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## Journal Article

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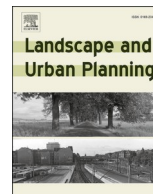
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## Research Paper

## Does rated visual landscape quality match visual features? An analysis for renewable energy landscapes

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## HIGHLIGHTS

- Rated coherence and legibility correlate with preference for energy landscapes.
- Rated visual landscape qualities and measured visual features are correlated.
- Landscape preference decreases with increasing renewable energy systems.
- Flatlands revealed low preference regardless of share of renewable energy systems.
- Rated landscape coherence is an index of place-technology-fit in energy landscapes.

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## ABSTRACT

Finding the “right” sites for developing renewable energy systems (RES) is one of the major challenges in planning strategies for energy transitions. The visibility aspects of such infrastructure are important factors that explain local opposition. Classical visibility and viewshed analyses of RES disregard people’s perceptions and estimations of new infrastructure. To address this void, we demonstrate an approach that combines rated visual landscape qualities with measured visual features. In doing so, we established visual stimuli with systematically controlled visual impact scenarios featuring the use of renewables in different landscape types. The study investigated how ratings of landscape qualities are affected by landscape changes stemming from RES. We also identified measurable visual features that might help to operationalize landscape qualities. Finally, we intended to improve the understand of how rated landscape qualities lead to preferences for different RES visual impact scenarios. Our results showed that rated coherence is strongly influenced by renewable energy infrastructure, whereas complexity ratings are affected mainly by variations in landscape types. These findings let us to conclude that the visual understanding and visual connectedness between energy systems and surrounding landscapes are core drivers of people’s visual preferences for landscapes altered with RES. Considering landscape qualities within impact assessments of RES can augment our grasp of how the visual character of a landscape changes through renewable energy infrastructure.

## 1. Introduction

To reach global climate targets and close the energy gaps resulting from phasing out nuclear or fossil energy production, countries increasingly focus on renewable energy resources such as wind, hydro-power, solar or biomass (Mathiesen, Lund, & Karlsson, 2011;

Wüstenhagen, Wolsink, & Bürer, 2007). In 2016, the production of wind and solar energy amounted to a global volume of only 1.5 Mio. GWh, whereas coal remained the major source of global electricity production (9 Mio. GWh, (World Energy Council, 2019) In the last three decades, the worldwide electricity demand has doubled from 11’000 TWh to 23’000 TWh and is expected to grow annually by up to 1% during the

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next decades (World Energy Council, 2019). Addressing growing energy demand combined with an enhanced focus on renewable energy, requires an increasing amount of land for energy production. Let us take Switzerland, which served as the study site in this work, a technical-economic production potential of approx. 14 TWh from wind energy and approx. 58 TWh of photovoltaic energy (Cattin et al., 2012) are estimated. Today, Switzerland annually produces 0.16 TWh and 2.2 TWh of electricity from wind and solar energy, respectively (Swiss Federal Office of Energy, 2019). According to the goals indicated in the “Swiss Energy Strategy 2050” the production of electricity from renewable energy should amount to 11.4 TWh in 2035 and 24.2 TWh in 2050. With these developments come fundamental transformations that are expected to reshape ecosystem services at the landscape scale (e.g., biodiversity, recreation, food production) (Nadai and van der Horst, 2010; Plieninger et al., 2016). Several services have been shown to conflict with the production of renewable energy (e.g., Hastik et al., 2015; Kienast, Frick, van Strien, & Hunziker, 2017; Santangeli et al., 2016). Exemplarily for Switzerland, Kienast et al. (2017) estimate that on 88% of the potential locations for wind energy production and on 32% of the potential areas for solar panels, compete with one or more other services. Therefore, the conflict of wind (Warren, Lumsden, O’Dowd, & Birnie, 2005; Wolsink, 2007) and photovoltaic energy infrastructure (Chiabrand, Fabrizio, & Garnero, 2009; Zoellner, Schweizer-Ries, & Wemheuer, 2008) with landscape aesthetics is an important factor for the decreased social acceptance of such projects. Over the last decades, studies have revealed that, in general, people visually prefer natural landscapes over built environments (e.g., Kaplan and Kaplan, 1989; Ulrich, 1986; Ulrich et al., 1991). Given that RES are artificial installations, studies conclude that adding RES to landscapes generally diminish visual landscape quality ratings (Zoellner et al., 2008). Specifically, in landscapes perceived as having high visual quality, the presence of RES strongly reduces visual quality compared to areas of low quality (Betakova, Vojar, & Sklenicka, 2015; Lothian, 2008; Molnarova et al., 2012). Although standardized visual impact assessments (VIA) are widely used in practice to quantify RES visual impact, these methods cannot illuminate *why people visually prefer certain landscapes altered with RES over others*. Correspondingly, the majority of VIAs quantify the visibility of RES instead of assessing RES siting-induced changes in the visual quality of landscapes (Wolsink, 2018). Inquiring into the visual qualities of RES-altered landscapes can elevate our understanding of the preference forming process for such landscapes. The insights accordingly derived can also help landscape planners and designers involve people in decision making on RES projects.

The overarching goal of this study was to investigate how people perceive RES-driven visual changes in different landscapes. All the goals pursued in this work, along with two concepts that constituted the theoretical framework are detailed in the succeeding sub-sections.

### 1.1. Perceiving and rating landscape qualities

Landscape perception is defined as “the seeing of [landscape] qualities” (Coeterier, 1996). This strong link between landscape and perception is underlined by the idea that a landscape is such only if it is perceived by people (Council of Europe, 2000). “Perception” orders the sensory input (e.g., seeing), matches it with mental concepts and integrates objects into a whole (Coeterier, 1996; Ware, 2011). Although landscape perception differs between genders, ages and social or cultural background (Stamps, 1999; Strumse, 1996; Zheng, Zhang, & Chen, 2011), there is a high consensus in human perception and preferences for specific landscapes (Bell, 2012; Hägerhäll et al., 2018; Kaplan and Kaplan, 1989; Ulrich, 1986; van den Berg and Koole, 2006). Two main paradigms explain the landscape preferences of people. The first is the paradigm constituted by “cultural theories,” which assume that landscape preference is strongly influenced by social and cultural characteristics (Bell, 2012). These theories see familiarity with the landscape or knowledge about the ecological values as key factors for preferences (Gobster, 1999). The second

paradigm is that comprising “evolution-based theories,” which explain landscape preferences as reflections of landscape qualities that were favorable for survival in early ages (Kaplan and Kaplan, 1989; Steg, 2013p. 38–46). From both paradigms evolved methods that transform physical landscape structures into psychological dimensions of landscape qualities (Bell, 2012; Coeterier, 1996; 2013: 38–46p. 38–46). Evolutionary theories encompass prospect-Refuge theory (Appleton, 1996), savanna Theory (Orians, 1980), and the preference matrix (Kaplan and Kaplan, 1989). The preference matrix, which is one of the most frequently used theories for assessing landscape qualities, distinguishes psychological dimensions of landscape preferences along two axes. The first encompasses two basic informational needs: “*understanding*” and “*exploring*”. The former refers to the need of humans to make sense of a scene, whereas the latter depicts the need to gather more information (Kaplan, 1987; Kaplan and Kaplan, 1989). The second axis discriminates between the immediacy with which information is processed (Kaplan, 1987; Steg, 2013), that is, completed immediately or within further mental steps (inferred) (Kaplan, 1987). The two axes span the four visual qualities “*complexity, coherence, mystery and legibility*” (Kaplan and Kaplan, 1989). Complexity is the immediate exploration and assessment of how many different visual elements are distinguishable and how much is going on in a scene (Kaplan, 1987). Coherence reflects immediate understanding and refers to a sense of order or context that guides a view and thus enables people to understand landscapes (Kaplan, 1987). Uniform textures and shapes increase redundancy and advance the distinction of specific areas within a scene, thereby strengthening one’s sense of coherence (Kaplan, 1987). Mystery represents an inferred exploration that captures hidden elements by assessing how much can hypothetically exist if one can further walk into a scene (Stamps, 2004). Exemplarily, the partial coverage of elements with foliage or changes in topography motivate further exploration of a landscape and, thus, increases mystery (Kaplan, 1987; Kaplan and Kaplan, 1989). Finally, legibility pertains to inferred understanding and describes the readability and possibility with which to navigate through a landscape (Stamps, 2004). Landmarks, such as mountains or lakes, influence the legibility of a landscape and enhances its orientation (Kaplan, 1987).

Lothian (2008) and Betakova et al. (2015) investigated the qualities of landscapes with and without RES. The authors concluded that in high-quality landscapes, RES strongly diminishes perceived landscape quality compared with low-quality areas. Pasqualetti (2000) specified that the artificiality of RES “rudely” interrupts peoples’ understanding of slow-growing nature and might consequently influence perceived permanence. To permanence, disturbance is an antagonist, whose presence indicates a lack of coherence (Tveit, Ode, & Fry, 2006). Permanence refers to a sense of continuity, which is an important factor for establishing place identity and place attachment (Twigger-Ross and Uzzell, 1996). In relation to wind turbines, Devine-Wright and Howes (2010) asserted that opposition to such projects is related to the disruption of place attachment. Johansson and Laike (2007) found that perceived unity most strongly predicts and explains opposition against wind turbines. Unity reflects ‘*How well the various components in the environment fit, and function together*’ (Johansson and Laike, 2007). Thus, unity and coherence are closely related, since both refer to a sense of hanging together (Kaplan, 1987) and the comprehension that “*the whole is more than the sum of its part*” (Kuiper, 1998; Tveit et al., 2006). In addition, Stanton (2016) conclude that the sense of hanging together and relations between object is important for people to judge scale of wind turbines.

This work treated “*landscape qualities*” as the perceived visual qualities of RES-altered landscapes. As indices of these perceptions, ratings ascribed to coherence, complexity, mystery, and legibility were defined in accordance with the preference matrix (Kaplan & Kaplan 1989). However, relying exclusively on visual landscape qualities in rating might be a critical shortcoming given the questionable reliability claimed by some researchers (Palmer, 2000; Stamps, 2004). Stamps (2004), for instance, conducted a meta-analysis and found low reliability and replicability for the preference matrix. Similarly, Palmer (2000)

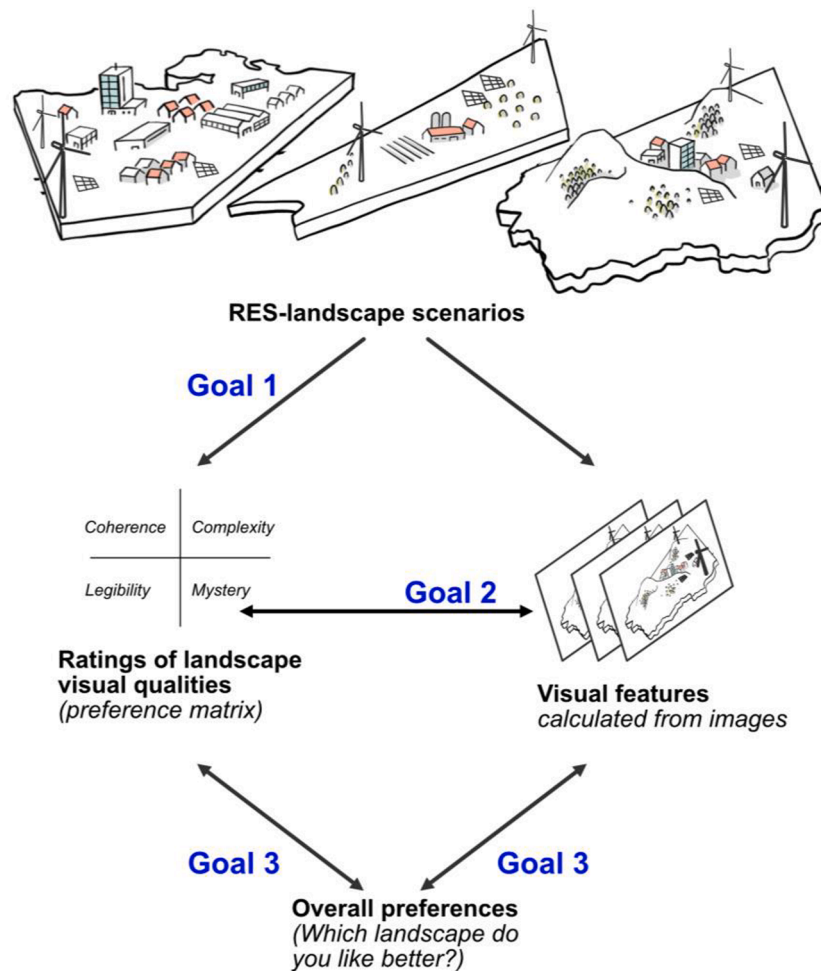


Fig. 1. Overview of the study goals.

showed that assessing visual landscape qualities using the matrix requires a substantial number of raters to obtain the minimum reliability score of 0.7. [Stamps \(2004\)](#) recommended that measures grounded on mathematical principles (i.e., entropy or visible extent) be used instead of individual landscape quality ratings.

### 1.2. Relating visual features to landscape qualities

As described above, there is strong evidence that the detection of visual features such as edges, shapes, colors, textures and patterns plays an important role in people's visual perception and, eventually, landscape preference ([Bell, 2012](#) p. 179). We emphasize, however, that this is only one—albeit important—entry point in examining landscape experience. Other entry points are place attachment and place meaning. We provide a short overview of quantitative studies that underscored relating visual features to preference ratings ([Berman et al., 2014](#); [Dramstad, Tveit, Fjellstad, & Fry, 2006](#); [Hunziker and Kienast, 1999](#); [Ibarra et al., 2017](#); [Kardan et al., 2015](#); [Ode, Fry, Tveit, Messenger, & Miller, 2009](#); [Valtchanov and Ellard, 2015](#)). Color tone (hue) and saturation diversity ([Kardan et al., 2015](#)), spatial frequency ([Valtchanov and Ellard, 2015](#)) and fractality ([Forsythe, Nadal, Sheehy, Cela-Conde, & Sawey, 2011](#); [Hagerhall et al., 2008](#)) are significant predictors of landscape preferences. Additionally, the image compression size revealed as an accurate proxy for image content complexity ([Tuch, Bargas-Avila, Opwis, & Wilhelm, 2009](#)), it might also function as such for landscape images. A work worth considering is that of [Rosenholtz, Li, and Nakano \(2007\)](#), who developed two indices for visual saliency and redundancy, namely, feature congestion and subband entropy.

Although the authors did not specifically test these with landscape images, both measurements address degree of visual organization and redundancy and may therefore be associated with perceived complexity or coherence. Empirically, [Kuper \(2017\)](#) found a direct correlation between rated complexity and measured entropy with perspective images of landscapes. In contrast to measuring the visual quality of landscapes using perspective images, landscape metrics were developed probe into ecological processes derived from analyses of landscape patterns on land cover or land use maps ([Cushman, McGarigal, & Neel, 2008](#); [O'Neill et al., 1988](#)). On the basis of information theory ([Shannon, 1948](#)) and fractal geometry ([Mandelbrot, 1983](#)), studies related landscape metrics to landscape preferences ([Frank, Fürst, Koschke, Witt, & Makeschin, 2013](#); [Fry, Tveit, Ode, & Velarde, 2009](#); [Hunziker and Kienast, 1999](#); [Ode et al., 2009](#); [Palmer, 2004](#)). Specifically, the number of patches on land cover maps, were shown to be significantly correlated with preference estimates of corresponding perspectives ([Dramstad et al., 2006](#); [Ode et al., 2009](#)). Further, edge density ([Palmer, 2004](#)), Shannon's diversity and the shape index ([Frank et al., 2013](#)) are correlated with landscape preferences. [Hunziker and Kienast \(1999\)](#) applied landscape metrics to perspective images in order to analyze gray-tone patches and patterns. Their results showed significant correlations of landscape preferences with Simpson's diversity and evenness as well as the interspersion index. Both interspersion and evenness might serve as proxies for coherence seeing as the increasing homogeneity of landscape patches enhances the sense of coherence ([Palmer, 2004](#)).

Visual features such as color, shape, texture, size, and contrast are principal components in visual impact assessments (VIA) of RES. These features have been used intensively to determine the contrasting effects

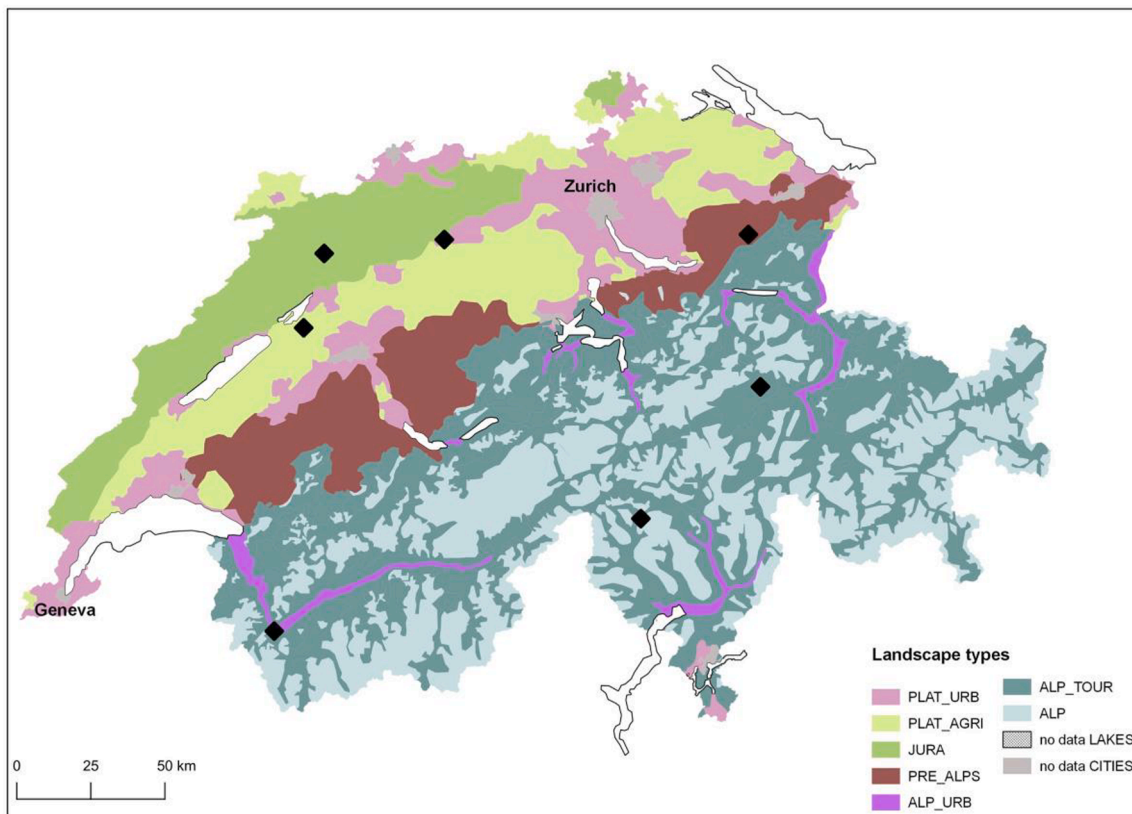


Fig. 2. Distribution of the landscape types used in this study. Black rectangle indicates the location of the vista in each landscape type.

of RES with surrounding landscapes (e.g., Bishop and Miller, 2007; Brahms and Peters, 2012; Torres Sibille, Cloquell-Ballester, Cloquell-Ballester, & Darton, 2009a; 2009b). Empirical explorations indicated that contrasting effects measured via color differences between wind turbines and backgrounds are strong predictors of perceived visual impact (Bishop and Miller, 2007; Lothian, 2008). The number of wind turbines and their distance to observers are strongly correlated with perceived visual landscape quality (Betakova et al., 2015). A more specific explanation was provided by Johansson and Laike (2007), who disentangled visual perceptions regarding wind turbines and found that contrasting effects directly influence perceived unity and, subsequently, the intention to oppose wind turbine projects.

In the present research, we treated the term “visual features” as pertaining to numerically assessed visual parameters of images containing RES-landscape scenarios. Although many studies investigated the visual effects of RESs, little is known about how visual features (i.e., colors, shapes, and textures) relate to the perceived visual qualities of RES-altered landscapes.

### 1.3. Goals and hypothesis

Stimulated by the theories and empirical findings described in Subsections 1.1 and 1.2, we defined three goals for our study (Fig. 1).

**Goal 1.** To understand how RES infrastructure influences landscape quality ratings, that is, ratings involving Kaplan and Kaplan’s (1989) dimensions: With previous research (e.g., Johansson and Laike, 2007; Pasqualetti, 2000) as basis, we expected landscape qualities to be affected by RESs. In particular, we expected that in natural landscapes, the sense of permanence, as defined by Pasqualetti (2000), is disrupted by RESs and thus potentially influences the rating of other landscape qualities.

**Goal 2:** To delve into the relationship between landscape quality ratings and measured visual features for RES-altered landscapes:

Motivated by Kuper (2017), who discovered a correlation between stated complexity and designed entropy, we assumed that additional relationships exist between visual features and visual landscape qualities in the context of RES-altered scenes.

**Goal 3:** To determine how landscape quality ratings and visual features correlate with the overall preference for RES-landscape scenarios: Studies showed associations between measured visual features and landscape preferences (e.g., Hunziker and Kienast, 1999; Ibarra et al., 2017; Kardan et al., 2015) and drew connections between rated visual landscape qualities and preferences scores (Kaplan, 1987; Kuper, 2017; van der Jagt, Craig, Anable, Brewer, & Pearson, 2014). Along the same lines, we hypothesized that both visual landscape qualities and visual features are related to preference for RES-altered landscapes.

## 2. Methods

To investigate landscape qualities and visual features in the context of RES, we elaborated visual stimuli with different landscape types. Each landscape type was altered with two levels of RES visibility. Thus, all 14 stimuli contain the two visual variables ‘landscape types’ (LANDSCAPE) and ‘visibility of renewable energy systems’ (RES\_VISIBILITY).

### 2.1. Visual stimuli

#### Landscape types (LANDSCAPE)

Firstly, we selected typical Swiss landscape types following the widely used biogeographic regionalization of Switzerland (Gonseth, Wohlgenuth, Sansonnens, & Buttler, 2001) (Fig. 2). We removed the landscape types of ‘large city centers’ because of planning restrictions for wind turbines in settlement areas. Additionally, we did not integrate landscapes, which contain lakes, due to the fact that water has a strong influence on landscape quality and preference ratings (Ibarra et al., 2017; Tveit et al., 2006). The final seven landscape types show

considerable potentials for the production of renewable energy, though at widely varying environmental costs (Kienast et al., 2017). However, according to the Swiss Energy Strategy 2050 (Swiss Federal Office of Energy, 2012) all of them are - in principle - valid sites to generate the required energy amount to phase out the nuclear power production. The final seven selected landscape types vary considerably in their topography and their land use. They cover the northern areas of flat plateaus primarily used for settlements (PLAT\_URB) or agricultural production (PLAT\_AGRI). Additionally, we considered the Jura ridges (JURA) and the hilly and less densely populated, northern pre-alpine areas (PRE\_ALPS). We then divided the alpine areas with steep terrains into the large inner-alpine valleys, with a relatively high population density (ALP\_URB), the alpine landscapes used for tourism (ALP\_TOUR), and the near-natural alpine regions (ALP). During a workshop 25 experts from the fields of landscape planning, wind and photovoltaic project development, as well as employees of the national energy and spatial planning authorities evaluated the seven landscape types. For each landscape type the experts rated several specific views from pedestrian perspective (vistas), according to the potential for representing a future energy landscape, encompassing wind turbines and photovoltaic panels. To visualize the vistas, we used landscape models based on light detection and ranging (LiDAR) data (XYZ). LiDAR in combination with image data represents the landscape characteristics (i.e., color, vegetation, topography) highly detailed. In addition, LiDAR data comes along with three-dimensional geographical coordinates and thus it is possible to site RES accurately in the models. Hence, we combined terrestrial (RIEGL VZ-1000) and airborne LiDAR data to colored 3D visualizations for all seven landscape types. Fig. 2 shows the locations of the vistas (rectangle) and the distribution of the landscape types. The final visualizations show a 160° field of view for each vista.

#### Visibility of RES (RES\_VISIBILITY)

In a second step, the middle 53.3° of each landscape visualization was altered with two scenarios of RES visual impact. Although we used VIA to develop the scenarios, we conservatively call this variable visibility because we neglect other aspects of visual impact (Wolsink, 2018). Both scenarios contain a concurrent visibility of wind and photovoltaic infrastructure. To control for the visibility of wind turbines and photovoltaic panels in each landscape, we made use of two objective visual impact assessments. Namely the ‘objective aesthetic impact of solar power plants index’ (OASPP, Appendix A.1; Torres-Sibille, Cloquell-Ballester, Cloquell-Ballester, & Artacho Ramírez, 2009b) and the ‘visual impact parameter for wind turbines’ (VIWT, Appendix A.2; Brahm and Peters, 2012). The OASPP combines four measures (i.e., visibility, color, fractality, and contrast, Appendix A.1) for the photovoltaic panels and ranges from 0 (no visual impact) to 1 (strong visual impact). We did not include a climatology coefficient as proposed by Torres-Sibille, Cloquell-Ballester, Cloquell-Ballester, and Artacho Ramírez (2009b) because atmospheric conditions were held constant across all landscapes. The VIWT considers the number of wind turbines, partial visibility, and distance from the observer and ranges from 0 (i.e., no visual impact) to (theoretically) infinity (Appendix A.2). In the *high* visibility scenarios, we show ten, and in the *low* visibility scenario three wind turbines. After the initial placement, we iteratively adjusted the exact locations of the turbines in order to reach a minimal VIWT of 1 in all landscape types (Appendix A.3). Subsequently, we placed the three wind turbines in the low visibility scenario in order to reach approximately 70% lower VIWT compared to the high scenario. For the photovoltaic infrastructure, we sited the panels clearly visible in the fore-, and mid-, and background of all landscapes so that OASPP range between 0.13 and 0.18 in the high and between 0.02 and 0.04 in the low visibility scenarios (Appendix A.4). This procedure allowed control for the variable RES\_VISIBILITY in two ways. Firstly, we could clearly distinguish between the LOW and the HIGH level of RES visibility in each landscape. Secondly, we kept the visibility of RES more or less constant between all landscape types within the LOW or the HIGH scenarios of RES visibility. Fig. 3 illustrates the two levels of RES\_VISIBILITY for all seven landscape types. We provide the full field of view (160°) in the data repository of this article.



Fig. 3. Visualization of the middle 53.3° field of view for each landscape type with the two levels of RES\_VISIBILITY.

Subsequently, we animated the visualizations with rotating wind turbine blades and moving clouds. We kept motion of rotor blades, atmospheric conditions, lightning and seasonality constant between all stimuli, since these parameters influence the visibility of RES (Apostol, Palmer, Pasqualetti, Smardon, & Sullivan, 2016p. 180). Finally, we rendered 30-second panoramic videos from pedestrian perspective with a resolution of 5760 by 1080 pixels (see additional data).

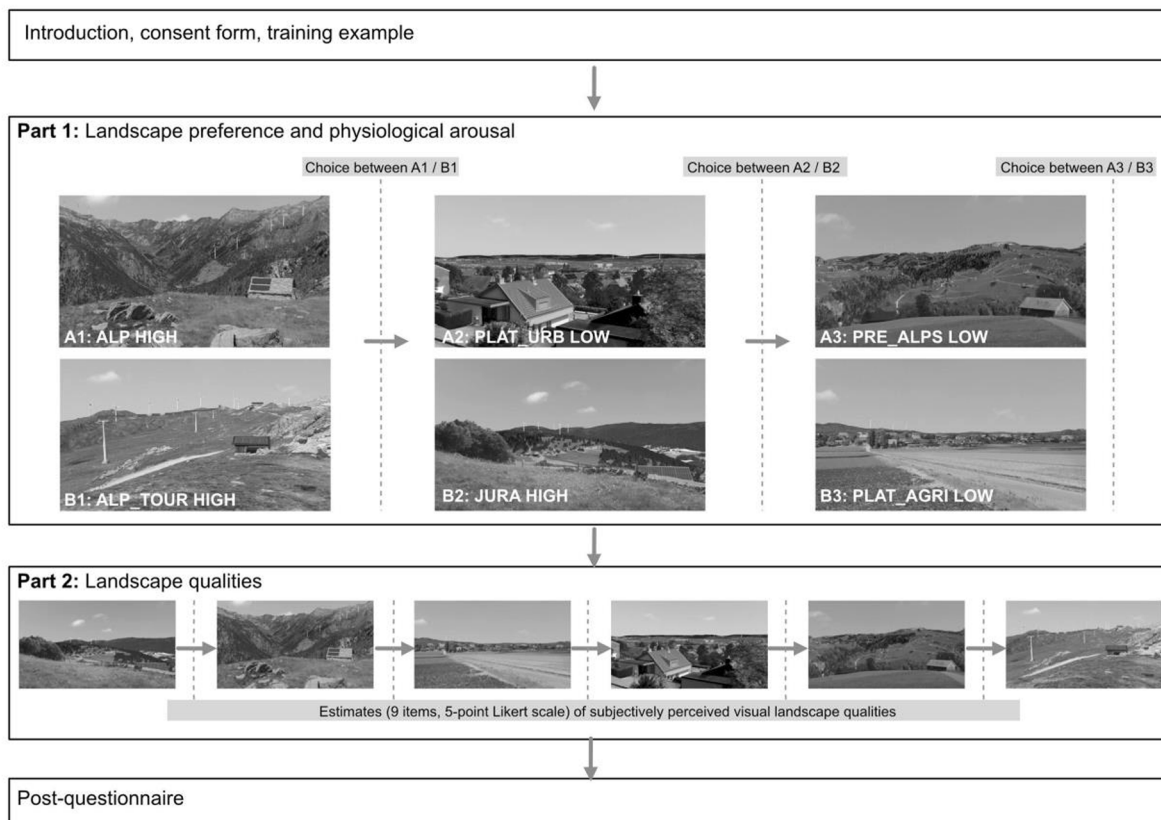


Fig. 4. Example of an experimental proceeding in the MVAL for one participant, presenting randomly six stimuli from the total amount of 14 stimuli.

## 2.2. Procedure

We collected the data for each participant individually in a laboratory lasting for app. 45 min. All participants reported being native German speakers, physically and psychologically healthy, with normal or corrected-to-normal vision and hearing. The study was approved by the ethics committee of ETH Zurich. Participants were compensated 30 Swiss franc after finishing the session. To keep experimental conditions (i.e. light, sound) constant, we used a Mobile Visual Acoustic Laboratory (MVAL; Manyoky et al., 2016). Within the MVAL we projected the stimuli on three 106° angled screens (7.1 m × 0.6 m). The entire experiment was performed with the software 'Experiments in Virtual Environments' (EVE; Grübel et al., 2017). This software allows the experimenter to interactively present questions to participants, while showing still images, videos or virtual realities. Particularly, we used this software to record physiological responses on landscape changes caused by RES (reported in Spielhofer et al., 2021). After signing the declaration of consent, the participants were familiarized with laboratory conditions and the keyboard control with a training trial. The training trial consisted of two 30-second scenes (videos of a moving blue circle and a moving red cube), presented to participants sequentially. Following the training stimuli pair, we asked participants to use the arrow keys on the keyboard in order to select their preferred stimulus. The main experiment was divided into two parts (Fig. 3). In the first part, participants completed three testing trials. Each trial consisted of two subsequently presented landscape-RES scenarios, followed by the participants choice of their preferred scenario. In addition to the preference, we measured participants' physiological arousal response, which is reported in XYZ. The three testing trials were separated by 20-second intervals consisting of a black cross on a gray background. We paired the stimuli so that one trial consisted of two 'HIGH' RES visibility videos, one trial consisted of a 'HIGH' and a 'LOW' RES visibility video, and one trial consisted of two 'LOW' visibility videos. The order of

these trial types and the landscapes that composed each trial type were randomized and counterbalanced across participants, except that a participant never saw the same landscape more than once. In the second part of the session (Fig. 4), we showed the same six stimuli from part one again in a new randomized order. Participants rated the landscape qualities for each of the six stimuli based on the landscape preference matrix (Kaplan and Kaplan, 1989). We closed the session with a post questionnaire to record participants' socio demographics.

## 2.3. Measures

In this section, we present the questions to assess people's preference and the rated landscape qualities for the landscape-RES scenarios. Further, we show the visual features, measured on each stimulus.

### Preferences

To assess people's landscape preference some studies used pairwise comparisons of stimuli (e.g., Courcoux and Semenou, 1997) other studies used rating (e.g., Schirpke, Tappeiner, Tasser, & Tappeiner, 2019). Particularly, for subjective ratings, the pairwise comparison method has been shown as useful due to the simplicity of the assessment (Courcoux and Semenou, 1997) and no substantial differences to ordinal rating scales revealed (Hunziker and Kienast, 1999; Stamps, 2004). Thus, we used pairwise comparisons in this study, to assess landscape preferences. In part 1 (Fig. 3) of the experiment, each participant saw three times two scenarios sequentially and choose their preferred scenario based on the question 'Which landscape do you like better' (original germ.: 'Welche Landschaft gefällt Ihnen besser?').

### Rated landscape qualities

To rate the landscape qualities, we used the four dimensions complexity, coherence, mystery and legibility from the preference matrix (Kaplan and Kaplan, 1989). We assessed the four landscape qualities with a set of nine questions and report the original German question and

**Table 1**  
Models to calculate effect of fixed effects on dependent variables landscape qualities or CHOICE with Likelihood-Ratio tests.

	Dependent variable	Fixed factors	Random factors
Linear mixed-effects model (lmer)			
three-fixed-factor model	Landscape qualities	LANDSCAPE + VISIBILITY+ (LANDSCAPE * VISIBILITY)	SUBJ_ID
two-fixed-factor model	Landscape qualities	LANDSCAPE + VISIBILITY	SUBJ_ID
one-fixed-factor	Landscape qualities	VISIBILITY OR LANDSCAPE OR GENDER OR AGE OR HOME_LANDSCAPE	SUBJ_ID
Null model	Landscape qualities	1	SUBJ_ID
Generalized linear model with binomial regression (glm)			
three-fixed-factor model	CHOICE	LANDSCAPE + VISIBILITY+ (LANDSCAPE * VISIBILITY)	No random effects included
two-fixed-factor model	CHOICE	LANDSCAPE + VISIBILITY	
one-fixed-factor	CHOICE	VISIBILITY OR LANDSCAPE OR GENDER OR AGE OR HOME_LANDSCAPE	
Null model	CHOICE	1	

corresponding English translation in [Appendix B.1](#). Thus, within part two of the experiment ([Fig. 3](#)), each participant answered all nine questions for each of the six scenarios with a 5-point Likert scale. The questions, scale and the wording were adopted from ([Kienast et al., 2015](#)). With slightly different wording but similar terms these questions were used in other studies ([Singh, Todd Donovan, Mishra, & Little, 2008](#); e.g., [van der Jagt et al., 2014](#)).

#### Visual features

Based on the middle view (1920 by 1080 pixels), of the first video frame we computed 20 visual features for each of the 14 stimuli. To select the visual features, we refer to measures which have been found as relevant in the context of landscape perception and preferences ([Appendix B.2](#)). Firstly, we applied pixel-based statistics, where information from each single pixel is extracted and summed up to the total amount of pixels of the image. These statistics mainly cover color aspects (*hue, sat, bright*), visual information density (*fc, se, bytes*) and spatial frequency (*sf<sub>low</sub>, sf<sub>high</sub>*). Secondly, we used landscape metrics with color classified images as input. We classified the images with 12 centers by the use of a k-nearest neighbor classifier ([Hunziker & Kienast, 1999](#)). Based on the 12 class RGB reduced images ([Appendix B.3](#)), all landscape metrics were calculated in R-Studio (V.3.5.5) on landscape level with the R-package 'landscape metrics' ([Hesselbarth, Sciaini, With, Wiegand, & Nowosad, 2019](#); [McGarigal, Cushman, & Ene, 2012](#)). Thirdly, we calculated the number of pixels and edges which are exclusively related to the RES.

#### 2.4. Data processing and analysis

With R studio version 3.5.1 ([R Core Team, 2018](#)) we conducted descriptive and inferential statistics. As a first step, we tested the inter-item reliability for the two items of coherence, complexity, mystery and the three items of legibility ([Appendix B.1](#)). We consider a Cronbach alpha of 0.7 as an acceptable reliability ([Palmer, 2000](#)) and averaged the corresponding items with the median for each participant. We then checked the data for normal distribution (Shapiro test) and examined homogeneity of variances (Levene test). Secondly, we assessed the effect of the two independent variables RES\_VISIBILITY and LANDSCAPE on each of the 20 visual features with split-plot ANOVAS. Split-plot ANOVAS were used because each LANDSCAPE contains two dependent levels of RES\_VISIBILITY. In a third

step, we examined the effects of RES\_VISIBILITY and LANDSCAPE on the landscape quality ratings and the binary choice data. In order to select an appropriate model for the landscape quality ratings and the choice, we compared general linear models (glm) with mixed effect models (lmer) with Likelihood-ratio tests ([Giampaoli and Singer, 2009](#)). For the landscape quality ratings, Likelihood-ratio tests revealed lower AIC for mixed effect models with integrated random effects compared to general linear models. Thus, we calculated the lmer with the R-package 'lme4' ([Bates, Mächler, Bolker, & Walker, 2015](#)). We considered the rated landscape qualities as dependent and the LANDSCAPE and RES\_VISIBILITY as independent variables ([Table 1](#)). Mixed models have the advantage that they can account for variation in the data that is related to further aspects and not explicitly expected in the hypotheses (i.e., random factors). We used the subjects (SUBJ\_ID) as random factors to account for the fact that the ratings of landscape qualities are not fully independent since we have a repeated measurement design (*each subject rated six times the landscape qualities*). Further, mixed models are more suitable for imbalanced study designs (*each participant assessed only 6 out of the total 14 scenarios*). In addition to the main effects (RES\_VISIBILITY & LANDSCAPE), we tested the effect of socio demographics on the landscape qualities ([Stamps, 1999](#); [Strumse, 1996](#); [Zheng et al., 2011](#)). Specifically, we examined the effect of GENDER, AGE and the fact that a stimulus might represent the participants' home landscape (HOME\_LT; [Hunziker et al., 2008](#)). In order to test the effect of age, we split our data into a group (AGE\_GROUP) with people younger than 30 years and a group with people older than 29 years. For the preference date, Likelihood-ratio tests revealed lower AIC for generalized linear models (glm) with binomial logit regression compared to mixed effect models. The inclusion of random effect would lead to model overfitting. In consequence, we applied a glm to determine the effect of LANDSCAPE and RES\_VISIBILITY on the binary choice data ([Table 1](#)). In order to calculate p and  $\chi^2$  values for the main effects within the lmer and the glm models, we used additional Likelihood-ratio tests. We compared the null-model with the one-fixed factor model to assess the effects of each individual fixed factor and the two-fixed factor model with the three-fixed factor model to determine the interaction effects of LANDSCAPE and RES\_VISIBILITY ([Table 1](#)). We then calculated the effect size ( $R^2$  &  $f^2$ ) with the R-package 'sjstats' ([Lüdtke, 2020](#)). For mixed models, we used marginal  $R^2$  which represents the explained variance from the fixed, without the random effects ([Nakagawa and Schielzeth, 2013](#)). According to [Cohen \(1992\)](#), we consider  $f^2 = 0.02$  as small effects,  $f^2 = 0.15$  as medium effects and  $f^2 > 0.3$  as strong effects. For the logit models of with the binary choice as dependent variable we calculated the coefficient of determination (D; [Tjur, 2009](#)).

With the median we aggregated the landscape quality ratings to the average quality rating for each scenario (N = 14). Similarly, we aggregated the binary choices to a preference score (PREF\_SCORE) for each scenario by dividing the total number the scenario has been shown by the number the scenario has been preferred. Finally, we applied Kendall and spearman correlations with a Bonferroni corrected alpha level for multiple testing to analyze the relationship between the average landscape qualities, the visual features and PREF\_SCORE. Non-parametric correlations were used because of a relatively small sample size (N = 14 scenarios) and not normally distributed data.

### 3. Results

A total of 135 participants (61 women and 72 men, mean age = 28 years, SD = 11.74, age range = 19–73 years) completed the experiment. Two participants were excluded because of software issues. The young AGE\_GROUP contains 98 participants (47 woman, 51 men, mean age = 22.4 years, SD = 2.28, range = 19–29 years), the older AGE\_GROUP 28 (11 woman, 17 men, mean age = 46.6 years, SD = 12.33, range = 32–73 years). Nine participants could not be included into an age group since they did not state their age.

The inter item reliability for each landscape quality was calculated for several data subsets and for the whole dataset ([Table 2, Appendix C](#)). Independent of the data subset, the two items of coherence and complexity as well as the three legibility items, revealed acceptable (>0.7)



**Table 2**

Inter-item reliability of the landscape qualities for the overall data set, the subsets of landscape types (LANDSCAPE) and the subset of RES\_VISIBILITY.

Landscape qualities	LANDSCAPE							RES_VISIBILITY		Overall
	PLAT_URB	PLAT_AGR	JURA	PRE_ALPS	ALP_URB	ALP_TOUR	ALP	LOW	HIGH	
Coherence	0.81	0.77	0.86	0.83	0.86	0.82	0.86	0.82	0.84	0.84
Complexity	0.71	0.78	0.82	0.75	0.71	0.7	0.85	0.78	0.79	0.78
Legibility	0.76	0.74	0.68	0.78	0.77	0.68	0.6	0.73	0.75	0.74
Mystery	0.54	0.73	0.7	0.67	0.46	0.72	0.72	0.66	0.58	0.62
N data subset	112	120	118	104	119	110	116	400	399	799

overall reliability. In consequence, we averaged the items with the median for each landscape quality. In contrast, the two items of mystery revealed too low overall reliability, hence the two items (MYST\_A, MYST\_B) will be treated as separate variables in the further analysis.

### 3.1. Rated qualities of RES altered landscapes

Since we have an unbalanced experimental design, the number of landscape quality ratings for each scenario varies between 48 and 70 (Appendix D.1). We calculated the median and Inter-Quartile Range (IQR) of the landscape quality ratings (Fig. 5) and reference to Appendix D.1 for exact values.

#### Main effects of RES\_VISIBILITY and LANDSCAPE on landscape qualities

Despite complexity, all landscape qualities revealed a significant effect on RES\_VISIBILITY. However, coherence ratings show the strongest effect on RES\_VISIBILITY ( $f^2 = 0.2$ , Table 3). Additionally, all landscape qualities varied significantly between the levels of LANDSCAPE. A strong effect ( $f^2 < 0.3$ ) of LANDSCAPE could be observed for Mystery\_B, Legibility and Complexity (Table 3). Mystery\_B revealed the only landscape quality with a significant and strong interaction effect of LANDSCAPE and RES\_VISIBILITY. Contrarily, the effect of different LANDSCAPES is stronger for complexity, legibility and Mystery\_A.

Coherence is the only landscape quality which shows a stronger effect on the levels of RES\_VISIBILITY compared to the levels of LANDSCAPE. Therefore, a post hoc analysis between the levels of RES\_VISIBILITY has been performed for each landscape type. In the near natural alpine landscape (ALP,  $df = 763$ ,  $T = -3.591$ ,  $p = .024$ ,  $d = -0.6$ ), the touristic alpine area (ALP\_TOUR,  $df = 763$ ,  $T = -3.502$ ,  $p = .032$ ,  $d = -0.58$ ) and the urban alpine valley (ALP\_URB,  $df = 763$ ,  $T = -4.588$ ,  $p = .0004$ ,  $d = -0.78$ ) post hoc analysis show significantly higher rated coherence in the low-, compared to the high visibility. In the urban and agricultural plateaus (PLAT\_URB & PLAT\_AGR), the hilly landscapes of the JURA and the pre alps (PRE\_ALPS) the degree of visibility of RES does not affect rated coherence significantly (Fig. 6).

#### Effects of socio demographics on landscape qualities

The effects of GENDER, AGE and HOME\_LT on the ratings of the landscape qualities have been tested with mixed linear models and Likelihood-Ratio tests (Table 1). The test revealed a significant, medium effect of AGE\_GROUP on coherence ( $\chi^2(1) = 7.302$ ,  $p = .007$ ,  $R^2 = 0.144$ ,  $f^2 = 0.17$ ). Additionally, a strong effect of GENDER and MYSTERY\_A evolved ( $\chi^2(6) = 3.922$ ,  $p = .048$ ,  $R^2 = 0.243$ ,  $f^2 = 0.32$ ) (Appendix E). The effect that high visibility is rated with lower coherence is stronger for young people compared to older people (Table 4).

### 3.2. Relation between measured visual features and rated landscape qualities

We report the descriptive statistics of the 20 visual features in Appendix D.2.

#### Correlation between visual features and landscape qualities

To test the correlation between 20 visual features and five landscape qualities, we correct the alpha level to  $p = .002$ , in order to correct for possible alpha inflation. To find relations between rated visual landscape qualities and measured visual features for  $N = 14$  scenarios, we applied spearman's rank and Kendall correlations (Fig. 7; see Appendix F, for exact numerical  $r$  and  $p$  values).

Only a few visual features correlate significantly ( $p < .002$ ) with the landscape qualities. The contiguity index with rated complexity ( $\tau = -0.582$ ,  $\tau p = .003$ ,  $r = -0.758$ ,  $p = .0016$ ) and the amount of RES related edges with rated coherence ( $\tau = -0.582$ ,  $\tau p = .003$ ,  $r = -0.75$ ,  $p = .002$ ). Additionally, we report a strong correlation between the high spatial frequency (sf\_high) and the individually treated item Mystery\_B ( $\tau = 0.736$ ,  $\tau p = 7.7e-5$ ,  $r = 0.88$ ,  $p = 2.5e-5$ ).

#### Main effects of RES\_VISIBILITY and LANDSCAPE on the visual features

Split-plot ANOVAS showed that most of the visual features vary significantly between the landscape types (LANDSCAPE) but not between the LOW and the HIGH RES visibility. Nevertheless, subband entropy ( $se$ ,  $F(1) = 6.069$ ,  $p = .05$ ), feature congestion ( $fc$ ,  $F(1) = 28.78$ ,  $p = .002$ ), file size of the stimuli (bytes,  $F(1) = 16.15$ ,  $p = .007$ ) and color hue ( $F(1) = 39.6$ ,  $p = .0008$ ) show an additional significant effect on the levels of VISIBILITY (Appendix G). The two visual features, which relate exclusively on RES (PIX\_RES, EDGE\_RES), vary much stronger between the levels of RES VISIBILITY compared to the levels of LANDSCAPE (Appendix G). This result is a proof that the visual balancing between the landscape types was successful and the combined visibility of wind and photovoltaic infrastructures is comparable between the different landscape types.

### 3.3. Preference scores for RES altered landscapes

Fig. 8 indicates that people generally prefer the LOW compared to the HIGH visibility scenario. However, in the flat areas with mainly settlements the HIGH scenario is more preferred compared to the LOW. The highest preference scores, independent from the amount of RES can be observed in the hilly and less densely populated areas of the JURA and the pre alps (PRE\_ALPS). Fig. A3, Fig. A4.

For the preference data, the comparison between the three-fixed-factor model and the two-fixed-factor model (Table 1) revealed a significant interaction between LANDSCAPE and VISIBILITY ( $\chi^2(1) = 17.134$ ,  $p = .008$ ,  $D = 0.09$ ). In addition, the comparisons between the one-fixed-factor models and the null model revealed significant effects for LANDSCAPE ( $\chi^2(6) = 51.843$ ,  $p < 2.6e-9$ ,  $D = 0.06$ ) and RES\_VISIBILITY ( $\chi^2(1) = 7.431$ ,  $p = .006$ ,  $D = 0.009$ ) on participants' preferences. These effects suggest that participants preferred low visibility of RES (compared to high visibility) and that this effect varied across landscapes. Notably, this trend can be observed for each landscape except for PLAT\_URB and PLAT\_AGR (Fig. 8).

#### Relation between visual features and preference scores

With a Pearson correlation we checked the relation between the 20 visual features and the preference score. Again, we consider an alpha level of 0.002 as a significance threshold. However, no correlation between the visual features and the preference score revealed significant (Appendix H.1)

#### Relation between landscape qualities and preference score

Finally, we applied Kendall and spearman rank correlation in order to find relations between the five aggregated ratings of landscape qualities and the preference score. We correct the alpha level to 0.01 since we tested only five possible correlations. Coherence ( $\tau = 0.538$ ,  $\tau p = .006$ ,  $p = .012$ ,  $r = 0.13$ ), legibility ( $\tau = 0.494$ ,  $\tau p = .013$ ,  $p = .003$ ,  $r = 0.72$ ) and mystery\_B ratings ( $\tau = 0.648$ ,  $\tau p = 7e-4$ ,  $p = 7e-4$ ,  $r = 0.79$ ), correlated significantly with preference scores. Mystery\_A ( $p = .48$ ,  $r = 0.2$ ) and complexity ( $p = .93$ ,  $r = -0.02$ ) did not show any significant relation with the preference score (Appendix H.2).

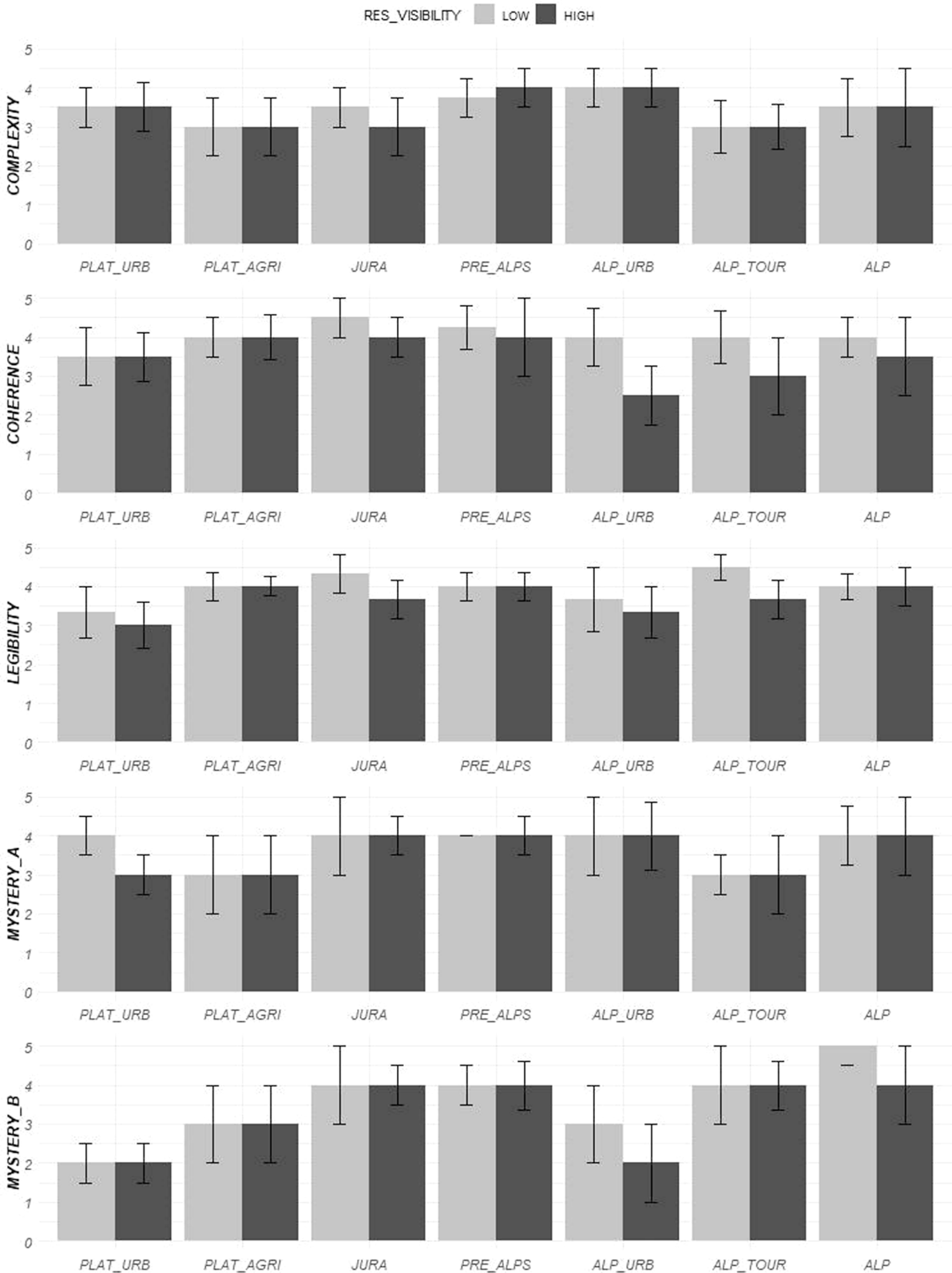


Fig. 5. Median and (IQR) of the landscape quality ratings.

4. Discussion

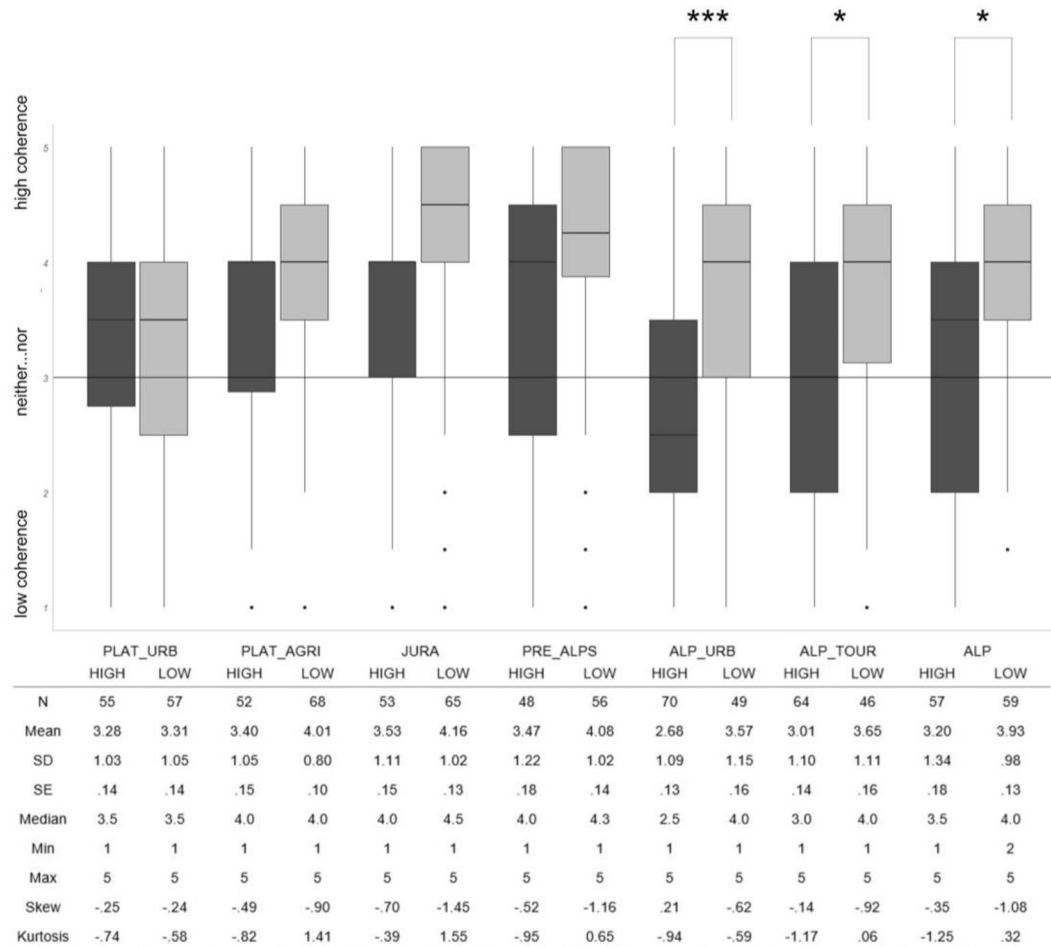
This section summarizes the results, discusses their implication for each goal separately and ends with a description of the study's limitations.

Goal 1: Rated qualities of RES altered landscapes

First, we investigated the influence of RES infrastructure on people's landscape quality ratings. Rated coherence varies stronger between the two levels of RES visibility compared to mystery, legibility and

**Table 3**  
Effects of VISIBILITY, LANDSCAPE and Interactions on landscape qualities (N = 798).

Landscape qualities	Fixed effects											
	RES VISIBILITY				LANDSCAPE				INTERACTION			
	$\chi^2(1)$	Marginal R <sup>2</sup>	Cohens f <sup>2</sup>	p	$\chi^2(1)$	Marginal R <sup>2</sup>	Cohens f <sup>2</sup>	p	$\chi^2(1)$	Marginal R <sup>2</sup>	Cohens f <sup>2</sup>	p
Coherence	71.804	0.17	0.2	2.2e-16	58.478	.153	0.18	9.16e-11	11.16	0.241	0.32	0.08
Complexity	0.018	0.064	0.07	0.667	137.78	0.239	0.31	0	8.35	0.25	0.33	0.21
Legibility	14.417	0.124	0.14	0.0001	120.28	0.257	0.35	0	8.8	0.272	0.37	0.18
Mystery_A	6.746	0.049	0.05	0.009	93.499	0.162	0.19	0	7.55	0.179	0.22	0.27
Mystery_B	15.877	0.027	0.03	6.76e-5	215.81	0.277	0.38	0	12.88	0.304	0.45	0.045



**Fig. 6.** Rated coherence for each landscape-RES scenario.

**Table 4**  
Effects of RES VISIBILITY, LANDSCAPE and Interactions on rated coherence, separated by AGE\_GROUP.

AGE GROUP	N	RES VISIBILITY				LANDSCAPE				INTERACTION			
		X <sup>2</sup>	p	R <sup>2</sup>	f <sup>2</sup>	X <sup>2</sup>	p	R <sup>2</sup>	f <sup>2</sup>	X <sup>2</sup>	p	R <sup>2</sup>	f <sup>2</sup>
<30	98	62.509	2.60E-15	0.1	0.11	45.64	1.40E-08	0.07		5.9514	0.428		
>30	28	7.412	0.006	0.03	0.038	12.662	0.048	0.061	0.065	7.6657	0.26		

complexity. Kaplan and Kaplan (1989) asserted that coherence is processed immediately. Consequently, or first result implies that people’s perception of RES altered landscapes contains a substantial affective component. Therefore, we support the finding of Maehr, Watts, Hanratty, and Talmi (2015). The authors discovered that measured physiological arousal, which expresses an immediate affective reaction, is higher for landscapes containing wind turbines than other infrastructure. Further, we found that people generally rated a high RES visibility as less coherent over a low impact. We conclude that an increasing

number of RES decreases the sense of coherence. This finding contrasts with the statement of Tveit et al. (2006) that enhancement of the visual redundancy should increase the sense of coherence in a scene. Although, RES add visual repetitions and uniformity to landscapes (Apostol et al., 2016), the sense of coherence might increase with only a low RES visibility up to a certain point. After reaching this point, which is specific for different landscape types, coherence decreases with more RES visibility. Further research should test the relationship between amount of RES and coherence more in detail. Aside from finding a generally lower rated

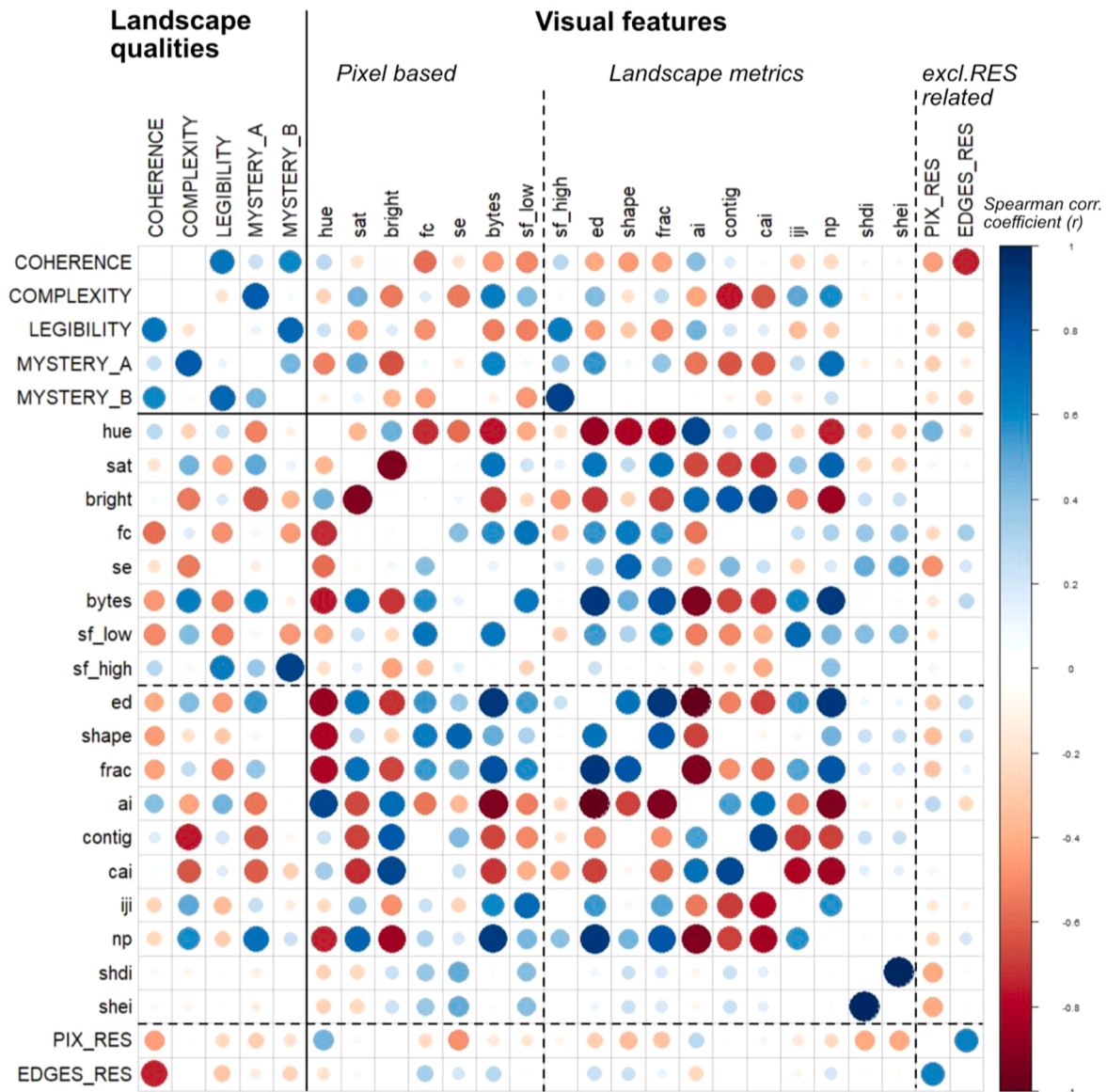


Fig. 7. Correlation matrix with averaged visual landscape qualities and visual features for N = 14 scenarios.

coherence of high RES visibility, we discovered this effect to be strongest in urbanized alpine areas, touristic alpine regions, and near natural alpine landscapes. Contrarily, in the densely populated flat plateau (PLAT\_URB), coherence is rated almost equally in high- and the low RES visibility scenarios. This finding indicates two things. Firstly, the visual coherence of the PLAT\_URB landscape is not affected by the amount of RES. Thus, from a visual perspective, this landscape seems to have potential for a stronger visibility of RES. Secondly, the degree of naturalness does not serve as a unique predictor for the coherence difference between low and high RES visibility scenarios. Most likely, the coherence differences between high- and low RES visibility is influenced by further landscape connotations. Therefore, we see coherence ratings as a potential indicator for the ‘place-technology-fit’ (Devine-Wright and Howes, 2010). However, further research needs to build up on this statement and test whether coherence mainly describes a visual part (e.g., scale; Stanton, 2016) or also a functional part of place-technology-fit.

In contrast to coherence, complexity varies strongly among the seven landscape types but not between the RES visibility scenarios. Complexity is an immediate exploration involving an assessment of how many visual elements are present in a landscape (Fry et al., 2009; Kaplan and Kaplan, 1989; Stamps, 2004). On the grounds of the landscape types

selected for our experimental stimuli, we implicitly represented this visual richness to some extent. Our results show that landscapes containing many man-made elements and diverse topographies are rated as more complex, whereas uniform flat areas with few man-made elements are less complex. Mystery and legibility are not related exclusively to RES visibility or the landscape types. Both dimensions need further processing (Kaplan and Kaplan, 1989) and might consequently entail more cognitive considerations, which possibly involve scrutinizing a landscape, including an RES, as a whole.

*Goal 2: Relationship between landscape qualities and visual features*

Motivated by the critiques of Stamps (2004) regarding the reliability of the preference matrix, we inquired into the association between measured visual features derived from the stimuli and the rated visual qualities of RES altered landscapes. The analysis revealed that rated complexity is negatively correlated with measured contiguity. Specifically, the analysis shows that diversity in land use and topography leads to lower contiguity and high complexity values. This finding is in line with La Fuente Val et al. (2006) who demonstrated that contiguity is inversely related to patch richness and positively correlated with the Shannon evenness index. However, compared to Kuper (2017) and Stamps (2004), we could not find a significant correlation between the measured entropy and the rated

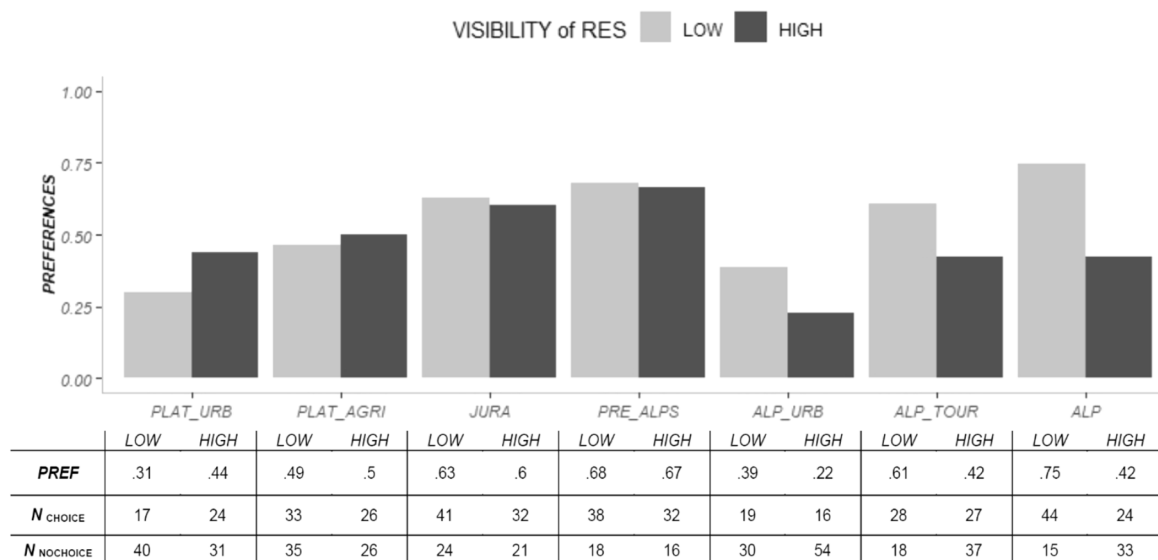


Fig. 8. The number of choices and no choices and the preference score for each of the 14 scenarios.

complexity of the scenes. This could be due to the slightly different formulation of the questions used to assess complexity in our German-language study. On the other hand, one has to consider that we did not calculate the entropy according to Shannon (1948), but the subband entropy according to Rosenholtz et al. (2007).

Rated coherence revealed as significantly correlated with counted edges, exclusively related to wind and solar infrastructure. The more RES edges are visible within a scenario, the less coherent the scenario, consistent with Kuper’s (2017) work. Within a plant context, the author showed that a high number of planted regions in a scene drives down ratings of coherence. Although the measured feature congestion was not significantly correlated with rated coherence, we propose to further investigate this relationship. Feature congestion varied significantly between the RES visibility scenarios, indicates a degree of visual organization and redundancy, and might thus influence coherence (Bell, 2012; Tveit et al., 2006). However, most of the visual features commonly used to operationalize landscape qualities potentially fail to measure RES-prompted landscape changes.

Goal 3: Preference for RES-altered landscapes

We found that visual preference is significantly influenced by the landscape types and by the RES visibility level. However, the two variables landscape types and RES visibility could only explain a very small part of the preference. Although we specifically asked about people’s visual preference for energy landscapes, this result implies that people think beyond visual aspects when evaluating such scenes. Overall, people prefer low RES visibility scenarios over high-visibility counterparts, in congruence with the findings of Betakova et al. (2015), who reported lower visual preferences for higher number of wind turbines. Independent of the number of RES, the hilly and sparsely populated pre alpine area is the most strongly favored landscape. By contrast, the inner alpine valley and the urban plateau are the least preferred. Interestingly, the urbanized plateau (PLAT\_URB), which is generally rated as of low visual quality, is the only landscape in which a high-visual-impact scenario is preferred over a low-impact equivalent. Thus, our results support those of Lothian (2008) and Betakova et al. (2015), who found that installing wind farms in high-visual-quality landscapes decreases visual quality, whereas adding wind turbines in low-visual-quality landscapes may increase visual quality.

We found no direct correlation between measured visual features and preferences, thus substantiating the finding of Fuente Val et al. (La Fuente Val et al., 2006). The study revealed only limited correlation of visual indices with scenic beauty estimations and conclude that might be attributed to the broad and very normative concept of landscape preference.

Rated complexity and the similar item of mystery (MYST\_A: ‘There is

much to discover in this landscape’) are unrelated to preference. Contrarily, coherence, legibility and one item related mystery (‘I would like to get to know this landscape better’) are correlated with visual preferences for RES altered landscapes. Hence, ‘making sense,’ ‘understanding,’ and ‘readability’ are more important factors for preferences of RES altered landscapes compared to diversity aspects. Similarly, Johansson & Laike (2007) demonstrated that ‘how well landscape components fit and function together’, are important aspects for the opposition against wind turbines.

Limitations

We worked under the premise that for successful energy transition, the right question is not ‘if’ RES should be established but ‘where’ and ‘how many’. Correspondingly, we showed only landscape stimuli containing RES. This decision prevented us from identifying a connection between a landscape change from RES presence to no RES presence. Our study design nonetheless cleared the way for illuminating the effects on people’s quality ratings and preferences with regard to different landscape types.

In addition, we showed only combined visual impact of wind and photovoltaic infrastructure. Future studies should show landscape stimuli separated by energy facilities in order to investigate differences in landscape quality ratings between wind turbines and solar panels. Although other researchers found connections between measured visual features and landscape preferences (Ibarra et al., 2017; Hunziker & Kienast, 1999; Kardan et al., 2015), we detected no direct relationship between visual features and rated preferences. This may be explained by the setting of our experiment, which involved only seven landscape types and therefore covered inadequate variance within single visual features. Further studies directed toward ascertaining this association may need a wider variety of landscape types and, thus, more visual stimuli. However, both mentioned issues lead to significantly more stimuli, which increases the risk that evaluations are influenced by fatigue effects.

Another shortcoming is that our study was conducted in German. The slightly different wording and formulation of the language could explain the differences in our results and those of research carried out in English. This issue might be of special interest in further meta-analysis, wherein the correct meanings of German and English terms are carefully considered.

Finally, we used the preference matrix (Kaplan and Kaplan, 1989) as only one of several methods for assessing people’s perception of landscape qualities. Because the preference matrix distinguishes between immediate and inferred ratings of landscape quality, we used this assessment to relate landscape qualities to measured immediate, physiological arousal responses (Spielhofer et al., 2021). Combining physiological data and landscape quality ratings leads to a better

understanding of the individual response and assessment of landscape changes caused by renewable energy infrastructure.

### 5. Conclusion

The visual aesthetic effects of RES on landscapes are important factors for resistance against energy infrastructure and therefore hamper the cultivation of sustainable societies. Our results revealed that landscapes with the potential to facilitate the establishment of connections with energy facilities might be visually preferred by people. Possible connectors can be visual (repetitive shapes, colors, and textures) but also contextual/functional in nature, such as other man-made elements or similar land uses. Further study is needed to specifically look into these visual and contextual connectors. We cannot directly formulate recommendations for landscape planners and policy makers, but value for these stakeholders may come in the form of this work’s unearthing of the potential to incorporate visual qualities into VIAs. Further our results can contribute to determine landscape specific visual thresholds, which incorporate visual qualities. Capitalizing on visual qualities might provide additional insights into what people think about landscape changes through RES instead of merely focusing on RES visibility. Finding suitable areas that incorporate people’s visual perception can help mitigate resistance against RES. Rated coherence can serve as a starting point given its suggested effectiveness in the assessment of RES-induced visual changes in landscapes. Future research should investigate coherence, its connection to place–technology fit, and possible objective visual features in the context of RES landscapes. Specifically, such scholarship

should account for the different connotations of various landscape types and how these are influenced by renewable energy systems.

### CRedit authorship contribution statement

**Reto Spielhofer:** Conceptualization, Data curation, Formal analysis, Investigation, Software, Visualization, Writing - original draft. **Marcel Hunziker:** Conceptualization, Methodology. **Felix Kienast:** Methodology. **Ulrike Wissen Hayek:** Investigation, Methodology, Visualization. **Adrienne Grêt-Regamey:** Funding acquisition, Supervision, Writing - original draft.

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### Appendix A. Visual impact of RES

Scenario development with calculated visual impact values for photovoltaic panels (OAI SPP) and wind turbines (VIWT).

#### Parameters OAI SPP

**Table A1.** Mean and standard deviation for calculated visual impact parameters of photovoltaic panels (OAI SPP), in the LOW and the HIGH Renewable Energy Systems (RES) SCENARIO levels (Torres-Sibille et al., 2009)

Feature	Visibility	Color	Fractality	Concurrence	Objective Aesthetic Impact of Solar Power Plants	Number of pixel covered with PV	Number of edge pixel relating to PV
<b>RES visual impact dimension</b>	Area (pixel) covered with PV related to background pixel	Color contrast of panel vs. close surrounding	Artificiality of installations against natural background	More than one type of solar panel within a plant produce concurrence and influence on perception	Weighted overall visual impact of PV system		
<b>Scale</b>	[0 -1]No PV – total view covered with PV	[0 – 1]No color contrast – high contrast between PV ad background	[0 – 2]Background has higher fractality as PV [If<1]PV has higher fractality than background [If>1]	[0 -1]Highest concurrence if two panel types are equally distributed	0 = No visual impact1 = highest visual impact		
<b>Calculation</b>	Calculation steps proposed by Torres-Sibille et. al., (2009) implemented in MATLAB script (appendix)					Pixel subtraction (Scenario – No-RES scenario)	MATLAB Canny edge detection
<b>LOW RES SCENARIO</b>	<i>mean</i>	0.1	0.014	0.044	0.3	0.095	16264
	<i>Standard deviation</i>	0.02	0.007	0.02	0.1	0.02	4606
<b>HIGH RES SCENARIO</b>	<i>mean</i>	0.15	0.02	0.04	0.64	0.16	26738
	<i>Standard deviation</i>	0.04	0.01	0.02	0.16	0.01	7432

#### Parameters VIWT

**Table A2.** Mean and standard deviation for calculated visual impact parameters of wind turbines (VIWT) in the LOW and the HIGH Renewable Energy System (RES) SCENARIO levels (Brahms and Peters, 2012).

	<i>Feature</i>	<i>Absolut number of WT</i>	<i>Effect of additional WT</i>	<i>Pratial visibility</i>	<i>Distance effect</i>	<i>Total visual impact wind</i>	<i>Number of pixels covered with wind turbine</i>	<i>Number of edge pixels relating to wind turbines</i>
	<b>RES visual impact dimension Scale</b>	Total number of WT placed in scene	Reduction effect of additional WT 1 = only single WT ~ 0.18 = add 30 + WT	Effect of partial visible WT in landscapes $\sum_{i=1}^{NUM\_WT} part\_vis_i(0 = all WT total invisible or no WT)$	Effect of distance to closest WT 1 = 0 m 0.03 ~ 10'000 m	Total calculated visual impact of wind turbines =RED_NUM_WT * PART_VIS_WT*EFF_DIST_WT		
	<b>Calculation</b>		Calculation steps proposed by (Brahrs und Peters., (2012) implemented in MATLAB script				Pixel subtraction (Scenario – No-RES scenario)	MATLAB Canny edge detection
<b>LOW RES SCENARIO</b>	<i>mean</i>	3	0.33	2.73	0.32	0.29	3341	1316
	<i>Standard deviation</i>	0	0	0.24	0.04	0.04	1845	1182
<b>HIGH RES SCENARIO</b>	<i>mean</i>	10	0.24	8.89	0.59	1.27	5085	3244
	<i>Standard deviation</i>	0	0	0.78	0.1	0.25	1982	920

VIWT for all scenarios (N = 14)

Fig. A3

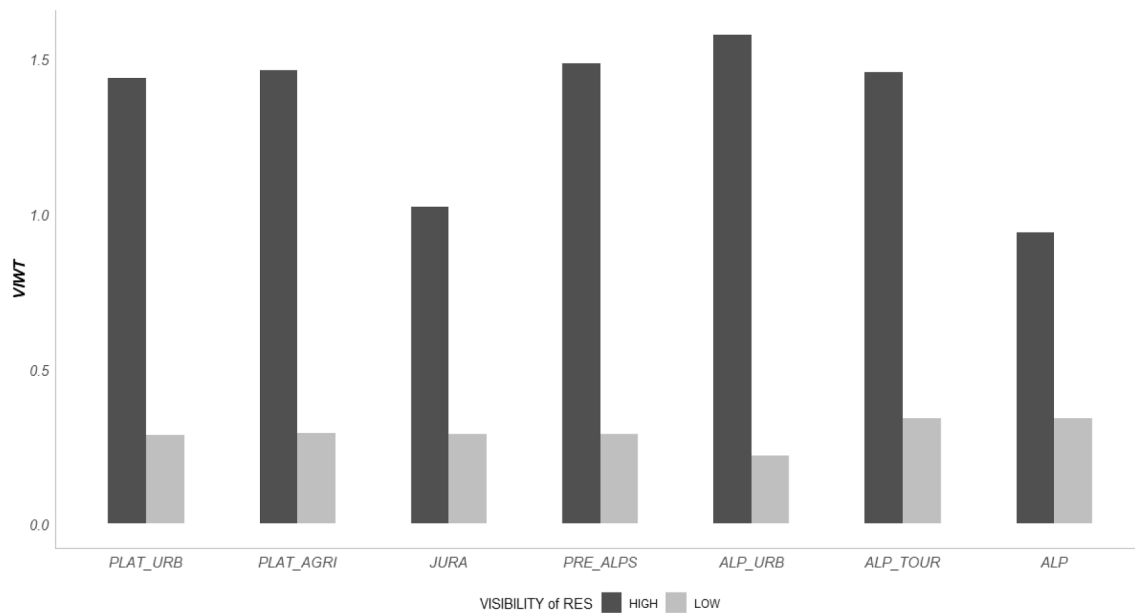


Fig. A3. VIWT for LOW and HIGH scenarios of all landscape types.

OASPP for all scenario (N = 14)

Fig. A4

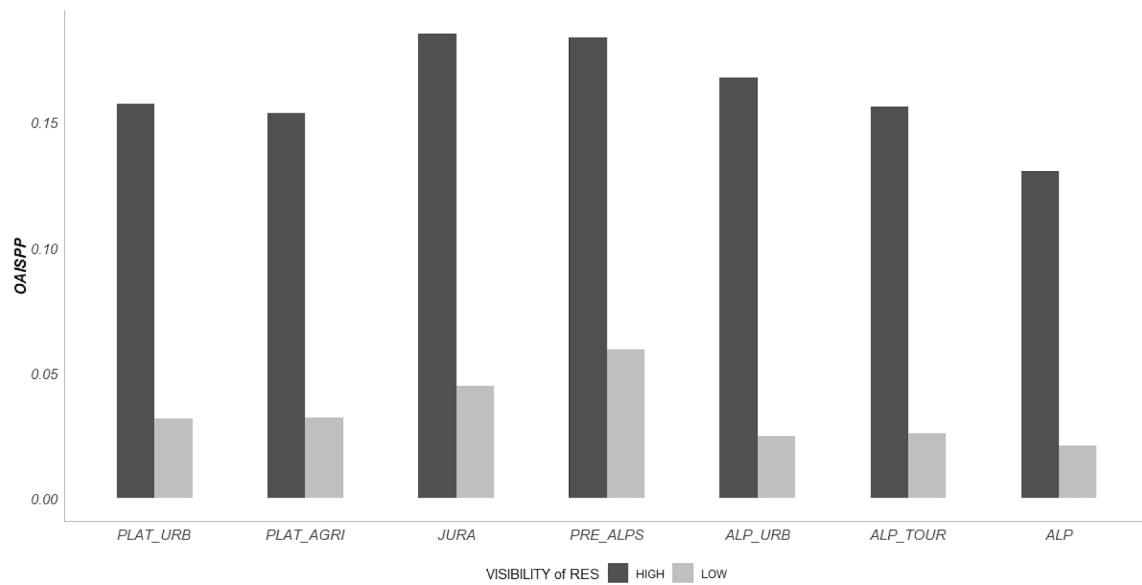


Fig. A4. OASPP for LOW and HIGH scenarios of all landscape types.

Appendix B. Measures

Table B1. Nine items to assess the landscape qualities based on the preference matrix (Kaplan & Kaplan, 1989). Originally the questions were asked in German. All statements have been answered on a 5-point Likert scale ranging from 1 = totally disagree (Germ. “Trifft gar nicht zu”) – 5 = totally agree (Germ. “Trifft sehr zu”).

Item	Question	Landscape quality
COMPL_A	“There are many different things in this landscape.” German: “In dieser Landschaft gibt es viel Verschiedenes.”	Complexity
COMPL_B	“This landscape is diverse.” German: “Diese Landschaft ist abwechslungsreich.”	Complexity
COHER_A	“This landscape is coherent in itself.” German: “Diese Landschaft ist in sich stimmig.”	Coherence
COHER_B	“The individual things or components of this landscape fit together.” German: “Die einzelnen Dinge oder Bestandteile dieser Landschaft passen gegenseitig zusammen.”	Coherence
LEGL_A	“This landscape is clear.” German: “Diese Landschaft ist übersichtlich.”	Legibility
LEGL_B	“There are landmarks in this landscape that help you find your way.” German: “In dieser Landschaft gibt es Orientierungspunkte, die einem helfen, sich zurechtzufinden.”	Legibility
LEGL_C	“I find my way around this landscape very well.” German: “Ich finde mich in dieser Landschaft sehr gut zurecht.”	Legibility
MYST_A	“There is much to discover in this landscape.” German: “In dieser Landschaft gibt es viel zu entdecken.”	Mystery
MYST_B	“I would like to get to know this landscape better.” German: “Ich möchte diese Landschaft gerne besser kennen lernen.”	Mystery

Table B2. Calculated visual features and their related concepts for visual perception of landscapes

Concept	Relevance for visual perception	Index (coding)	(Source) / calculation
<i>Pixel based measures</i>			
Color & contrast	Color tone	Hue ( <i>hue</i> )	(Berman et al., 2014; Kardan et al., 2015) MATLAB image processing toolbox
	Color intensity	Saturation ( <i>sat</i> )	
	Light and shadow	Brightness ( <i>bright</i> )	
Visual information density	Visual saliency / redundancy	Feature congestion ( <i>fc</i> )	(Rosenholtz et al., 2007) Free available MATLAB script
		Subband entropy ( <i>se</i> )	
Spatial frequency	Visual complexity	JPEG file size ( <i>bytes</i> )	(Tuch et al., 2009) File size on storage (Valtchanov and Ellard, 2015) Gaussian filter and Fourier transformation. Python script provided by D. Valtchanov
	Sharpness	Low spatial frequency ( <i>sf_low</i> )	
		High spatial frequency ( <i>sf_high</i> )	
<i>Landscape metrics</i>			
Area & edges	Detection of edges → perceived naturalness	Edge density ( <i>ed</i> )	(Kardan et al., 2015) MATLAB image processing toolbox
Shape	Complexity or naturalness of shapes → landscape preference	Shape index ( <i>shape</i> )	(Ode et al., 2009)
		Fractality ( <i>frac</i> )	(Forsythe et al., 2011; Hagerhall et al., 2008)
		Contiguity ( <i>contig</i> )	(La Fuente Val, Atauri, & de Lucio, 2006) → antagonist of evenness

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Concept	Relevance for visual perception	Index (coding)	(Source) / calculation
Core area	Area shape interaction	Core area ( <i>cai</i> )	
Aggregation	Dispersion / interspersion	Dispersion ( <i>ai</i> )	(Ode et al., 2009)
	High interspersion values if same patches are homogeneously distributed → related to landscape preferences	Interspersion ( <i>iji</i> )	(Hunziker and Kienast, 1999)
	Subdivision of patches → landscape preference in agricultural landscape context	Number of patches ( <i>np</i> )	(Dramstad et al., 2006; Ode et al., 2009)
	Diversity of patches landscape → preference in agricultural landscape context → complexity	Shannon diversity index ( <i>shdi</i> )	(Dramstad et al., 2006)
	Evenness of patches, relation to landscape preferences	Shannon evenness index ( <i>shei</i> )	(Hunziker and Kienast, 1999; La Fuente Val et al., 2006)
<i>Related exclusively on RES</i>			
Amount of edges related to RES	Aspect of visual contrast	( <i>edges_res</i> )	MATLAB canny edge detection
Amount of pixels related to RES		( <i>pix_res</i> )	Manual calculation with Adobe Photoshop
RGB Images decomposed with 12 classes			

### Appendix C. Reliability analysis

Each participant rated the landscape qualities for six stimuli. Here we report Cronbach alpha separated for each of the six trails.

Landscape quality	RATING ORDER					
	1st	2nd	3rd	4th	5th	6th
Coherence	0.79	0.86	0.92	0.78	0.85	0.82
Complexity	0.72	0.73	0.82	0.83	0.8	0.8
Legibility	0.71	0.81	0.69	0.71	0.76	0.75
Mystery	0.63	0.64	0.51	0.65	0.6	0.7
N data subset	132	133	133	133	133	134

### Appendix D. Descriptive statistics

For the landscape qualities, we report the descriptive statistics separated by individual scenarios (Table D.1).

Table D1. Descriptive statistics for the landscape qualities

Landscape qualities	SCEANRIOS													
	PLAT_URB		PLAT_AGRI		JURA		PRE_ALPS		ALP_URB		ALP_TOUR		ALP	
	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH
COHERENCE [MED]	3.5	3.5	4	4	4.5	4	4.25	4	4	2.5	4	3	4	3.5
COHERENCE [SE]	0.14	0.14	0.1	0.15	0.13	0.15	0.14	0.18	0.16	0.13	0.16	0.14	0.13	0.18
COMPLEXITY [MED]	3.5	3.5	3	3	3.5	3	3.75	4	4	4	3	3	3.5	3.5
COMPLEXITY [SE]	0.14	0.13	0.09	0.14	0.1	0.12	0.1	0.12	0.13	0.09	0.13	0.11	0.13	0.15
LEGIBILITY [MED]	3.33	3	4	4	4.33	3.67	4	4	3.67	3.33	3.5	3.67	4	4
LEGIBILITY [SE]	0.12	0.12	0.09	0.12	0.09	0.1	0.12	0.11	0.13	0.11	0.09	0.1	0.09	0.12
MYSTERY_A [MED]	4	3	3	3	4	4	4	4	4	4	3	3	4	4
MYSTERY_A [SE]	0.13	0.15	0.12	0.16	0.13	0.12	0.1	0.13	0.16	0.12	0.17	0.14	0.14	0.17
MYSTERY_B [MED]	2	2	3	3	4	4	4	4	3	2	4	4	5	4
MYSTERY_B [SE]	0.15	0.15	0.14	0.17	0.12	0.15	0.12	0.15	0.16	0.15	0.17	0.15	0.11	0.16
N	57	55	68	52	65	53	56	48	49	70	46	64	59	57
SCEANRIOS														
PLAT_URB PLAT_AGRI JURA PRE_ALPS ALP_URB ALP_TOUR ALP														
LOW HIGH LOW HIGH LOW HIGH LOW HIGH LOW HIGH LOW HIGH LOW HIGH														
N CHOICE	17	24	33	26	41	32	38	32	19	16	28	27	44	24
N NOCHOICE	40	31	35	26	24	21	18	16	30	54	18	37	15	33
PREFERENCE	0.31	0.44	0.49	0.5	0.63	0.6	0.68	0.67	0.39	0.22	0.61	0.42	0.75	0.42

Table D2. Descriptive statistics for the visual features, measured on N = 14 scenarios

Image Statistics	Mean	SD	SE	Median
Pixel based measures				
hue	0.316	0.065	0.017	0.332
sat	0.352	0.044	0.012	0.369
bright	53.543	6.028	1.611	51.900
fc	2.466	0.360	0.096	2.488

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Image Statistics	Mean	SD	SE	Median
se	4.501	0.243	0.065	4.462
bytes	3201570.857	654711.232	174978.937	3058877.5
sf_low	7.756	0.178	0.048	7.763
sf_high	7.902	0.226	0.060	7.871
<b>Landscape metrics</b>				
ed	3447.157	1493.666	399.199	3041.314
shape	1.367	0.058	0.015	1.376
frac	1.259	0.031	0.008	1.26
ai	82.820	7.477	1.998	84.852
contig	0.287	0.049	0.013	0.270
cai	6.100	2.448	0.654	5.119
iji	58.024	5.238	1.400	59.245
np	126341.929	69948.262	18694.459	126,128
shdi	2.350	0.048	0.013	2.354
shei	0.946	0.019	0.005	0.948
<b>Related exclusively on RES</b>				
PIX_RES	20464.357	13465.360	3598.769	18277.000
EDGES_RES	6204.071	5539.226	1480.420	3864.500

**Appendix E. Socio demographics**

Fixed effects of age, gender and if the rated landscape was similar to the landscape where the participant live.

Landscape qualities	Fixed effects of socio demographics											
	AGE				HOME LANDSCAPE				GENDER			
	$\chi^2(1)$	Marginal R <sup>2</sup>	Cohens f <sup>2</sup>	p	$\chi^2(1)$	Marginal R <sup>2</sup>	Cohens f <sup>2</sup>	p	$\chi^2(1)$	Marginal R <sup>2</sup>	Cohens f <sup>2</sup>	p
Coherence	7.009	0.144	0.17	0.008	0.655	0.131	0.15	0.418	0.068	0.13	0.15	0.794
Complexity	0.114	0.142	0.17	0.736	0.109	0.147	0.17	0.741	1.127	0.151	0.18	0.288
Legibility	0.101	0.129	0.15	0.749	36.923	0.131	0.15	1.229e-9	1.891	0.142	0.17	0.169
Mystery_A	0.779	0.121	0.14	0.342	1.476	0.115	0.12	0.224	2.753	0.243	0.32	0.048
Mystery_B	1.296	0.243	0.32	0.274	27.414	0.249	0.33	1.6e-7	0.773	0.247	0.33	0.379

**Appendix F. Correlation analysis**

Correlation analysis with N = 14 scenario and a corrected alpha level of 0.002.  
Correlation coefficient (r)

	COHERENCE	COMPLEXITY	LEGIBILITY	MYSTERY_A	MYSTERY_B
hue	0.275	-0.262	0.226	-0.525	-0.125
sat	-0.182	0.455	-0.429	0.495	0.121
bright	0.080	-0.549	0.177	-0.647	-0.372
fc	-0.578	0.169	-0.486	0.090	-0.451
se	-0.187	-0.547	-0.015	-0.147	0.020
bytes	-0.468	0.644	-0.534	0.604	-0.130
sf_low	-0.508	0.429	-0.521	0.099	-0.464
sf_high	0.288	0.081	0.648	0.376	0.886
ed	-0.415	0.424	-0.451	0.552	0.055
shape	-0.455	-0.204	-0.301	0.090	0.002
frac	-0.433	0.253	-0.508	0.380	-0.033
ai	0.415	-0.424	0.451	-0.552	-0.055
contig	0.174	-0.758	0.209	-0.631	-0.090
cai	0.073	-0.635	0.165	-0.613	-0.279
iji	-0.262	0.490	-0.358	0.244	-0.134
np	-0.240	0.587	-0.288	0.697	0.222
shdi	0.086	-0.090	0.059	-0.130	-0.046
shei	0.086	-0.090	0.059	-0.130	-0.046
PIX_RES	-0.446	0.055	-0.235	-0.284	-0.200
EDGES_RES	-0.749	-0.037	-0.314	-0.147	-0.262
<b>Significance level (p)</b>					
	COHERENCE	COMPLEXITY	LEGIBILITY	MYSTERY_A	MYSTERY_B
hue	0.342	0.366	0.436	0.054	0.670
sat	0.533	0.102	0.126	0.072	0.681
bright	0.786	0.042	0.545	0.012	0.190
fc	0.030	0.563	0.078	0.759	0.106
se	0.523	0.043	0.958	0.615	0.946
bytes	0.091	0.013	0.049	0.022	0.659
sf_low	0.064	0.126	0.056	0.737	0.095
sf_high	0.318	0.782	0.012	0.185	0.000

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	COHERENCE	COMPLEXITY	LEGIBILITY	MYSTERY_A	MYSTERY_B
ed	0.140	0.131	0.106	0.041	0.852
shape	0.102	0.483	0.296	0.759	0.994
frac	0.122	0.383	0.064	0.180	0.911
ai	0.140	0.131	0.106	0.041	0.852
contig	0.553	0.002	0.474	0.016	0.759
cai	0.805	0.015	0.573	0.020	0.334
iji	0.366	0.075	0.208	0.401	0.648
np	0.409	0.027	0.318	0.006	0.446
shdi	0.771	0.759	0.840	0.659	0.876
shei	0.771	0.759	0.840	0.659	0.876
PIX_RES	0.110	0.852	0.418	0.326	0.493
EDGES_RES	0.002	0.899	0.274	0.615	0.366

**Appendix G. Visual features**

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
<b>PIX_RES</b>					
LANDSCAPE	6	4.49E + 08	7.48E + 07	4.42	0.047 *
RES_LEVEL	1	1.81E + 09	1.81E + 09	106.71	4.81e-05 ***
Residuals	6	1.02E + 08	1.69E + 07		
<b>EDGES_RES</b>					
LANDSCAPE	6	76,886,638	12,814,440	1.289	0.383
RES_LEVEL	1	262,337,401	262,337,401	26.385	0.002 **
Residuals	6	59,655,324	9,942,554		
<b>cai_mn</b>					
LANDSCAPE	6	76.52	12.753	55.322	5.45-05 ***
RES_LEVEL	1	0.01	0.006	0.024	0.882
Residuals	6	1.38	0.231		
<b>contig_mn</b>					
LANDSCAPE	6	0.03	0.005	43.156	0.0001 ***
RES_LEVEL	1	>0.0001	>0.0001	0.101	0.761
Residuals	6	0.0006	0.0001		
<b>enn_mn</b>					
LANDSCAPE	6	3.607	0.601	69.376	2.81e-05 ***
RES_LEVEL	1	0.007	0.007	0.862	0.389
Residuals	6	0.052	0.87		
<b>frac_mn</b>					
LANDSCAPE	6	0.012	0.002	17.521	0.001 **
RES_LEVEL	1	>0.0001	>0.0001	0.228	0.649
Residuals	6	0.0007	0.0001		
<b>shape_mn</b>					
LANDSCAPE	6	0.039	0.006	14.776	0.002 **
RES_LEVEL	1	0.0009	0.0008	1.896	0.217
Residuals	6	0.003	0.0004		
<b>ai</b>					
LANDSCAPE	6	718.1	119.68	84.846	1.55e-05 ***
RES_LEVEL	1	0.3	0.26	0.181	0.685
Residuals	6	8.5	1.41		
<b>ed</b>					
LANDSCAPE	6	28,656,295	4,776,049	85.031	1.54e-05 ***
RES_LEVEL	1	10,194	10,194	0.181	0.685
Residuals	6	337,010	56,168		
<b>iji</b>					
LANDSCAPE	6	312.04	52.01	7.077	0.015 *
RES_LEVEL	1	0.58	0.58	0.079	0.788
Residuals	6	44.09	7.35		
<b>np</b>					
LANDSCAPE	6	6.16E + 10	1.03E + 10	38.072	0.0001 ***
RES_LEVEL	1	4.38E + 08	4.38E + 08	1.627	0.249
Residuals	6	1.62E + 09	2.69E + 08		
<b>shdi</b>					
LANDSCAPE	6	0.014	0.003	0.881	0.559
RES_LEVEL	1	0.0004	0.0004	0.169	0.695
Residuals	6	0.016	0.003		
<b>shei</b>					
LANDSCAPE	6	0.002	0.0004	0.881	0.559
RES_LEVEL	1	>0.0001	>0.0001	0.169	0.695
Residuals	6	0.003	0.0004		
<b>sf_low</b>					
LANDSCAPE	6	0.319	0.053	3.866	0.062 .
RES_LEVEL	1	0.013	0.013	0.918	0.375
Residuals	6	0.082	0.014		
<b>sf_high</b>					
LANDSCAPE	6	0.655	0.109	72.847	2.43e-05 ***

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	Df	Sum Sq	Mean Sq	F value	Pr(>F)
RES_LEVEL	1	0.001	0.001	0.879	0.385
Residuals	6	0.009	0.002		
<b>frac</b>					
LANDSCAPE	6	0.078	0.013	1119.783	7.09e-09 ***
RES_LEVEL	1	>0.0001	>0.0001	3.523	0.11
Residuals	6	>0.0001	>0.0001		
<b>bright</b>					
LANDSCAPE	6	472.4	78.73	1.02e30	<2e16 ***
RES_LEVEL	1	0	0	1.18e-01	0.643
Residuals	6	0	0		
<b>bytes</b>					
LANDSCAPE	6	5.57E + 12	9.29E + 11	18817.5	1.5e-12 ***
RES_LEVEL	1	7.97E + 08	7.97E + 08	16.15	0.007 **
Residuals	6	2.96E + 08	4.94E + 07		
<b>ec</b>					
LANDSCAPE	6	2.00E + 09	333,382,549	842.367	1.66e-08 ***
RES_LEVEL	1	6.98E + 05	697,991	1.764	0.232
Residuals	6	2.38E + 06	395,769		
<b>fc</b>					
LANDSCAPE	6	1.6839	0.281	8456.39	1.65e-11 ***
RES_LEVEL	1	0.001	0.001	28.78	0.002 **
Residuals	6	0.0002	>0.0001		
<b>se</b>					
LANDSCAPE	6	0.765	0.128	631.467	3.94e-08 ***
RES_LEVEL	1	0.001	0.001	6.069	0.049 *
Residuals	6	0.001	>0.0001		
<b>hue</b>					
LANDSCAPE	6	0.055.	0.009	17753.9	1.79e-12 ***
RES_LEVEL	1	>0.0001	>0.0001	39.6	0.0007 ***
Residuals	6	>0.0001	>0.0001		
<b>sat</b>					
LANDSCAPE	6	0.026	0.004	80.694	1.85e-10 ***
RES_LEVEL	1	>0.0001	>0.0001	2.557	0.161
Residuals	6	>0.0001	>0.0001		
Signif. co		: 0 ****	0.001 ***	' 0.01 '	** 0.05 ' 0.1 ' ' 1

## Appendix H. Preferences

### H.1 Relation (R & p) between visual features and preference score

	R	p
hue	0.301	0.296
sat	0.011	0.970
bright	-0.151	0.607
fc	-0.692	0.006
se	-0.187	0.523
bytes	-0.437	0.118
sf_low	-0.556	0.039
sf_high	0.618	0.019
ed	-0.327	0.253
shape	-0.319	0.267
frac	-0.319	0.267
ai	0.327	0.253
contig	0.002	0.994
cai	-0.121	0.681
iji	-0.209	0.474
np	-0.108	0.714
shdi	0.046	0.876
shei	0.046	0.876
PIX_RES	-0.011	0.970
EDGES_RES	-0.305	0.288

### H.2 Relation between landscape qualities and preference scores

	R	p
COHERENCE	0.710	<b>0.004</b>
COMPLEXITY	-0.024	0.935
LEGIBILITY	0.723	<b>0.003</b>
MYSTERY_A	0.204	0.483
MYSTERY_B	0.793	<b>0.001</b>

## Appendix I. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.landurbplan.2020.104000>. The following link to the papers data repository on mendeley data: <https://dx.doi.org/10.17632/wvf56j6nps.1>.

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