviharmoonia varieeruvusest (artikkel II), andes võimaluse mõista värviharmoonia varieeruvuse mehhanisme maastikus.

GIS-põhise maastiku digimudelil põhineva maastikukooskõla uuringu kõige tähelepanuväärsem tulemus on mõõdukas positiivne seos maastikukooskõla indeksi ja kumulatiivse pildistamissageduse vahel juhul, kui need muutujad on arvutatud maastikulaikude piires. Maastikuklasside sisene kalkulatsioon tugevdab selle seose tugevust, nt Spearmani korrelatsioon muutub 0.41-st laikude puhul 0.87-ni klasside puhul (artikkel III).

VK.com ja Flickr kohtseotud Eesti loodusfotode põhjal testiti ökosüsteemi kultuuriteenuse kolme näidet: passiivne maastikuvaatlus, aktiivne välipuhkus ja elusloodusse vaatlus. Inimesed võtavad maastikuvaatluse ja rekreatsiooniga seotud fotodel arvesse maastiku värviharmooniat. Erinevalt värviharmooniast seondub maastikukooskõla eeskätt elusloodusse vaatluse fotodega. Samas ei seondu värviharmoonia elusloodusse vaatlustega (artikkel IV).

Edasised uurimisvajadused

Värviharmoonia ja maastikukooskõla seondusid tihedalt maakatte klassidega – värviharmoonia suureneb maakatte looduslikkusega, kuid kõrgem maastikukooskõla on seotud maakatte kultuuriliste muutustega. Sellest tulenevalt oleksid vajalikud edasised uuringuid, et eristada maastikukooskõla ja värviharmoonia mõju pildistamiseelistustele maakatte kui sellise tekitatud mõjutustest. Praeguste uuringute alusel saame näidata mõnd korrelatsiooni ja uurimusliku statistika tulemusi. Edaspidi oleks vaja uurida pakutud indeksite ajalist muutumist, et selgitada põhjuslikke seoseid maastiku visuaalse ülesehituse ja pildistamise (maastiku)eelistuste vahel, aga ka seostada neid üksikasjalikumalt ökosüsteemiteenuste kaskaadi erinevate elementidega.

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I

ORIGINAL PUBLICATIONS

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GeoJournal
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Deconstructing landscape pattern: applications of remote sensing to physiognomic landscape mapping

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Abstract In 1939, Carl Troll pointed out that "air photo interpretation is to a large extent landscape ecology". From that time forward, remote sensing has been applied across different disciplines to comprehend the holistic and dynamic spatial layout of the visual Earth environment. However, its applicability in the domain of landscape character assessment, landscape design and planning is still questionable. The purpose of this paper was to synthesise some historical and current applications of remote sensing for the decomposition of the continual visual landscape from a bird's eye perspective and to explore the potential for bridging geographic processes with visual perception and an appreciation of the landscape pattern. From the point of view of landscape ecology, the organisation of the landscape pattern [namely, the size, shape (form), number, density and diversity, the complexity of landscape elements, and colours and textures of the land cover] is crucial for the cognition of both the visual landscape experience and the geographic processes. There are numerous pieces of evidence from the literature that remote sensing data are widely implemented in the modelling of physiognomic landscape. The synthesis of the literature concludes with perspective directions of remote sensing applications, such as mapping the status of the ecosystem (landscape) services provision, the delineation of the boundaries of the protected areas based on the quality of the visual environment, and the assessment of the sustainability of the land use practices, regarding their impact on landscape aesthetics extent.

Keywords Visual landscape · Landscape character · Landscape attributes · Landscape indicators · Earth observations · Remote sensing

Introduction

One of the most challenging tasks in contemporary environmental management and planning, as well as holistic natural resource management, is the operationalisation of intangible values of nature. This

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presents problems of implementation in holistic natural resource management and their implementation into the decision-making process. These values often formalised in the form of cultural ecosystem services (CES) assessment (Daniel et al. 2012; Fish et al. 2016; Hirons et al. 2016; Dickinson and Hobbs 2017) or a non-tangible natural (environmental) resources assessment (Saastamoinen 2016). The aesthetic beauty of nature, including the visual (physiognomic) landscapes, is a common class of all the CES classifications, being one of the most frequently studied among the ecosystem services (Czúcz et al. 2018). It is recognised that the pattern of the visual landscape, with its symbiotic relationship with the landscape processes, influences the landscape values and preferences of people, framing their activities within the Earth's environment; the landscape concept serves as a socio-ecological medium, making ecosystems socially meaningful and manageable (Morrison et al. 2018). From the beginning of the systematic observations of Earth from space, including USA aerial photography surveys shortly after the First World War (Lee 1922), the 1921 Halifax air survey mission in Canada (Werle 2016) and satellite imagery since the 1970s (Antrop 2000), remote sensing (RS) has significantly contributed to the in-depth understanding of the geographic processes underlying the Earth's appearance (Miklós et al. 2019). They have also contributed to knowledge of its composition, structure and dynamics (Gulinck et al. 2000; Ode et al. 2008), as well as the modelling of the visual landscape per se (Ervin 2001; van Lammeren 2011). The terms "visual landscape" and "physiognomic landscape" are used interchangeably (Nijhuis et al. 2011). The difference is that the concept of the physiognomic landscape seems to be more suitable for mapping purposes, assuming a bird's-eye perspective, while the visual landscape naturally requires the horizontal or oblique perspective (Antrop and Van Eetvelde 2017a), thus, we give preference to the "physiognomic landscape" term. Following on from the ideas of Granö (Granö et al. 1997), Booth et al. (2017) propose a distinction between view-based vista aesthetics and landscape aesthetics, where the environment is experienced in close proximity. Obviously, this distinction also highlights the difference of landscape perspectives (Antrop and Van Eetvelde 2017a), which utilise, on the one hand, the in situ views and require a viewshed analysis for GIS-based applications, whereas some other landscape aesthetics studies are based on merely geographic methods from top-view perspective, such as remote sensing and, in this connection, are less observer-dependent.

However, despite the crucial role that remote sensing plays in recent physiognomic landscape research, its role has not yet been extensively discussed beyond the geomatics in general. Furthermore, the potential of Earth observation in the mapping and assessment of the landscape visual quality remains underestimated and understudied. The quantification of landscape physiognomy is problematic, due to the wide examination of the aesthetic, axiological, cultural, psychological and social aspects of the perceived environment (hence, encountering some of the problems with the replicability and reliability in psychology and social sciences (Baker 2015), thus the respective quality of landscape assessment research, involving a strong observer component, remains questionable).

Noticeably, there is strong evidence in the growing body of literature (Fig. 1), of a potential bridge between remote sensing with the aesthetics of landscape (Crawford 1994; Antrop 2000; Yokoya et al. 2014; Fry et al. 2009; Dronova 2017). However, most authors use remote sensing simply as a source of data for mapping and the operationalisation of the environmental indicators. For example, for the purpose of physical landscape monitoring (Kienast et al. 2015) or as a source of data for land cover classifications and further landscape heterogeneity estimations with common landscape metrics (Plexida et al. 2014). Few empirical studies have suggested new RS-derived indicators, specifically for the purpose of mapping the extent of landscape beauty. For example, some of those studies focus on the spatial organisation of the perceived environment or link such indicators to the landscape values and preferences (Ayad 2005; Ozkan 2014; Karasov et al. 2018). We argue that traditional landscape-related surveys will complement the objective remotely sensed data, increasing the replicability and reliability of landscape science. Of course, remote sensing methods impose some constraints, as will be discussed further, but the advantages of unmanned aerial vehicles (UAV) imagery and satellite-based Earth observations, strengthened by volunteered geographic information (VGI) and surveys, can hardly be overestimated. Visual perception and remote sensing have a deep intrinsic connection, based on the

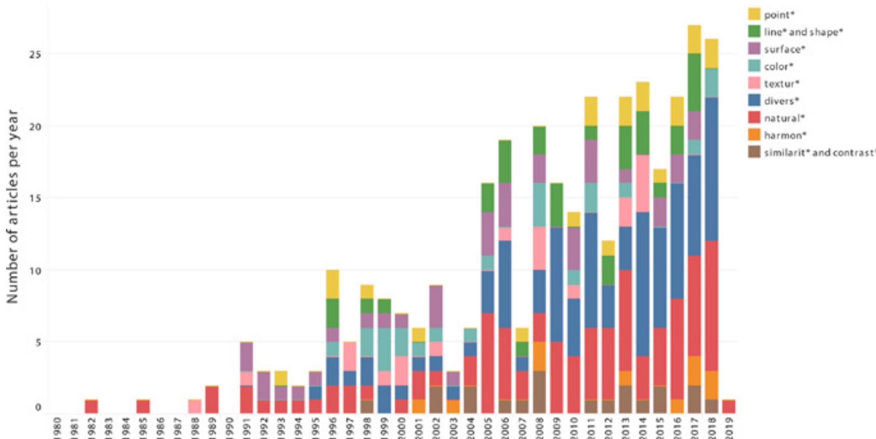

Fig. 1 Growing numbers of articles in peer-reviewed journals (indexed by the Web of Science Core Collection indices and Scopus per year) operationalising scenic landscape-related attributes with the application of remote sensing. The plot is based on the key queries reflecting landscape attributes searched in conjunction with the remote sensing terms ("remote sensing", "satellite", "earth observation", "UAV", "drone") as well as with the landscape queries (physiognom*, scenic, landscap*). The cumulative number of studies indicates the evolutionary potential of remote sensing to landscape physiognomy examination. Noticeably, diversity- and naturalness-related topics have recently become increasingly popular. Time-related search queries were excluded from analysis due to a large number of remote sensing articles dealing with time series data

detection of environmental attributes in the visible spectrum (Pettorelli et al. 2018). This connection results in numerous attempts to apply remote sensing techniques to examining the Earth's environment as perceived by people, while just a few of those are articulated as a visual landscape study.

Figure 1 (made with Tableau Public 10.5 software, Seattle, Washington, USA) provides evidence of the growing interest in visual landscape examination with remote sensing techniques. The figure was developed to examine the current state in this interdisciplinary field. We aimed to find the papers using cognitive concepts such as "harmony", "diversity", "similarity", as well as the features of visual landscapes (points, lines, surfaces, colours, and textures) within the remote sensing framework. Figure 1 suggests naturalness and diversity are the most commonly occurring concepts among the recent remote sensing studies. Naturalness primarily relates to land cover classifications and transitions between relatively natural and artificial land cover classes. Remote sensing papers also utilize the harmony concept to describe the dynamic balance between the natural and artificial land cover, as well as nature-friendly land use (Cao et al. 2013; Fujiki et al. 2018).

However, bridging geographical and aesthetic knowledge with the help of remote sensing, still has several significant uncertainties and a lack of transdisciplinary studies. This bridging is needed for a deeper understanding of the functioning regime, in terms of the landscape operationalisation and management of the perceived environment as well as the assessment of cultural ecosystem services related to the visual landscape, It seems that this problem exists, because whilst common applications of remote sensing work with the indicators of the quality of the physical environment (Fig. 2, applications A), there is a need to promote the development of remote sensing-based indicators of the quality of the physiognomic landscape (Fig. 2, applications B).

To address this need, this paper aimed to examine the applications of remote sensing technologies to the analysis of the visual (physiognomic) landscape. Also, the respective benefits and constraints within the

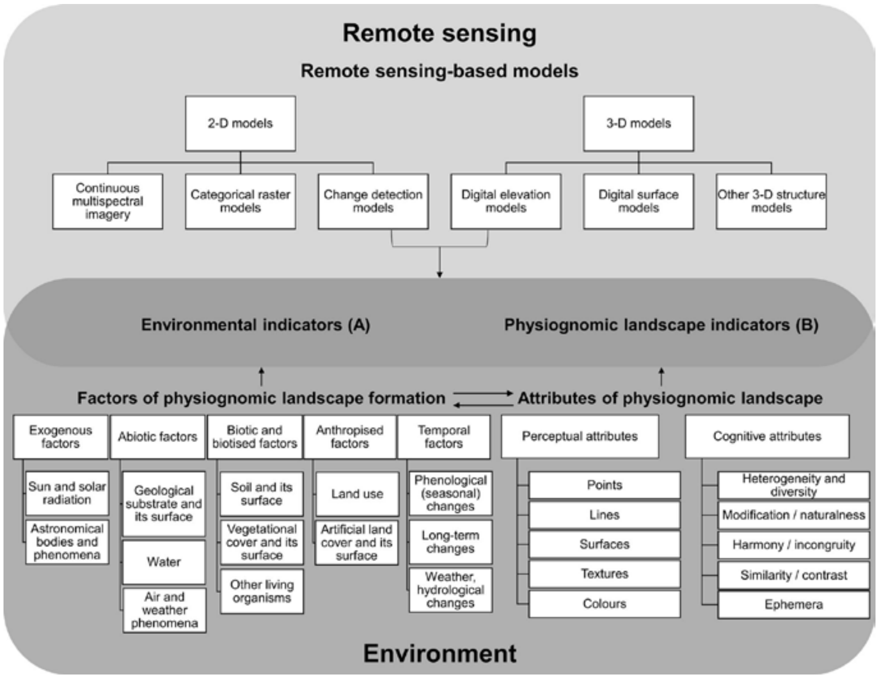

Fig. 2 Conceptual scheme of remote sensing applications to the perceived environment. The physical environment, which is perceived visually, constitutes the respective physiognomic landscape (serving as a factor for the formation of different perceptual and cognitive phenomena). Remote sensing-based models are designed to deal with the physical environment mainly through its physiognomy from a bird's eye perspective, and in this way, are used to examine the attributes of the physiognomic landscape, with the respective indicators. Environmental indicators describe the quality of the environment, while physiognomic landscape indicators refer to the quality of the visual environment

frameworks of the assessment and mapping of the landscape beauty are discussed, especially regarding the operationalisation of the landscape values and preferences. Provided with a wide variety of landscape- and remote sensing-related literature, as well as, more recently, some transdisciplinary studies, we selected a list of 131 original research papers 15 literature review studies, and 25 books, book chapters and reports. We selected them based on a partial or full focus on the assessment and mapping of the visual landscape, utilising, directly or indirectly, the remotely sensed data. For example, landscape studies using the CORINE land cover database for Europe, derived from satellite-based Earth observations were included in this review because they are indirectly based on land cover classifications. The number of studies related to physiognomic landscape mapping with remote sensing in some way, is vast and therefore our list of references is far from comprehensive. At the same time, we ignored papers dealing with thermal remote sensing for landscape studies for example, if they did not involve visual problematics. We started searching with a combination of keywords, such as "remote sensing" or "Earth observation" together with "aesthetics of landscape", "landscape aesthetics", "visual landscape", "physiognomic landscape", and "landscape beauty" within the research databases Thomson Reuters Web of Science and Scopus, as well as search engines, such as Google Scholar and Semantic Scholar.

Specifically, we established our research questions as follows:

1. How are the cognitive and perceptual landscape concepts reflected in remote sensing studies?
2. How do the subjective "landscape-oriented" principles complement the objective remote sensing-based indicators for the quality of physiognomic landscapes?
3. What are the related challenges of further remote sensing applications to the mapping and assessment of the physiognomic landscape?

The spectrum of landscape interpretations and scales

It is rare to find a recent landscape-related paper that does not mention the definition of landscape proposed in the European Landscape Convention as follows: "an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors" (Council of Europe 2000). This meaning of landscape is close to the geometric concept of area, whilst also continuing the geographic tradition (dating back to A. von Humboldt), which considers the landscape as having some sort of an intangible "character" or organisation of the objective landscape components. In this way, still allowing for different human and artistic interpretations, it serves as a core for related directions of landscape science, including landscape policy, landscape quality objectives identification, landscape protection, landscape management, and landscape planning. Obviously, landscape within these disciplines (such in the landscape management) is referred to as a material phenomenon, namely, the Earth environment, with the associated subjective psychological and social aspects (Simensen et al. 2018). These aspects are hard to quantify and even in the case of quantification assessments are rarely reproducible. Being perceived, the environment could be also referred to as a mental phenomenon, and this dichotomy of reality and its mental representation as a scientific subject are difficult to resolve. Our perceptions are not equal to the objects of the environment themselves.

This issue was elaborated by one of the most influential philosophers of the XIX and XX centuries—Edmund Husserl. Husserl formulated a representative theory of perception: physical object affects observer's sensory apparatus, and in this way, the mental representation of the physical object appears in observer's consciousness (Zahavi 2003, p. 17). To focus on the mental phenomena, Husserl suggested suspending the impact of reality on one's research; this process is roughly called "phenomenological reduction" in contrast to naturalistic reduction (meaning the traditional objective intentionality of "hard science" directed on the physical reality). It is important to understand, that remote sensing, as an integral part of "hard science"—alongside the naturalistic reduction of the environment, is able to serve the phenomenological reduction by mapping the environment as it appears to an observer with no regard to its biophysical conditions. In the context of landscape science this approach would result in mapping the character of geometric primitives of the environment (points, lines, surfaces), environmental colours, extent of environmental harmony, complexity, naturalness, contrast, etc. (Fig. 2) since remote sensing concepts often meet mental psychological and landscape concepts at some point (Fig. 3).

Figure 3 illustrates the idea of the operationalisation of the selected psychological concepts of the visual landscape quality by means of remote sensing. For instance, complex patterns and textures of the perceived environment captured with multispectral satellite imagery could be examined by reducing them to the relationships between the pixels:

- similarity or contrast of spectral values,
- their orderliness or entropy,
- correlation or homogeneity within the particular neighbourhood to generalise and detect the complexity and organisation of the visual environment (Fig. 4).

According to the most well-known theory of landscape preferences by Kaplan and Kaplan (1989), diversity and coherence (organisation) of the visual landscape are the strongest predictors of landscape preferences. Remote sensing provides a comprehensive set of indicators for objective assessment of these and other drivers of landscape values.

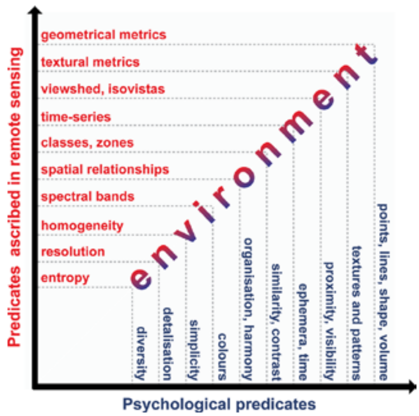

Fig. 3 Parallels between the predicates used in remote sensing, psychology and landscape science: (1) entropy as mathematical function describes landscape diversity; (2) spatiotemporal and spectral resolution of imagery corresponds to the details (or generalisation) of a landscape image; (3) remote sensing-based calculations of homogeneity indicate simplicity of landscapes; (4) spectral bands of the visible spectrum correspond to the human vision of colours; (5) spatial relationships between the pixels are responsible for harmony and organization mapping; (6) classification of imagery is based on similarity inside the classes of land cover; (7) time series of imagery describe feeling of time; (8) viewshed analysis is based on the landscape proximity concept; (9) textural and geometrical metrics are based on the human ability to extract patterns from visual images

Contemporary landscape science seems to centre around the aforementioned psychological and remote sensing concepts. However, despite the fact that the vast majority of papers use the standard definition from the European Landscape Convention, there is still no final scientific consensus about the use of the concept of landscape. This is because of the inherent dichotomous nature of landscapes. Irrespective of the area concept, landscape explicitly or implicitly means a phenomenon, emerging from both objective and subjective (perceptual and cognitive) processes (Fig. 3). The problem is exacerbated by the fact that the landscape discourse is avoided in “remote sensing”-focused papers due to the uncertainty of the concept, authors limit themselves to more definite and objective land units, such as land cover, inland water, terrestrial and marine environments. Landscape, here, seems to be unnecessary—indeed, no matter how the Earth surface is observed from some distance, it will be called or conceptualised, as the Earth’s surface. In this connection, the question raised is the following: What kind of remote sensing studies of the environment deal with the landscape? In other words, what are the criteria for treating some scientific works as dealing with or contributing to landscape problems?

Historically, the introduction of the landscape concept into scientific (first of all, geographic) vocabulary is attributed to Alexander von Humboldt (Antrop 2013), who used the German word Landschaft, inspired by Dutch landscape paintings (Kwa 2005). Etymologically, the roots of the word “landscape” are

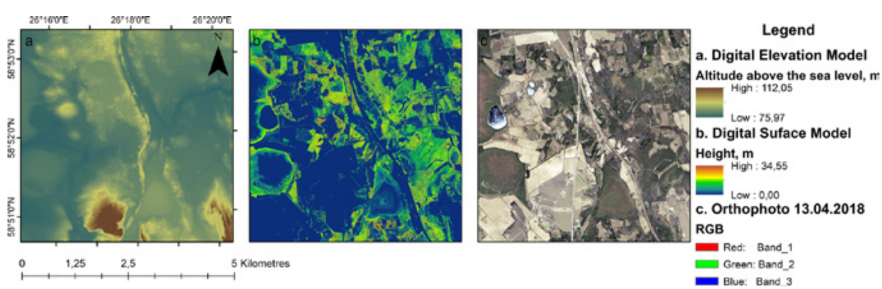

Fig. 4 Remotely sensed data for the area of Eastern Estonia (**a** LiDAR-based digital elevation model, **b** LiDAR-based normalised digital surface model, **c** multispectral orthophotograph captured 13.04.2018, natural colours band combination) which are commonly used to deconstruct the physiognomic landscape. There are easily recognisable linear patterns, as well as various textures typical for different land cover classes (water bodies, crop fields, forest), orthophotograph reflects the perceivable colours of land cover, DEM and DSM model surface of perceived environment. Pixels assigned to spectral or elevation values are in relationships of similarity and contrast, diversity (data credit: Estonian Land Board, Maa-amet)

found in German languages, with an emphasis on the piece of territory and administrative connotations, while its older analogues, in other languages (for example, in ancient Hebrew, French or Spanish), have more scenic connotations. However, starting in the XIX century, the concept of the landscape was firmly fixed in a variety of disciplines in science, humanities and the arts. There are several attempts to categorise all the approaches that categorise and operationalise the landscape. For example, Angelstam et al. (2013) distinguished the biophysical, anthropogenic, intangible as well as coupled social-ecological interpretations of landscape. A biophysical approach to landscape mapping includes physiographic landscape mapping or ecoregion mapping (Bailey 1983; Olson and Dinerstein 1998), which are mainly focused on the categorization of soil, vegetation, climate and biodiversity variables. Therefore, such landscape mapping approach easily utilises remote sensing data, while is not focusing on the physiognomic landscape features and landscape perception principles. Similarly, other authors distinguish between landscape approaches by describing them as an image, a natural complex, a natural-socio-economic complex, a structure of land cover or a holistic entity (Miklós et al. 2019). From this list, landscape, as a structure of land cover, seems to be the most convenient for the remote sensing application. Indeed, this approach, originating in the American school of landscape ecology (Forman 1995) is the most fruitful, in terms of filling the gap between tangible and intangible components of landscape structure. This is in contrast to "hard" geographic or the objective landscape characterisation (Mücher et al. 2010; Miklós et al. 2019) and "soft" humanitarian approaches, such as holistic landscape character assessment as defined by Miklós et al. (2019). Emphasising the organisation of the environment as sensed from space or airborne crafts, is the best way to meet the most important assumptions of the landscape definition in the European Landscape Convention, namely, the human visual perception, the character of the Earth environment within a defined area and factors, leading to this character.

Antrop and Van Eetvelde (2017b) synthesised all the diversity of the landscape deconstruction principles into 5 main models, including "Element, Component, Structure", "Point, Line, Polygon, Surface", "Patch, Corridor, Matrix, Mosaic", "Mass, Screen, Space", and "Landmark, District, Path, Node, Edge". For our purposes, we limited ourselves to an amended model, namely, the "Point, Line, Polygon, Surface" model (with the addition of colour and textures but the removal of polygons, since they can be represented with lines). We also indirectly used "Patch, Corridor, Matrix, Mosaic", reduced to a mosaic of patches, to discuss the landscape heterogeneity, by utilising the land use/land cover classification widely.

The deconstruction of landscape patterns necessitates spatial comparisons, classification and assessment of the visual quality of different landscapes. Hence, landscape values and preferences gain the raising scientific interest (often within the cultural ecosystem services framework). Therefore, the following common aspects of the landscape are defined, and whatever is considered landscape is treated as an objective entity (system, complex) or a subjective phenomenon of the mind (mind image):

1. Spatial and organised;
2. Meaningful and valuable for its observers;
3. Originating in the perceived environment, assessable using remote sensing.

Attempts to quantify the landscape attributes have resulted in the creation of a variety of landscape metrics (landscape indices) appropriate for a GIS-analysis of landscapes. However, the remote sensing part in these studies is extremely limited. Usually, landscape scientists work on the fully processed land cover classifications (such as CORINE land cover models) and the digital elevation models (DEMs), and they rarely process the raw or slightly pre-processed satellite imagery, orthophotos and LiDAR (light detection and ranging) data. Additionally, remote sensing experts are not interested in the aesthetic problems of Earth observation but prefer examining more concrete phenomena, such as crop monitoring, urban sprawl or pollution mapping. Remote sensing imagery, in this regard, serves as a substitute for the traditional land-based surveys. Landscape indicators make the landscape pattern assessable, often using remotely sensed data thus the following chapter will be dedicated to the remote sensing applications used in the typical examinations of the physiognomic landscape attributes. These attributes are selected and generalised from the landscape character assessment studies (Ode et al. 2008; Fry et al. 2009), landscape aesthetics manuals (U.S. Forest Service 1995), the theory of landscape preferences (Kaplan and Kaplan 1989), the landscape design theory (Bell 2004) and governmental guidelines (BLM 1986; Tudor 2014). They provide a comprehensive set of attributes of physiognomic landscapes, assessable with remote sensing-based indicators ("Appendix", see also electronic supplementary material).

Figure 4 presents the logic on how the remote sensing data can be utilised for physiognomic landscape deconstruction. Imagery pixels serve as the elementary unit of physiognomic research and can be treated as points (especially true for LiDAR data) and, taken altogether, as surfaces (DEM and DSM). During the visual examination of these images, one can easily capture the linear elements of the landscape (roads, lake shoreline). One can also distinguish between the land cover classes (categorise image mentally) as well as recognise the textural differences within the image (among the different vegetation patches). Overall a pixel mosaic and land cover variety create a feeling of diversity, as well as to some extent, harmony (or incongruity). Some pixels are similar, while others are to an extent, contrasting (lakes and surroundings, for example). Thereby, the proposed image serves as a case for quick visual deconstruction of the visual landscape using remotely sensed data.

Indicators of the perceptual attributes of the physiognomic landscape

Indicators of points

The concept of a point in physiognomic landscape studies varies significantly. For example, according to Bell (2004), different visual elements are regarded as points, including isolated standing buildings or trees, sources of lights, such as stars, and the focal point of lines of convergence. Continuing with this logic, all the objects of the environment, mapped as points in geospatial data collections, such as OpenStreetMap (OSM Community, n.d.) or the Countryside Survey in UK (Wood et al. 2018) are narrowed down to dimensionless points in the observed landscape (depending on scale). These points include features such as ponds, water features, buildings and landmarks with different functional purposes, We argue that this logic is based on saliency as a perceptual quality of the objects, to be distinguished among others in the visual scene due to their eye-catching character and the specifics of the pattern of human eye movements. Saliency mapping provides an objective method towards the real modelling of landscape perception using, for example, a correlation analysis. A high correlation of photo pixels means a low saliency potential (Dupont et al. 2017). In this regard, landscape points are treated simply as the objects, in contrast to the rest of the visual environment. Consequently, remote sensing-based mapping of point objects in the physiognomic landscape should be based in spatial autocorrelation or pixel-based texture metrics, such as the Grey-Level Co-Occurrence Matrix texture metrics (Haralick et al. 1973; Hall-Beyer 2017). This approach is already utilised for the detection of stand-alone palm trees, with high-resolution satellite imagery (Idbraim et al. 2016). However, no studies were found connecting in situ eye-tracking analysis with remote sensing-based textural mapping, thus, this lack of results frames the respective potential for further research. At the same time, cutting-edge remote sensing techniques were recently used to examine single trees as landscape features with high-resolution data from UAVs (Dandois et al. 2017), this is potentially useful for the assessment of landscape aesthetics. The density and spatial configuration indices (such as entropy) of point landscape data are the most obvious GIS-applicable indicators of landscape character, following the remote sensing-based detection of single landscape elements.

Indicators of lines

Various elements of the visual landscape are modelled as lines, including the edges of landscape patches and different networks (water streams, roads and pedestrian trails, streets, ridges and valleys). In these cases, we ignore their width depending on their scale and purpose. Usually, the overall length of the lines, their density and topological regularities (based on graph theory, such as connectedness), and their line shape characteristics, such as the fractal dimension, are treated as meaningful for visual landscape quality. Remote sensing is widely used for the detection of linear features of the landscape, including geological fractures (Yang et al. 2011). Remote-based digital elevation models, processed from digital surface models (DSMs), such as the Japan Aerospace Exploration Agency (JAXA) Advanced Land Observing

Satellite (ALOS) 30-m Digital Surface Model (T. Tadono et al. 2014), are used for mapping water drainage networks. This has further implications for the GIS-based analysis of scenic landscape quality (de Almeida Rodrigues et al. 2018), as the positive impact of water landscape elements on the landscape values and preferences is well recognised (Ode et al. 2008; Swetnam et al. 2017). The shape of linear landscape elements is another important aesthetic variable (U.S. Forest Service 1995; Bell 2012) as is the geometric properties of landscape lines. For instance, the fractal dimension of lake coastlines (Sudakov et al. 2017), the fractal dimension of polygonal patches (Olsen et al. 1993) and the indices of urban morphology (Li and Yeh 2004) are also successfully derived from mapping products, based on satellite imagery. Texture features are reported to be successful for predicting the height, circumference, stand density of trees in a forest and other structural parameters (Kayitakire et al. 2006; Ozdemir and Karnieli 2011) responsible for the formation of a forest silhouette in the landscape. Some shape indicators for building classification in LiDAR remote sensing data have also been developed (Lu et al. 2014). Thereby, remote sensing techniques, used in conjunction with the GIS-analysis, perform well regarding the detection and monitoring of the linear features of physiognomic landscape. They are also useful for obtaining an accurate assessment of their aesthetic properties through indicators, such as the fractal dimension (Bell 2012) or other metrics.

Indicators of surfaces

Continuous geographic phenomena, such as land surface, topography, vegetation canopy and urban structures contribute to the physiognomic landscape. Remote sensing-based operationalisation of such phenomena results in two major types of digital models, namely DSMs and DEMs. DSMs and DEMs are commonly produced from:

- Synthetic-Aperture Radar (SAR) imagery, such as Shuttle Radar Topography Mission (SRTM) data (Farr et al. 2007),
- satellite-based stereo mapping data from sensor, such as ALOS PRISM (Tadono et al. 2017),
- Airborne Laser Scanning (ALS) data obtained with LiDAR technology for areas up to the national level—for example, in Estonia (Estonian Land Board 2018) or Finland (National Land Survey of Finland 2018),
- UAV imagery with custom photogrammetry processing (Long et al. 2016).

Different spectral, spatial and temporal resolutions, as well as coverage of remotely sensed data, determine the different applications for the surface detection and characterisation. For instance, recent advances allow automated surface material mapping with hyperspectral remote sensing data and DSM, obtained with stereo imagery (Heiden et al. 2012). As shown above, the fractal dimension is frequently used to characterise the shape of the linear landscape elements. The same operation as the surface form indicator is also possible for raster models, such as satellite imagery (Lam 1990) or topographic models, such as DEMs (Polidori et al. 1991; Xu et al. 1993). This is yet an uncovered potential for landscape aesthetics assessments, based on the assessment of the visual quality of the DEMs and DSMs. There is also a growing interest in the fractal dimension mapping from SAR data. This mapping is directly linked to the properties of the physiognomic landscape under consideration, such as the landscape topography and the complexity of the landscape elements (Di Martino et al. 2017). The final products of the DEM classification (landforms) are used in map-based landscape aesthetic assessments as a source of data for landform contrast estimations (Booth et al. 2017). The smoothness and waviness of topographies and the terrain roughness estimated from satellite-derived DEMs are also strong predictors of the aesthetic values of landscape (de Almeida Rodrigues et al. 2018).

ALS data has a growing potential for the modelling and discretisation of the perceived environment as a continuous surface. LiDAR technology provides a source of data for digital surface model (DSM) and digital elevation model (DEM) production, as well as a reliable classification of products. Thus, it is a comprehensive toolkit for physiognomic landscape deconstruction as both points and surfaces, especially in combination with hyper- and multispectral remote sensing data (Yokoya et al. 2014). To comprehend the landscape pattern with LiDAR data, numerous LiDAR-based metrics for 3D landscape models have been created (Chen et al. 2014; Lu et al. 2014; Cheng et al. 2017). With multitemporal LiDAR data, the evolution of the physiognomic landscape can be traced

(Mitasova et al. 2011). On the other hand, visibility analysis is a more prominent trend in LiDAR-based studies, since it allows for the identification of the optimal viewpoints within the landscape. It also provides a map of the visual exposure of objects in order to estimate the visual impact of the landscape elements (Domingo-Santos et al. 2011) and performs a viewshed analysis for point data, such as houses (Vukomanovic et al. 2018). Indicators of the cultural ecosystem services provision (Burkhard and Maes 2017) can be obtained from location-based social media content in the form of points (geotags of photographs, uploaded to the social media such as Flickr or VK.com). ALS-based DEMs and DSMs are also very common in archaeological studies (Fryskowska et al. 2017; Witharana et al. 2018), allowing for the detection of historical remains and the uncovering of the historical value of the physiognomic landscape (Ode et al. 2008). The role that ALS data plays in the visualisation and assessment of aesthetic properties of vegetation canopy can hardly be overestimated: one of the first attempts in this direction was made recently by Vauhkonen and Ruotsalainen (2017).

Indicators of texture

The evaluation of texture, as an innate property of the physiognomic landscape (usually varying between fine and coarse or rough), is very common in landscape character assessments and scenic resource assessments; hence, it is important for landscape design purposes (U.S. Forest Service 1995; Bell 2004). Texture characteristics depend on the size of the landscape elements, the distance between them and are scale-dependent. Texture mapping in remote sensing applications began in the early seventies with the first theoretical paper in this direction by Haralick et al. (1973). Easily computable texture metrics, based on the Grey-Level Co-Occurrence Matrix (GLCM), have become very popular, with the rapid accumulation of the remotely sensed data at increasingly better spatial resolution. Despite the slightly different nature compared to the understanding of texture in landscape research (where the texture is usually articulated as fine or coarse), these metrics substantiated a solid ground for the mapping of land cover texture as the characteristic of the relationships between the pixel pairs (similarity, contrast, diversity, orderliness of pixel values). These principles of texture interpretation provide a bridge between the quantitative and subjective interpretations of the relationships between the elements of the physiognomic landscape and are modelled in the raster model. The potential of Haralick's texture metrics applied to the mapping of the characteristics of the physiognomic landscape is just gradually being uncovered, and thus, only a few studies were found. These studies are dedicated to the examination of the visual landscape quality and textural features of the land cover extracted from the remotely sensed data, therefore this topic definitely deserves a detailed description. It should be mentioned, though, there are other approaches to texture analysis suggested, including Tamura's textures (Tamura et al. 1978), wavelet texture analysis (Picuno et al. 2011) or variogram (Berberoğlu et al. 2010). However, in the landscape-related domain of remote sensing science, Haralick's GLCM-based textures seem to be dominating, while landscape texture is indicated with landscape metrics (Sahraoui et al. 2016).

In a pioneering work within this direction, Ozkan (2014) attempted to find the correlation between the texture metrics for the IKONOS satellite imagery (result of the Principal component analysis PC_1 band as having the highest variation) and the results of the visual quality assessment of the landscape within the woodlands of Istanbul in Turkey (alongside the Bosporus strait). The article hypothesised that:

1. First-order pixel-based Grey-Level Co-Occurrence Matrix (GLCM) texture index, namely, Standard deviation of grey levels (SDGL);
2. Second-order pixel-based GLCM texture metrics, namely, correlation (GLCMC), entropy (GLCME) and homogeneity (GLCMH);
3. Object-based measures of texture: mean of sub-objects/std. dev. (MSOSD), the average mean the difference to neighbours of sub-objects (AMSO), the area of sub-objects/mean (ASOM) and the area of sub-objects/std. dev.

(ASOSD) were related to the visual quality of the landscapes under consideration as represented by the quantitative scores allocated to the in situ photographs by the participants in the survey. Ozkan reported strong and positive Pearson correlation with the scores of the visual landscape quality for the pixel-based SDGL ($r = 0.82$, $P < 0.01$), as well as for the object-based MSOSD and AMSO ($r = 0.61$ and $r = 0.67$ respectively, $P < 0.01$). A moderate positive Pearson correlation was also observed for the pixel-based GLCMC metric ($r = 0.56$, $P < 0.01$), and ASOM and ASOSD showed a moderate negative correlation ($r = -0.57$, $r = -0.52$ respectively, $P < 0.01$). The GLCMH correlation was poor ($r = 0.36$), and GLCME showed almost no correlation to the landscape quality ($r = 0.05$, $P < 0.05$).

The textural metrics for continuous raster data also corresponded to the estimation of the landscape metrics for classified data. For example, GLCM-based Entropy, derived from the red and infrared bands of ASTER satellite imagery (window size between 900×900 and 1200×1200 m) was reported as most highly correlated to the different landscape metrics within the forested areas (Ozdemir et al. 2012). Therefore, the textural metrics seem to be very important for the landscape analysis, since commonly being pixel-based, they do not require image classification before their computation, while image classification biases the results in landscape studies (Shao and Wu 2008). Avoiding this bias constitutes the advantage of landscape texture mapping with remote sensing techniques compared to landscape examination with common landscape metrics.

Indicators of colours

Colours are the attributes of the perceived environment, and their importance to people was recognised at the beginning of the 20th century (Granö et al. 1997). The first maps of landscape colours were designed at that time as well. Later, colour discourse, to some extent, shifted from the domain of environmental science and geography to landscape design (Bell 2004) and architecture (O'Connor 2010), despite the fact that colours were still articulated as important landscape attributes (Bell 2012; Ode et al. 2008; U.S. Forest Service 1995), and colour diversity recognised as positively related to landscape values and preferences (Zhao et al. 2013). However, even in this case, rare empirical studies, involving the examination of landscape colours are 1) often observer-dependent (Bishop 1997) and 2) based on a ground viewing perspective (Sowiŕska-ŕwierkosz 2016). Colour diversity and contrast are the most common landscape attributes in studies, involving such components (BLM 1986; Arriaza et al. 2004; de la Fuente de Val et al. 2006; Lengen 2015), while colour harmony only becomes a problem at the landscape scale (Sullivan and Meyer 2016).

Remote sensing studies often use colours mapping for non-aesthetic purposes, for example to examine the water dissolved organic and inorganic matter (Bukata et al. 2018) or vegetation greenness (usually not only with a green band of multispectral imagery but with various vegetation indices, utilising the invisible near-infrared bands, such as NDVI). NDVI is used as a standalone predictor of the aesthetic value of the landscape (Vukomanovic and Orr 2014; Vukomanovic et al. 2018), however there has been no confirmation that it affects the objective aesthetic variables, such as the colour harmony of the land cover (Karasov et al. 2018). Almost no papers on the spectral properties of the landscape (namely: land cover) from the remote sensing perspective in the context of the physiognomic landscape quality were found. This is despite the fact that the spectral properties of the landscape are analysed for scanned images (Clay and Marsh 1997), The exceptions are the recent work on the remote sensing-based mapping of the colour harmony of land cover (Karasov et al. 2018) and the spectral analysis of the plasticulture impact on the landscape quality (Picuno et al. 2011). Remote sensing-based analysis of the spectral properties of land cover in the visible spectrum (colouristic analysis) is a huge gap in our existing knowledge that needs to be filled, especially owing to the rapid development of less atmosphere-dependent remote sensing methods (such as UAV-derived imagery). Increasing the spatial and temporal resolutions of satellite imagery supports this direction of landscape research because the colours of the perceived environment are very dependent on the phenological and seasonal effects. The accurate detection and monitoring of the colouristic properties of the land cover with remote sensing data, in the context of their emotional and aesthetical meaning for observers, is a relevant task for contemporary and future Earth observation applications.

Indicators of the cognitive attributes of the physiognomic landscape

Indicators of heterogeneity and diversity

Landscape heterogeneity, in all the interpretations, is likely the most well-studied concept in landscape science, according to a recent review on this topic (Dronova 2017). Originating from a classical geographic genetic approach, landscape heterogeneity is connected with the variety, diversity, complexity and richness of the physiognomic landscape (Fry et al. 2009; Ode et al. 2008), and thus, here, we used all of these concepts interchangeably. These landscape attributes are commonly recognised as positive factors of landscape values and preferences (BLM 1986; Kaplan and Kaplan 1989). The respective relationship, however, seems to be non-linear but rather an inverted U-shaped (Kaymaz 2012). In turn this means the diversity in highly visually attractive landscape needs to be present in moderation (Bell 2012; de la Fuente de Val et al. 2006; U.S. Forest Service 1995). Indeed, existing studies, indicating landscape diversity mostly with Shannon entropy (known also as Shannon–Wiener diversity index as landscape index) and other diversity indices (fractal dimension for linear elements, shape indices, Renyi's, Simpson's, Pielou's diversity indices, etc. (McGarigal and Marks 1995; Rocchini et al. 2013)) report a wide range of correlation strength between the map- and view-based landscape diversity and landscape preferences. The correlations vary from relatively positive (Hunziker and Kienast 1999; Franco et al. 2003; de la Fuente de Val et al. 2006; Dramstad et al. 2006) to completely negative (Ode and Miller 2011), and thus, the association of the perceived diversity with the values and preferences of the landscape is not simple. In line with the theoretical findings, the authors of these empirical studies usually note, that diversity should somehow be limited, making the landscape legible for observers (hence, concepts of landscape coherence, harmony and legibility are raising) and decreasing the mismatch between the landscape elements, composing diverse elements into some coherent pattern (Ode et al. 2010). Therefore, the main message of the vast majority of papers dealing with landscape heterogeneity in the visual context is that diverse, visually rich landscapes should not be messy to be aesthetically attractive. Quite a large number of heterogeneity indices for remote sensing data are designed to detect not only pure diversity but also, to some extent, their organisation into some system, while organised diversity directly refers to the information concept. In this connection, these indices are frequently referred to information and are discussed with regard to the physiognomic landscape and scenic values (Uuemaa et al. 2013). There are numerous aspects of landscape diversity (Mander et al. 1999; Dronova 2017), leading to the development of various applications of mathematical advances to landscape attributes of every kind.

A "family" of heterogeneity metrics can be applied to all the elements of the physiognomic landscape detectable with remote sensing, including:

- point landscape data (Fjellstad et al. 2001; Cheng et al. 2017),
- vegetation communities and plants (Nagendra et al. 2013),
- colours (Karasov et al. 2018),
- textures (Sahraoui et al. 2016),
- topography and landforms (Vukomanovic and Orr 2014; Booth et al. 2017; de Almeida Rodrigues et al. 2018),
- soil cover (Uuemaa et al. 2008),
- land use and land cover patches (Cadenasso et al. 2007),
- the shape of the linear elements and polygons (Li and Yeh 2004; Martín et al. 2016; Booth et al. 2017),
- the temporal change of the landscape pattern (Pham et al. 2011).

Unsurprisingly, these remote sensing studies have significantly contributed to this topic. For instance, Ayad (2005) deployed remotely sensed data in land use/land cover diversity mapping and linked it with the landscape visual quality. A modified fractal dimension index is suggested to measure the landscape diversity for a Landsat TM image (Olsen et al. 1993). Vegetation diversity is a frequent subject of remote sensing studies, and successful examples of spectral and textural measures of the biological and structural diversity of urban forests were presented recently (Ozkan et al. 2016, 2017). Vegetation and land cover/land use changes are also frequently examined through the lens of the landscape metrics change (Velli et al. 2018). Cloud points (LiDAR scanning output) are even more promising for landscape diversity estimation. For example, a mobile laser scanning (MLS) LiDAR data for urban street landscapes was utilised for calculating the suggested landscape diversity index (function of number and area of landscape classes and average height of the points in the class). This was reported as moderately, but still positively correlated with the general urban habitability score, as surveyed with respondents (Cheng et al. 2017).

The excessive landscape heterogeneity and the respective visual diversity lead to, as shown above, the decreasing visual landscape quality, which is described as landscape cluttering (Nijhuis et al. 2011). Remote sensing-based land use/land cover data is used in GIS-analyses of landscape configurations in order to evaluate the extent of landscape cluttering (Wagtendonk and Vermaat 2014) and its impact on the scenery. It is noteworthy that remote sensing-based indicators of landscape heterogeneity are so successful for landscape characterisation that they are even able to explain up to 59% of the variability of one poverty index for urban areas (Duque et al. 2015), eliminating the distinction between physical and social phenomena. The potential of RS-based landscape heterogeneity studies in the visual context lies in the application of diversity indices to a wider number of landscape elements, such as points, textures, pixels, as elementary units of the satellite imagery, orthophotographs, and UAV-derived and LiDAR data of very high spatial resolution as a landscape model. Furthermore, there is a need for a deeper understanding of the innate nature of the diversity indices for harmony and coherence, cluttering estimations and mappings, since a simple correlation of diversity to scenic preferences does not meet the psychological regularities of the landscape valuation to the full extent.

Indicators of harmony and incongruity

Landscape harmony refers primarily to the pleasant arrangement of the landscape attributes (U.S. Forest Service 1995). As discussed above, to a large extent, it depends on diversity or complexity estimations (Mander et al. 1999; Ode et al. 2010; Ode and Miller 2011; Wagtendonk and Vermaat 2014), which are widely recognised as a landscape attribute and are positively associated with scenic preferences (Kaplan and Kaplan 1989; U.S. Forest Service 1995; Ode et al. 2008; Martín et al. 2016; Sowiɾska-ɾwierkosz 2016). Landscape harmony is also closely related to landscape coherence as an added value to the landscape as a system (Bell 2012) and is connected with the ecological concepts of biological connectivity or physical connectedness (Mander et al. 2010; Ode et al. 2010; Martín et al. 2016).

The foremost application of remote sensing is the detection of land cover and land surfaces, and this detection is associated with landscape harmony to different extents. For example, the detection of aesthetically polluting plastic covers for plant cultivation (Picuno et al. 2011) or the pixel-based differentiation of land cover according to the extent of its colour harmony (Karasov et al. 2018). Remote sensing-based land cover and land use (LULC) data is a valuable source of landscape coherence mapping in both ecological (patch connectedness) and visual (unity of the scene) contexts (Ode et al. 2010; Martín et al. 2016). Numerous other landscape indices, such as the contagion index (McGarigal and Marks 1995; Sahraoui et al. 2016), PLADJ (Uuemaa et al. 2008; Pham et al. 2011) and many others (Gong et al. 2013), were designed to assess the objective landscape fragmentation, including the visual context. Increasing the spatial resolution of remotely sensed data, for example, by wider use of unmanned aerial systems (UAS) instead of satellite imagery, frames the perspectives of this direction. There are already successful examples of visual disorder detection for urban areas with such kind of data (Grubesic et al. 2018). GLCM-based and other texture metrics are a huge uncovered potential as a landscape harmony indicator, since they are very promising for the explanation of the visual landscape quality (Ozkan 2014) and the mapping of pixel relationships, meeting harmony assumptions (Karasov et al. 2018).

Indicators of cultural modification and naturalness

Natural landscapes are more visually attractive, than man-modified or artificial ones (Kaplan and Wendt 1972; Zube 1974; Balling and Falk 1982; Coeterier 1996; Ode et al. 2008) and are perceived as more visually coherent (Hansson et al. 2012). Ode et al. (2008) suggested that the percentage of natural vegetation and water is an indicator of the naturalness of the landscape. A simpler approach is the estimation of the area of patches, corresponding to the natural (Martín et al. 2016) or artificial land cover and land use (Ayad 2005). Similarly, the cost distance from the roads (Terrain Ruggedness Index as a cost surface) is used as the index of naturalness or, vice versa, the cultural modification (Karasov et al. 2018).

Remote sensing data is easily used to detect the extent of urbanization and vegetation loss, indicating the cultural modification of the landscape (Sawaya et al. 2003; Wilson et al. 2003; Rêgo et al. 2018). Classifications and utilising spectral properties of the landscape surfaces are common in the recognition of natural vegetation (Jahel et al. 2018) and the monitoring of land use change intensities (Estoque and Murayama 2015). Urban sprawl is the typical subject of remote sensing studies, examining the substitution of natural or semi-natural environmental surfaces by artificial ones (Chiang et al. 2014). Backward processes, such as the regreening of the industrially modified landscapes and land reclamation, are also assessable using remote sensing (Boerchers et al. 2016; Townsend et al. 2009). The potential of remote sensing applications in the detection and monitoring of the range of environmental conditions, corresponding to natural, semi-natural or completely artificial landscape elements, therefore, lies in their more accurate accounting. At the moment, the extent of naturalness is often determined by LULC classified data with the respective delimitations or it is focused on phenomena (vegetation loss, urban sprawl) rather than on the physiognomic attributes themselves. In this way, remote sensing applications for such purposes are currently rather hypothetical but are, of course, promising.

Indicators of similarity and contrast

Similarity and contrast are landscape attributes that are crucially important for both landscape perception and remote sensing, because they determine the mental discretisation and GIS-based classification and regionalisation of the continuous environment into the discrete classes of objects, thus generalising reality. These concepts are directly connected to landscape aesthetics, sometimes in a strange manner. For example, both contrasting and similar colour combinations are treated as aesthetically attractive (BLM 1986; U.S. Forest Service 1995; Arriaza et al. 2004; de la Fuente de Val et al. 2006; Karasov et al. 2018), depending on the specific colour features. Similarities and contrasts affect the distinguishability of the objects from their background, being extremely important in this vein for landscape perception and appreciation (Dupont et al. 2017). Remote sensing-based applications to landscape similarity/dissimilarity mapping utilise landscape indices (Niesterowicz and Stepinski 2016), GLCM-based textural metrics (Karasov et al. 2018; Ozkan 2014), and topographic variables, such as the relative relief contrast (Booth et al. 2017). There is a lack of knowledge regarding the RS-based mapping of landscape similarities and contrasts in a visual context, and thus, there is a need for further investigation in this field.

Indicators of ephemera (temporal dynamics)

Last, but not least, the temporal dynamics of the landscape seem to be the most popular topic throughout all the landscape studies, utilising a remote sensing approach, since it is based on change detection methods. Seasonal and weather-driven changes, as well as successional and other long-term changes (Fry et al. 2009; Bastin et al. 2012), are easily assessable with remote sensing data. Temporal data adds reliability to the landscape quality assessment due to the dynamic nature of the landscape (Antrop 2000). Historically, Crawford (1994) was among the first to undertake the application of remote sensing to visualise the landscape quality ranking, using complex remote sensing-based indicators for physiognomic landscape classification. He used the Landsat MSS product and radar data in order to perform the maximum likelihood classification of the land cover and established some visual quality criteria; these included landforms (slope steepness as indicator), structures (indicated by texture of MSS Band 5 band), tree cover (band ratio vegetation index (RVI) as indicator), water bodies extent (extracted from land cover classification), activity (as determined by the predominant land use), outlook (the number of the potential viewpoints within each landscape unit), diversity (number of identified land cover classes per landscape unit), and contrast (average texture for all MSS bands). As a result, the maps of the Landscape Visual Quality ranking were designed for two different years, adding a temporal perspective to the study. Similarly, any remote sensing-based study can be enriched with a multitemporal analysis of the status and the trends in the quality of the physiognomic landscapes.

There are many approaches to analyse landscape elements as temporal phenomena using remote sensing with vegetation indices (Ferreira et al. 2003; Hill et al. 2011), spectral signatures (Arroyo-Mora et al. 2018), image classification (Kadmon and Harari-Kremer 1999; Sesnie et al. 2008) and multitemporal LiDAR processing (Eitel et al. 2016; Putman et al.

2018), etc. We confirm the results of Uuemaa et al. (2013), suggesting that the changes in the land use/land cover remain the most widely exploited application of remote sensing to landscape study, despite the fact that remote sensing applies to the change detection of all the physiognomic landscape elements (Kennedy et al. 2009). Due to the lack of freely available satellite free imagery combining very high spatial and temporal resolution, UAVs and airborne sensors as well as (in the case of significant technical evolution) the satellite sensors with a very high spatiotemporal resolution seem to be the most promising in this regard. An accurate accounting of the gain and loss of the visual quality of the landscape helps to analyse the extent of the sustainability of land use practices and all kinds of environmental management. Therefore, adjustment of the management goals and methods correspondingly and instantly mitigates the negative impact of human activity on landscape and preserves it in the desired function for the coming generations.

Discussion

The results are meaningful in different regards. We attempted to demonstrate that the remote sensing and Earth observation themselves are based on the human cognitive specifics, being developed by people and for people. However, despite this psychological basis, the respective psychological problematics (landscape perception and landscape appreciation) are not widely implemented into the remote sensing studies. The vast majority of the reviewed studies used remote sensing to solve the particular scientific tasks, described above, while just a few authors directly mentioned the visually perceived environment as the subject of their papers (Ayad 2005; Karasov et al. 2018; Ozkan 2014; Vukomanovic et al. 2018). We articulate this problem and claim that one of the promising directions for further remote sensing development is a wider use in remotely sensed data in physiognomic landscape research. This will complement the in situ surveys of visual landscape quality and increase the overall quality of research in the interdisciplinary environmental science domain. Visual landscape quality is extremely important to sustain the well-being of billions of people; nevertheless, its assessment by means of remote sensing remains highly understudied. At the same time, soil, water, vegetation, and air quality are among the most well-studied applications for monitoring with remotely sensed data (Miklós et al. 2019).

Therefore, we emphasize the necessity of the remote sensing-based monitoring of the main parameters of visual landscape quality utilising remote sensing approach. Of course, indicators of soil, water, vegetation, and air quality are much clearer and more justified. At first glance, the extent of landscape aesthetics may look intangible and hard to estimate (by the way, it is). However, borrowing from the regularities of human perception for various visual stimuli from psychological literature, such as in case with mapping the degree of colour harmony of land cover (Karasov et al. 2018), we may achieve a highly reliable (of course depending on the spatiotemporal resolution of remotely sensed data) time- and cost-effective monitoring of the visual quality of the environment on a permanent basis. The same is true also for other psychological attributes, such as visual diversity, complexity, coherence, legibility, naturalness, seasonality, etc., which are assessable by means of remote sensing. Numerous authors, as shown above, even though they did not know it, provided an empirical basis for accounting these psychological attributes from space as applied to the physical objects of the environment. By means of remote sensing, one may see that so-called "hard science", of studying the state of the environment in the case of remote sensing, combined with several perceptual attributes can be reoriented towards the focus on these perceptual attributes (or phenomena) themselves. In other words, above and beyond the role of remote sensing in biophysical indicators mapping, remote sensing should be reflective and attempt to investigate visible landscape characteristics among with traditional "hidden" variables, such as vegetation indices.

Consequently, cutting edge remote sensing techniques for environmental applications allows the transition from mapping the traditional environmental problematics (land cover mapping, vegetation monitoring, assessment of habitat and ecosystems, biodiversity mapping, etc.) towards the mapping of intangible values of nature (mapping the visual quality of land cover, vegetation appearance mapping, assessment of cultural ecosystem services provision, mapping the degree of landscape attractiveness, etc.). Similarly, in habitat modelling, remote sensing data could be applied to modelling the multifunctionality of the landscape (applicability for various purposes related, among others, to leisure and recreation), especially taking into account achievements of the citizen science and crowdsourcing methods. Google Street View and alternative services such as Mapillary, or location-based social media, for example, VK.com and Flickr, provide a great source of ground-based data of the visual environment, available to verify and enrich the results, obtained from a top view perspective. Nature protection and the extent of land use sustainability would benefit from including reliable maps of visual environmental conditions to the decision-making process, instead of, or complementing, the traditional surveys of visual landscape quality in situ (Dramstad et al. 2006; Janečková Molnárová et al. 2017; Sullivan and Meyer 2016).

And last, but not least—regular monitoring of the visual landscape quality from space is in line with existing global and regional environmental policies. For example, the global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development suggests to "integrate ecosystem and biodiversity values into national and local planning, development processes, poverty reduction strategies and accounts" (UN General Assembly 2018). More precisely the same logic is inherent in the European Landscape Convention proposing "to assess the landscapes thus identified, taking into account the particular values assigned to them by the interested parties and the population concerned" (Council of Europe 2000). Each country has its own national legislation and policy implications, but the idea is shared among them: to preserve and even enhance the quality of the environment. Therefore, contributions from remote sensing to the examination of the visual landscape are important in the context of implementing the global and local targets in environmental policy. Visual landscape quality is essential for nature-based recreation and tourism, contributing to the national natural capital and GDP accounting, therefore remote sensing techniques in visual landscape quality assessment are among the prerequisites for sustainable economic growth.

Closing remarks

In summary, all the history of active and passive satellites, airborne and UAV remote sensing provides solid evidence in favour of the applicability of Earth observation data for the purpose of physiognomic landscape mapping and assessment. There is already a sufficient number of remote sensing techniques for each attribute of the physiognomic landscape, described in the respective literature. The increasing spatial, temporal and spectral resolution of the satellite imagery makes regular monitoring and change detections for all the attributes of the physiognomic landscape potentially possible. At the same time, this opportunity has not yet been fully put into practice. The mappings of the physiognomic landscape with remote sensing remains limited and is still rather uncertain. Reporting mainly the correlations and tending to avoid the exploration of the causal relationships; this avoidance is not surprising, considering the rapid growth of the quality of remotely sensed data and the corresponding time for its adaptation for the common needs of landscape science. However, the increasing number of remote sensing techniques potentially or actually used for physiognomic landscape mapping is encouraging. Perhaps, we will see a regional and global mapping of physiognomic landscape and its quality solely with remotely sensed data in the near future. What is more, the implementation of physiognomic landscape quality assessment derived from remote sensing data could be easily applied to the delineation of protected areas and used for the other nature protection purposes, providing the evidence-based knowledge for decision-makers. However, currently, we must note a lack of the comprehensive use of remote sensing data for the mapping of the landscape aesthetics extent per se and in the context of cultural ecosystem services provision.

It is foreseeable that the problem of the indirect use and rare mention of remote sensing in landscape studies will gradually be solved in the coming years. Land use and land cover classifications, DEMs and DSMs, while considered simple GIS-datasets, make remote sensing more visible for the academic community in landscape science. Most likely, we still have to face the issue of the multiple meanings of the term "landscape", where remote sensing experts have tended to avoid its use or use in an objective sense, with minimal regard to its aesthetic properties and mainly focused on environmental variables. More research is required on this terminology bias and extraction of the knowledge from the remote sensing-based mapping of the attributes of the physiognomic landscape from the existing literature, as well as the implementation of the new remote-sensing-based indicators of these attributes into the practice of remote sensing research. Notwithstanding the above, remote sensing is a unique example of the synergy of both the objective and subjective connotations of the landscape concept. These connotations are inherently built into the human visual perception of the Earth's environment but are also for all kinds of evidence-based environmental monitoring. This fact removes the contradictions contained in the European Landscape Convention, and thus, remote sensing plays a crucial role in the implementation of its goals.

Alongside that, there are some challenges to overcome with remote sensing to make it completely appropriate for the purpose of physiognomic landscape mapping. First, all the remote sensing-based physiognomic landscape mapping products should be validated with in situ scenery data, linking the top perspective with a ground or person perspective—for example, crowdsourced photographs or street-level imagery. That is particularly true for colouristic and textural landscape attributes, which can be mapped with remote sensing since the validation of the LULC classifications is quite an easy task. Furthermore, the freely available satellite imagery of the best spatial (10 m in the visible spectrum) and temporal resolution (5 days at the equator) is provided by Sentinel-2, and such imagery is still not the best by far compared to the commercial solutions. All the reliable and practically applicable physiognomic landscape mapping and quality assessments should be based on imagery with centimetric spatial resolution and daily temporal resolution, coherent to the human scale of landscape perception. For example, the Estonian Land Board recently made their database of orthophotographs publicly available for the entire territory of Estonia. Acts of this nature are extremely important for the future of remote sensing in this country. Hopefully, with international efforts, accessibility to the sources of freely available remotely sensed data of very high spatial resolution will only increase. Another challenge is linking the indicators of the physiognomic landscape not only to the visual landscape values and preferences, as it is usually done, but to purely objective environmental variables, thus uncovering the hidden regimes of the natural self-organisation and human organisation of the landscape. Societies and economies of the countries will benefit from a better knowledge about the naturally and anthropogenically induced processes and phenomena in a visual context in order to preserve and spread the functioning regimes of the highly valuable landscapes over all the Earth's territories, therefore supporting nature protection and sustainable land use practices.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Table 1.

Table 1 Approaches for quantifying the perceptual and cognitive attributes of physiognomic landscapes

Qualitative landscape attributes	Quantitative physiognomic indicators	Method or technology for quantification	Sources/references
Points	Viewpoints and iconic places	Density of viewpoints	Ode et al. (2008)
	Other point landscape elements of all the scales	LiDAR-based point-clouds, LiDAR metrics	Mitasova et al. (2011) and Nijhuis et al. (2011)
Lines (shapes)	Fractal dimension	Area-perimeter relationships of patches	Siu-Ngan Lam (1990), Schirpke et al. (2013) and Sudakov et al. (2017)
	Line density	Summarised line lengths and total landscape area ratio	McGarigal et al. (2002) and de Almeida Rodrigues et al. (2018)

Table 1 continued

Qualitative landscape attributes	Quantitative physiognomic indicators	Method or technology for quantification	Sources/references
	Shape complexity	Shape sinuosity (a function of patch perimeter and area)	Booth et al. (2017)
Surfaces (forms)	Fractal dimension	The fractal dimension of contours, characterising the surface or of variograms, either of the whole surface or some of its profiles	Siu-Ngan Lam (1990) and Mesev et al. (1995)
		Pixel-by-pixel fractal dimension mapping, using a sliding window	Di Martino et al. (2017)
	Terrain roughness	Terrain Ruggedness Index, the standard deviation of altitude, slope variability	Bishop and Hulse (1994), Riley et al. (1999), Germino et al. (2001), Vukomanovic and Orr (2014), de Almeida Rodrigues et al. (2018) and Vukomanovic et al. (2018)
	Water-body size	Area of water inside an area unit	Booth et al. (2017)
	Visible surface	Viewshed density or viewshed area inside the area unit or other visibility analyses	Ode et al. (2008), Schirpke et al. (2013), Vukomanovic and Orr (2014), Burkhard and Maes (2017), de Almeida Rodrigues et al. (2018) and Vukomanovic et al. (2018)
	3D landscape metrics	Based on the structure of the digital surface model and digital elevation model, LiDAR data	Chen et al. (2014) and Chen and Xu (2016)
Textures	Pixel-based texture metrics (first-order or second-order metrics) as patterns of the local spatial variation of the pixel values	Kernel-based estimations	Haralick et al. (1973), Warner (2011) and Hall-Beyer (2017)
	Object-based texture metrics	Based on the pixel grouping	Ozkan (2014)
	Vegetative interspersion	Total number of pixels along the perimeters of the vegetation patches	Booth et al. (2017)
Colours	Colour diversity	Number of colours, their contrast	Arriaza et al. (2004), de la Fuente de Val et al. (2006) and Swetnam et al. (2017)
	Colour harmony	Second-order pixel-based textural metrics applied to HSV or HSL band composite (obtained from RGB composite), with further GIS-processing	Karasov et al. (2018)
	Greenness	Spectral indices calculation, such as NDVI (normalized difference vegetation index)	Bremer et al. (2011), Vukomanovic and Orr (2014) and Vukomanovic et al. (2018)
Heterogeneity, complexity, diversity	Patch density	Number of patches per unit of area	McGarigal and Marks (1995), Antrop and Van Eetvelde (2000), McGarigal et al. (2002), de la Fuente de Val et al. (2006) and Booth et al. (2017)

Table 1 continued

Qualitative landscape attributes	Quantitative physiognomic indicators	Method or technology for quantification	Sources/references
	Patch size standard deviation	Root-mean-square deviation in patch size	
	Patch-level diversity and evenness indices	Shannon entropy	
	Pixel-based texture metrics	Kernel-based estimation of entropy and other multicollinear metrics, often using Grey Level Co-occurrence Matrix	Haralick et al. (1973), Anys et al. (1998), Warner (2011) and Hall-Beyer (2017)
	Fractal dimension	See above (here regarding the geometric complexity of patches)	de la Fuente de Val et al. (2006) and Plexida et al. (2014)
	Spatial autocorrelation	Getis statistic for satellite imagery products and local Moran's I measure the pattern of land cover	Fan and Myint (2014)
	Terrain diversity	Terrain Ruggedness Index (TRI), VAR index of topographic heterogeneity	McGarigal and Marks (1995), de la Fuente de Val et al. (2006) and Vukomanovic and Orr (2014)
	Heterogeneity index	The proportion of the pairs of pixels of the grid, corresponding to the different land cover classes	Fjellstad et al. (2001) and Dramstad et al. (2006)
Cultural modification and naturalness	The proportion of landscape class of high naturalness (including water) or cultural modification	Class area and landscape area ratio	Arriaza et al. (2004), Palmer (2004), Ayad (2005) and Swetnam et al. (2017)
	Line sinuosity	See above	Booth et al. (2017)
	Fractal dimension	See above	Antrop and Van Eetvelde (2000), Taylor (2002) and Hagerhall et al. (2004)
	Fragmentation extent	Getis statistic as an indicator of fragmentation	Fan and Myint (2014)
Harmony, coherence, incongruity, disturbance, fragmentation	Landscape coherence (of geographic attributes)	Spatial autocorrelation (Moran's I) of soils and land use intensity	Mander et al. (2010)
	Fragmentation extent	See above	Fan and Myint (2014)
	Fractal dimension	See above	Lam et al. (2018)
	Contagion index	Function from a number of patch classes, the proportion of landscape occupied by each class and the number of adjacencies between the pairs of pixels of the different classes	McGarigal et al. (2002) and Sahraoui et al. (2016)
	Interspersion and juxtaposition index	Function from the patch adjacencies in the landscape	McGarigal and Marks (1995) and Sahraoui et al. (2016)
	Cohesion index	Estimation of the physical connectedness of the patches	McGarigal et al. (2002) and Plexida et al. (2014)
	Connectivity indicator CCI	The distance-based function of the connectedness	Mancebo Quintana et al. (2010) and Martín et al. (2016)

Table 1 continued

Qualitative landscape attributes	Quantitative physiognomic indicators	Method or technology for quantification	Sources/references
Similarity and contrast	Pixel-based texture metrics	Based on the Grey Level Co-occurrence Matrix	Haralick et al. (1973), Warner (2011) and Hall-Beyer (2017)
	Landform contrast (relative to forest or wetland patch)	Dividing the relative relief height by the average width of the wetland	Booth et al. (2017)
	Land-cover contrast	Number of different land cover types per area unit	Booth et al. (2017)
Ephemera, landscape dynamics and trajectories	Change of landscape attributes and the related indicators, metrics	Change of entropy and other indicators, multi-temporal analysis	Yeh and Li (2001), Herold et al. (2002), Jessel (2006) and Fuchs et al. (2009)
	Phenological and climatic indicators: temperature, precipitation, vegetation development	Related remote sensing techniques, visual interpretation	Ulbricht and Heckendorff (1998), Sobrino et al. (2000), Zhang et al. (2003), Ahas et al. (2005), Ganguly et al. (2010) and Belgiu and Csillik (2018)
	Change indices	Based on the land use/land cover classes transitions or environmental variables	Lambin and Ehrlich (1997), Käyhkö and Skånes (2006)
	Land use/land cover transitions	GIS-modelling and mapping	NextGIS Team (2018)
	Proportion of the land use/land cover classes and water with seasonal change	Landscape metrics, multi-temporal GIS-analysis	Ode et al. (2008)

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Mapping the extent of land cover colour harmony based on satellite Earth observation data

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Abstract The concept of colour harmony, being rarely used in geography, landscape and environmental studies, has been significantly developed in psychology, art and computer science within the different approaches: colour wheel geometry and, more recently, numerical models applied to colour combinations. Using the main numerical principles of colour harmony, borrowed from the psychological literature, this study aims to investigate the ways of mapping the extent of the colour harmony of land cover, based on satellite Earth observations and explain the spatial distribution of colour harmony scores. The naturalness of environment, as well as heat and moisture balance, are confirmed to be the main drivers of the colour harmony of land cover. Crowd-sourced photographs, collected from Mapillary service, were used to link satellite and ground-based estimations of the colour harmony of land cover as "proof of concept". They have a limited applicability for ground-based assessment of scenic colour harmony. Therefore, remote sensing data provide a significant support for nature conservation and sustainable management, being used for mapping of the colour harmony of land cover as an indicator of the visual quality of the perceived environment.

Keywords Colour harmony · Land cover · Landscape aesthetics · GLCM · Landsat

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Introduction

Land cover is often discussed in geography as a component of the landscape pattern (Antrop 2000); therefore, the spatiotemporal organisation of intrinsic land cover properties is a notable field of geographical research. A holistic approach to geographic phenomena assumes that the landscape as a whole is more complex than the sum of its composing parts. Consequently, examination of the relationships between land cover colours and their correspondence to environmental conditions is a task that is still within of the scope of geography and environmental science. Colour harmony is a widely known umbrella term that emerged in colour science and art to reflect all of the subjective human judgements regarding the compatibility of colours and their relationships, and land cover currently is commonly studied using remote sensing data. We understand colour harmony as pair colour harmony after Schloss and Palmer (2011, p. 551): “how strongly an observer experiences the colours in the combination as going or belonging together, regardless of whether the observer likes the combination or not”. Chamaret (2016) distinguishes three categories of colour harmony models: geometrical (based on classical assumptions regarding the mutual locations of the colours under consideration on the colour wheel; for example, Itten (1973) has developed one of the best-known theories in this direction), more recent numerical models (making colour harmony quantifiable) and a conceptual contingent model suggested by O’Connor (2010). Clearly, numerical models of colour harmony are the most applicable for purposes of mapping because of their quantitative character. Therefore, the term “colour harmony” will be used further in the context of psychological numerical models with no regard to classical colour wheel models. In this way, we borrow several empirical principles of colour harmony from psychology, architecture and colour science and apply them to multispectral satellite images, converted into HSV (Hue-Saturation-Value) colour space, based on human perceptual specifics commonly used in remote sensing applications and applicable for colour harmony estimates.

An objective of this study was to investigate the ways in which the colour harmony principles from the following literature review could be transferred from different disciplines to land cover-focused remote sensing and GIS to reveal the regularities applicable for more adequate and efficient nature protection and land conservation. It is important to know, how the geographical organisation of the environment affects the extent of the land cover colour harmony perceived visually. The degree of land cover colour harmony could be considered a valuable aesthetic cultural ecosystem service, as well as an indicator of ecosystem disturbance, requiring mapping of the status and trend.

Within this framework, we address four research questions with Earth observation data from space, examining the spatial distribution and main drivers of the land cover colour harmony, and we link the results to street-level geotagged photographs as Volunteered Geographic Information (VGI), representing the actual landscape views for land-based observers:

1. How consistent are the maps of the extent of colour harmony produced within the different frameworks?
2. How does the mean colour harmony index vary for different land cover classes?
3. Which geographic attributes explain the distribution of colour harmony values?
4. How does remotely assessed colour harmony extent correspond to actual scenery alongside the roads?

Colours and colour harmony as attributes of the visual environment

The Landsat-7 ETM+ Handbook defines colour as a “property of an object, which is dependent on the wavelength of the light, it reflects or, in the case of a luminescent body, the wavelength of the light it emits. If in either case, this light is of a single wavelength, the colour seen is a pure spectral colour, but, if the light of two or more wavelengths is emitted, the colour will be mixed” (Williams 2009, p. 168). Colours were recognised as a subject of geographic studies and the first maps of colours of the perceived environment were already prepared in the second half of the XX century (Semenov-Tyan-Shansky 1928; Granö 1929, 1997). In subsequent years, colour studies in geography have mostly shifted to other areas: landscape ecology (Antrop and Van Eetvelde 2017) and landscape photography (Lenclos 2004), colour schemes in cartography, map design and visualisations (Brewer 1994, 2004; Peterson 2009; Bláha and Štěrba 2014); colour image segmentation (Xin et al. 2006), and map perception (Dong et al. 2016). Development of colour theory in geography is currently limited. There are only a small number of attempts to calculate the colour harmony of the visual environment in geography-related disciplines, not in geography itself (and even then the colour harmony is often articulated, but not calculated and mapped). A methodology for mapping land cover colour harmony, based on remotely sensed data, will contribute to filling this gap in geography, as well as in the landscape management and nature protection contexts.

The colour harmony of land cover, serving as the subject of this paper, is an important feature of the visual environment (Sullivan and Meyer 2016). Colour harmony as a landscape attribute is discussed in landscape aesthetics (BLM 1986; Blocker et al. 1995), landscape architecture (O'Connor 2006; Orzechowska-Szajda 2015; Tarajko-Kowalska 2016; Zennaro 2017), landscape ecology (Sowiꞅska-ꞅwierkosz 2016), landscape design (Guochao et al. 2014; Dhang and Mudi 2015) and forestry (Zhang et al. 2017), whereas no merely geographic empirical studies on colour harmony were found.

Indeed, there is a growing body of literature that recognises colours, their combinations and features as factors of landscape values and preferences in geography-related disciplines (Amir and Sobol 1990; Bell 2004; Acar and Sakıcı 2008; Junge et al. 2015; Polat and Akay 2015; Dronova 2017), as important variables of environmental visual assessment (BLM 1986; Arriaza et al. 2004; Uzun and Muuml 2011), and in landscape character assessment (Tveit et al. 2006). It is now well-established from a variety of studies that the amount and diversity of colours within the scenery positively affect visual values and preferences, and emotional response (Hands and Brown 2002; de la Fuente de Val et al. 2006; Lengen 2015; Jie et al. 2016; Sowiꞅska-ꞅwierkosz 2016; Polat and Akay 2015; Swetnam et al. 2017). Several authors argue that general human colour preferences depend on the colours of the liked and disliked objects of the visual environment. For example, bluish colours are preferred, being associated with clean water and sky (Palmer and Schloss 2010). Harmony indicators are commonly used to protect areas. The harmony of colours is used in the USA to assess the scenic value of protected areas (BLM 1986; Blocker et al. 1995) and, in terms of Visual Resource Inventory (VRI), "pleasing colour relationships" among others substantiate the respective visual harmony of the environment (Sullivan and Meyer 2016, p. 173). The first attempts to quantify the colour harmony of the perceived environment are made in landscape architecture (O'Connor 2006), landscape ecology (Sowiꞅska-ꞅwierkosz 2016) and computer science (Shen et al. 2016). However, such studies deal with photographs or in situ views only and do not allow monitoring and mapping of colour harmony for relatively large areas, including protected ones. Whereas the planning of recreational and nature-based tourism activities, as well as nature conservation and sustainable management practices, require an understanding of the natural and anthropogenic regimes constituting a visual environment of high quality and beauty in order to preserve its most convenient state. Recent studies on colour harmony within colour science, computer science, and the psychology of perception and art provide highly homogeneous principles of colour harmony extent, applicable for use in GIS and remote sensing software to map the degree of land cover colour harmony on the landscape scale.

Several brief overviews of the history of colour harmony models and applications, including a geometrical approach with the colour wheel and a numerical approach, could be found in several works (Burchett 2002; Westland et al. 2007; Palmer et al. 2013; Chamaret 2016). Bearing in mind that the following numerical models of colour harmony have been developed for two-colour combinations, we can apply them separately for pairs of pixels in the satellite image. We neglect the different interpretations of the term "colour harmony" itself in the following papers (for example, some authors do not distinguish between the principles of colour harmony and preferences), assuming that the results of all the authors reflect some aspects of colour harmony. It should also be noted that colour harmony does not necessarily correspond to colour preferences while influencing them positively (Schloss and Palmer 2011). Caivano (after Janello) argues (1998, p. 392), that colour harmony implicates constancy (or similarity, homogeneity) of Hue or Saturation or Lightness scores of the colours under the comparisons. Ou and Luo (2006, p. 201) point out several principles of two-colour harmony, including "(a) Equal-hue and equal-chroma; (b) High lightness; (c) Unequal lightness values". These findings are confirmed more recently by Szabo et al. (2010, p. 46). Schloss and Palmer, in contrast, found that hue similarity, low saturation and low lightness contrast are responsible for higher colour harmony ratings (Schloss and Palmer 2011, p. 561). Finally, Nemcsics argues that "the most highly ordered colours, according to their saturation and lightness, have the highest harmonious content" (Nemcsics 2012, p. 255).

Remote sensing studies widely apply HSV transformation of satellite imagery for colour-related purposes. Despite the existence of several colour systems, HSV is one of the simplest, often being used for common remote sensing tasks, such as shadow detection (Arévalo et al. 2008), water surface detection (Pekel et al. 2014) and monitoring (d'Andrimont and Defourny 2018), image fusion and landslide detection (Marcelino et al. 2009), mineral identification (Baykan and Yılmaz 2010), vegetation monitoring (Pekel et al. 2011) and many other applications. Such a wide range of remote sensing techniques, presuming transformation of the Red–Green–Blue (RGB) band combination of satellite images to the HSV colour space, is not surprising, since the RGB band combination is the standard "natural colour" combination, representing the land surface very close to the specifics of human visual perception. There are also other band combinations of satellite imagery, such as well-known "false colour" combinations. However, these combinations include bands, capturing the reflected solar radiation with other wavelengths, for instance, the near-infrared band (NIR) instead of the Red band in case of the false colour composite. The part of the spectrum, perceived visually, in most cases varies approximately within 400–700 μm and the spectral sensitivity of human eyes is supported by three types of cones, sensitive to three main colours: the same red, green and blue. The RGB composite of Landsat 8 OLI image satellite bands corresponds to visible light wavelengths (0452–0673 μm), being applicable for studies aiming to examine the visually perceived Earth environment.

Data and methods

Study area

In this study, we attempt to examine the colour harmony of land cover within a study area in Eastern Estonia. There are several protected areas, such as the Vooremaa protected landscape and the Alam-Pedja nature reserve (partially). The selection of the study area was conditioned by two considerations: (1) testing the suggested methodology on heterogeneous land cover (from urban structures to forests, agricultural land and wetlands as land cover types, used as a subject of different disciplines) and (2) examining the colour harmony rates within protected and non-protected areas to reveal the potential of further nature conservation. The Vooremaa protected area is one of the study landscapes of the HERCULES project (Kolen et al. 2015). Therefore, this study contributes to its objectives, providing a targeted case study on the colour harmony as a landscape value of typical Estonian land cover.

The physiognomy of Eastern Estonia is to a considerable extent a product of glacial activity. Being relatively flat orographically, there are moraine hills and lakes within the Vooremaa protected landscape, with a local landscape pattern of forested depressions and cultivated drumlines (Fig. 1). The Alam-Pedja nature reserve covers a complex of 5 bogs with rivers and their floodplains (e.g., Emajõgi, Põltsamaa and Pedja) and forests between them. These protected areas provide a habitat for endangered species as well as precious cultural ecosystem services for local communities and visitors from Tartu city, including hiking, swimming, wildlife watching, camping, and studying due to a variety of wetlands, rivers, forests, flora, fauna, and a traditional rural landscape. Land cover within non-protected areas includes different types of natural and managed forest and grasslands. Tartu city is the second-largest city in Estonia, providing a specimen of the unique Estonian urban landscape.

Data sources and processing

A cloud-free part of the Landsat-8 scene dated 17-06-2017 (Fig. 2) was used with original spatial resolution (30 m). The satellite image was radiometrically and atmospherically corrected (FLAASH technique) using ENVI 5.3.1 (Exelis Visual Information Solutions, Boulder, Colorado, USA). The red, green and blue bands of the image were transformed into HSV colour space with an ENVI tool. Hue corresponds to the colour itself, for instance, red, green, or blue. Saturation (or Chroma, depending on colour space) refers to the amount of grey, and Value (or Lightness, Brightness, depending on colour space) is usually associated with the amount of white in the colour. The CORINE 2012 land cover data (Fig. 3) and the EU-DEM 1.1 digital elevation model were obtained through the Copernicus Land Monitoring Service. A sample of 5 viewpoints (each 150th within the Vooremaa protected area), downloaded with the API of Mapillary service (sequence key: k2OrMPJk8gCYvM-goVwSxfg, user mhohmann) dated 23-06-2017 was used to demonstrate the link between remote-sensing-based and in situ data. The choice of the data was determined by the atmospheric conditions (cloud-free imagery), the absence of snow cover and relatively high values of seasonal vegetation growth (summertime).

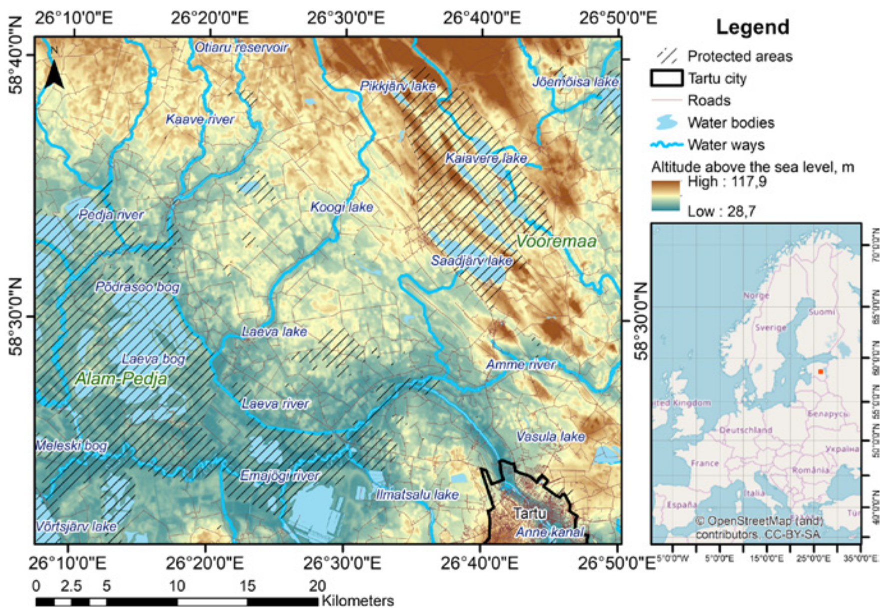

Fig. 1 Study area with some physiographic elements (geographic position related to Europe is marked with red on the inserted map). Protected areas are mainly associated with streams and water bodies and their surroundings. (Color figure online)

Haralick's texture metrics for the Grey-Level-Co-Occurrence Matrix (GLCM) were used, namely, Homogeneity (GLCMH), Contrast (GLCMC) and Second Moment (GLCMSM), implemented in ENVI 5.3.1, (Table 1, Fig. 4), and the equations are in Table 1, based on the papers by Haralick and Shanmugam (1973) and Hall-Beyer (2017a). We chose the moving window of 13 pixels following a medium sized moving window, suggested by Hall-Beyer (2017b) to keep the balance between detailing and generalisation of the final grids. The GLCM Homogeneity texture metric was used to indicate the similarity between pixel pairs in the Hue, Saturation and Value dimensions. The resulting three grids were processed with the Fuzzy Overlay tool in ESRI ArcMap 10.5 (function "Or") in order to obtain the map of the colour harmony index after Caivano (1998). The resulting GLCM Homogeneity grids for Hue and Saturation, the GLCM Contrast for Value grid and the resulting grid of the Focal statistics (function "Sum") tool were used after a Fuzzy Membership transformation in the same Fuzzy Overlay analysis to produce the index map of colour harmony after Ou and Luo (2006) and Szabo et al. (2010). Next, we used the GLCM Homogeneity for Hue, the Mean and Focal statistics values for Saturation and the GLCM Contrast metric for the Value grid to obtain with the Fuzzy Overlay tool a map of the land cover colour harmony according to the principles by Schloss and Palmer (2011). Finally, the map of land cover colour harmony after Nemcsics (2012) was computed with Fuzzy Overlay analysis of the GLCM Second Moment grids for the Saturation and Value bands of the image. However, in order to simplify the further analysis, the four resulting grids of colour harmony distribution were summed with the Map algebra tool in ESRI ArcMap 10.5 into one summarised Colour Harmony Index (CHI).

Using the Zonal statistics tool in ESRI ArcMap 10.5, the mean values of CHI for each CORINE 2012

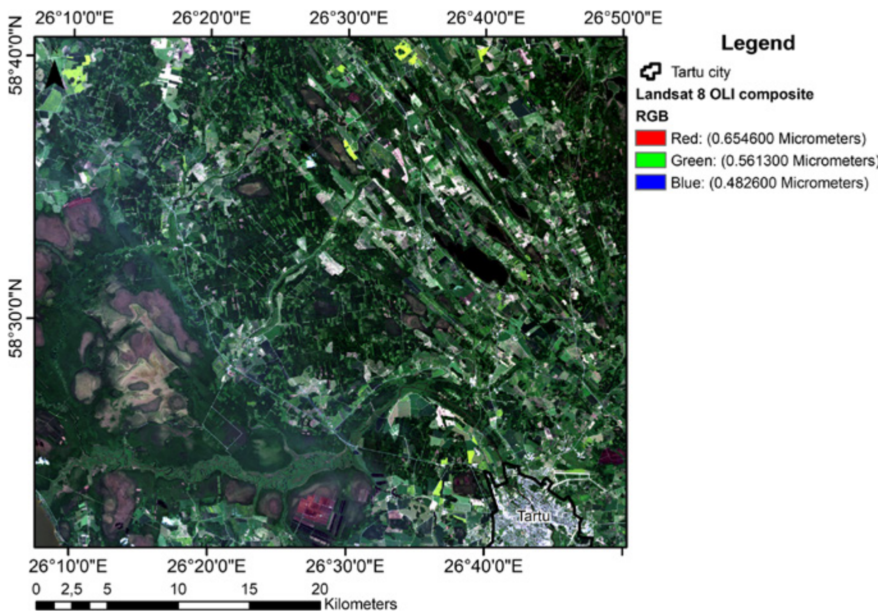

Fig. 2 Pre-processed Landsat 8 OLI scene (RGB composite), further converted to HSV colour space to measure colour harmony

Table 1 GLCM-based Haralick's texture metrics and their equations

Pixel-based GLCM texture metrics	Equation
Homogeneity (GLCMH)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{1}{1+(i-j)^2}P(i,j)$
Contrast (GLCMC)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}P(i,j)(i-j)^2$
Second moment (GLCMSM)	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\{P(i,j)\}^2$

$P(i,j)$ *the* probability of co-occurrence of pixel values i and j, N_g the number of distinct grey levels in the quantized image (64 in our case)

land cover class were obtained and all the present land cover classes were ranged in order to distinguish the extent of mean colour harmony associated with each class. We would like to emphasise that colour harmony computation and mapping are based on known studies. We did not carry out any subjective experimental observations or judgements on colour harmony in our modelling. We borrowed all of the principles from the literature.

Several variables were calculated as potentially explanatory for regression analysis, including the SAGA Wetness Index (SAGA TWI), the Terrain Ruggedness Index (TRI) as a standalone variable, the Greenness, Brightness and Wetness Tasseled Cap transformation grids, the brightness temperature grid, grids of distance cost from roads and buildings (OpenStreetMap spatial data for roads and buildings, TRI as a cost surface), the non-normalised albedo index after Smith (2010), and the DEM grid as a standalone variable. As a result of applying the randomForest R package with mean squared error as an indicator, as well as after excluding multicollinear variables with a variance inflation factor (VIF) method, the following explanatory variables were chosen: the cost distance from roads (corresponds to Costd_roads) as a degree of transport accessibility, the

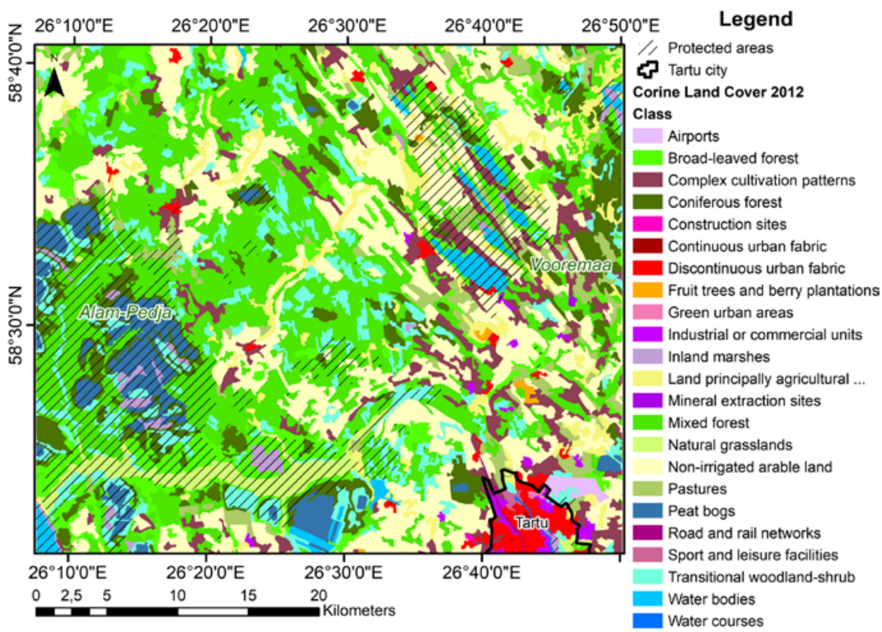

Fig. 3 CORINE land cover of the study area: protected areas include mainly wetlands, various forests and water bodies

SAGA TWI index as a realistic degree of the impact of topographical conditions on hydrological processes, and the at-satellite brightness temperature and albedo as indicators of the land cover heat budget. All the grids for the selected explanatory variables were generalised in SAGA GIS (Conrad et al. 2015) with a Simple Filter (based on the mean neighbourhood value, the size of the moving window is 13 pixels) to match the spatial resolution of the summarised Colour Harmony Index grid. Next, a 5000 random point shapefile covering the study area was created, and the values of all the explanatory grids and the dependent summarised CHI were assigned to these sample points. The CHI was Box–Cox transformed to meet the regression model assumptions of the dependent variable normal distribution. The Generalised Additive Model—GAM (Wood 2017), implemented in the mgcv R package (Wood 2011; Team 2017), was used to model the relationships between the CHI and explanatory geographic attributes. The GAM was applied to the Box–Cox transformed CHI with the following settings: penalised cubic regression splines for a Gaussian family of distributions, and the cross-validation method was used to detect the optimal degrees of freedom. The GAM model has several advantages compared to common linear models: flexibility, efficacy in the detection of non-linear effects and automated smoothing of the splines.

A LiDAR-based digital surface model (DSM, spatial resolution—8 m) of the Vooremaa protected area and its surroundings was used in Viewshed analysis via the plug-in for QGIS, performed for samples of the Mapillary viewpoints with the observer height of 1.0 m and a 90° maximum horizontal view angle in order to map the area visible from each Mapillary viewpoint. The Estonian Land Board collected LiDAR elevation data of excellent quality for this area in 2010 and 2014 with a Leica ALS50-II scanner at 2400 m altitude. Next, the mean CHI for each viewshed was calculated.

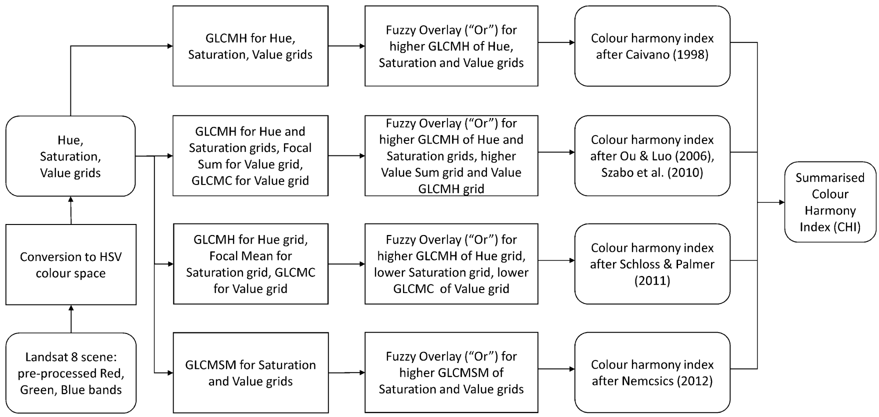

Fig. 4 General GIS-procedure for summarised Colour Harmony Index computation. Rectangles correspond to the GIS operations, and rectangles with rounded corners correspond to the raster grids (maps)

Results

How consistent are the maps of the extent of colour harmony, produced within the different frameworks?

The purpose of the first stage of the work was to test the applicability of remote sensing data, processed with Haralick's textural metrics, to the mapping of land cover colour harmony. Figure 5 compares maps of colour harmony according to the principles and authors, mentioned above, whereas Fig. 6 illustrates the results of summarised Colour Harmony Index mapping. Obviously, since the principles of colour harmony vary, the resulting maps of colour harmony extent also significantly differ: for example, the maps "a" after Nemcsics (2012) and "d" after Caivano (1998) are the least sensitive to colour harmony changes. Nevertheless, the four resulting maps are in accordance and, despite the different transition zones, give a similar overview of the maximum and minimum spatial colour harmony distribution. Thereby, the map of the summarised Colour Harmony Index aims to combine all the intermediate maps of colour harmony distribution. Notice that Haralick's textural metrics for pairs of pixels meet the assumptions of the numerical colour harmony models under consideration, focusing on the two-colour combinations.

How does the mean colour harmony index vary for different land cover classes?

Figure 7 (made with Tableau Public 10.5 software, Seattle, Washington, USA) presents the mean CHI score for each CORINE 2012 land cover class. Water bodies, different forest types and wetlands obtained the highest colour harmony scores. Culturally modified vegetation, such as arable land, plantations and pastures, has moderate colour harmony scores and industrial and urban areas are the least harmonious. Unexpectedly, areas, associated with water courses are among the least harmonious land cover classes, while airports are among the medium ones. Therefore, there is a clear trend, demonstrating the negative relationship between the extent of land cover cultural modification and its colour harmony degree.

Which geographic attributes explain the distribution of colour harmony?

This stage of analysis aimed to examine the relationships between the Box–Cox transformed summarised CHI of land cover and selected geographic attributes, representing variables of man-made infrastructure, topography and surface energy balance using the GAM. Table 2 shows the results of CHI modelling according to changes of distance cost from roads

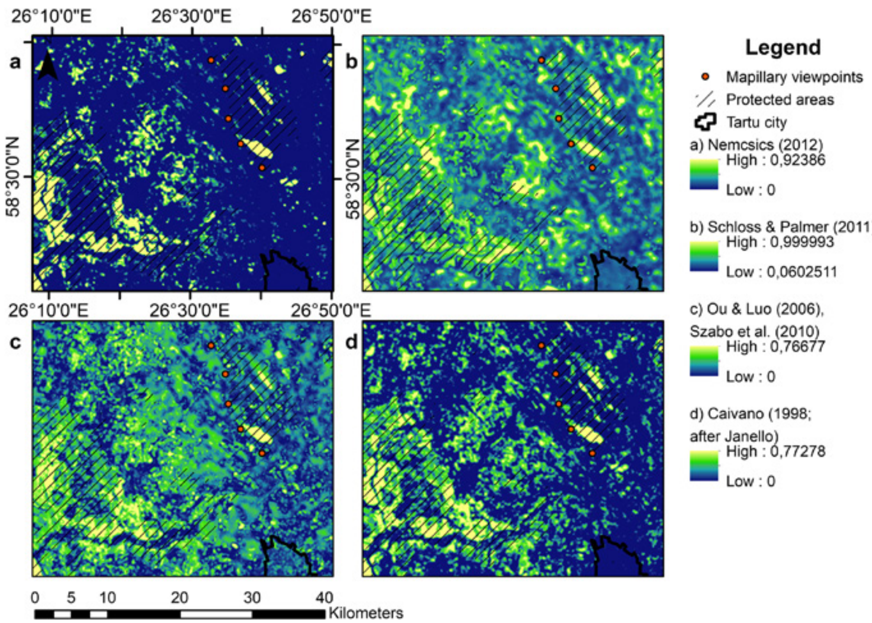

Fig. 5 Maps of colour harmony extent, created with different principles (according to the authors, mentioned in the legend): lighter areas correspond to higher land cover colour harmony, and darker areas correspond to lower colour harmony. All the maps are different, though consistent. Protected areas include land cover of the highest colour harmony

(Costd_roads), values of the SAGA Wetness Index (SAGA TWI), the brightness temperature (BT) and albedo index (Albedo).

Figures 8 and 9 illustrate the response of CHI to changes of albedo, brightness temperature, SAGA Wetness Index and distance cost from roads. Albedo has a clearly defined negative relationship with the CHI, whereas the relationship between brightness temperature and CHI is U-shaped, demonstrating a non-linear character. The least brightness temperature values (approx. 21–23 °C) are typical for crop fields, and the maximum values are for settlements and bogs. The SAGA Wetness Index shows that increasing topographic wetness linearly and positively influences the respective colour harmony. Increasing remoteness from the roads and the respective decreasing human disturbance also positively affect the colour harmony level. Altogether, the mentioned factors explain up to 54% of the CHI variability, but some factors still remain unclear. Nevertheless, colour harmony as a textural characteristic of the land cover Hue, Saturation and Value dimensions could be modelled, based on the spectral features of land cover, topography and cultural modification with transport infrastructure.

How does the remotely assessed colour harmony extent correspond to actual scenery alongside roads?

No significant differences were found between the Mapillary scenes “a”, “b”, “c” and “d”, whereas scene E provides the presence of crop fields and settlements (Fig. 10). Therefore, the highest mean colour harmony score of picture B is unexpected. The lowest mean colour harmony scores belong to scenes A and E. For the foregoing reasons, the in situ

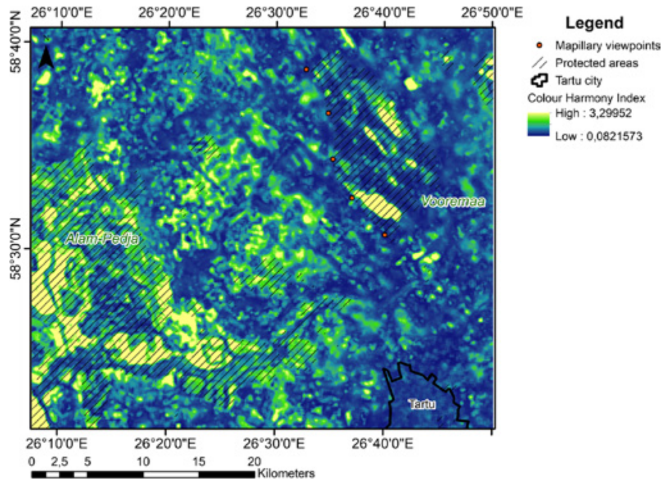

Fig. 6 Summarised Colour Harmony Index, generalising all the colour harmony maps. Protected areas include land cover of high colour harmony, whereas urban (Tartu city) and rural areas have low colour harmony. See Mapillary scenes on Fig. 10, labelled in the North-Western direction

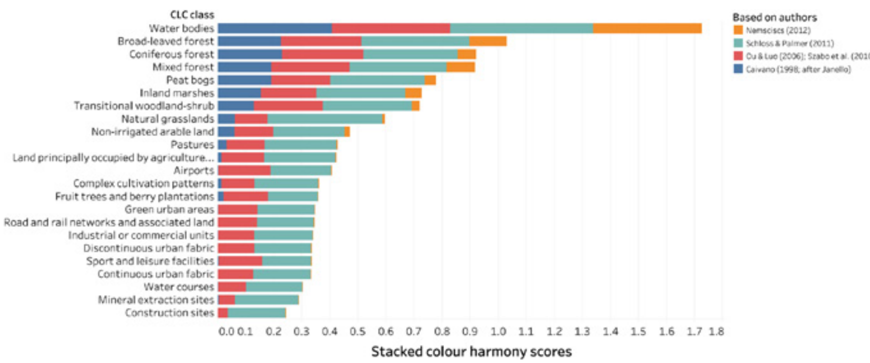

Fig. 7 Stacked mean colour harmony after each author for each CORINE land cover class, arranging land cover classes according to their inherent colour harmony. The decrease of colour harmony is associated with man-made structures and culturally modified land cover

collected data from Mapillary service has limited applicability as Earth observation data for colour harmony calculation and remote sensing verification purposes. Instead, more "landscape-oriented", than "road-oriented" photographs should be used.

Overall, these results indicate that the main principles of colour harmony from the numerical psychological models could be transferred to GIS-analysis and mapping, based on remote sensing data, for quantitative studies within environmental aesthetics and GIS-based landscape character assessment. Furthermore, there is a regular relationship between the colour harmony ratings and environmental geographic attributes revealing the objective drivers of colour harmony: regimes of moisturisation and heat supply and cultural modification.

Table 2 Results of the GAM applied to summarised Colour Harmony Indices

	Estimate	SE	t value	Pr (> |t|)
Box–Cox transformed CHI				
Intercept	− 0.624442	0.006861	− 91.01	< 0.01
	edf	Ref.df	F	*p* value
Approximate significance of smooth terms				
Costd_roads	8.854	8.990	60.02	< 0.01
SAGA TWI	1.000	1.001	494.55	< 0.01
BT	8.397	8.895	82.27	< 0.01
Albedo	7.961	8.576	183.12	< 0.01

R-sq.(adj) = 0.54; deviance explained = 54.3%; GCV = 0.23648; scale est. = 0.23519; n = 4996

Discussion

The results are significant in at least two major respects. Mapping of land cover colour harmony and its spatial distribution, constituting the main objective of the study, complements previous research concerning the assessment of environmental scenic resources (BLM 1986), landscape aesthetics and management (Blocker et al. 1995), fundamental landscape research (Bell 2012; Antrop and Van Eetvelde 2017;) and landscape design (Bell 2004), as well as numerous applied studies, including colour as an attribute of landscape character (Tveit et al. 2006). What is more, mapping land cover colour harmony reveals additional possibilities for using Earth observations from space and VGI (such as crowdsourced photographs) for assessment of the visual quality of the environment. Identification of the main geographic attributes influencing land cover colour harmony could be applicable for preservation and implementation of environmental functioning regimes supporting the valuable state of the visual environment.

How consistent are the maps of the extent of colour harmony produced within the different frameworks?

The approach of mapping colour harmony from space has some obvious limitations. First, the spatial resolution of the satellite imagery affects the respective results of colour harmony mapping. In our case, we performed landscape scale GIS-analysis common for Landsat imagery applications, but further implementation of such methods could include orthophoto and Sentinel 2 imagery with better spatial and temporal resolution to capture more detailed colour harmony, comparable with in situ views. Moreover, the scale and quality of GIS-analysis is also subject to the choice of Haralick GLCM textural metrics and the size of the moving window. Haralick's metrics are often multicollinear (Hall-Beyer 2017a) and, therefore, provide similar results. Of course, atmospheric conditions, the quality of atmospheric correction, and the

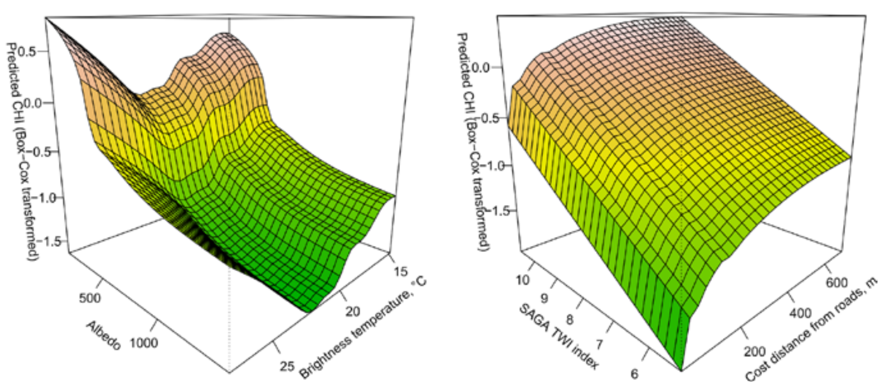

Fig. 8 Box–Cox transformed Colour Harmony Index, plotted against the albedo, brightness temperature, SAGA Wetness Index and cost distance from roads, explaining the spatial distribution of land cover colour harmony

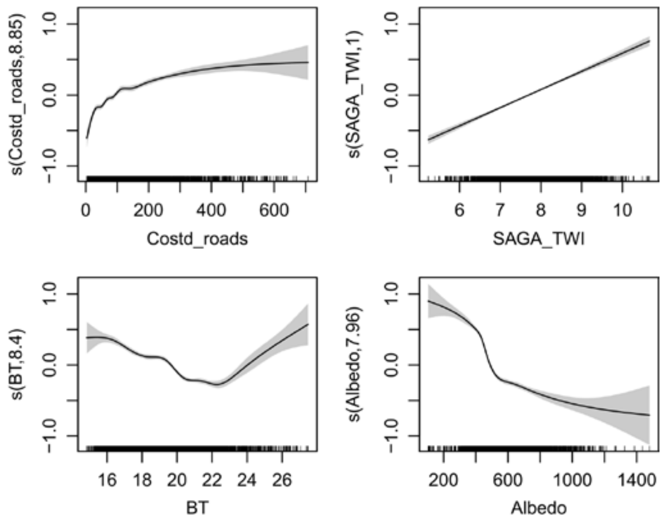

Fig. 9 Splines for the cost distance from roads, the SAGA Wetness Index, brightness temperature and albedo with 95% confidence intervals. Only the topographic SAGA Wetness Index has a linear relation to the summarised Colour Harmony Index

Scene	Mapillary ID	Mean CHI
a	sRgQfplqx_89WHmk0lKGmg	0,24
b	VOsOgZrSCBuwavp-D6rMzA	0,89
c	-rjsSf6q70yNrsfxM3H-8Q	0,50
d	y_Wpf8Pag8eJwdDjgc-bSA	0,45
e	kxW8yQ27owDnWpTC1f3D1g	0,31

Fig. 10 Mapillary scenes (crowdsourced street-level photographs), compared to the mean Colour Harmony Index for verifying the respective viewsheds. Labelling the scenes in a North-Western direction (locations of the viewpoints see in Figs. 5 and 6)

specifics of satellite sensors impose constraints on the applicability of the proposed approach. However, all the mentioned limitations are typical for any remote sensing studies, so the proposed approach does not contain any unique bias. To the best of our knowledge, there are no similar studies, but the application of GLCM metrics to derive colour textures has already been undertaken (Benčo and Hudec 2007), as well as in emotional contexts (Machajdik and Hanbury 2010). Our research complements those studies, quantifying the amount and diversity of colours as predictors of the perceived environmental visual quality, and presenting land cover colour harmony as a potential predictor for such studies.

How does the mean colour harmony index vary for different land cover classes?

Sowiſska-ſwierkosz, presenting her new ecological indicator, the Form and Colour Disharmony Index (FCDHI), already associated the disharmonious colours of land cover objects with rural, urban and man-made structures (Sowiſska-ſwierkosz 2016). We also suggest that the extent of land cover cultural modification negatively influences its colour harmony and, consequently, the overall landscape harmony (Amir and Sobol 1990). Several unexpected findings, such as low colour harmony ratings for water courses and a higher rating for airports, could be explained by the minor inadequacy of land cover classification and the scale of the colour harmony mapping. No correlation was found between the colour harmony and vegetation indices (such as Tasseled Cap Greenness or NDVI, LAI), so the bioproductivity and health of the vegetation could not be associated with colour harmony as an aesthetic value, supporting some previous findings (Casalegno et al. 2013). At the same time, forests show very high colour harmony, as in the paper by Zhang et al. (2017).

Which geographic attributes explain the distribution of colour harmony values?

Heat and moisture supply, as well as transport accessibility within the study area, explain approximately 54% of the colour harmony changes. Unfortunately, the only thing we can do with the cubic splines from the GAM model is to plot them, so there is no equation for the relationships between the explanatory variables and colour harmony. The relation between the brightness temperature and colour harmony ratings is non-linear: cold water bodies and warmer bogs have the highest colour harmony scores, whereas moderately warm crop fields have lower colour harmony. Albedo, being the highest for concrete man-made structures and the lowest for water bodies, negatively relates to colour harmony. In accordance with the present results, previous studies have demonstrated that naturalness is one of the important landscape attributes positively affecting visual values and preferences (Ode et al. 2009).

How does remotely assessed colour harmony correspond to the actual scenery alongside roads?

Whereas crowdsourced photographs such as VGI are widely used for land cover studies (Antoniou et al. 2016; Laso Bayas et al. 2016; See et al. 2017), the landscape-scale colour harmony mapping shows a weak association with the actual colour harmony of detailed photographs. Assessment of photograph colour harmony is a separate scientific task (Nishiyama et al. 2011; Chamaret et al. 2014), so we attempted to visually compare sampled Mapillary photographs with the mean colour harmony ratings of the respective viewsheds. In a further perspective, the set of photographs from phenocams could be used to accurately calibrate the colour harmony calculations, based on remote sensing data. In this connection, colour harmony mapping from drones could also be a better option than satellite imagery. Obviously, the top view provides additional limitations on applicability to the common landscape view, but it fulfils the requirements of mapping and management purposes.

Conclusions

In this investigation, the aim was to examine calculation and mapping of land cover colour harmony based on remote sensing data and Haralick's GLCM textural metrics for purposes of GIS-based assessment of the perceived environment visual quality. This study found that generally, remote sensing data are applicable for colour harmony mapping and, furthermore, for multitemporal monitoring and analysis of changes in colour harmony degree. It was confirmed that Haralick's textural metrics provide an adequate toolkit to measure the spatial relationships between satellite imagery pixel pairs, meeting the assumptions of the numerical colour harmony models under consideration and focusing on two-colour combinations. We also assumed that land cover is a substantial part of the visual environment. Land cover's colour harmony, perceived on the ground, affects emotional response, influencing the subjective feeling of landscape character value. However, the link between top-view maps of colour harmony and actual on-ground scenery remains weak, framing the perspectives for further studies.

This study has shown that mapping land cover colour harmony as a geographical task could be performed with the synergy of remote sensing and GIS techniques, including the calculation of GLCM metrics, overlay and focal statistical analysis. The second major finding was that the CORINE land cover classes are colouristically harmonious to a different extent (increase of land cover cultural modification decreases its colour harmony). Further, the generalised additive model (GAM) revealed that the main drivers of land cover colour harmony are the following: distance cost from the roadways, heat budget indicators (albedo and brightness temperature) and topographical SAGA wetness index. Furthermore, the relationship between ground-based photographs and colour harmony maps is established as "proof of concept."

The evidence from this study suggests that nature conservation and sustainable management initiatives have one additional GIS-based indicator for monitoring of the visual quality of the perceived environment, colour harmony. Combining the achievements of psychology, aesthetics and art with remote sensing tools and techniques, we obtain a powerful colour harmony mapping tool over time. This methodology has potential not only in the detection of aesthetically attractive places but also provides an opportunity for accurate accounting of the gain and loss of land cover colour harmony resulting from various socio-economic activities and natural dynamics. The long-term perspective of this direction of study is implementation of colour harmony indicators in decision-making tools and practices, based on Earth observations from space on continental and global scales. Mapping land cover colour harmony for larger areas, detection of colour harmony changes occurring over the last years, and colour harmony forecasting, are the foreseeable continuations within the initiated approach.

From the applied perspective, practitioners of landscape management and nature conservation could benefit from the further multitemporal land cover colour harmony as an aesthetical measure and attribute of landscape character to preserve the valuable visual environment. Protected areas are rarely delineated based on ecosystem services (Rose et al. 2015); therefore, land cover colour harmony, considered a cultural ecosystem service, could complement existing principles for the spread of protected areas. As seen above, lands with a land cover of high colour harmony are more typical for protected areas (e.g., wetlands, forests, and water bodies) than for other territory. To conclude, remotely sensed information used for colour harmony mapping could play a substantial role in the assessment of the effectiveness of nature protection and conservation, as well as for successful avoidance, mitigation and offsetting of nature use regimes that lead to land degradation or disturbance.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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III

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Original Articles

Landscape coherence revisited: GIS-based mapping in relation to scenic values and preferences estimated with geolocated social media data

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ABSTRACT

Previous research in environmental psychology and landscape science has demonstrated that the complexity (based on diversity) of the visual landscape positively influences landscape values and public preferences through a relationship with landscape coherence. In this study, we suggest one possible GIS-based indicator of landscape coherence calculated for a digital landscape model (DLM). It measures the degree to which the visual landscape as a whole exceeds the set of its overlapping components (landforms and land cover) regarding diversity. We verified the performance of the index within the National Park Peneda-Gerês (Northern Portugal) as a study area with cumulative viewsheds based on Flickr and Panoramio geolocated content. The results demonstrate a scale-dependent, positive relationship between the proposed index of landscape coherence for the categorical models and the landscape values. The findings of this study can be applied to landscape planning and management, providing an easy-to-use GIS-based indicator of landscape character assessment.

1. Introduction

Landscape coherence has been increasingly recognised as an object of environmental research at least since the 1920 s. For instance, Granö (1929; English translation, 1997) identified coherence (in English edition) as one of the key features of geographic phenomena: “When we examine the combinations of phenomena found in the perceived environment and the variations and changes in these, it is possible to detect regular dependence and coherence relationships existing within a given region” (Granö et al., 1997, p. 12). Granö compared landscape to the visible distant environment, so his citation above is a good starting point (historically and logically) for discussing the phenomenon of landscape coherence. Since then, authors have usually referred to the landscape coherence concept in two distinct contexts: a visual context of subjective, cognitive landscape coherence, most known within the information processing theory of landscape preferences by Rachel and Stephen Kaplan (Kaplan and Wendt, 1972; Kaplan and Kaplan, 1989), and an ecological context of objective vertical landscape coherence as the regularity of vertical, horizontal or temporal landscape structure (van Mansvelt, 1997). Such distinctions have their origin in the dualistic nature of landscape, recognised in the European Landscape Convention and in considerable landscape-related papers: landscape is an umbrella term covering (depending on the authors) a wide spectrum of concepts within the so-called “hard” (focused on the physical environment, monitoring- and mapping-friendly) and “soft” (focused on landscape perception and appreciation) approaches (Miklós et al., 2019). A considerable amount of literature was published on this topic within the mentioned frameworks, particularly regarding the development of quantitative indicators of landscape coherence, which are far better developed for ecological coherence studies (Ode et al., 2008). Obviously, opposing approaches require different methods and ecological and psychological studies of landscape coherence did not overlap until recently when several conceptual articles laid the groundwork for interdisciplinary landscape coherence studies (Fry et al., 2009; Dronova, 2017).

Despite the differences, supporters of both psychological and ecological approaches in landscape science base their logic on the concepts of diversity and complexity (Tveit et al., 2006; Mander et al., 2010; Uuemaa et al., 2008, 2013; Dronova, 2017), as well as on the attempt to estimate the extent of landscape coherence depending on their

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approach with subjective or objective methods. Since the paper reports the empirical results, near-full theoretical framework on the topics of landscape diversity, variety, coherence, complexity, heterogeneity and related issues may be found in other works (Christensen, 1997; Gustafson, 1998; Bell, 2012; Antrop and Van Eetvelde, 2017; Dronova, 2017; Kuper, 2017). Moreover, the theoretical concepts for the respective quantitative GIS-based indicators are discussed Baker and Cai (1992), McGarigal and Marks (1995), Plexida et al. (2014), and Adamczyk and Tiede (2017). However, we outline these concepts regarding the GIS-analysis applied in the current study.

The similarity between the terms "landscape diversity" and "landscape complexity" may be confusing since both terms emerge in visual and ecological contexts to describe landscape heterogeneity, even though they do not represent it directly (Dronova, 2017). There is no consensus in use of these terms; in environmental psychology and other visual studies; they are often synonymous with some kind or another variation in landscape structure (Ulrich, 1986; Herzog, 1989; Kaplan and Kaplan, 1989; Herzog and Barnes, 1999; Tveit et al., 2006; Kaymaz, 2012; Martín et al., 2016). However, complexity is often referred to the landscape patch-level attributes such as forms and shapes (Xu et al., 1993; Antrop and Van Eetvelde, 2000; Plexida et al., 2014; Lam et al., 2018) or, alternatively, to the number of diverse landscape elements or their spatial organisation into the whole (Antrop and Van Eetvelde, 2017), creating a kind of superstructure over the basis of diversity. We are employing the most adopted opinion that landscape diversity and complexity are synonyms; however, we define landscape diversity as a simple number of landscape units/elements of interest (in topography, vegetation, land cover etc.) within some view or mapping neighbourhood, while landscape complexity is a logarithmic function from such a number (such as the Shannon-Weaver Diversity Index and related indices of information entropy). At the same time, we disregarded this distinction drawn above since it is not widely recognised and could be confusing and we will use terms diversity and complexity interchangeably in the remaining text.

Theoretically, there are good reasons to interpret the phenomenon of cognitive landscape coherence as resulting from the emergence of diverse and complex visual landscape, making it understandable, legible, systematic, ordered and holistic, rather than chaotic. In other words, coherence differs the landscape as a whole (similarly to Gestalt in psychology) from a set of disconnected features of Earth surface. According to Bell (2012), landscape coherence is "… an ordered structure that we can understand and where the comprehension of the whole is more significant than the individual parts" (Bell, 2012, p. 104). From an applied perspective, concepts of coherence and harmony of landscape are very closely related: "Coherence describes the ability of the landscape to be seen as intelligible, rather than chaotic; harmony is related to unity, it exhibits a pleasant arrangement of landscape attributes" (U.S. Forest Service, 1995, p. 1-15). Sevenant and Antrop (2009) also refer to coherence as "unity" of the scene, while earlier findings tend to distinguish unity as a holistic cognitive property of the landscape and coherence – as a property of its separate attributes (Coeterier, 1996). Another definition emphasises the holistic nature of coherence: "the organisation of the elements in the scenes" (Pazhouhanfar and Kamal, 2014, p. 150) and coherence is directly equated to organisation (Kuper, 2017). Landscape coherence is sometimes treated as a dimension of landscape legibility (Guiducci and Burke, 2016), whereas often it is defined as a separate variable along with landscape legibility (Kaplan and Kaplan, 1989; Herzog and Leverich, 2003). Authors usually connect cognitive landscape coherence to concepts of "harmony", "balance and proportion", "uniformity", and "unity" (Tveit et al., 2006; Bell, 2012). Visual harmony is a core concept, used for the identification of scenic landscape values (Sowiſska-ſwierkosz, 2016; Sullivan and Meyer, 2016; Kuper, 2017; Karasov et al., 2018) and landscape coherence is often reported to be positively associated with high scenic landscape values (Herzog, 1989; Kaplan and Kaplan, 1989; Stamps, 2004; Dramstad et al., 2006; Martín et al., 2016; Kuper, 2017), which compete with landscape complexity in explaining people's scenic preferences.

Landscape coherence is an integral attribute of landscape character according to the vast majority of the authors and methodologies (Kaplan and Kaplan, 1989; U.S. Forest Service, 1995; Tveit et al., 2006; Mander et al., 2010; Bell, 2012; Hansson et al., 2012; Kaymaz, 2012; Antrop and Van Eetvelde, 2017). Despite the varying correlations in the different roles, it plays a pivotal role in landscape character assessment because it is the feature that essentially distinguishes the beautiful landscape as we imagine it from the notional "waste dump" of the same or even higher diversity and complexity. Even though solid evidence that landscape diversity (complexity) positively correlates with visual preferences (Uuemaa et al., 2013) and multifunctionality (Voigt et al., 2014) exists, the respective relationship appears to be an inverted U-shape, such as in the case of landscape clutter, meaning that excessive diversity decreases the visual quality of landscape (Falk and Balling, 2010). A shortened definition of landscape clutter by Veeneklaas et al (2006), cited by Wagtendonk et al. (2014), also clearly connects the concepts of variety and coherence: "Landscape clutter is an intrusive increase in the level of variety in a landscape, combined with a lack of coherence. People experience variety as pleasant as long as it is limited to diversity within an appropriate pattern…. The process of cluttering leads to an overall disorderly impression, where various land use types exist side by side without clear coherence or where many intrusive elements can be seen" (Wagtendonk et al., 2014, p. 86). Again, "variety in the landscape creates added interest when present in moderation" (U.S. Forest Service, 1995, p. 1–15); "landscapes with high diversity could have low perceived legibility if their components cannot be understood in a coherent form" (de la Fuente de Val et al., 2006, p. 403). Stamps (2004) assumed the link between landscape complexity and coherence but did not suggest an objective measure of coherence in this context. Hence, it follows as a logical consequence that coherence is understood as an attribute of landscape character, adding more logic and pattern to the diverse set of mentally distinct landscape elements, turning them aesthetically attractive due to their organisation (no matter, resulting from the self-organising natural evolution of Earth or management). In this way, intangible landscape coherence should be considered as a precious cultural ecosystem (landscape) service, whose extent is a subject of gain and loss depending on the sustainability of land use practices. It also deserves a monetary expression due to the association with natural beauty, which is widely recognised as a cultural ecosystem service (Haines-Young and Potschin, 2011; Czúcz et al., 2018).

Without the operationalization of the scenic landscape values (meaning without their quantitative assessment and internalisation into the decision-making process and natural capital accounting), it will be impossible to achieve even near-sustainable ecosystem/landscape management. Landscape coherence as one of the key drivers of landscape preferences is linked in this way not only with travel and tourism industry, creating 10,4% of the global GDP in 2017 (D'Emery et al., 2018), but also with everyday life of the billions of people creating the appropriate habitability conditions and providing the cultural ecosystem services in green areas. Therefore, creating efficient ways to reliably assess and map the landscape coherence extent is of direct practical value for land managers, government authorities, as well as the responsible business. What is more, nature protection will benefit from consideration of the flow of the provided cultural ecosystem services for delineation of the protected areas and monitoring its status and trend over time. Mapping is a geographical toolkit, providing the possibility to see "a big picture" is one of the cost- and time-effective ways of quick and precise landscape character assessment for large areas with indicators. For mapping purpose, we suggest defining landscape coherence as follows: the extent of organisation and systematicity, inherent in the decomposed pattern of physiognomic landscape within a particular view or mapping neighbourhood. At the moment no cognitive landscape coherence-driven GIS-based methods of landscape coherence mapping have been identified, while the suggested indicators will be discussed further.

Currently, the conceptual diversity of landscape coherence studies determines the respective variety of proposed GIS-based indicators for its assessment. As we mentioned before, the main issue in applying the landscape coherence concept to GIS-analysis lies in its dualistic nature. On the one hand, it describes objective landscape fragmentation, ecological connectivity, and physical connectedness within the physical landscape; on the other hand, landscape coherence is a cognitive phenomenon emerging as a result of visual landscape observation.

Studies based on the objective approach of landscape coherence assessment used different GIS-based methods. First of all, Adriaensen et al. (2003) applied least-cost modeling to the landscape matrix as an indicator of functional ecological connectivity, as discussed by Jongman et al. (2004) within the physical landscape (Gurrutxaga et al., 2010). This method allows for mapping the degree to which physical patches are horizontally interconnected (this idea corresponds to the idea of landscape coherence as a factor, composing landscape elements into a whole); however, this method does not involve any subjective scenic connotations of landscape coherence. Secondly, spatial autocorrelation (Moran's I) was used as an indicator of soil similarity and land use patterns (Mander et al., 2010). This indicator works well to map the extent of vertical landscape coherence, but again with no regard to the principles of cognitive landscape coherence adopted in the literature. Thirdly, the GIS-applicable landscape division indices and landscape connectivity indices (Jaeger, 2000; Saura and Pascual-Hortal, 2007; Mancebo Quintana et al., 2010; Nowak and Grunewald, 2018) are usually used to evaluate the horizontal landscape coherence extent. This method is one of the most widely used, but it is based on a purely ecological concept of landscape fragmentation, so it does not allow to quantify how the fragmented patches within landscape are organised. Fourthly, De la Fuente de Val et al. (2006) connected landscape coherence to landscape homogeneity, which could be quantified with several GIS-based metrics, for example, based on a grey-level co-occurrence matrix homogeneity index (Haralick et al., 1973). Although understandable, this idea is completely opposed to the concept of landscape diversity and complexity – obviously similar patches are more likely to present something visually coherent and harmonious. Nevertheless, this approach is questionable because it does not complement landscape complexity but rather presents the exact opposite of the complexity indicator. It is easy to see that, used in combination, homogeneity and diversity indices contradict each other. Finally, there are other landscape metrics measuring landscape fragmentation available (McGarigal et al., 2002), as well as autocorrelation indices, implemented in GIS-software, such as ArcGIS (Ode et al., 2008). These are designed following the same logic for horizontal landscape coherence estimation with initial ecological meaning and hardly applicable for the purposes of the subjective landscape coherence mapping.

While we are still on the subject of complexity and its relation to landscape coherence, Shannon's entropy should be mentioned. Shannon's entropy (also called Shannon-Weaver Diversity index) is the most widely used index to indicate the diversity and complexity of the landscape (McGarigal and Marks, 1995; Antrop and Van Eetvelde, 2000, 2017; McGarigal et al., 2002; Frank et al., 2013; Plexida et al., 2014; Niesterowicz and Stepinski, 2016; Adamczyk and Tiede, 2017; Kuper, 2017). As we argued above, landscape diversity and complexity and landscape coherence have a deep inner connection: Shannon entropy indicates the diversity of landscape, while landscape coherence organizes diversity. What is more, organisation is at the core of information theory, as Weaver was thinking about organized complexity: "problems which involve dealing simultaneously with a sizable number of factors, which are interrelated into an organic whole" (Weaver, 1961). Thereby, there seems to be a research gap in underestimation of Shannon's entropy applicability for the objective landscape coherence estimation with cognitive landscape coherence. Shannon's entropy for equiprobable observations turns into its particular case, Hartley entropy, which, as will be shown further, has a feature of additivity and, thereby, allows comparison of amounts of information within the whole and its parts: complexity of the whole due to its system properties should be higher than the summarised complexities of its components. This principle meets the assumptions of subjective landscape coherence and could be utilized for objective vertical landscape coherence mapping.

At the moment, cognitive landscape coherence studies, with its origins in environmental psychology and landscape architecture, involve mainly subjective fields or photo-based judgements (Kaplan and Kaplan, 1989; Hansson et al., 2012; der Jagt et al., 2014; Kuper, 2017). Other authors attempt to link subjective landscape visual quality and spatial pattern, described with the objective GIS-based methods mentioned above. Many theoretical works exist in this regard (Kuiper, 1998; Hendriks et al., 2000; Fry et al., 2009; Ode et al., 2010) while fewer use objective mappings of landscape coherence in relation to the visual quality of the environment (Martín et al., 2016, 2018). These papers just borrow indicators of objective landscape coherence and apply them for finding the relationship with landscape preferences. However, they do not attempt to design the indicator specifically suitable for subjective landscape coherence estimation with objective methods. There are numerous studies utilising remote sensing and GIS-based indicators to explain the scenic beauty extent, cultural ecosystem services provision pattern, etc. (Crawford, 1994; Ayad, 2005; Fry et al., 2009; Uuemaa et al., 2013; Ozkan, 2014; Yokoya et al. 2014; Vukomanovic and Orr, 2014; Booth et al., 2017; Dronova, 2017; Vukomanovic et al., 2018); however, none of them is dedicated specifically to landscape coherence from the perspective of landscape organisation. Overall, these studies highlight the need for a GIS-based indicator of landscape coherence, using an objective fragmentation approach, but conceptually originated within the cognitive landscape coherence. Consequently, there is a lack of evidence on the performance of GIS-indicators of landscape coherence in the visual context, although there is vast body of literature on GIS-based indicators of other drivers of landscape values and preferences.

Regardless of the variety in approaches and applications, the landscape coherence concept seems homogeneous enough to be calculated, based on landscape metrics of diversity and complexity. Our definition of landscape coherence, formulated above, focuses on the organisation of some diversity of landscape, measurable with functions of information entropy. In this way, our approach resolves the existing contradictions between the described subjective and objective landscape coherence definitions and applications; emerging in the theory of the cognitive landscape coherence. It could be easily implemented in vertical landscape coherence mapping, as will be illustrated below. Therefore, based on the literature review and links between landscape diversity and coherence proposed by Ode et al. (2010), we argue that there is a need to develop an objectively measurable GIS-based indicator of visual (cognitive) landscape coherence for landscape patches and classes. Informational indices of landscape variety (in particular, indices of distributional complexity, such as the Shannon diversity index [SDI] or, as we suggest in this paper, Hartley's entropy) provide the basis for this indicator. The basic assumptions are the following:

- the complexity of landscape as a whole exceeds the cumulative complexity of its components;
- such additive complexity reveals the emergent system properties of landscape (landscape pattern);
- landscape with recognisable pattern is interpreted as legible, coherent and, correspondingly, more aesthetically valuable and preferable.

Such an approach does not require any observers and field surveys to estimate the extent of landscape coherence; even though the performance of the proposed objective landscape coherence mapping could be verified with methods indicating landscape attractiveness;

examination of such performance will serve as a core of this paper.

This study presents and discusses a conceptual framework of GIS-based assessment and mapping landscape coherence as organised physiognomic complexity to meet the assumptions of subjective landscape coherence with novel objective methods. We used Hartley's entropy (a particular case of Shannon's diversity index for equiprobable data) as a measure of diversity and understand the organisation extent as a ratio between the diversity of the physiognomic landscape as a whole and summarised diversity of its components. We designed calculations and mapping within areas, reflecting the scale-dependent holistic landscape properties (Antrop and Eetvelde, 2017). The resulting map of landscape coherence extent was examined in visual context using cumulative viewshed analysis for the user-generated content of location-based social media Flickr and Panoramio. The content of location-based social media often serves as a proxy for landscape aesthetic values and cultural ecosystem services provision (Luque et al., 2017; Langemeyer et al., 2018), complemented with transport and visual accessibility of landscape (van Zanten et al., 2016).

Since the existing mapping methodologies for landscape coherence are designed to focus predominantly on the landscape structure with no regard to the objective metrics of landscape attractiveness (such as frequency of photographs within a particular area), there is the need to examine the objective structure of the perceived environment, considering the spatial patterns of its pictorial representations in digital media. To address this need, the following research questions were formulated to reveal the regularities of landscape coherence within the study area:

A. How does the GIS-based model represent the objective landscape organisation utilising the landscape coherence concept?
B. How does the landscape coherence indicator relate to the uneven spatial pattern of photographs taking frequency evidenced from the location-based social media?
C. How is the suggested indicator applicable to landscape management and planning?

2. Material and methods

2.1. Study area

We chose the National Park Peneda-Gerês as a study area. It is located in the northwestern part of Portugal (Fig. 1). It covers an area of 702,9 km^2, including the mountains of Peneda, Soajo, Amarela, Gerês, the Plateau of Mourela, and the Plateau of Castro Laboreiro. It was established by the Law №187/71 of May 8, and it is the only nationally protected area with a status of a national park; it is acknowledged by the International Union for Conservation of Nature (IUCN) (Bento-Gonçalves et al., 2011).

Geologically, the park is mainly composed of different granitic rocks, creating mountainous systems with peaks of up to 1559 m surrounded by narrow valleys. The formation of granitic rocks occurred approximately 300 million years ago and suffered intense fracturing in the final stage of the Hercynian and Alpine orogenies (about 29 million years ago). The younger granitic rocks preserve a more vigorous relief and are typical of the highest mountains of the park, where remnants of layers of sedimentary glacial, fluvial and torrential rocks occur, whereas the older ones, mainly of metamorphic type, dating back to the Silurian and Devonian periods (for instance, Castro Laboreiro land), present lower altitudes and smoother morphologies. According to climatic changes in the Quaternary period, glaciers rounded several main valleys. The fractures in the rocks have made river valleys deep and straight, and rivers are water-rich enough to be used for electric power generation. The climate of the park belongs to a Mediterranean type, but with strong Atlantic influence, expressed in high precipitation values (Vieira et al., 2011).

The surface and subsurface water flows and gravitational forces are responsible for transferring and rearranging sediments and soils – mainly Cambisols and Rankers (Vieira et al., 2011). This process makes the bottom of the valleys fertile, while generally in the park, soil fertility is irregular (Vieira et al., 2011). Urban systems are developing in the valleys as well as national transportation infrastructures. Portuguese shepherds, at least for the past 400 years, lead the cattle along river valleys to the high-lying pastures, where they graze livestock for three months every year (Bento-Gonçalves et al., 2012). Thus, the complex system of valleys and mountain ridges determines (in connection with climatic factors) all the biotic and social organisation of the Peneda-Gerês National Park and supports a diversity of micro-environmental conditions (Soares et al., 2005).

In summary, we chose the National Park Peneda-Gerês as a study area because of its

- Status as the only national park in Portugal with high nature protection and recreational value;
- Developed tourist infrastructure, numerous points of interest and landmarks and a transboundary location that attracts tourists and transit visitors who take photographs, which also serve as research date; and
- Complex landscapes that are due to well-expressed topographic, climatic, biotic diversity, and uneven cultural modification that result in a diversity of relief and land cover.

All of this make the park a spectacular study area for purposes of landscape coherence assessment.

2.2. Data

We assumed that the physiognomy of the study area can be represented in the form of 2,5D digital landscape model (DLM) as a combination of a classified 3D digital elevation model (DEM) and a 2D digital land cover model (Lammeren, 2011). The holistic nature of the landscape, according to Antrop (2017), is revealed through the mapping landscape properties on different geographical scales, since holon is a whole and, at the same time, a part of another holon of a more general level of organisation. Therefore, we suggest mapping the landscape coherence for DLM with a spatial resolution of 10 m, within various zones:

- floating circle of 990 m;
- cells of hexagonal grid of 1000 m;
- patches and classes of DLM of mesoscale (Fig. 2), composed of 4 TPI (Topographic Position Index classification) landforms (Jenness, 2006) and CORINE land cover 2012 classes (Copernicus Land Monitoring Service).

Hexagonal grid is discussed as the most efficient way of visual landscape analysis from the computational point of view (Adamczyk and Tiede, 2017), whereas distances exceeding 1200–1400 m are inappropriate for the analysis of physiognomic landscape, since human eye unable to distinguish objects in such a distance (Nijhuis et al., 2011). The spatial resolution of the CORINE land cover 2012 is 100 m, and in combination with TPI landform classification this land cover was used to design the digital landscape model of coarse spatial resolution (Fig. 2) to use its patches and patch classes as mapping units for landscape coherence, estimated with the digital landscape model of fine spatial resolution (10 m).

We designed DEM based only on digitised hypsometric contours, each with 10 m, with no regard to the point hypsometric values at local elevations or depressions, using Topo to Raster tool in ArcMap 10.3.1. Then, DEM was discretised into elementary landforms, used further as a basis for patches of DLM. Elementary landforms were discussed by Minár and Evans (2008) as "landform elements with a constant value of altitude, or of two or more readily interpretable morphometric

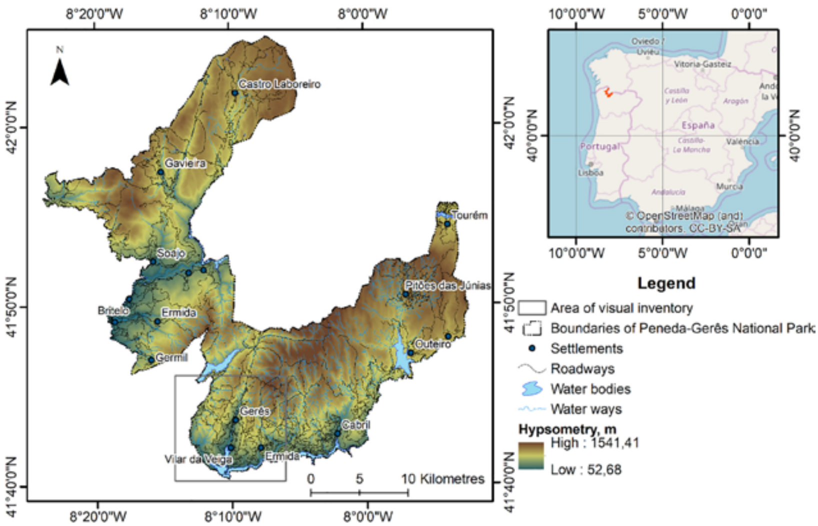

Fig. 1. Topography and geographical location of the study area in the Iberian Peninsula (mapped with red).

variables, bounded by lines of discontinuity" (Minár and Evans, 2008, p. 244). In this study, we used slope steepness, solar aspect, and general curvature as the main geomorphometric variables for elementary landform classification (Table 1). These variables were chosen according to their geographical meaning, linking abiotic landscape processes with landscape physiognomy (pattern). For example, the slope steepness determines the intensity of lateral water flows (runoff), erosion and accumulation intensity, soil depth, insolation, and characteristics of vegetation. Sun aspect of slopes describes runoff directions and the local distribution of heat and moisture (Clymo and Whittaker,

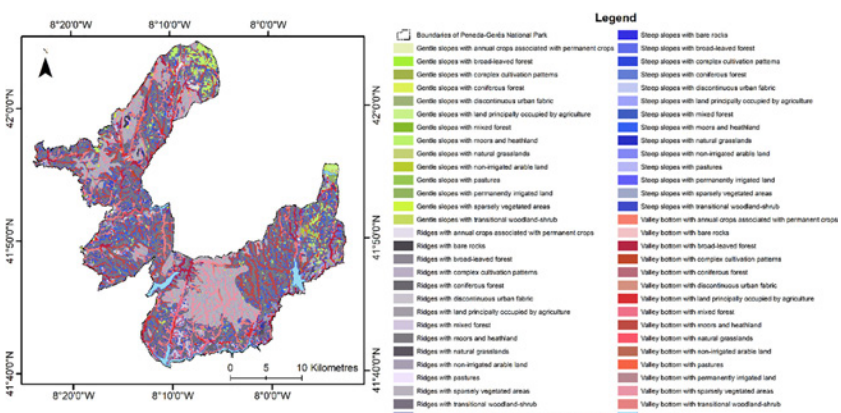

Fig. 2. Physiognomic classification within the area of Peneda-Gerês NP as a parametric model (composite) of TPI landforms and CORINE land cover, reflecting a visual landscape pattern. Its patches and classes are used further as polygons for landscape coherence calculation alongside the floating kernel and regular hexagonal grid.

Table 1
The categories of the main geomorphometric parameters.

Author/criteria	Classes					
Slope steepness						
Zhuchkova and Rakovskaya (2004): the increase in slope steepness	Gentle slopes: 4–10°	Rolling slopes: 10–20°	Moderately steep slopes: 20–30°	Steep slopes: 30–45°	Very steep slopes: 45–60°	Extremely steep slopes: > 60°
Solar exposition						
Clymo and Whittaker (1970): the increase in dryness	Northeast to North		Northwest to East		West to Southeast	South to Southwest
General (standard) curvature						
Curvature: directions of erosion and deposition			Concave: < 0			Convex: > 0

1970). General curvature, considering both the profile and horizontal curvatures, equally characterises the spatial distribution of runoff, as well as the regularities of erosion and deposition of sediments. Functional characteristics of the listed processes of landscape configuration provide a bridge to its visual interpretation.

In total, we distinguished 66 elementary forms of relief as unique parametric combinations of the slope steepness, solar aspect, and curvature (Table 1). The classes of the slopes were defined according to the slope classification for the mountainous territories by Zhuchkova and Rakovskaya (2004; cited in Svidzinska, 2014). The ecological row by Whittaker links heat and moisture supply with the solar exposition of the slopes (Clymo and Whittaker, 1970). The general curvature was used to distinguish between the concave and convex regions. Therefore, while slope steepness is responsible for the intensity of erosion, solar exposition determines the directions of erosion and microclimatic conditions of vegetation growth. The general curvature is an integral indicator of regularities of redistribution of the materials on the Earth surface. In combination, these geomorphometric variables indicate abiotic natural regularities of visual landscape appearance.

We created the digital land cover raster grid to map features of biotic and cultural modification of the landscape. This land cover model was designed based on the supervised classification of mosaics of satellite imagery SPOT and RapidEye (spring of 2011). These images were collected due to their high spatial resolution, allowing for the detection of the maximum heterogeneity of land cover. The imagery was preprocessed: radiometrically calibrated and atmospherically corrected. Supervised classification was performed using standard respective GIS tools (according to the spectral characteristics of the imagery in different band combinations, such as false colours, natural colours) and land cover classes were distinguished similarly to the existing CORINE land cover classification for 2012. In total, we mapped 11 land cover classes (Fig. 3).

Overlay combination of the digital model of elementary landforms (classified DEM of 10 m spatial resolution) and our digital land cover model has resulted in a digital landscape model of fine spatial resolution (10 m) with 661 classes.

2.3. Calculation

Numerous techniques have been developed to assess the diversity of landscape. For example, there are many landscape metrics (or indices), implemented into software such as FRAGSTATS (McGarigal et al., 2002) or plug-ins for traditional GIS (Adamczyk and Tiede, 2017). Since in landscape ecology, landscape is often structured within the so-called patch-corridor-matrix model (Forman, 1995), quantitative methods for measuring size, shape, density, and variety of landscape elements have become very popular – in particular, as these features relate to visual attractiveness of landscape. Patches and other elements of the landscape are distinct, so the methods from the information analysis are commonly applied. Indeed, in the case of distinct objects under consideration, the question, "What landscape patches do we see from that point?" implicates uncertainty, associated with the necessity to choose between landscape classes and patches, and such uncertainty is assessable with informational entropy (for example, as Shannon entropy). The answer to this question removes the respective uncertainties, caused by the entropy of landscape patches, so the recipient obtains some amount of information. This measure of information does not relate to the meaning of landscape for the recipient of information (observer): it is only a syntactic information, or "the objective structures of the arrangement of signs" (Naveh and Lieberman, 1990, p. 33).

For purposes of information content calculation, the formulas of information entropy, suggested by Hartley and Shannon, are commonly used. Shannon's entropy (Shannon-Weaver Diversity Index) is the most popular metric of diversity and complexity in ecology and landscape ecology (Frank et al., 2013; Uuemaa et al., 2013; Plexida et al., 2014; Niesterowicz and Stepinski, 2016; Adamczyk and Tiede, 2017; Kuper, 2017).

$$H = \sum_i p_i log_b p_i \tag{1}$$

H is the Shannon entropy value, p_i is the probability of the observation (land patch/facet/class i) appearing among other observations (landscape, composed of various land patches, facets, classes).

Hartley's formula is a simple particular case of Shannon's formula (Eq. (1)) for sets with equiprobable elements, and it proclaims that the amount of information (I), which is needed to determine a particular element of text/landscape is the binary (or other) logarithm of the total number of elements (N):

$$I = log_2 W = nlog_2 m \tag{2}$$

I stands for the amount of information, W is a possible number of different land patches/facets/classes; m refers to all land patches/facets/classes; n is the number of land patches/facets/classes in the one part of a set (in our case - in one floating circle with a diameter of 33 pixels). The size of the floating circle was chosen to detect the heterogeneity of the physiognomic landscape of the park while do not exceed the 1000 m, as it is close to the human ability to distinguish objects within the viewscape (Nijhuis et al., 2011). Applying the formula (Eq. (2)) to the raster models of elementary landforms and land cover, two rasters were obtained, showing the amount of information in elementary forms of relief and land cover classes.

Arndt (2004) in his book "Information Measures…" postulates for the sets E_N, E_M, E_{MN}, consisting of equiprobable N, M, MN elements:

$$I(E_{MN}) = I(E_N) + I(E_M) \tag{3}$$

$I(E_{MN})$ stands for the amount of information, $I(E_N)$ is the amount of information in the set E_N, $I(E_M)$ is the amount of information in the set E_M. It means that "The sum of the pieces of information of two independent sets E_N and E_M is equal to the information of the union set E_{MN} (all sets consist of elements occurring with equal probability)" (Arndt, 2004, p. 51). In this way, a major advantage of Hartley's

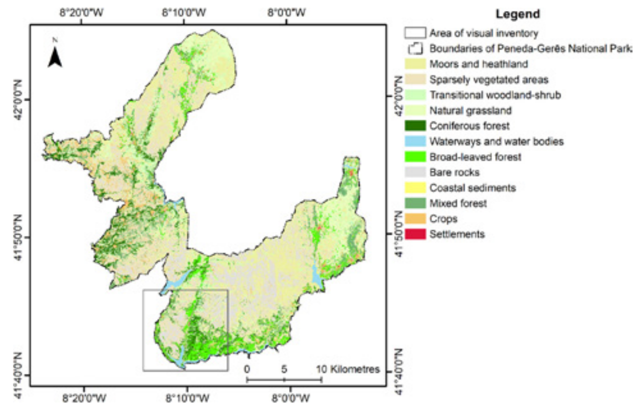

Fig. 3. Land cover model of the study area, composing with elementary landforms a digital landscape model for landscape coherence estimation and mapping.

formula is a feature of additivity: the amount of information from independent sources will be equal to the algebraic sum of the amounts of information, provided by each source (Eq. (3)). This provides an opportunity to measure the extent of mutual dependency of the sources of information and their organisation as something holistic. We excluded the assumption of the equal probability of appearance of landscape units for our purposes.

Thereby, if the complexity of the digital landscape model, indicated by Hartley entropy, exceeds the algebraic sum of the complexities of elementary landforms and land cover (indicated by Hartley entropy as well), the respective ratio indicates the holistic effect of emergence (landscape coherence). Following this logic and emergent theory of information (Hartley's emergence coefficient), suggested by Lutsenko (2002), we designed our indicator of physiognomic landscape coherence, indicating a connection between the complexities of relief and land cover systems, creating additional complexity of the visual landscape, when taken within some more general zones, such as kernel or polygons (Fig. 4).

In formula (Eq. (2)), the amount of information is calculated as a double logarithm from a possible number of spatial units – elements of relief and land cover classification. According to the emergent theory of information (Lutsenko, 2002), the amount of information in the composite, combining relief and land cover classes (DLM) will be more than the algebraic sum of the amounts of information in relief and land cover classes separately and greater than unity:

$$\varphi = \frac{I_{landscape}}{I_{relief} + I_{land\ cover}} \tag{4}$$

where φ is the landscape coherence, $I_{landscape}$ stands for the amount of information in the digital landscape model (composite of land cover and elementary landforms raster grids), I_{relief} is the amount of information in the elementary landforms raster grid, $I_{land\ cover}$ is the amount of information in the land cover raster grid. In this way, Eq. (4) serves as the indicator of the landscape coherence – extent, in which the amount of information in the whole landscape exceeds the amount of information in its components, revealing the degree of systematicity and organisation in the landscape according to our definition of landscape coherence in the Introduction. Landscape coherence could be literally equalized to the extent of the emergence of landscape as a system; the theory of information is used to reduce its complexity. From a subjective point of view, this ratio (Eq. (4)) indicates the holistic system-forming properties of the landscape, increasing its readability for the observer. In other words, if the observer can reduce all the complexity of visual landscape to only several regularities, this landscape is likely coherent.

2.4. Cumulative viewshed analysis, based on Flickr and Panoramio photographs

Viewsheds are proven to be representative as indicators of

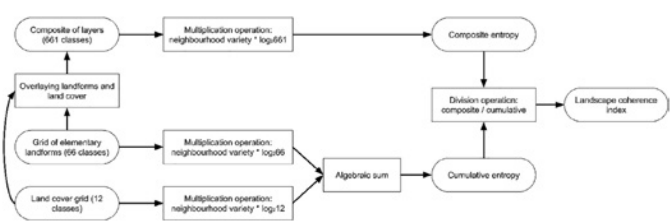

Fig. 4. General GIS-procedure for deriving the landscape coherence index for digital landscape model. Raster grids are shown in the rounded rectangles, GIS-operations – in the rectangles.

landscape values, based on landscape aesthetics (Nijhuis et al., 2011) and respective cultural ecosystem (landscape) services (Luque et al., 2017). Visitation rate, aesthetical values of landscapes and cultural ecosystem services provision have been widely examined with volunteered geographic information (VGI), including user-generated content of social media Flickr and Panoramio (Casalegno et al., 2013; García-Palomares et al., 2015; Sessions et al., 2016; van Zanten et al., 2016; Figueroa-Alfaro and Tang, 2017; Langemeyer et al., 2018; Martín et al., 2018; Oteros-Rozas et al., 2018). A cumulative viewshed is a sum of binary viewsheds, representing visible and non-visible areas from some set of geographic locations. In this way, the cumulative viewsheds are commonly used to examine overlapping visual fields in a landscape (Guiducci and Burke, 2016). Being obtained from the data, collected from location-based social media Flickr and Panoramio (currently unsupported), cumulative viewsheds represent the most frequently photographed pixels in DSM. Flickr was chosen due to its open API, providing free access to publicly available geolocated photographs, uploaded by millions of users globally, whereas Panoramio was a more place-oriented service, also frequently used in GIS-analysis. Geographical coordinates and metadata of photographs, taken within the study area were collected using Flickr API; Panoramio geolocated data were collected before its closure using SAS.Planet software. Then the cumulative viewshed analysis was done for collected Flickr and Panoramio geographical coordinates as observation points using Viewshed Analysis plug-in for QGIS, with observer height of 1,6 m and search radius of 10 000 m (Fig. 5). A digital surface model ALOS DSM of spatial resolution 30 m and vertical error up to 5 m (Jain et al., 2018) was used. The obtained model of the cumulative viewsheds represents the frequency of photographing each pixel in DSM. Places, which were not photographed, were mapped as No Data pixels and were not used in the further statistical analysis.

The values of cumulative viewsheds for each pixel in DSM were summarised within the polygons of landscape coherence mapping (Fig. 5, panels a, b) and the obtained data were normalised using Box-Cox transformation to meet the assumptions of the regression line, describing the summarised cumulative viewsheds as a response on landscape coherence score within each polygon. Plotting and statistical analysis were conducted using R (Team, 2017) within Exploratory software (Exploratory, Inc.).

3. Results

A. How does the GIS-based model represent the objective landscape organisation utilising the landscape coherence concept?
   Fig. 6 presents the maps, resulting from utilising the formula (Eq. (4)), designed in ArcMap 10.3.1. Depending on the used GIS technique (kernel, hexagonal grid, landscape patches and classes), four GIS-based visualisations have been created. We assumed that the nearly 1000 m wide zones (kernel and hexagonal cells) for landscape coherence mapping successfully detect the specifics of landscape units with 10 m resolution.
B. How does the landscape coherence indicator relate to the uneven spatial pattern of photographs taking frequency evidenced from the location-based social media?
   Further plotting for scores of cumulative viewsheds, based on Flickr and Panoramio geolocated content, compared to the scores of the landscape coherence within the landscape patches and classes (i.e. on a chorological and typological levels) revealed a positive relationship (Fig. 7, panels a, b). Scores of cumulative viewsheds as indicators of landscape values were Box-Cox transformed to meet the assumptions of the regression line (normal distribution of the dependable variable). These results are significant at the p-value < 0.05 level for all the plots. Landscape coherence estimated for the physiognomic patches explains up to a quarter of the variation in photo taking (Fig. 7, panel a), while generalisation to the level of physiognomic classes (Fig. 7, panel b) increases the explanatory power of landscape coherence to about 60% for Flickr and Panoramio geolocated content respectively.

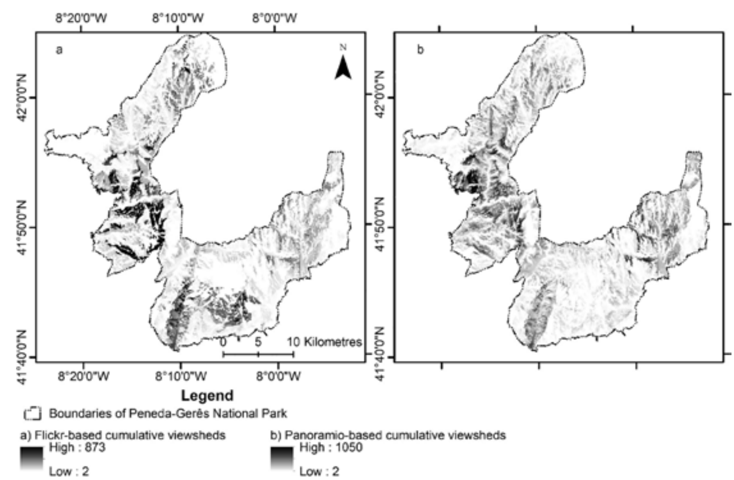

Fig. 5. The spatial pattern of Flickr-based (a) and Panoramio-based (b) cumulative viewsheds, based on ALOS Global Digital Surface Model (DSM) "ALOS World 3D − 30 m". Both maps are highly consistent, representing the frequency of taking photographs of each pixel in DSM as an indicator of landscape accessibility and preferences of photographers (visitors).

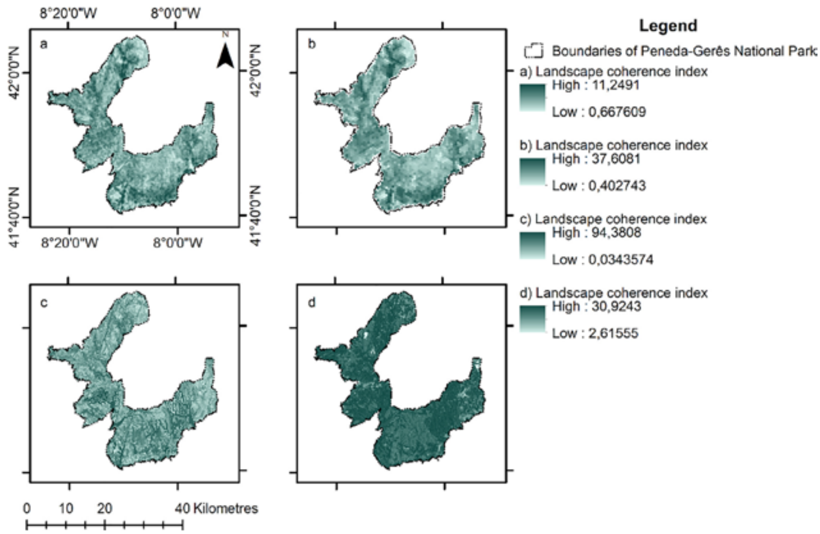

Fig. 6. Spatial pattern of landscape coherence index: a) mapped within a kernel (floating circle) of 33 pixels in diameter (approximately corresponds to 990 m); b) mapped within a regular hexagonal grid (each cell is 1000 m wide); c) mapped within the physiognomic patches, parametrically composed of TPI landforms and CORINE land cover (i.e. on the chorological level); d) mapped within the physiognomic classes, parametrically composed of TPI landforms and CORINE land cover (i.e. on the typological level). Chorological and typological models (panels c and d) have been used in a further analysis to be linked to the spatial distribution of geolocated photographs.

C. How is the suggested indicator applicable to landscape management and planning?
Specific landscape classes, being the subject of management are coherent to a various extent. Fig. 8 provides the results of ranging the physiognomic classes according to their landscape coherence content. Our results suggest, that valley bottoms and ridges, steep slopes of diverse land cover and and moderate agricultural modification indicate the highest level of landscape coherence. Gentle slopes are mainly related to the lowest landscape coherence. Classes containing mostly agricultural areas, forests, transitional types of

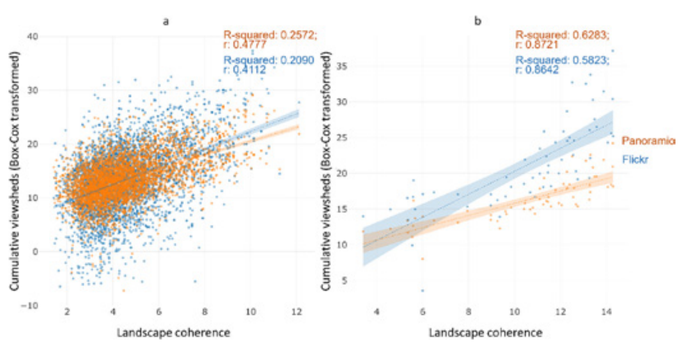

Fig. 7. Relationships between the Flickr- and Panoramio-based cumulative viewsheds and landscape coherence for the Peneda-Gerês National Park area. Plots show Box-Cox-transformed response data (cumulative viewsheds) with corresponding regression line and 95% confidence intervals; r refers to Spearman's correlation. Panels show the relationships: a) between the Flickr- and Panoramio-based cumulative viewsheds and landscape coherence on the physiognomic patch (chorological) level; b) between the Flickr- and Panoramio-based cumulative viewsheds and landscape coherence on the physiognomic class (typological) level.

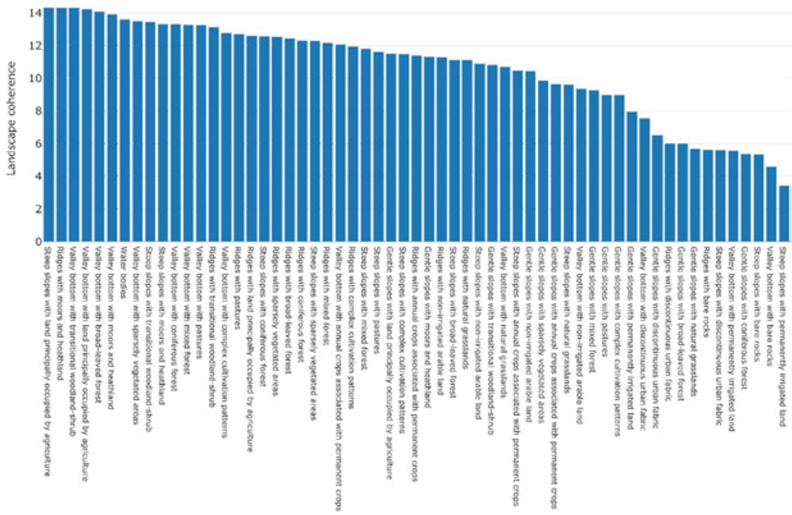

Fig. 8. Physiognomic classes (mapped on the Fig. 2) ranged concerning the degree of landscape coherence. The decrease in landscape coherence predominantly corresponds to the urban fabric, bare rocks and irrigated land, as well as gentle slopes.

vegetation, and water bodies reveal high landscape coherence, while urban fabric and bare rocks demonstrate low landscape coherence. Water bodies as covering large-scale orographic depressions of several landforms are grouped into one physiognomic class, representing a relatively high landscape coherence.

4. Discussion

4.1. Interpretation of results and relation to other studies

As mentioned above in the literature review, the vast majority of the cognitive (visual) studies tend to avoid GIS-based assessments of landscape coherence, focusing rather on psychological methods (Kaplan and Kaplan, 1989; Hansson et al., 2012) or borrowing on ecologically-based GIS-indicators of landscape fragmentation (Mander et al., 2010; Martín et al., 2016). In contrary, the backward process (implementation of landscape aesthetic theory into GIS-analysis) is only on its theoretical stage of development (Ode et al., 2008; Fry et al., 2009). Since landscape coherence is an emergent, holistic feature of the landscape as a whole, Hartley's entropy was chosen (due to its feature of additivity) as an indicator of landscape complexity, revealing the emergence of landscape as a system. The proposed GIS-based indicator complements a "vertical coherence" concept (Hendriks et al., 2000), based on supervised faceting (categorisation) of landscape model, referring to the structural landscape connectedness concept rather than to the ecological connectivity (Jongman et al., 2004). Overall, these results indicate that landscape coherence, calculated and mapped in the proposed way, can serve as a predictor of photo-taking frequency, indicating landscape values and preferences (Langemeyer et al., 2018). Viewshed analysis, utilising Flickr and Panoramio volunteered geographic information, shows the increment of the score of photo-taking frequency following the increase in the scores of landscape coherence within the landscape patches and classes. These results suggest that there seems to be an association between the extent of holism, systematicity and organisation of visual landscape and the degree of its visual attractiveness in case we assume that visual environment influences people's decisions to take photographs.

The current study found that GIS-based landscape coherence index can have a positive association with landscape values and preferences evidenced from user-generated content of location-based social media, confirming previous reports on this topic (Sevenant and Antrop, 2009; Hansson et al., 2012). However, utilising the proposed GIS-driven approach within the landscape classes (i.e. on a typological level) increased the explanatory power of landscape coherence index as related to photo taking frequency, indicated with viewsheds analysis compared to the mapping landscape coherence within the landscape patches. The positive impact of increased generalisation of the spatial patterns under consideration indicates the scale-dependent nature of the holistic organisation of the physiognomic landscape: some landscape attributes of landscape facets become more expressive when seen in the landscape facets of higher hierarchical levels (Antrop and Van Eetvelde, 2017). We tested the adequacy of the suggested GIS-based indicator, comparing it to the digital footprint stored in location-based social media, rather than explained scenic values and preferences within the study area. Therefore, further studies are required to link sociologically rigorous subjective judgements on landscape preferences and values to the suggested model.

Our findings are predominantly theory-driven, rather than locally oriented; therefore, they are still not unimplemented in the practices of landscape management within the study area. However, they are significant in two respects: this case study shows that map-based results help to recognise those landscape classes and patches that contribute to the increase in the overall scenic resources of the park. What is more, the sustainability of the land use practices could be verified with this map-based method, as agricultural areas within the study area are coherent to a various extent. Similar case studies, utilising mapping the extent of landscape coherence (Uuemaa et al., 2008; Mander et al., 2010; Martín et al., 2016, 2018) did not examine their methods in the context of scenic preferences, their methodology is rather ecological while our model utilises psychological premises for GIS-analysis.

The results of this research contribute to filling the gap between GIS-based landscape metrics of diversity (complexity) and objective landscape coherence estimations, capturing the landscape pattern systematicity and legibility for the observer as a function of physiognomic diversity. The results themselves are not surprising, but they support a suggested GIS-based indicator of landscape coherence, making it operational and applicable to landscape character assessment. In contrast to other findings (de la Fuente de Val et al., 2006; Martín et al., 2016, 2018), the viewsheds with the highest score are those with the highest degree of landscape heterogeneity, so the homogeneity of landscapes is unconfirmed as a factor of preferences (as related to landscape coherence in visual, not functional aspect). Conversely, our results suggest the link between the landscape heterogeneity and respective coherence: within the study area more diverse areas have higher landscape coherence estimations, confirming previous reports (der Jagt et al., 2014; Martín et al., 2016; Kuper, 2017). Consequently, the applicability of suggested index to areas, homogeneous in orographic or land cover relations (for instance, in Estonia, the Netherlands, or desert countries in Africa) is still high, while requiring much more detailed GIS data of very fine spatial resolution. Moreover, we neglected soil diversity in this study, although it is an inherent part of landscape pattern (Antrop and Marc, 2000). Unexpectedly, agricultural areas, located in steep slopes and valley bottoms, obtained the highest landscape coherence scores. We explain this by traditional land use and low level of agricultural intensification, typical for Peneda-Gerês NP, as well as active geochemical migration and deposition of sediments and soils on such landforms. Low intensity agriculture, though, is discussed as contributing to the landscape diversity (Mander et al., 1999).

In addition, there is one conceptual question that has been raised: since landscape is often referred to as a purely cognitive construct, capturing the organisation of environment, perceived visually, and this research was focused on physiognomy of the Earth (mosaics of landforms and land cover), the obtained index of landscape coherence should be more correctly named as index of physiognomic coherence. However, given some etymological and historical aspects of the notion of landscape (Antrop, 2000), the European Landscape Convention (Council of Europe, 2000) and some fundamental studies (Bell, 2012), do not distinguish landscapes as purely mental patterns or purely physical entities. Moreover, some studies within moderate, holistic approach recognise both the perceptual and cognitive specifics of physical landscape observation (Antrop and Van Eetvelde, 2017). In this way, following this mainstream consensus in landscape ecology regarding landscapes as physical phenomena, perceived visually, we tend to keep the name of the suggested indicator as the index of landscape coherence. It does not mean, though, that coherence as an aesthetical category can be trivialised to simple GIS-based operation. Landscape coherence is emerging as a cognitive feature of a person, observing the visual environment; it is a subjective feeling. Therefore, many more studies should be done to examine different holistic effects of landscape as a whole compared to the sum of its components. For example, landscape metrics of diversity include Shannon information entropy, which does not have a feature of additivity, proper to Hartley entropy, so the ratio, presented and discussed in this paper, is not the case for Shannon-based estimations. Shannon information entropy may capture not only the variety of landscape classes or patches, but also indicate the evenness of their distribution as a factor of landscape legibility.

Furthermore, papers, extracting landscape values from location-based social media, such as Flickr, Panoramio (recently closed) or Instagram (with a recently closed API for external developers), suggest accessibility as one of the main factors, determining the spatial pattern of landscape photographing (van Zanten et al., 2016). The infrastructural accessibility is beyond the scope of this study, even though some of its effects could be interpreted regarding multi-functionality and diversity of landscape. For example, “brown” infrastructure, such as roads and ways (often with roadside disperse settlements) adds to the visual landscape diversity, increasing variety of possible people’s activities (such as travelling, eating at cafes, shopping, visiting relatives) and modifying organisation of natural landscape. In this way, the suggested indicator indirectly considers the presence of human-made infrastructure and settlements as a factor, affecting individual decisions to take photographs or visit particular places. Nevertheless, since in the National Park Peneda-Gerês roads are designed predominantly following the valley bottoms and, in this way, physical conditions within the park determined the roads distribution and the respective vistas, roads provide a significant bias for spatial analysis of photographs in this area.

4.2. Data quality and processing

Adequacy of the estimation of diversity metrics is influenced by the size of a floating circle (other names are sliding or moving window or kernel), since diversity is calculated within the neighbourhood of each pixel in the image. In this way, the choice of the floating window is a choice of the scale of the resulting map. On the one hand, the floating window of a larger size reflects the properties of spatial homogeneity of larger landscape patches, while the impact of the separate pixels on the resulting image decreases, as well as the spatial resolution of the pattern. However, the small floating window may not provide a sufficient amount of statistical information for the adequate characterisation of the land cover objects (Kolodnikova and Protasov, 2004). Too-large floating windows can skew the results because of the impact of the edges of the land cover patches and the initial image itself. Authors have demonstrated that floating window of approximately 20 × 20 pixels is the best applicable to the textural processing of the land cover elements, such as crop fields, pastures, and forested areas (Potapov, 2003). Based on the cited papers, the floating window size in this study was designed as 33-pixel-wide circle, close to 1 km in diameter. Nevertheless, there is a wide variety of potential options for more accurate processing of landscape models, depending on local landscape character, for example using various diameters of the moving windows to capture multiscale landscape heterogeneity.

What is more, landscape metrics are discussed to be very sensitive to the data quality, and extreme values (outliers) may occur due to the specifics of computational algorithms. In our study, the use of a floating circle approach caused an indication of surprisingly linear patterns of Hartley entropy scores. Also, the quality of the classification of land cover and relief along with relatively low quality of ALOS digital surface model and geospatial accuracy of Flickr content, used for viewshed analysis, may bias this research. To address the problem of over differentiated patterns of coherence and cumulative viewsheds, as well as to reduce the effects of the data quality, mapping landscape coherence was conducted within more generalised physiognomic patches and classes. Depending on the parametric principles of physiognomic classification (TPI landform classification and CORINE land cover in our study) and extent of generalisation, different patterns may appear, so the respective choices affect the results. Also, our results of measurements of Hartley entropy are based on the landscape and land cover categories, as well as on the classes of elementary landforms, not on the patches or spatial facets themselves. It is important to bear in mind the possible bias also in the field survey responses since the obtained scores of scenic values are affected by subjective impressions, personal background, gender, age and motivation of the respondents, which were not taken into consideration.

5. Conclusions

The purpose of the study was to substantiate a new GIS-based indicator of landscape coherence as an informational concept and test its usability and effectiveness with a comparison to the spatial pattern of the most frequently photographed areas (represented as cumulative viewsheds). Our results indicate that interpretation of landscape coherence as a degree of systematicity and organisation of visible environment can be successfully implemented in the GIS analysis based on psychological concepts of landscape appreciation. Thereby, our results contribute to the existing knowledge on how the GIS-based indicators could be used in the landscape aesthetics domain. The second major finding was that the spatial pattern of the most photographed areas of the National Park Peneda-Gerês has a statistically significant positive relationship with the spatial pattern of landscape coherence index. The extent of landscape coherence estimated with the suggested GIS-driven approach (with digital landscape model of the physiognomic situation within the study area) could be considered as positively influencing the decision to take photographs within the particular physiognomic landscape patches and classes. Urbanised areas and bare rocks, gentle slopes have the lowest landscape coherence content.

The most important limitations of the study are the classification and scale decisions. Accuracy and generalisation of the digital landscape model used in this research, affect the resulting maps. In addition, validation of the research was limited due to the various content of the user-uploaded photographs from the location-based social media and ignoring the photographic data from outside the study area. Notwithstanding these limitations, the study suggests that proposed GIS-based indicator of landscape coherence, computed and mapped in the described way, could be further linked to behavioural data and perception-based indicators to inform decisions in land use planning, landscape management and nature protection.

Landscape management and planning would benefit from a wider implementation of the interdisciplinary GIS-based and environmental psychology-inspired methods, combining the advantages of both. Environmental psychology, widely utilising the concept of landscape coherence, recently provided us with a relevant theoretical and statistical base on how people perceive and appreciate the harmony of landscape. GIS- and remote-sensing techniques provide experts with a cost- and time-effective toolkit of estimation and mapping the extent of landscape coherence for different scales, from local to global. Our results, while preliminary, suggest that our indicator of landscape coherence along with other map-based indicators of landscape harmony (Karasov et al., 2018) could be a successful predictor of the people's preferences in the visual environment, promoting adequate decision-making in landscape protection, conservation and recreation planning, landscape design. Such indicators can complement relatively controversial and effort-consuming psychological surveys, as well as possibly vague expert opinions.

Further studies need to be conducted to validate the proposed index of landscape coherence within different study areas, various environmental settings and physiognomy, with multitemporal GIS and remote sensing data. Content-wise, image recognition techniques or manual tagging and classification should be used to extract only meaningful user-generated content from the location-based social media. Moreover, since the proposed method is based on general principles of the information theory, its application can be extended to all spatial models, where the holistic effects (for example, system emergence) are explored. As Hartley information entropy is only a particular case of Shannon information entropy for equiprobable units of study, there is a definite need to examine the mathematical opportunities for implementation of Shannon information entropy for the computation of landscape coherence index. The study will further continue with an examination of the main factors of spatial organisation of landscape coherence extent. The findings of this study have some important implications for future practice – for example, in the design of aesthetically attractive visual landscapes of high visual capacity and resilience, as well as for purposes of landscape management, protection and nature conservation.

CRediT authorship contribution statement

Oleksandr Karasov: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Visualization. **António Avelino Batista Vieira:** Resources, Writing - review & editing, Supervision. **Mart Külvik:** Project administration, Supervision, Writing - review & editing, Resources. **Igor Chervanyov:** Conceptualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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IV

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Communication

On How Crowdsourced Data and Landscape Organisation Metrics Can Facilitate the Mapping of Cultural Ecosystem Services: An Estonian Case Study

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Abstract: Social media continues to grow, permanently capturing our digital footprint in the form of texts, photographs, and videos, thereby reflecting our daily lives. Therefore, recent studies are increasingly recognising passively crowdsourced geotagged photographs retrieved from location-based social media as suitable data for quantitative mapping and assessment of cultural ecosystem service (CES) flow. In this study, we attempt to improve CES mapping from geotagged photographs by combining natural language processing, i.e., topic modelling and automated machine learning classification. Our study focuses on three main groups of CESs that are abundant in outdoor social media data: landscape watching, active outdoor recreation, and wildlife watching. Moreover, by means of a comparative viewshed analysis, we compare the geographic information system- and remote sensing-based landscape organisation metrics related to landscape coherence and colour harmony. We observed the spatial distribution of CESs in Estonia and confirmed that colour harmony indices are more strongly associated with landscape watching and outdoor recreation, while landscape coherence is more associated with wildlife watching. Both CES use and values of landscape organisation indices are land cover-specific. The suggested methodology can significantly improve the state-of-the-art with regard to CES mapping from geotagged photographs, and it is therefore particularly relevant for monitoring landscape sustainability.

Keywords: cultural ecosystem services; automated image recognition; natural language processing; topic modelling; landscape coherence; colour harmony

1. Introduction

Almost 50 years ago, in the 1970s, Philippe Saint-Marc interpreted the outdoor environment as a social service supporting a good quality of life and public well-being [1]. Ever since then, this logic has been elaborated upon with the concept of cultural ecosystem services (CESs) [2,3] and a geographic perspective connecting the ecosystem (landscape) structure and functions with benefits and values [4]. Accordingly, the capacity of landscapes to provide CESs among other ecosystem services is now considered a prerequisite for landscape sustainability in connecting the Earth's patterns and processes to individual values and preferences [5–7].

However, CESs have proven difficult to quantify, and consequently they are difficult to manage. Therefore, many authors have discussed CESs in the context of metrics, including economic assessment and quantitative mapping [8–12]. Currently, having a proper understanding, quantitative assessment, and an incorporation of CES into decision-making processes is considered crucial for achieving sustainable development goals and other policy targets [13–16]. The most advanced approach to the classification of the CES is being developed in the Common International Classification of Ecosystem Services (CICES) [17]. Our work examines, in the Estonian context, the following classes of CESs according to the CICES:

a) characteristics of living systems that enable aesthetic experiences (experiencing landscape beauty, passive recreation);
b) characteristics of living systems that enable activities promoting health, recuperation, or enjoyment through active or immersive interactions (active outdoor recreation); and
c) characteristics of living systems that enable activities promoting health, recuperation, or enjoyment through passive or observational interactions (e.g., watching organisms: plants, animals and mushrooms).

The vast majority of CES assessments are based on surveys, interviews, participatory mapping, workshops, and other kinds of offline engagements with pre-selected individuals, such as local communities, key stakeholders, or experts [8,18–20]. However, the last two decades have seen a growing trend towards crowdsourcing applications in this field. In particular, the use of publicly available location-based social media (LBSM) data—mainly geotagged photographs—stored in online photo repositories (Flickr and Panoramio), applications (Instagram and Strava), and social networks (VK.com and Twitter) has proliferated [21]. Passively crowdsourced digital footprint has been used for (a) the assessment of touristic place visitation rates [22], (b) mapping landscape values across spatial scales [23,24], (c) mapping landscape aesthetic flow [25], (d) analysing spatial CES distributions [12,26], etc.

However, the amount of geotagged data in the online repositories of varying and often non-relevant content poses an issue for content selection and classification. The most common approaches of content analysis include manual selection [25–27] or photo-user-days mapping within the InVEST ecosystem service models [22,28,29]. Therefore, image recognition services and machine learning models have been gaining attention more recently. For instance, machine learning algorithms provided by Clarifai (Clarifai Inc., New York, NY, USA) and Google Cloud Vision were recently reported to be very promising for CES recognition and mapping [30,31], and natural language processing was applied to categorise social media users in relation to outdoor recreation [32].

In our study, the objectives are to (a) identify and map CES use in Estonia by using a combination of automated content image recognition and topic modelling on photos from selected social media platforms, and (b) quantify the association between two types of landscape attributes reflecting subjective landscape organisation, i.e., the landscape coherence and colour harmony of land cover, and CES flow. Landscape coherence is a landscape attribute, which, according to existing reports, rather positively influences landscape preferences by generalising order and organisation of recognisable elements of landscape pattern [33]. It can be mapped with a geographic information system (GIS)-based indicator in relation to photographing preferences [34]. Colour harmony is also discussed as an important aesthetic variable of visual landscape [35] and is recently mapped with satellite imagery and textural metrics [36], but it has received much less attention in literature compared to landscape coherence. Suggested objective indicators of landscape coherence and colour harmony of land cover remain understudied in the context of CES use and require testing across various environmental settings and scales.

The paper is developed around a simple framework of CES use classification and its linkage to landscape attributes, assessable with remote sensing- and GIS-based indicators. Section 2 justifies the study area choice and introduces the methods used to extract knowledge on CES use and landscape attributes from geolocated photographs and GIS data, respectively. Section 3 presents the results of CES use mapping in relation to the GIS- and remote sensing-based indicators, as well as land cover types. Section 4 discusses the results in the wider context of added research value compared to existing research papers. Section 5 concludes with the main findings and directions of further work.

2. Materials and Methods

2.1. Study Area

According to DataReportal, 98% of Estonians are Internet users to some extent, and 57% are active users of social media [37]. This high level of Internet penetration, combined with a well-developed touristic policy and infrastructure, as well as the significant share of the Russian-speaking community in the total population (VK.com is based in Russia) render Estonia a good study area for social media and CES-related studies. Moreover, the diverse environmental conditions and numerous protected areas in Estonia enhance opportunities for analyses from geographic and nature conservation perspectives.

2.2. Mapping of Cultural Ecosystem Service (CES) Represented in Social Media in Estonia

To test the applicability of topic modelling for CES identification and classification, we used geotagged photo-series analysis [38], retrieving metadata by means of application programming interface (API) calls (including geographic coordinates, user and photo ID, date of taking, web-links to photographs) for publicly available images uploaded to Flickr.com and VK.com services from 2015 to 2018. Flickr and VK.com continue to provide access to their non-private geolocated content, while Panoramio discontinued its service and Instagram has not shared its data with third parties since 2015. We additionally used the GIS-data for buildings in Estonia [39] to remove the metadata for indoor photographs. In total, metadata for 21,242 geographically outdoor photographs were retrieved and combined into a single dataset. We then applied content image recognition to these photographs with automated Python API requests to Clarifai's service (Clarifai Inc., New York, NY, USA). We used the general model with a cut-off greater than 90% for the probability that the tag is correct.

We then tested topic modelling (Latent Dirichlet Allocation (LDA) algorithm) implemented in the Orange data mining software [40] to classify the tags into a number of topics and deleted the irrelevant ones (assuming that photographs sharing the same tags represent the same "topic"). As a result, the pre-processed dataset consisted of 9983 photographs. After some initial testing, we decided on three topics for the LDA analysis. The LDA algorithm was useful in two aspects: (a) identification of the non-relevant photographs (for example, we removed the photographs, sharing topics of tags related to driving and cars, indoor design, architecture, fashion and beauty, military service) and (b) identification of the relevant topics in the rest of the photographs' tags.

As the LDA algorithm calculates the probability score, indicating the likelihood of the set of tags for each photograph belonging to each topic, we assumed that the assigned photographs belong to the topic with the highest probability score. Owing to the potential overlap with this fuzzy distinction between the topics of each photograph, we decided to post-process the results manually by interpreting the context of each photograph in addition to its content. For instance, photographs of pets were transferred from the topic of wildlife watching to outdoor recreation, and photographs with a minor presence of people or their recreation-related equipment were moved from landscape watching to outdoor recreation. We devised an a priori hypothesis about the small number of relevant CESs, according to the CICES classes (3–5), and the very first test of LDA algorithm resulted in three relevant CES-related topics. In case we applied LDA with a higher number of intended topics, some minor subclasses of recreation appeared, but these minor classes of recreational CES are beyond the scope of this study. We identified the following topics corresponding to the groups of CESs:

a. Landscape watching. This consists of the following tags: nature, outdoors, landscape, tree, nobody, wood, sky, travel, water, and summer (6154 photographs; 17 manually transferred from topic 3).

b. Active outdoor recreation. This consists of the following tags: people, recreation, adult, fun, man, leisure, outdoors, one, sport, and action (2345 photographs; 770 manually transferred from topic 1, and 114 from topic 3).

c. Wildlife watching. This consists of the following tags: nature, outdoors, no one, flora, leaf, wild, wildlife, season, animal, growth (1484 photographs; 124 manually transferred from topic 1, and 2 from topic 2).

We mapped CES use from the photo locations to examine whether people (subconsciously) consider some selected aesthetic landscape attributes that represent landscape organisation [34,36], and these attributes can be derived from remote sensing data [41].

2.3. Impact of Landscape Organisation on CES Use

The colour harmony of land cover is a landscape attribute often neglected in landscape studies [41] but is potentially responsible for visual landscape quality [35] and is assessable using remotely sensed data. We used Landsat 8 OLI cloudless summertime mosaics for the territory of Estonia with a 5 km buffer zone pre-processed with the Google Earth Engine. The red (B4), green (B3), and blue (B2) bands, corresponding to the natural colours band combination, were converted into the hue-saturation-value (HSV) colour space to quantify colour harmony. We assumed that the hue and chroma (saturation in HSV space) similarity, which is listed among the universal principles of colour harmony [42], can be quantified for the hue and saturation raster datasets. Such assessment can be done using the grey level co-occurrence matrix (GLCM) homogeneity index (GLCMH, Equation (1)) [43], which measures the similarity of image pixel pairs [44] (Figure 1a,b):

$$GLCMH = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{1}{1+(i-j)^2} P(i,j) \quad (1)$$

where $P(i,j)$ is the probability of co-occurrence of pixels i and j, and N_g is the number of distinct grey levels in the quantised image (64 in this study).

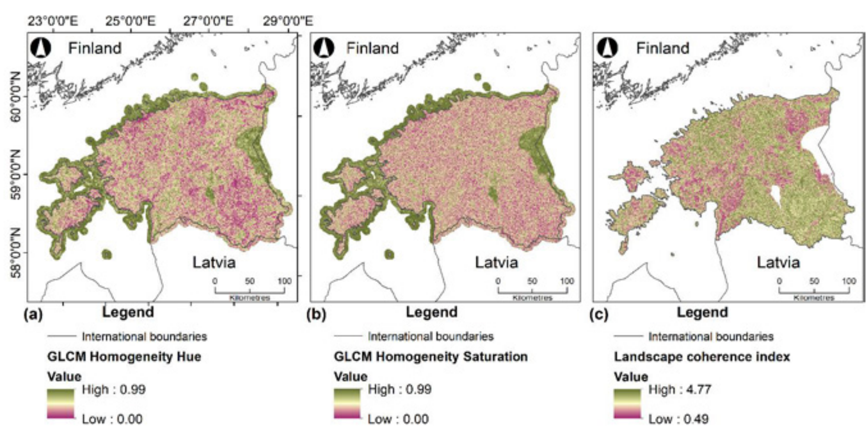

Figure 1. Spatial distribution of the values of the landscape organisation indices: (**a**) grey level co-occurrence matrix (GLCM) homogeneity for hue-saturation-value (HSV) hue component (colour harmony index); (**b**) GLCM homogeneity for the HSV saturation component (colour harmony index); (**c**) landscape coherence index. Higher values of colour harmony indices indicate water bodies (sea and lakes). Higher values of landscape coherence index indicate urban areas and, particularly, complex landscapes of Southern Eastern and Northern Estonia.

It should be mentioned that colour harmony depends on "how strongly an observer experiences the colours in the combination as going or belonging together, regardless of whether the observer likes the combination or not", (p. 551, [45]). Therefore, it is rather a component of the formal landscape aesthetics and, in theory, does not necessarily reflect landscape preferences.

We interpret landscape coherence as a degree of order inherent to the landscape pattern that is composed of diverse and distinct landscape elements and features [46]. Landscape coherence is one of the classic subjective landscape attributes responsible for the emergence of landscape values [33]. Increasing the landscape coherence extent generally leads to a moderate increase in landscape preferences [34]. Therefore, we assess the vertical landscape coherence using the landscape coherence index (LCI, Figure 1c, Equation (2)) proposed by Karasov et al. [34], which is based on the concepts of the emergent theory of information, as presented by Lutsenko [47]. We calculate the LCI within a circular neighbourhood of seven pixels for the CORINE land cover model and the Topographic Position Index (TPI) landform classification, obtained with the respective SAGA GIS module [48].

$$LCI = \frac{I_{landscape}}{I_{land\ cover} + I_{land\,forms}} \tag{2}$$

where LCI is the landscape coherence index; $I_{land\ cover}$ and $I_{landforms}$ are the Hartley functions for the land cover/land use (LU/LC) model and the TPI-based landform classification based on the digital elevation model [43], respectively; and $I_{landscape}$ is the Hartley function for the parametric composite (digital landscape model) of the LU/LC model and TPI-based landforms.

The landscape coherence index benefits from the feature of additivity of the Hartley function (Equation (3)), which is a particular case of Shannon's information entropy (Shannon diversity index):

$$I = n_i log_2 m \tag{3}$$

where m is the total number of observations (landscape or land cover classes, types of landforms), and n is the number of observations in neighbourhood i.

The logic of landscape coherence calculation is based on the following assumption: for independent landforms and land cover, the algebraic sum of the amount of information, according to the Hartley function for landforms and land cover, will be equal for the amount of information for their parametric composite or digital landscape model. If the landforms and land cover models, which compose the digital landscape model, interact and are not independent, the summarised Hartley functions for these datasets will give a smaller value than the value of the Hartley function for the pixels of a digital landscape model. The ratio between Hartley functions for the digital landscape model and its components highlights the extent of systematic features of landscape and can be related to landscape preferences. Hypothetically, the increase in landscape coherence contributes to the visual landscape quality and therefore to CES use.

We then performed a viewshed analysis, identifying the visible surface from the set of observation points, namely the geolocations of the selected photographs from each group of CESs (see Section 2.2) and for the same number of randomly selected locations, which serve as pseudo-absence data (Figure 2). We used the PixScape software [49] on the European Digital Elevation Model (EU-DEM), version 1.1 [50] with the maximum visible distance and observer height set to 5 km and 1.6 m, respectively. The median LCI, hue homogeneity, and saturation homogeneity were calculated for each viewshed and compared between the actual (presence) and random (pseudo-absence) geolocations using Wilcoxon's rank-sum test with continuity correction (see Appendix A for details), implemented in the Exploratory software (Exploratory Inc. (Delaware US) Sacramento, CA, USA).

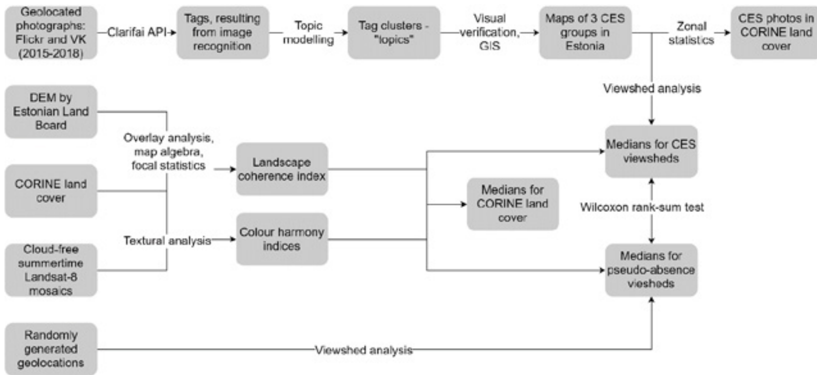

Figure 2. Research workflow of the cultural ecosystem services (CES) mapping in relation to the calculated landscape organisation indices.

3. Results

3.1. Mapping of CES Represented in Social Media in Estonia

Figure 3 presents the results of the CES mapping obtained with the application of topic modelling (geographical coordinates of the photographs from the combined Flickr and VK.com dataset, classified into three categories of CES groups). The clear linear patterns of the photographs highlight the main flows of people alongside the main roads and coastlines of Estonia. The exploratory buffer analysis for OpenStreetMap road data indicates that transport accessibility is extremely important for CES use. To be precise, 6148 out of 6153 landscape-watching photographs, 2311 out of 2345 outdoor recreation photographs, and 1483 out of 1484 wildlife-watching photographs have been taken no farther than 500 m from the roads and trails of all types. Although indoor photographs have been removed from the analysis (see Section 2.2), many photographs were taken in the main cities (Tallinn, Tartu, Narva, etc.), especially in their suburban zones. Additionally, the protected areas are conspicuous as approximately 59% of the total number of selected photographs were taken within these regions. A full list of the protected areas is presented in the Table S1 (Supplementary Materials).

An exploratory analysis of land cover (CORINE land cover 2018, Figure 4) shows that most of the photographs were taken in coniferous forests, agricultural areas, mixed forests, and transitional woodland-shrub areas. All the CES groups under consideration are well represented in these land cover classes. On the contrary, water bodies and courses, sea, peat bogs, inland marshes, and natural grasslands are frequented more for landscape watching than for the other groups of CES. Outdoor recreation is present in complex cultivation patterns and green urban areas. Wildlife watching frequently occurs in broad-leaved forests and pastures. In this way, more "natural" land cover classes are much better represented in the study datasets of passively crowdsourced photographs. However, land, which is principally occupied by agriculture, is among the leaders in enabling CES use.

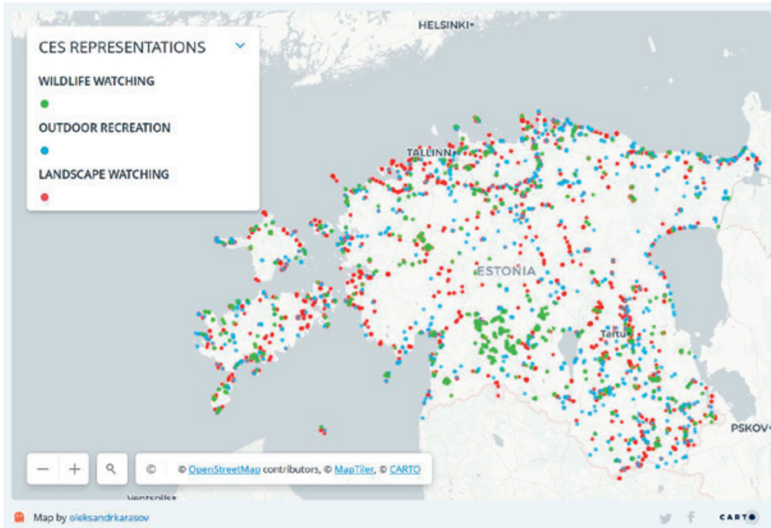

Figure 3. Geotagged photographs representing actual use of three groups of CES in Estonia (2016–2018): landscape watching (passive recreation), outdoor recreation activities, and wildlife watching. The web-map, designed in Carto, is available via the following link: https://oleksandrkarasov.carto.com/builder/1e69e28a-9705-45a9-8276-471a330da2ff/embed.

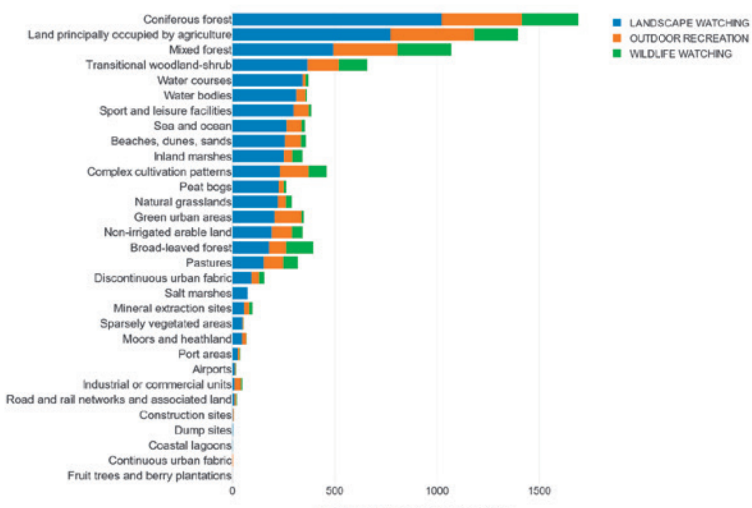

Figure 4. CES use in Estonia encompasses (with a few exceptions) predominantly natural and semi-natural land cover (CORINE land cover 2018). Land cover classes are ranked in order of decreasing number of landscape watching photographs.

3.2. Impact of Landscape Organisation on CES Use

As is clear from Figure 5, we see that the median hue and saturation similarity values are remarkably higher for the actual rather non-vegetated (median value of the normalized difference vegetation index (NDVI) lower than 0.1) viewsheds corresponding to landscape watching and outdoor recreation than for the pseudo-absence viewsheds. The indicators used exhibit similar behaviours for the landscape watching and outdoor recreation viewsheds, whilst colour harmony does not seem to influence wildlife watching.

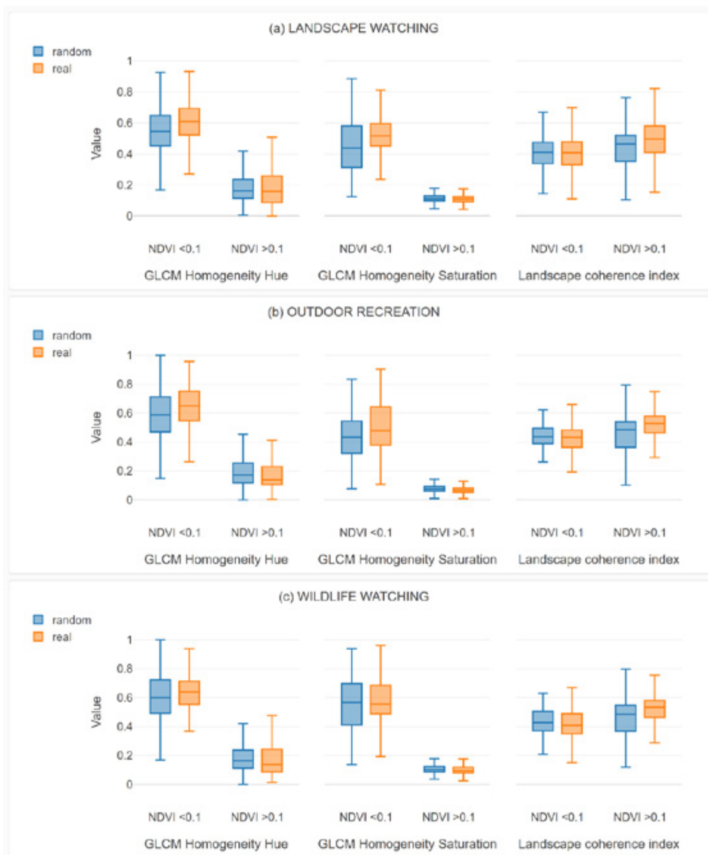

Figure 5. Comparison of medians of landscape coherence and harmony-based visual quality indices for each group of CESs within viewshed areas for actual geotagged photographs ("real") and randomly simulated locations ("random"): (**a**) landscape watching; (**b**) outdoor recreation; (**c**) wildlife watching. Boxplots are designed separately for median normalized difference vegetation (NDVI) index values for each viewshed being higher 0.1 and lower 0.1 to present the index performance for rather vegetated and non-vegetated area (mainly water bodies and streams). Colour harmony indices are higher for actual CES viewsheds in the case of non-vegetated areas, while landscape coherence index is higher for photographs of vegetated areas. The GLCM homogeneity index for the saturation of pixel pairs does not indicate wildlife watching in any case.

According to the Wilcoxon rank sum test with continuity correction, all the distribution differences except for colour harmony indices for wildlife watching are statistically highly significant, suggesting that most CES-related photographs were taken with consideration for land cover of higher colour harmony and landscape coherence (Figure 6). It is highly likely that colour harmony values affect landscape watching and outdoor recreation, while landscape coherence seems to have a clear positive influence on wildlife watching and a weaker positive influence on landscape watching and outdoor recreation.

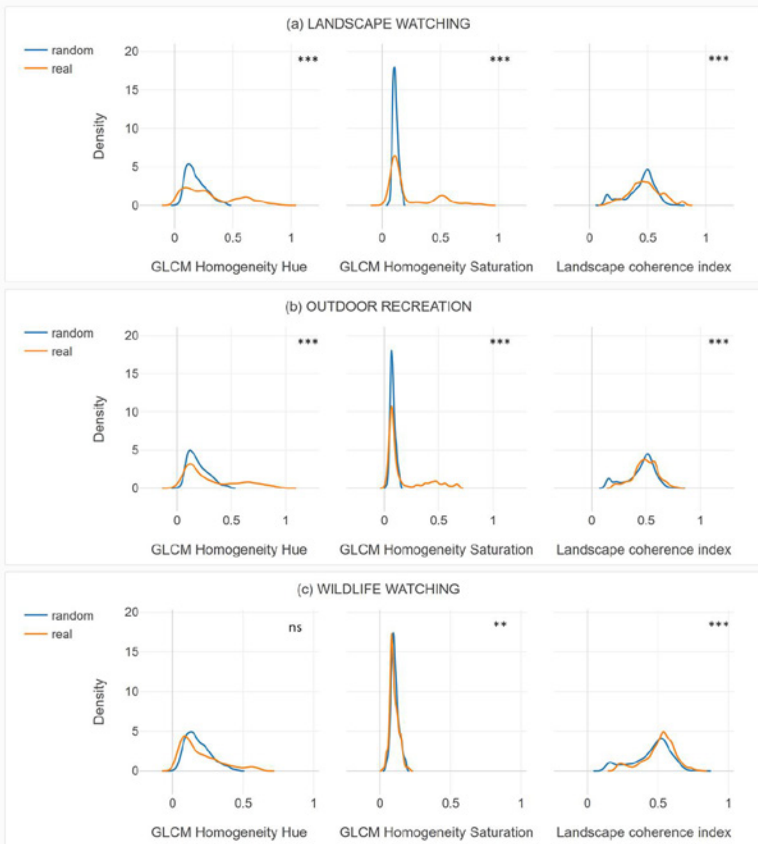

Figure 6. Density plots representing the results of the Wilcoxon rank sum test with continuity correction, applied to the medians of landscape coherence and harmony-based visual quality indices for each group of CESs within viewshed areas for actual geotagged photographs ("real") and randomly simulated locations ("random"): (**a**) landscape watching; (**b**) outdoor recreation; (**c**) wildlife watching. Significance levels: *** p-value less than 0.001; ** p-value less than 0.01; ns—not significant. Alternative hypothesis: two-sided. Confidence level: 0.95.

A visual exploration of land cover with regard to LCI and colour harmony indices reveals a complementary character of the considered landscape organisation indices (Figure 7). Landscape coherence is the highest for culturally modified land covers—urban fabric, urban green areas, and agricultural areas—and lower for natural areas, the minimum being observed for peat bogs and water bodies. Colour harmony, in contrast, is the highest for water forest and peat bogs. Therefore, colour harmony and landscape coherence extents are highly dependable on the land cover type: higher cultural modification of landscape results in the increasing orderliness and complexity, while colour harmony increases for homogeneous and predominantly natural (while often managed) land cover.

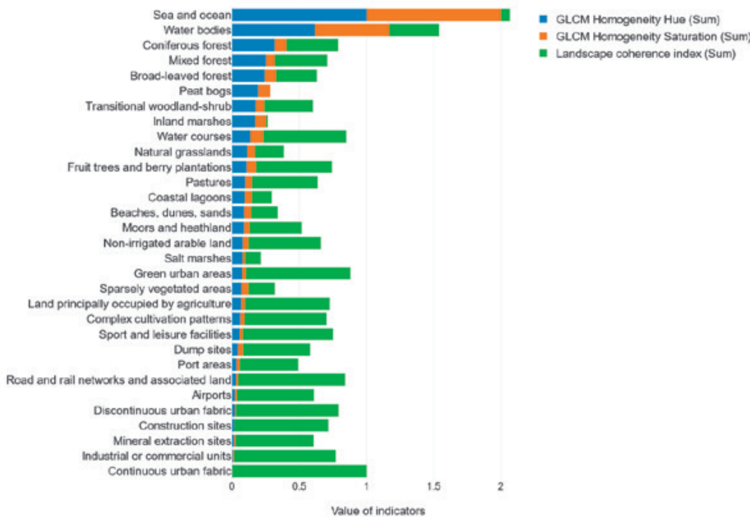

Figure 7. CORINE 2018 land cover classes ranged in order of decrease in GLCM homogeneity for the hue component of HSV colour space, indicating transition from water-related and natural land cover to urban-related areas. Landscape coherence generally increases in this direction.

4. Discussion

4.1. Mapping of CES Represented in Social Media in Estonia

Our results contribute to addressing the challenge of CES mapping by studying the relationships among the three categories of outdoor geotagged photographs and remote sensing-based landscape characteristics [24]. The distribution pattern of the CES-related photographs is in line with previous findings [23] as we confirm transport accessibility and naturalness to be the main factors influencing the probability of taking outdoor photographs [51]. Photographs from different CES groups often overlap spatially, indicating landscape multifunctionality. Landscape multifunctionality is important for the overall distribution of landscape values; hence, our approach can contribute to evidence-based trade-off analyses and the detection of hotspots of cultural landscape functions through CES patterns [52,53]. There is also a synergy between our nationwide CES mappings and the ESMERALDA project [54]. Our cross-disciplinary approach, integrating bio-physical and socio-cultural methods, allows for CES mapping and assessment across various spatial and temporal scales and is applicable to both urban and non-urban environments.

Much of the CES use seems concentrated within nature protection areas, revealing the efficiency and efficacy of the nature conservation policy in Estonia as well as the potential for further expansion of protected areas, which can contribute to an increase in nature-based tourism [55]. Thereby, we confirm the LBSM data as a valuable source of data for nature conservation as well as for CES mapping [21,56,57].

Our results continue the methodological approach that has been initiated in previous research [30–32]. The LDA topic modelling algorithm significantly facilitated the process of LBSM data assigned with the content-related tags as a result of automated image recognition with Clarifai. Therefore, we confirm that the LDA method of topic modelling is highly relevant and valuable for a rapid assessment of cultural ecosystem services use over large areas [31]. When all the photographs representing non-relevant topics have been removed, we applied the LDA algorithm to the relevant tags only, and some testing showed that three topics of tags sufficiently represent their diversity and meet our needs. The automated character of topic modelling often results in a meaningless classification, so the exact number of relevant topics (3) was found by trial and error (while a priori we assumed that there are just a few major CES categories). Further analysis would result in accounting for minor CES categories, such as picnicking, cycling, or playing tennis outdoors, but such detailed classification was beyond the scope of our study.

Obviously, the proposed methodological combination is not a complete substitute for traditional visual content analysis; instead, it should be used as an initial procedure for CES use assessment and followed with a quick visual verification. For example, we transferred to the outdoor recreation category those photographs that were automatically selected for landscape watching if they contained minor presence of people or their equipment; since presence of pets was automatically interpreted as wildlife (the general machine learning model provided by Clarifai does not account specifically for this distinction), we also manually moved these photographs to the category for outdoor recreation. Photographs with minor presence of wild animals classified as related to landscape watching were also manually transferred to the wildlife watching category.

4.2. Impact of Landscape Organisation on CES Use

In line with previous studies, landscape coherence was found to have a positive but rather weak association with CES use in our countrywide study [34]. Vertical landscape coherence increases for places of significant cultural modification (more legible urban and agricultural areas). Thereby, we confirm LCI performance as indicative of the orderliness of the landscape pattern, but unexpectedly it has a rather small impact on CES use. Wildlife watching occurs in places with higher LCI. This is potentially because people are more likely to take photographs of animals, plants, and mushrooms near their homes (such as green urban areas) in some understandable settings rather than in a more natural environment. Other authors have additionally explored the hotspots of wildlife watching near cities [29]. As some photographed areas have higher LCI, compared with the values for random locations, signs of anthropic modification (parks, suburban areas, agricultural fields, and other elements of cultural landscape) can be additionally important for CES use, complementing pure naturalness [58].

Colour harmony indicators (HSV hue and saturation similarities, indicated with GLCM homogeneity) showed a larger difference between the photographed viewsheds and random background viewsheds, suggesting that people tend to take photographs with a preference for land covers of greater colour harmony. However, as there is an association between land cover classes (CORINE land cover 2018) and colour harmony, the bias may be caused by the effect of the land cover itself; for instance, sea, water bodies, forests, and peat bogs additionally have powerful intrinsic and other values. Therefore, our results should be treated with caution, and colour harmony mappings should contribute to the general understanding of landscape rather than perform as the standalone indicators of landscape preferences.

4.3. Other Sources of Bias

It is most likely that elderly persons and children are the least represented age strata in LBSM. However, Flickr and VK.com were launched in 2004 and 2006, respectively, and have become very popular among diverse user groups, while general Internet penetration in Estonia is growing also [59]. We can expect that in the coming years, LBSM social media will become more orientated towards elderly people owing to the regular ageing of active Internet-users. Unfortunately, the LBSM data—unlike surveys—provide little or no information on the individuals' sex and gender, age, education level, family status, ethnic origin, etc. Nevertheless, the LBSM data are free from some survey-specific issues, such as recollection and mind biases, which occur owing to intrusive surveying [52,60]. Therefore, in our opinion, social media data provide added value to CES studies.

5. Conclusions

Our results are based on photographs uploaded to the social media sites, Flickr and VK.com, which can be used to represent the actual use of some CESs (landscape watching, outdoor recreation, and wildlife watching), and are linked to spatial landscape indices in Estonia. Their spatial analysis enables a better understanding of the geographic organisation of the environment and its potential for providing CES and supporting nature appreciation in an urbanised society [61]. Evidence from our study suggests that social media users prefer taking photographs of landscapes and outdoor activities in areas with greater colour harmony, whilst landscape coherence is linked strongly only to wildlife watching and, to a lesser extent, other CESs.

Topic modelling significantly reduced the time needed for the content analysis of the photographs, and our CES mapping depends on the quality of this automated image content analysis. Therefore, future research could be targeted towards comparing different machine learning algorithms and including the temporal component. The suggested methodological combination of machine learning and natural language processing algorithms advances the existing common methods of CES assessment based on passively crowdsourced photographs, and it is sufficiently robust to be applied across the regional, continental, and global scales. In turn, the test of GIS-based landscape organisation metrics in relation to CES use shows that they can also facilitate the prospects of rapid and reliable landscape visual quality assessment up to the global scale, which does not depend on local subjective landscape evaluations and complements regional landscape character assessment. Drawbacks of the approach are related to the representativeness of the social media data as a source of knowledge about CES use and also to limitations of the GIS and remote sensing applicability for physio-gnomic landscape research. Notwithstanding, we have demonstrated that the combined usage of LBSM data, automated image recognition, natural language processing, satellite imagery, and GIS data is highly relevant for evidence-based ecosystem management and nature protection.

Supplementary Materials: The following are available online at http://www.mdpi.com/2073-445X/9/5/158/s1, Table S1—Number of CES-related photographs per protected area.

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Appendix A

Results of the applied statistical analysis (Wilcoxon rank sum test with continuity correction) for median values of landscape organisation metrics within the viewsheds based on CES-related and randomly generated geolocations. The landscape coherence index was rescaled (0; 1) to meet the scale of colour harmony estimations in Results.

Table A1. Summary statistics.

Indicator	U Statistic	p Value	Difference	Conf High	Conf Low
Landscape watching					
GLCM homogeneity hue	14,795,531.5	9.88×10^{-98}	−0.061	−0.055	−0.068
GLCM homogeneity saturation	14,594,742.5	2.91×10^{-107}	0.017	−0.015	−0.018
Landscape coherence index	16,273,215.5	2.01×10^{-41}	−0.033	−0.029	−0.039
Outdoor recreation					
GLCM homogeneity hue	2,356,245	2.21×10^{-17}	−0.032	−0.024	−0.040
GLCM homogeneity saturation	2,293,880	8.59×10^{-23}	−0.011	−0.008	−0.013
Landscape coherence index	2,280,950.5	5.18×10^{-24}	−0.035	−0.029	−0.042
Wildlife watching					
GLCM homogeneity hue	1,140,081	0.095	0.007	0.015	−0.001
GLCM homogeneity saturation	1,168,362	0.004	0.004	0.006	0.001
Landscape coherence index	898,071.5	3.34×10^{-18}	−0.037	−0.029	−0.046

Table A2. Detailed statistics.

Indicator	Type	Number of Rows	Mean	Confidence Low	Confidence High	Standard Error of Mean	Standard Deviation	Minimum	Maximum
Landscape watching									
GLCM homogeneity hue	random	6153	0.20	0.20	0.20	0.00	0.12	0.01	1.00
GLCM homogeneity hue	real	6153	0.31	0.30	0.31	0.00	0.23	0.00	0.93
GLCM homogeneity saturation	random	6153	0.13	0.13	0.13	0.00	0.08	0.01	1.00
GLCM homogeneity saturation	real	6153	0.24	0.24	0.24	0.00	0.21	0.00	0.93
Landscape coherence index	random	6153	0.42	0.41	0.42	0.00	0.16	0.00	0.87
Landscape coherence index	real	6153	0.47	0.47	0.48	0.00	0.14	0.00	1.00
Outdoor recreation									
GLCM homogeneity hue	random	2345	0.21	0.21	0.21	0.00	0.13	0.00	1,00
GLCM homogeneity hue	real	2345	0.31	0.30	0.32	0.01	0.25	0.00	0.96
GLCM homogeneity saturation	random	2345	0.09	0.09	0.10	0.00	0.09	0.00	1.00
GLCM homogeneity saturation	real	2345	0.20	0.19	0.20	0.00	0.22	0.01	0.90
Landscape coherence index	random	2345	0.44	0.43	0.44	0.00	0.15	0.00	0.87
Landscape coherence index	real	2345	0.49	0.49	0.49	0.00	0.12	0.00	1.00
Wildlife watching									
GLCM homogeneity hue	random	1484	0.20	0.20	0.21	0.00	0.14	0.00	1.00
GLCM homogeneity hue	real	1484	0.23	0.22	0.24	0.00	0.19	0.01	0.96
GLCM homogeneity saturation	random	1484	0.13	0.12	0.13	0.00	0.11	0.01	0.94
GLCM homogeneity saturation	real	1484	0.16	0.15	0.16	0.00	0.17	0.00	1.00
Landscape coherence index	random	1484	0.44	0.43	0.45	0.00	0.16	0.00	0.80
Landscape coherence index	real	1484	0.48	0.48	0.49	0.00	0.15	0.00	1.00

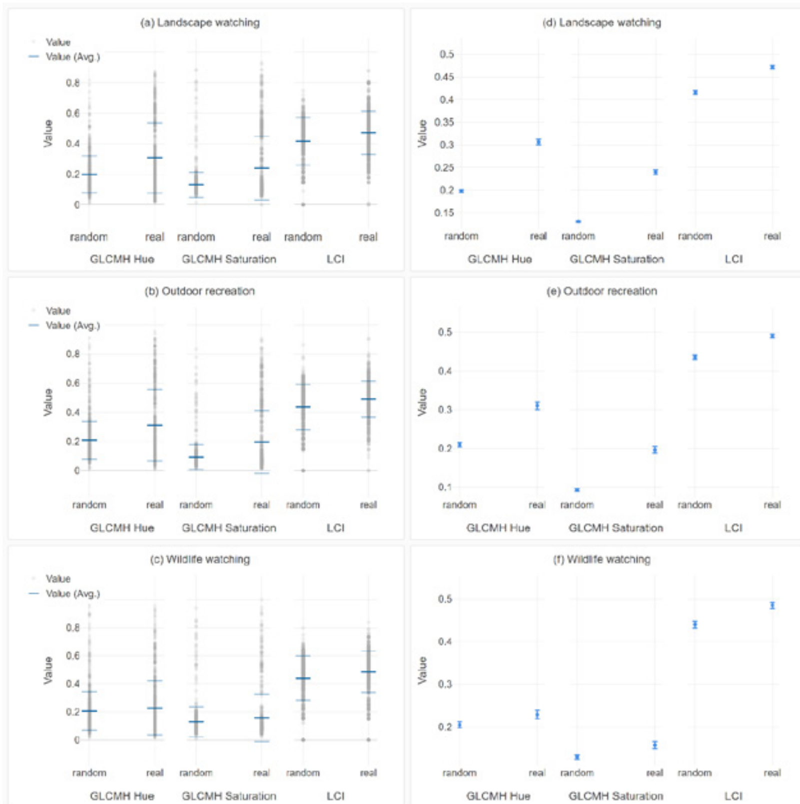

Figure A1. Complementary visualisation plots of the Wilcoxon test results. Scatters: (**a**) landscape watching; (**b**) outdoor recreation; (**c**) wildlife watching. Error plots: (**d**) landscape watching; (**e**) outdoor recreation; (**f**) wildlife watching.

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Dotsent **Tiina Tosens**, professor **Ülo Niinemets**
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