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

Karasov, Oleksandr

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Authors: Oleksandr Karasov, Mart Külvik, Iuliia Burdun

Affiliations and addresses:

Oleksandr Karasov, Mart Külvik: Chair of Environmental Protection and Landscape Management, Institute of Agricultural and Environmental Sciences, Estonian University of Life Sciences, Kreutzwaldi 5, 51014, Tartu, Estonia.

Iuliia Burdun: Department of Geography, Institute of Ecology & Earth Sciences, University of Tartu, Vanemuise 46, 51014, Tartu, Estonia. E-mail: iuliia.burdun@ut.ee, phone +37256734170

The e-mail address, and telephone number of the corresponding author: oleksandr.karasov@student.emu.ee, +37258977794

ORCIDs. Oleksandr Karasov: 0000-0001-6121-4625. Mart Külvik: 0000-0002-8241-6637. Iuliia Burdun: 0000-0002-1436-2550

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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

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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 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; 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 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.

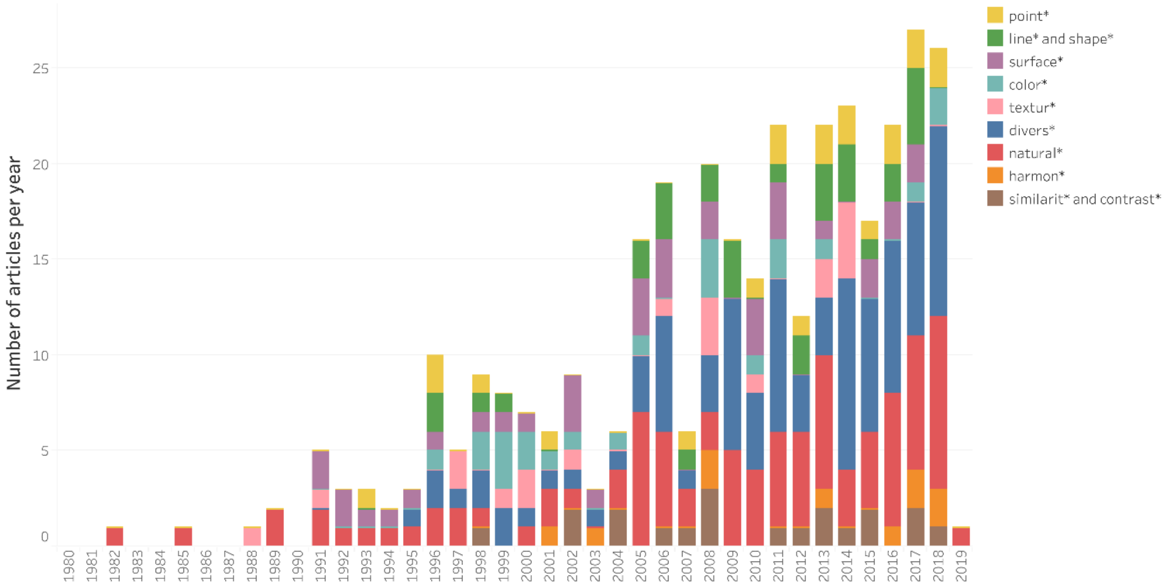

Fig. 1 Growing numbers of articles in peer-reviewed journals (indexed by the Web of Science Core Collection indices and Scopus per year) operationalising scenic landscape-related attributes with the application of remote sensing. The plot is based on the key queries reflecting landscape attributes searched 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

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).

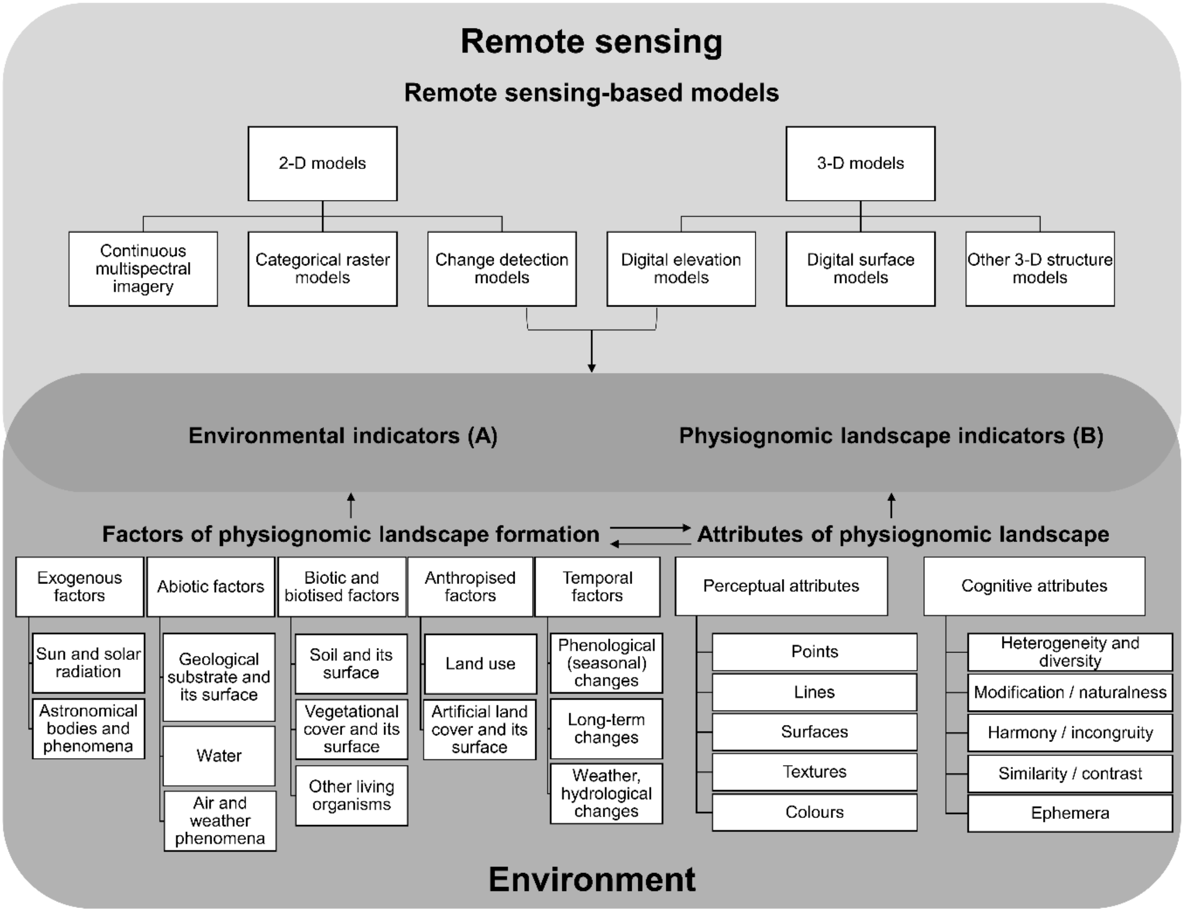

Fig. 2 Conceptual scheme of remote sensing applications to the perceived environment. The physical environment, which is perceived visually, constitutes the respective physiognomic landscape (serving as a factor for the formation of different perceptual and cognitive phenomena). Remote sensing-based 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

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 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. 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.

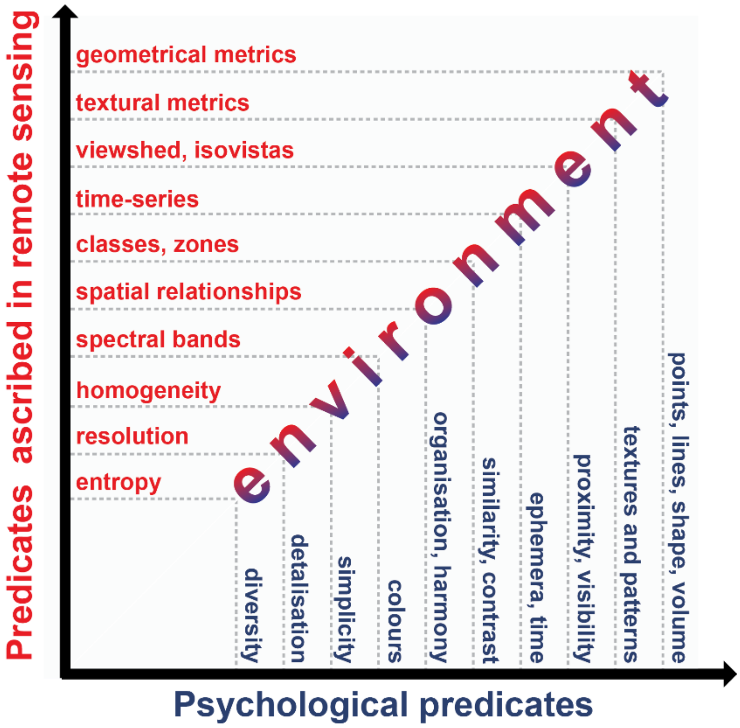

Fig. 3 Parallels between the predicates used in remote sensing, psychology and landscape science: 1) entropy as mathematical function describes landscape diversity; 2) spatiotemporal and spectral resolution of imagery corresponds to the details (or generalisation) of a landscape image; 3) remote sensing-based 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 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 (2017a) 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 (Annex 1, 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.

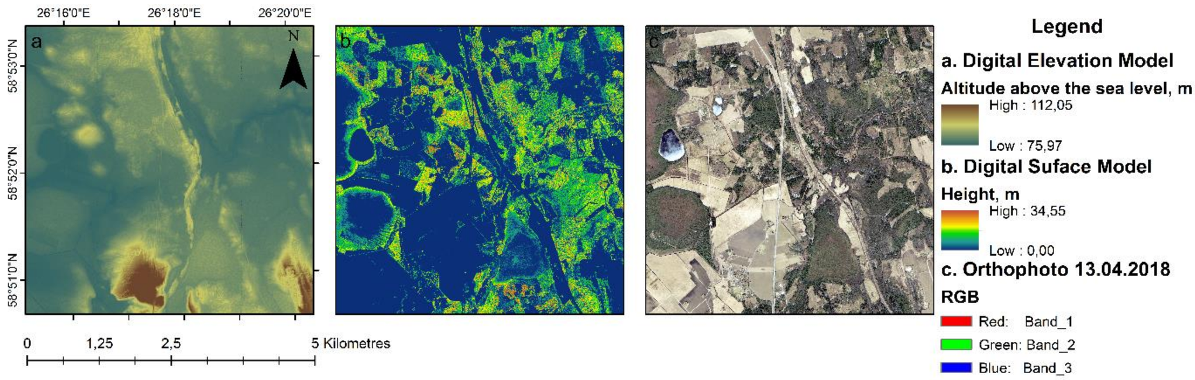

Fig. 4 Remotely sensed data for the area of Eastern Estonia (panel a – LiDAR-based digital elevation model, panel b – LiDAR-based normalised digital surface model, panel c – multispectral orthophotograph captured 13.04.2018, natural colours band combination) which are commonly used to deconstruct the physiognomic landscape. 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)

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 2017b). 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 (Sowiſska-ſwierkosz 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; Sowiſska-ſwierkosz 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 metres 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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Annex 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; Nijhuis et al. 2011
Lines (shapes)	Fractal dimension	Area-perimeter relationships of patches	Siu-Ngan Lam 1990; Schirpke et al. 2013; Sudakov et al. 2017
	Line density	Summarised line lengths and total landscape area ratio	McGarigal et al. 2002; de Almeida Rodrigues et al. 2018
	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	Siu-Ngan Lam 1990; Mesev et al. 1995

		variograms, either of the whole surface or some of its profiles	
		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; 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; 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; Chen and Xu 2016
Textures	Pixel-based texture metrics (first-order or second-order metrics) as	Kernel-based estimations	Haralick et al. 1973; Warner 2011; Hall-Beyer 2017a; 2017b

	patterns of the local spatial variation of the pixel values		
	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; 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; 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; Booth et al. 2017
	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; Hall-Beyer 2017a; 2017b
	Fractal dimension	See above (here regarding the geometric complexity of patches)	de la Fuente de Val et al. 2006; 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; 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; 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; Swetnam et al. 2017
	Line sinuosity	See above	Booth et al. 2017

	Fractal dimension	See above	Antrop and Van Eetvelde 2000; Taylor 2002; 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	S.-N. 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; Sahraoui et al. 2016
	Interspersion and juxtaposition index	Function from the patch adjacencies in the landscape	McGarigal and Marks 1995; Sahraoui et al. 2016
	Cohesion index	Estimation of the physical connectedness of the patches	McGarigal et al. 2002; Plexida et al. 2014
	Connectivity indicator CCI	The distance-based function of the connectedness	Mancebo Quintana et al. 2010; Martín et al. 2016

Similarity and contrast	Pixel-based texture metrics	Based on the Grey Level Co-occurrence Matrix	Haralick et al. 1973; Warner 2011; Hall-Beyer 2017a 2017b
	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; 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; 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; Lambin and Ehrlich 1997
	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

PHYSIOGNOMIC LANDSCAPE FEATURE TYPOLOGY

Figures 1-6 provide evidence for physiognomic landscape decomposition with remote sensing- and GIS-based data (sample area from South-Eastern Estonia). Two kinds of physiognomic landscape attributes are described: points, lines, surfaces, colours, textures as geometric attributes; diversity, naturalness, harmony, and contrast as cognitive attributes. Ephemera, or temporal pattern is another landscape attribute which is not covered here since it emerges from any time-series data capturing any physiognomic landscape indicator.

Given the landscape scale of kilometres, buildings could be generalized as point landscape features; transport infrastructure, waterways and shorelines correspond to linear landscape features; digital elevation model is a land surface indicator; colours are derived from satellite imagery (combination “natural colours”); textures are particular metrics, representing pixel relationships within the satellite image.

Shannon diversity index is used as an indicator of land cover diversity; CORINE land cover model intrinsically conveys naturalness and cultural modification; harmony is a concept frequently applied to colour pairs (for instance, pairs of pixels in satellite imagery), and contrast is a texture-based indicator for pixel values. Pixels of satellite image are used as elementary units of information about a physiognomic landscape.

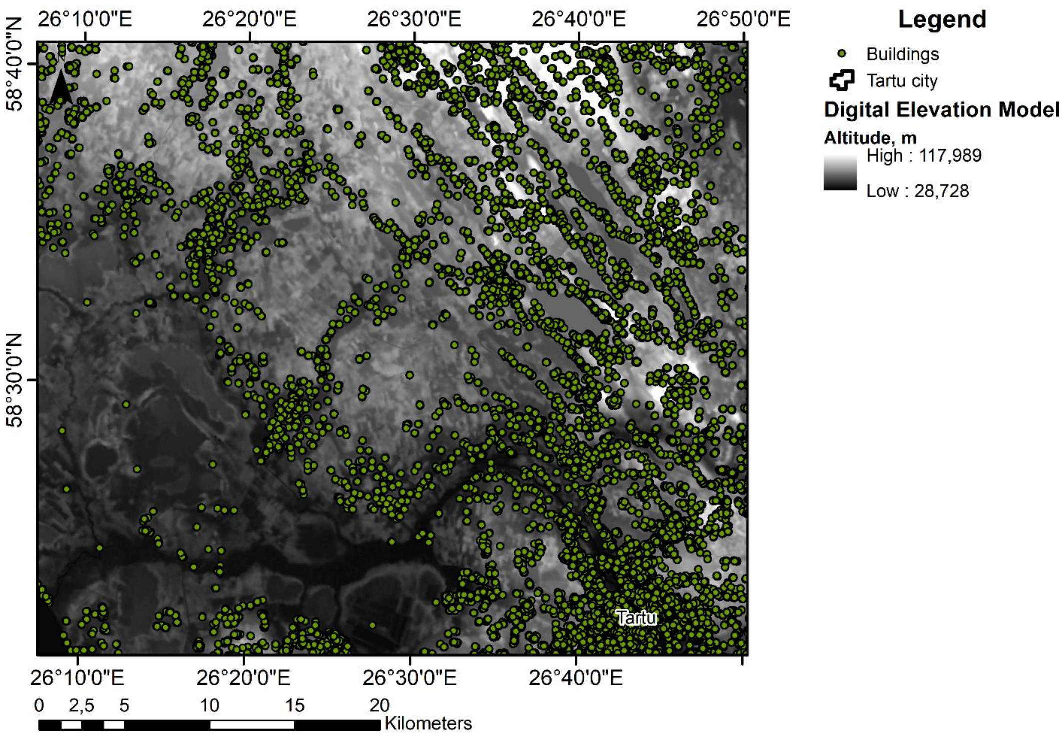

Fig. 1 Buildings as point features (data credit: Estonian Land Board 2019) and digital elevation model as a land surface feature of the physiognomic landscape (hereinafter area: Southern-Eastern Estonia, Tartu city)

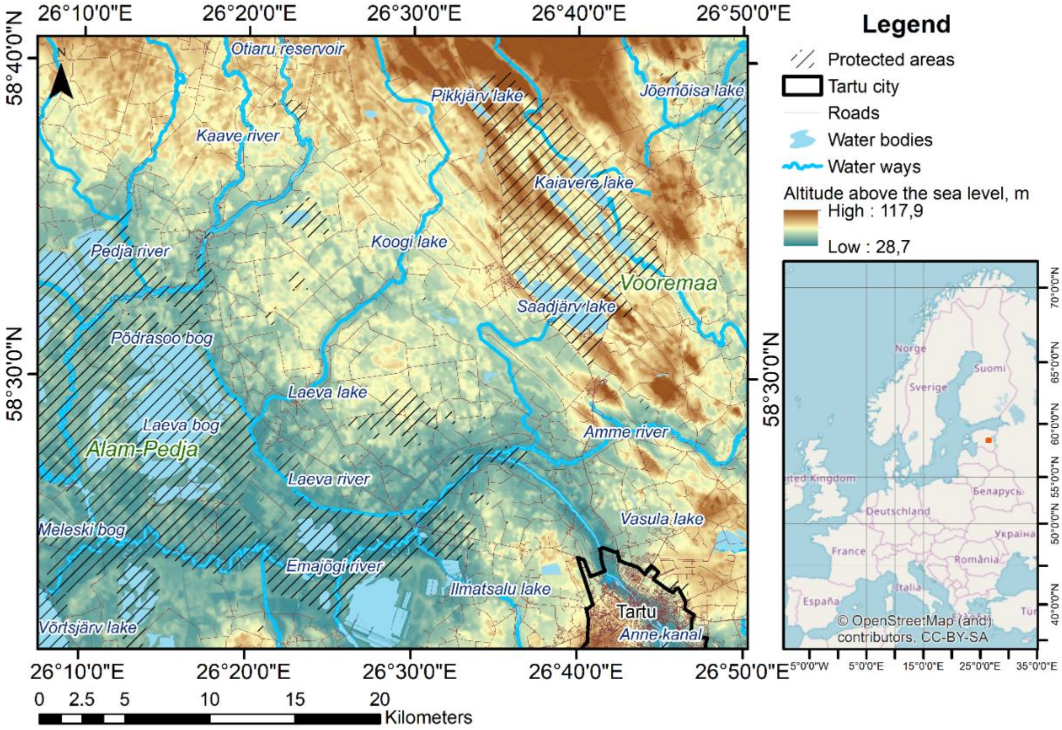

Fig. 2 Water- and road-ways, water bodies shorelines as linear features of physiognomic landscape (image credit: https://doi.org/10.1007/s10708-018-9908-x)

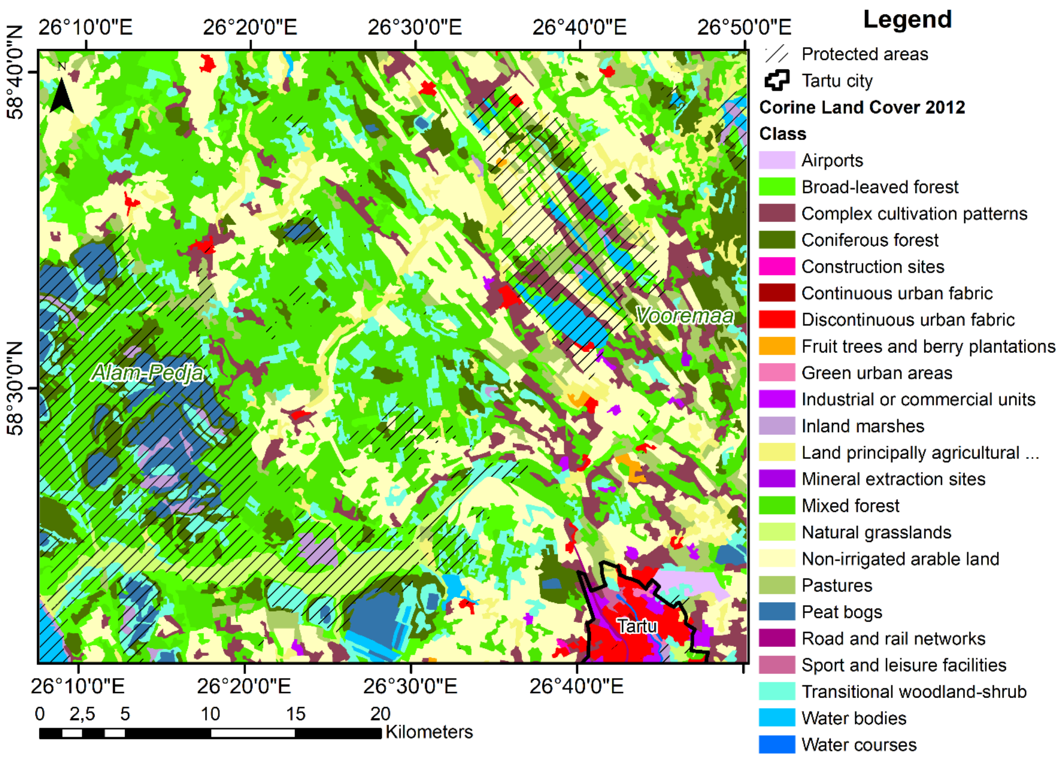

Fig. 3 Indicator of naturalness: CORINE land cover classes could be treated as more "natural" and more "anthropogenic" (image credit: https://doi.org/10.1007/s10708-018-9908-x)

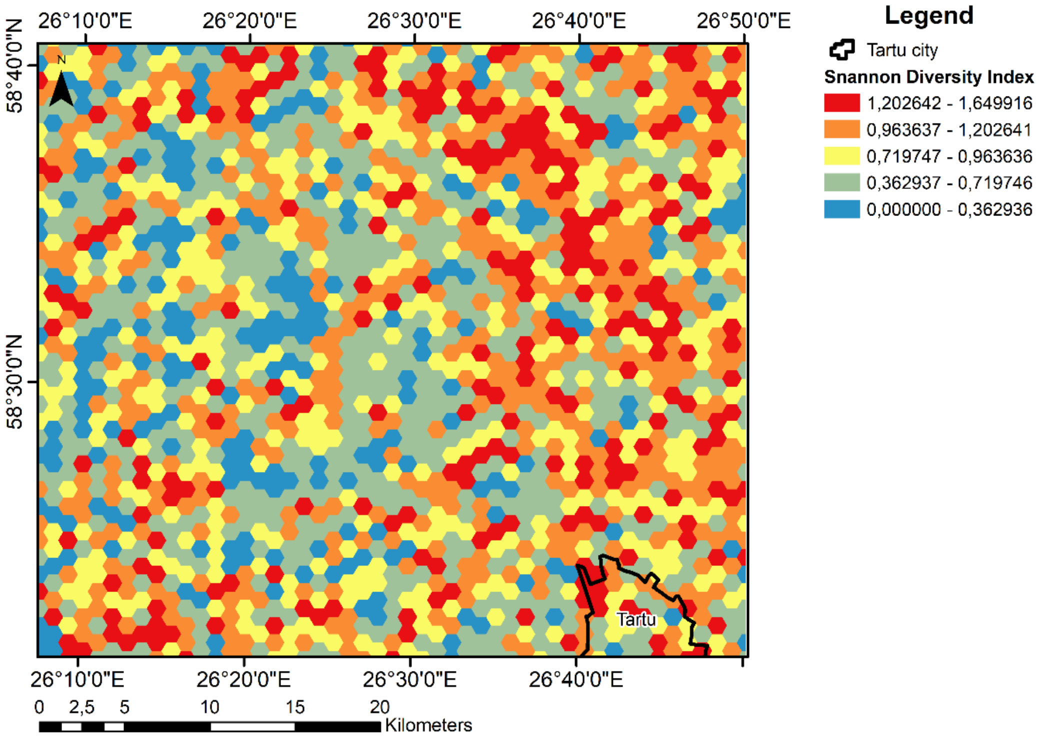

Fig. 4 Indicator of diversity: Shannon diversity index (SHDI) per hexagonal grid zone (1 km wide), based on the CORINE land cover classes (calculated with ZonalMetrics toolbox v1 http://dx.doi.org/10.1016/j.cageo.2016.11.005)

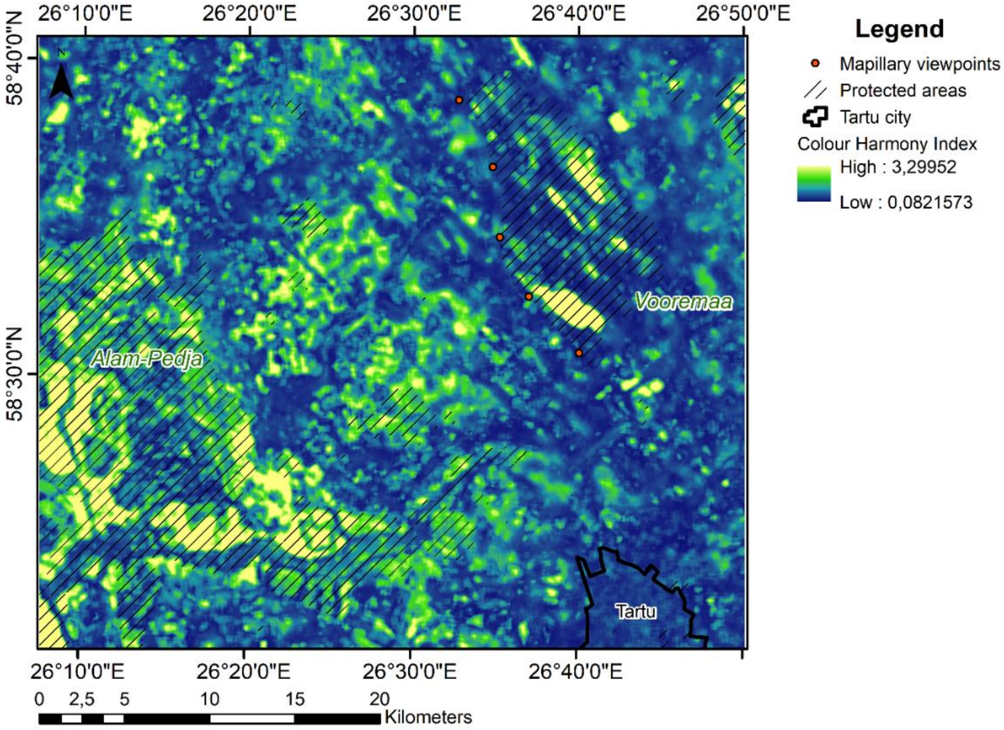

Fig. 5 Colour and harmony indicator: Colour Harmony Index as indicator for colour harmony of land cover calculated for Landsat 8 pre-processed scene (image credit: https://doi.org/10.1007/s10708-018-9908-x)

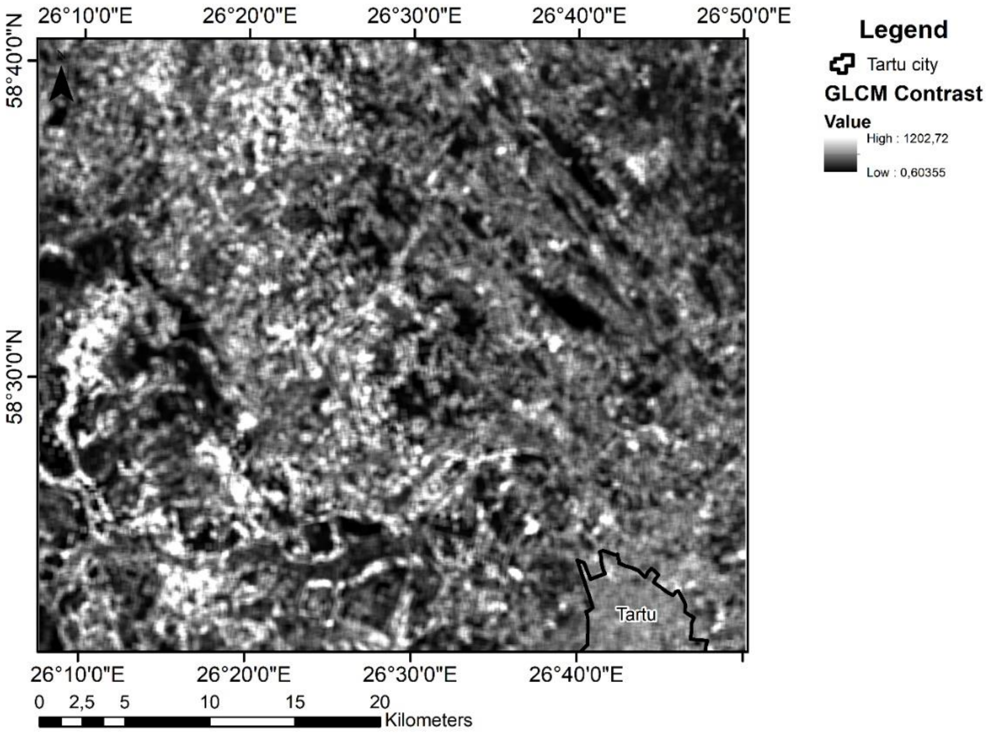

Fig. 6 Indicator of contrast and texture: Contrast index based on Co-Occurrence Grey-Level Matrix for Landsat 8 satellite image, converted to HSV colour space (Value component)

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Surfaces (forms)	Fractal dimension	Fractal dimension of contours, characterising the surface or of variograms, either of the whole surface or some of its profiles	Siu-Ngan Lam 1990; 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	Bishop and Hulse 1994; Riley et al. 1999; Germino et al. 2001;

		deviation of altitude, slope variability	Vukomanovic and Orr 2014; de Almeida Rodrigues et al. 2018; Vukomanovic et al. 2018
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	Change indices	Based on the land use/land cover classes	Lambin and Ehrlich 1997; Käyhkö and

		transitions or environmental variables	Skånes 2006(Lambin and Ehrlich 1997)(Lambin and Ehrlich 1997)(Lambin and Ehrlich 1997)(Lambin and Ehrlich 1997)(Lambin and Ehrlich 1997)
	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