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Physiological and behavioral reactions to renewable energy systems in various landscape types

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A B S T R A C T

Renewable energy systems (RES) can impact landscape aesthetics and influence the public's perception of the landscape and their acceptance of large infrastructure projects. Perceptual processes have consequences for both physiological and behavioral reactions to visual landscape changes and have not been systematically assessed in the context of RES. In this paper, we measured participants' physiological (electrodermal activity) and behavioral (i.e., landscape preferences) responses to landscapes with different amounts of RES. The visual stimuli were composed of either a low or high amount of wind turbines and photovoltaic systems in seven different landscape types. Participants were asked to choose their preferred landscape image from pairs of sequentially presented images while we recorded their electrodermal activity. The results revealed that participants were significantly more physiologically aroused while viewing landscapes with high RES compared to landscapes with low RES. We also found that the participants significantly preferred landscapes with low RES to landscapes with high RES and that this effect was larger for some landscapes than others. The results also revealed significant differences in preferences among landscape types. Specifically, participants tended to prefer the more natural landscapes to the more urban landscapes. A systematic analysis of the visual features of these stimuli revealed a positive correlation between physiological arousal and the visual impact of photovoltaic systems. Overall, we conclude that both physiology and behavior can be relevant for studies of landscape perception and that these insights may inform planners and policy makers in the implementation of landscape changes related to RES.

1. Introduction

The Fukushima reactor accident (2011) highlighted the risks of nuclear power and prompted various countries to phase out nuclear energy production [1–3]. In order to close the energy gap resulting from the phasing out of nuclear energy and to achieve the CO2 emission targets, renewable energy systems (RES) are being increasingly promoted by nations around the world [4–6]. Since RES are distributed in space, their visual impact ([7] i.e., artificial form, color and textures) on landscapes can lead to conflicts with local citizens and other stakeholders [8,9]. In the future, such infrastructure is expected to fundamentally reshape the visual appearance of landscapes and, as a consequence, may affect people's perception of these landscapes [10–13]. In general, the transition towards renewable energy production receives support on national scales but lacks acceptance at local levels [12,14,15]. Notably, the perceived landscape changes caused by wind and photovoltaic energy infrastructures are among the most decisive factors towards public acceptance of local projects [16–20]. In order to develop a strategy for promoting infrastructure developments, researchers should systematically assess the manner in which visual changes caused by the addition of RES in various landscapes affect behavior and physiology.

In general, reasoning about visual stimuli can be influenced by cognitive and affective processes and result in both behavioral and physiological responses [15,21–24]. We follow the model that

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landscapes can trigger physiological responses directly via sensory-perceptual reactions or indirectly through cognitive processes [25]. In this article, we define "affect" as a stimulus-specific reaction that is automatically and implicitly evoked through sensory processes [22]. In contrast, "emotion" is a broader term that can be defined as the result of the interaction between cognition and affect [26]. In order for individuals to accept landscape changes that may benefit society, their cognitive and affective processes need to be considered by planners and policy makers [22,26–28].

Visual changes caused by the addition of RES can be accompanied by a change in the emotions associated with a landscape and may involve a strong affective component [13,29]. Within an on-site study, Johannsson and Laike [12] found that a composite emotional state measure (including activation, orientation, evaluation, and control) predicted the intention to accept wind turbines by itself. However, a regression model with several additional factors (e.g., attitudinal and perceptual factors) explained significantly more variance. Similarly, Sánchez-Pantoja and colleagues [30] asked participants to estimate their emotional response to photographs including either building-integrated or conventional building-attached photovoltaic systems and demonstrated that the building-integrated photovoltaic systems were rated as more pleasant.

Russel [31] proposed a two-dimensional model of affective reactions called the *circumplex model.* According to this model, affective states can be located along arousal and valence dimensions. With respect to landscapes, Ulrich's psycho-evolutionary theory of affective responses to environments suggested that natural landscapes may cause a physiologically measurable decrease in arousal [32–34]. Indeed, Chang et al. [35] tested the agreement between psychological (e.g., perceived restorativeness scale) and physiological (e.g., blood volume pulse) measures of responses to natural landscape stimuli. Their results revealed that stimuli with higher restorativeness ratings elicited lower arousal.

Recently, Maehr and colleagues [36] measured participants' physiological arousal while they viewed landscape images with either wind turbines, other industrial constructions, or churches. Participants were also asked to rate the emotional impact of each landscape in terms of arousal and valence using the Self-Assessment Manikin (SAM [37]). Their results revealed that landscapes with wind turbines were more physiologically arousing than landscapes with churches, less arousing than landscapes with other industrial constructions in terms of self-report, and more pleasurable (i.e., higher valence) than landscapes with other industrial constructions [36]. This study indicates the potential of physiological arousal measurements for assessing affective reactions to visual landscape changes but also suggests that, without correction for multiple comparisons, it is difficult to disentangle the effects of subtle landscape changes on different affective measures.

As in Maehr and colleagues [36], many researchers have measured physiological arousal using skin conductance [38,39]. Skin conductance refers to changes to the electrical potential of the skin resulting from sympathetic activity of the autonomic nervous system (rather than thermal sweating) and is often measured at the medial phalanges of the fingers [40]. Skin conductance signals can be subdivided into a slowly and continuously changing tonic skin conductance level (SCL) and the phasic skin conductance response (SCR [38]). The number of SCRs (nSCR) indicates a fast changing, stimulus specific intensity of an emotion [41] and serves as a valid indicator for arousal [38,42]. In general, skin conductance is an index of implicit emotional responses that occur without conscious intentions [38,43] and thus may be used to distinguish between the affective and cognitive mechanisms underlying landscape perception.

Previous studies have assessed the cognitive aspects of acceptance for wind turbines in terms of political attitudes (e.g. [44,45]), process-related effects (e.g. [46,47]), and perceived side effects (see [17]). Questionnaires are often used to collect emotion and preference data in a relatively short amount of time. However, the exclusive use of questionnaire data to examine landscape perception neglects the affective processes underlying landscape perception that may not be consciously accessible [48]. Indeed, survey responses about RES and landscape perception have been found to be susceptible to social influence [49]; knowledge and previous experience [50] and anticipation, concerns, or beliefs [49,51].

As an alternative to questionnaires, some researchers have presented participants with landscape images and asked them to rate particular images or compare multiple images in terms of the images' visual characteristics [52]. Studies that focused on the visual impact of wind turbines generally agree that landscape type plays a significant role for preferences [52]. There is a controversial discussion as to whether wind turbines are preferred closer to Persson [53] or further from people's residences [17,54]. Independent of landscape type, Devine-Wright [55] argues that both the specific landscape and the connotations associated with this landscape (e.g., leisure and tourism [56]) help determine people's preferences. Interestingly, few works focus on preferences for photovoltaic systems in landscapes. In general, photovoltaic systems are perceived as positive (e.g. [15]). Indeed, combining photovoltaic systems with existing infrastructure in high alpine areas is well-accepted [57]. However, using a visual Q sorting method, Naspetti and colleagues [20] showed that small photovoltaic installations on roofs are more preferred than large ground-mounted systems in rural areas.

Both preference and physiological responses may be connected to low- and high-level visual features of landscape images [58–60]. Low-level features (e.g., form, orientation, colors) are processed earlier along the visual pathway than high-level features [61] and have been related to various aspects of landscapes (e.g. [58,60,62–64]. Specifically, color features such as hue and saturation have been found to predict landscape preferences and naturalness ratings, respectively [62]. In addition, spatial features have been found to trigger different physiological responses. For example, Hägerhäll and et al. [58] found that a medium degree of fractality elicits activity in the frontal and parietal lobes, measured by electroencephalography. Similarly, the low spatial frequencies of scenes significantly influence eye-blinking rates, which may indicate lower cognitive load and less stress for natural scenes compared to urban environments [60].

In contrast, high-level visual features involve top-down processing [63,65] and are associated with expectations and current goals derived from the individual's own experiences [66]. Similarly, Ibarra and colleagues [63] argue that landscape preferences strongly relate to visual design features that contain semantic information (e.g., shape of water body). In the present study, we define high-level visual features as the visual impact of RES. Visual impact represents the visual magnitude of specific landscape interventions [67]. Here, researchers have developed quantitative indicators such as the Objective Aesthetic Impact of Solar Power Plants (OAISPP [14];) and the Visual Impact of Wind Turbines (VIWT [68]) in order to assess the impact of high-level visual features associated with RES within landscapes. Previous research has also found that low- and high-level visual features of landscape images affect aesthetic preferences and may be extended to include physiological responses [62,63,69,70]. However, these studies have not yet systematically assessed the effect of different landscape types altered with RES on skin conductance.

In the present study, we systematically manipulated images of Swiss landscapes to include low or high amounts of wind turbines and photovoltaic systems and measured participants' physiological arousal as they performed pairwise comparisons among the images. We also attempted to correlate both physiological arousal and preferences with low- and high-level visual features. Based on previous research [36], we hypothesize that RES visual impact will be positively related to physiological arousal. In addition, we expect this relationship to be explained by high- and low-level visual features of the stimuli [59–61]. Our second hypothesis is that RES visual impact will affect landscape preferences. With this work, we aim to understand the impact of RES on individuals' landscape perception and, more broadly, the manner in which infrastructure changes to landscapes may be preferred by people.

2. Materials and methods

2.1. Participants

A total of 101 participants (47 women, mean age = 23.5, SD = 4.4, age range = 19–47 years) were recruited using the University Registration Center for Study Participants (https://www.uast.uzh.ch). A large proportion of the recruited participants had a natural/environmental science (33%), engineering (18%), or life-science (11%) background. A minority of the sample actively supports a natural protective association (19%). However, the participants often vote environment-friendly parties (29%), moderate-liberal parties (19%), and/or left-oriented political parties (17%). Compared to the entire Swiss population, our sample represents a young, well-educated and environment-friendly group. Two participants were excluded because of software issues. 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 (protocol number 2017-N-69). Participants were compensated 30 CHF for approximately 45 min of participation.

In order to determine the appropriate number of participants, we conducted a power analysis for linear mixed models using the R package SIMR [71]. Because SIMR employs Monte Carlo simulations, this package can handle non-normal response variables and accommodate a wide range of model specifications. We determined that a sample of 92 participants was sufficient to detect an η^2 of approximately 0.022 (small to medium) assuming a power of .8, an alpha of .05, and 200 iterations for the Monte Carlo simulations.

2.2. Audio-visual stimuli

We generated the stimuli using 3D landscape simulations of RES scenarios, developed on the basis of a previous study of the Switzerland's physical potential for renewable energy production [9]. We selected specific landscapes (i.e., vistas) that were representative of each of the seven main biogeographic regions of Switzerland [72]. These regions are visually distinguished by the extent of urbanization and the roughness of their topography. Specifically, these regions include the northern areas of flat plateaus that are primarily used for agricultural production (PLAT_AGRI) or settlements (PLAT_URB). We also considered two hilly and less densely populated, northern pre-alpine areas (PRE_ALPS) and the Jura (JURA). In addition, the Alps, with steep terrain, were divided into the large inner-alpine valleys, with a relatively high population density (ALP_URB), the alpine landscapes used for ski tourism (ALP_TOUR), and the near-natural alpine regions (ALP). Fig. 1 provides an overview of the appearance and distribution of these seven landscape types. We reconstructed each vista as a 3D landscape visualization from a pedestrian perspective using light detection and ranging (LiDAR) data. The LiDAR data was colored using photos taken with a Nikon D700 camera, mounted on top of the scanner (Riegl VZ-1000). Subsequently, we imported the colored point clouds into the 3D graphic processing software CINEMA 4D. In order to minimize the effects of different weather and lightning conditions on physiological arousal measurements, we kept several atmospheric parameters constant for all seven landscape types. Specifically, we accounted for the type of sky and clouds, the light intensity of the sun, the color tone of the daylight, and the atmospheric refractions during the video rendering process. In each scene, we defined and rendered a 160° panoramic field of view to generate the video with moving clouds for a more vivid impression. We also recorded ambient sound with a sound-field microphone (four-channel, first order ambisonics) for each vista. During post-processing we excluded disturbing soundmarks and generated a congruent ambient sound for each landscape [73].

For each visualization, we created two simulations by adding two different visual impact scenarios of RES (i.e., LOW and HIGH) to only the middle 53.3° (center screen) of the visualization (see Fig. 1). The ambient sounds were held constant for different levels of RES because the distances from the wind turbines to the observer were too large for the observer to perceive their sound. To create comparable simulations for the two RES scenarios of each landscape, we calculated two high-level visual features, specifically the OAISPP [18] and the VIWT [68]. The OAISPP combines four measures (i.e., visibility, color, fractality, and contrast) 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 and colleagues [18] because atmospheric conditions were held constant across visualizations. 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. See Appendix A.1 and A.2 for the OAISPP and VIWT values of the final visualizations.

These 3D visualizations were used to render 30-s panoramic videos with a resolution of 5760 pixels by 1080 pixels. The animations in these videos included rotating blades on the wind turbines and moving clouds in the sky. The final stimuli consisted of 14 videos (2 RES scenarios for each of the 7 landscapes, see supplementary data). For each of the final stimuli, we also calculated 10 low-level visual features (see Appendix B) that have all been used in the context of landscape perception in previous research [58,59,62,70]. Specifically, we computed feature congestion (FC), subband entropy (SUB_ENTR), JPEG compression size (JPEG), edge counts (EC), fractality (FRACT), low spatial frequencies (SF_LOW), high spatial frequencies (SF_HIGH), image hue (HUE_MEAN), hue variability (HUE_SD), and image saturation (SAT_MEAN). FC represents the visual overload of an image, based on the variation of contrasts, orientation and luminance [64]. SUB_ENTR refers to the organization, grouping, and degree of redundancy of objects within a scene, approximated with encoding efficiency [59,64,65]. Furthermore, JPEG has been proposed as a proxy for visual complexity and may influence affective responses [59]. EC and FRACT are indices of perceived naturalness [58,62,70,74]. FRACT is a similarity measurement of image patterns over different scales and has been found to trigger physiological responses [58]. Spatial frequencies refer to different numbers of repeating elements per unit of distance as determined by a Fourier transform. SF_LOW and SF_HIGH are relatively coarse- and fine-grained spatial frequencies, respectively, and have been related to cognitive and affective processes [60].

In order to assess participants' emotional states, we employed the three dimensions (i.e., arousal, valence, and dominance) of the Self-Assessment Manikin (SAM) questionnaire [37]. Each dimension was represented by images along a 9-point scale. In addition, we used an online questionnaire to assess participants environmental perspective, energy-related attitudes and their concerns about trust and justice in the context of RES. Furthermore, we asked participants about their perception of their neighborhood and their concerns regarding RES. Finally, we collected participants socio-demographic characteristics.

The experiment was conducted in the Mobile Visual Acoustic Laboratory (MVAL; for a detailed description see Ref. [75]) in order to ensure constant light and sound conditions. The MVAL is an aluminum structure (5 m × 5 m x 2.5 m) with sound absorbing curtains and three large projection screens (Fig. 2). The stimuli were projected onto these screens using three HD projectors (EPSON EH-TW6700). The landscape sounds were replayed using a 5.0 surround sound system, mounted according to the ITU-R BS.775 standard. Participants sat 2.15 m in front of the center screen with their non-dominant hand resting on an armrest in order to reduce movement artifacts in the EDA data [76]. Participants used their dominant hand to control a computer mouse to indicate their preferences. Skin conductance electrodes (MTL118F) from ADInstruments (https://www.adinstruments.com) were attached to the middle phalanges of the index and ring fingers of the non-dominant hand without pretreatment of the skin. These electrodes were also attached to a FE116 GSR Amp and a Powerlab 8/35 recording device from ADInstruments.

Regarding software, we used Cinema4D (https://www.maxon.net), Adobe Premiere Pro (https://www.adobe.com), the digital audio

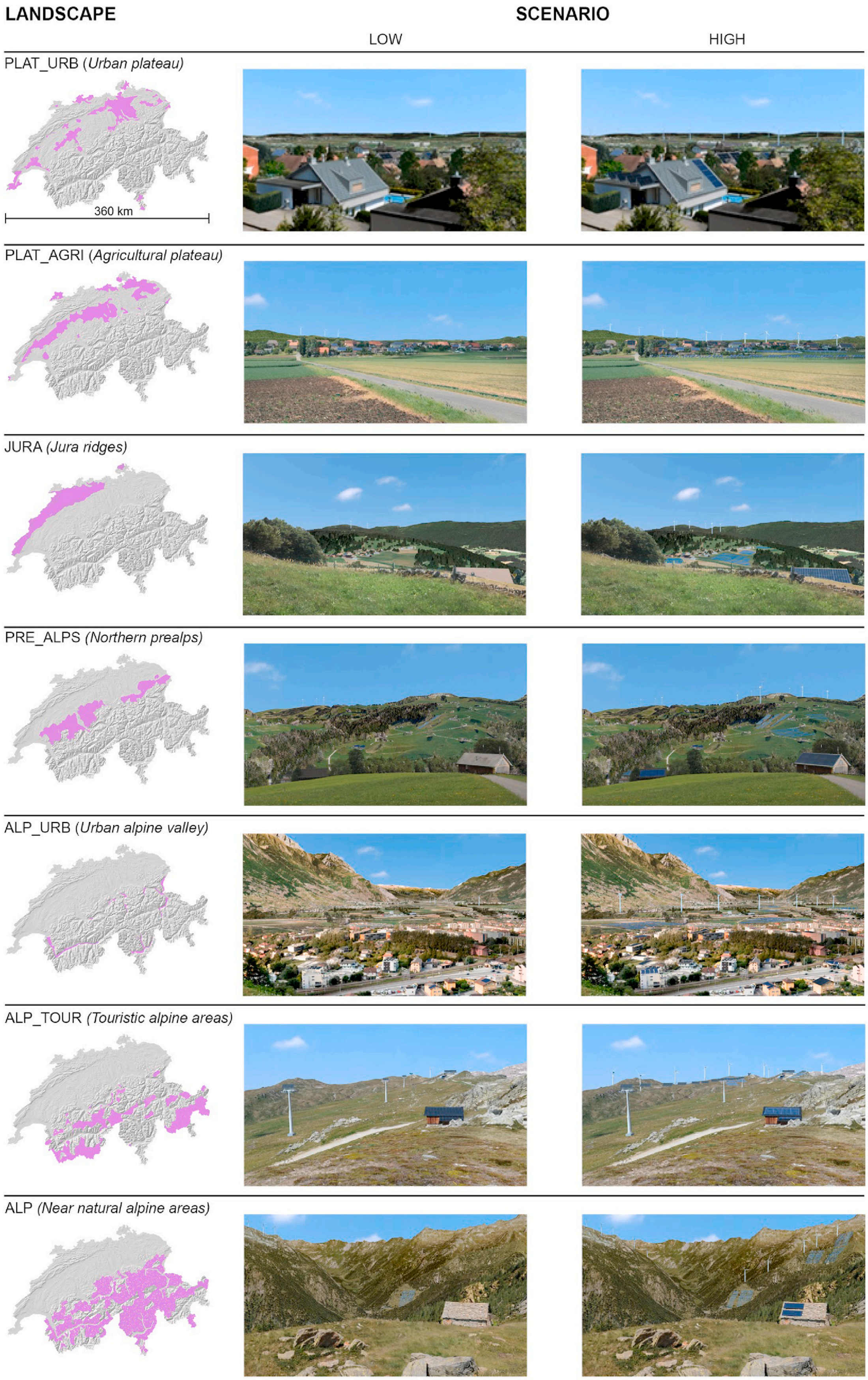


Fig. 1. Cartographic maps indicating the areas of the seven landscapes and the 3D landscape visualizations corresponding to the low and high RES scenarios. The base relief map of Switzerland was reproduced by permission of swisstopo (JA100120).

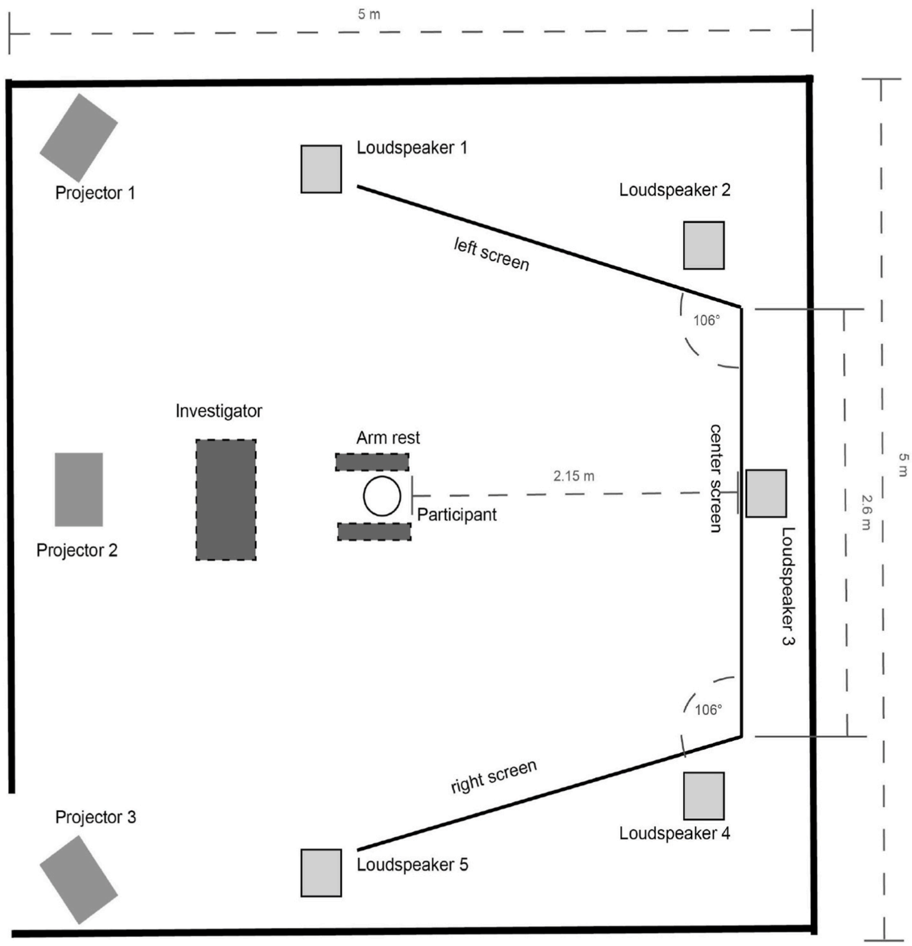


Fig. 2. Overview diagram of the experiment setup in the Mobile Visual-Acoustic Laboratory (MVAL).

workstation REAPER (https://www.reaper.fm) and the Experiments in Virtual Environments framework (EVE [77]) for creating and presenting the stimuli. For collecting and analyzing the skin conductance data, we used LabChart 8.14 (https://www.adinstruments.com), Matlab R2016b /R2017a (https://www.mathworks.com), and Ledalab 3.4.9 (http://www.ledalab.com). All inferential statistics were conducted using Rstudio [90] (version 3.5.1).

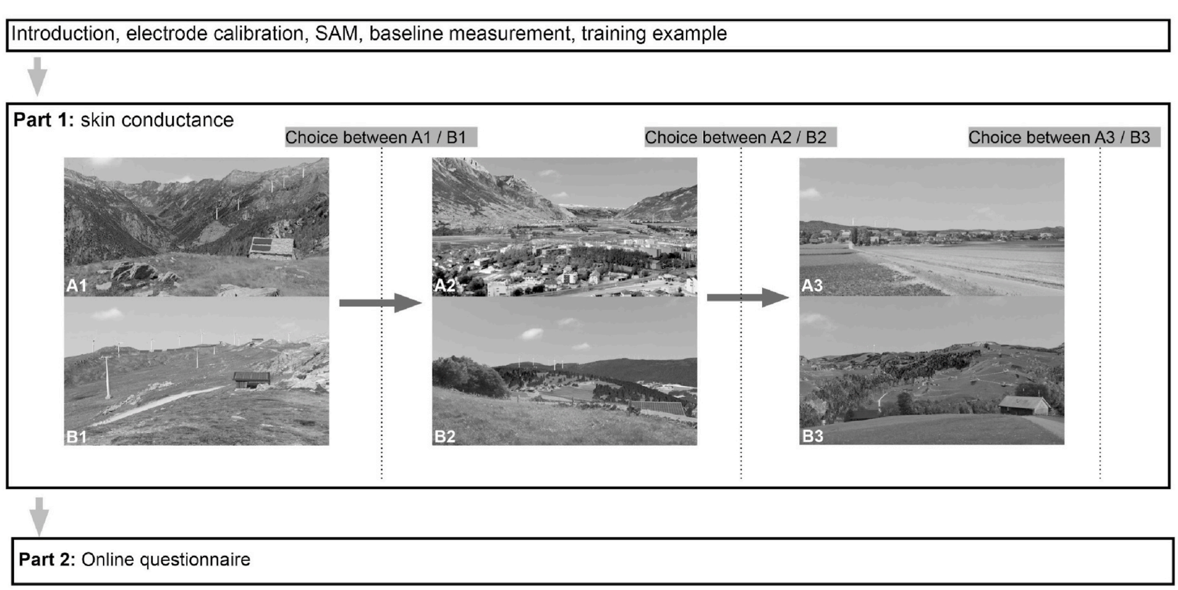


Fig. 3. Illustration of the study procedure with greyscale images representing different stimuli. Participants chose their preferred landscape image among two stimuli for each of three trials, separated by 20-s intervals.

2.3. Testing procedure

Data was collected for each participant individually in a laboratory session (Fig. 3) that lasted approximately 45 min. After reading an information sheet and signing the consent form, participants sat in a chair at the center of the MVAL. The experimenter then attached and calibrated the EDA electrodes [78] and turned off the lights. Participants were instructed to remain still without crossing their feet throughout the experiment. Participants were then asked to complete the Self-Assessment Manikin (SAM) and read a short fairy tale *(mean reading time = 223.*13 s*)* that was presented on the center screen of the MVAL to obtain a baseline measure of EDA. During one practice trial, two 30-s training stimuli (videos of a moving blue circle and a moving red cube with individual ambient sound for each video) were presented to participants sequentially, and they were asked to use the arrow keys on the keyboard to select their preferred stimulus.

Participants then completed three similar testing trials with three pairs of the landscape videos showing RES scenarios. These testing trials were separated by 20-s intervals consisting of a black cross on a gray background. The stimuli were paired so that one trial consisted of two high-RES landscape videos, one trial consisted of a high-RES landscape video and a low-RES landscape video, and one trial consisted of two low-RES landscape videos. The order of these trial types and the landscapes that composed each trial type were randomized and counterbalanced across participants, except that the same landscape was never seen by a participant more than once. At the end of each trial, participants were asked "*Which landscape do you like better?*" After finishing the testing trials and removing the electrodes, participants completed the post-experiment questionnaires outside of the MVAL. Data from the post-experiment questionnaires were collected for comparison with a larger online study and will be reported elsewhere.

2.4. Experimental design and analysis

We first considered the distribution of ratings for the SAM dimensions (i.e., arousal, valence, and dominance) in order to ensure that the participants were not psychologically aroused at the beginning of the experiment.

We had two independent variables, specific landscape types (LANDSCAPE; 7 levels) and RES visual impact scenarios (SCENARIO; high versus low). In order to avoid the direct comparison of high and low versions of the same landscape, we used a mixed, imbalanced study design. We also refrained from repeating the landscapes for any individual participant in order to prevent habituation effects in the physiological data. As a result, participants viewed six different landscapes that were divided into three pairs. The two main dependent variables for this study are ΔnSCR and landscape preferences.

The skin conductance data was first exported from LabChart to Ledalab. In Ledalab, this data was then down sampled from 1000 Hz to 10 Hz and visually inspected for artifacts. No artifacts were detected. Subsequently, we used Continuous Decomposition Analysis in order to extract nSCR from each participant's skin conductance data within particular response windows [79]. These 33-s response windows were defined as the period between 1 s after stimulus onset and 4 s after stimulus offset in order to capture all of the activity related to the stimulus [79]. This algorithm was optimized twice in order to model the impulse response function, and the threshold for peak detection was set at 0.01 μS. Baseline nSCR was calculated as mean nSCR for all 30-s response windows for each participant while reading the short story. Baseline nSCR was then subtracted from nSCR for each video's response window to provide a measure (ΔnSCR) of reactivity to the stimuli [80].

After correcting for baseline of nSCR, we checked the data for violations of the normality and homogeneity assumptions in order to use parametric linear mixed models. Normality is a common assumption for parametric statistical tests [81], and different methods can be used to evaluate normality. In our case, we visually inspected the density plot of ΔnSCR data and applied a Kolmogorov-Smirnov test. We checked for violations of the homogeneity of variance assumption with Levene's tests. These tests revealed non-normality of the residuals, but ΔnSCR was homogeneous across experimental groups. Because of the large number of data points per experimental condition, our linear mixed models should be robust to non-normality [82]. One (of 594) data points was an extreme outlier beyond six standard deviations of the mean and was removed from the analyses.

In order to test for the effects of LANDSCAPE and SCENARIO on ΔnSCR with a mixed imbalanced design, we used five nested linear mixed effects models (see Table 1) with the *lme4* package [83]. In the three-fixed-factor model, both independent variables (LANDSCAPE and SCENARIO) and their possible interaction were represented by fixed effects. For testing whether the interaction between LANDSCAPE and SCENARIO was significant, we compared this three-fixed-factor model to a two-fixed-factor model with fixed effects for only LANDSCAPE and SCENARIO. For testing the fixed effect of only the variable LANDSCAPE, we compared a one-fixed-factor model to a null model without any fixed effects. Similarly, we compared a one-fixed-factor model for SCENARIO to the same null model. Other variations in the stimuli that were not represented by the fixed effects were included as random effects. The random effects structure for each model was exactly the same. Specifically, we included random effects for stimulus order over the three trials (ORD_OVER), stimulus order within a trial pair (ORD_PAIR), and the participant (SUBJ_ID).

Following Bolker [84], we used another set of five nested generalized linear mixed models (GLMM) in order to analyze the (binary) preference data (Table 1). The fixed factors LANDSCAPE and SCENARIO for the three-fixed-factor, two-fixed-factor, one-fixed-factor, and null models were exactly the same as the models for ΔnSCR. However, for the preference data, we only included random effects for stimulus order over the three trials (ORD_ALL) and participant number (SUBJ_ID). We did not include a random effect for stimulus order within a pair because otherwise, we would have violated the assumption of independence by including more than one data point per choice. Because we only used two random effects, we fit the GLMM with Laplace approximation [84].

Table 1
Linear mixed effects models to test fixed effects on nSCR and landscape preference (CHOICE).

	Dependent variable	Fixed factors	Random factors
Model			
three-fixed-factor model	ΔnSCR	LANDSCAPE + SCENARIO+(LANDSCAPE * SCENARIO)	ORD_PAIR + ORD_ALL + SUBJ_ID
two-fixed-factor model	ΔnSCR	LANDSCAPE + SCENARIO	ORD_PAIR + ORD_ALL + SUBJ_ID
one-fixed-factor	ΔnSCR	SCENARIO	ORD_PAIR + ORD_ALL + SUBJ_ID
one-fixed-factor	ΔnSCR	LANDSCAPE	ORD_PAIR + ORD_ALL + SUBJ_ID
null model	ΔnSCR	–	ORD_PAIR + ORD_ALL + SUBJ_ID
three-fixed-factor model	CHOICE	LANDSCAPE + SCENARIO+(LANDSCAPE * SCENARIO)	ORD_ALL + SUBJ_ID
two-fixed-factor model	CHOICE	LANDSCAPE + SCENARIO	ORD_ALL + SUBJ_ID
one-fixed-factor	CHOICE	SCENARIO	ORD_ALL + SUBJ_ID
one-fixed-factor	CHOICE	LANDSCAPE	ORD_ALL + SUBJ_ID
null model	CHOICE		ORD_ALL + SUBJ_ID

Likelihood ratio tests were used to estimate the random effects. In addition, the data were not overdispersed, so we estimated the fixed effects using Wald Z statistics.

Finally, we applied Spearman rank correlations to assess the extent to which these two dependent variables (ΔnSCR and preferences) were correlated to the two high-level and 10 low-level visual features of the stimuli. Given that we correlated 12 visual features with each dependent variable, we used a Bonferroni correction (a = 0.004) to account for possible alpha inflation.

3. Results

As expected, arousal ratings tended towards the middle of the 9-point scale at the beginning of the experiment (see Table 2). However, both valence and dominance ratings tended to be slightly above the middle of the scale.

For ΔnSCR, the comparison between the three-fixed-factor model and the two-fixed-factor model did not reveal a significant interaction between LANDSCAPE and SCENARIO ($X^2(6) = 7.631$, $p = .266$). The comparisons between one-fixed-factor models and null model did not reveal a significant effect of LANDSCAPE on ΔnSCR ($X^2(6) = 5.674$, p = .461) but did reveal a significant effect of SCENARIO on ΔnSCR ($X^2(1) = 8.262$, p = .004). This effect suggests that physiological arousal was higher during videos with more RES (see Fig. 4).

For the preference data, the comparison between the three-fixed-factor model and the two-fixed-factor model revealed a significant interaction between LANDSCAPE and SCENARIO ($X^2(6) = 16.469$, $p = .011$). In addition, the comparisons between the one-fixed-factor models and the null model revealed significant effects for LANDSCAPE ($X^2(6) = 23.525$, $p < .001$) and SCENARIO ($X^2(1) = 6.181$, $p = .013$) on participants' preferences. Together, these effects suggest that participants preferred low RES (compared to high RES) and that this effect varied across landscapes. Notably, this trend is visible for each landscape except for PLAT_URB and PLAT_AGRI (Fig. 5).

We also found significant correlations between ΔnSCR and VIWT ($r(12) = 0.600$, $p = .024$), between ΔnSCR and OAISPP ($r(12) = 0.714$, $p = .004$), and ΔnSCR and SUB_ENTR ($r(12) = -.545$, $p = .044$). However, only the correlation between ΔnSCR and OAISPP survived a Bonferroni correction for multiple comparisons ($\alpha = .004$). See Table 3 for all of the correlations between ΔnSCR/preferences and high-/low-level visual features. In Appendix C, we report additional correlations between ΔnSCR and the component scores for VIWT and OAISPP. Notably, none of the correlations between preferences and visual features were significant. Together, these results suggest that ΔnSCR was related to high-level visual features of the landscapes, although preferences (and not ΔnSCR) varied across landscapes.

4. Discussion

In the present study, we used behavioral and physiological measures to investigate the perception of renewable energy infrastructure in various landscape types. Towards this end, participants were shown pairs of videos based on LiDAR data from real locations in different landscapes of Switzerland and asked to choose their preferred video while we recorded their skin conductance. We can accept our main hypothesis that RES visual impact affects physiological arousal because participants' skin conductance was higher for stimuli with more RES. This trend was consistent for six of the seven landscapes. Our subhypothesis that these relationships could be explained by low- and high-level visual features was partially supported because physiological arousal was correlated with only 1 of 2 high-level visual features (i.e., the visual impact of photovoltaic systems; OAISPP). We can also accept our second hypothesis that RES visual impact affects landscape preferences because participants tended to choose stimuli with a low amount of RES (compared to high amounts), especially for alpine regions. Together, these results suggest that the combination of physiological and behavioral measures can be used to assess the impact of RES on landscapes and that landscape assessment needs to consider differences between individuals' responses to RES across different landscapes.

Most of our analyses use linear mixed models in order to investigate the effects of RES impact and landscape on physiological arousal and landscape preferences. These models allow us to find associations between aspects of the stimuli that we systematically varied (e.g., the amount of RES in a video) and participants' responses that we measured (e.g., physiological arousal). One of the main advantages of linear mixed models is that we can account for variations in the data that can be attributed to less relevant aspects of the stimuli (i.e., random factors). For example, the order of landscape pairs among trials was considered a random factor because its effects were not relevant for our particular research questions, although they might be relevant for other studies.

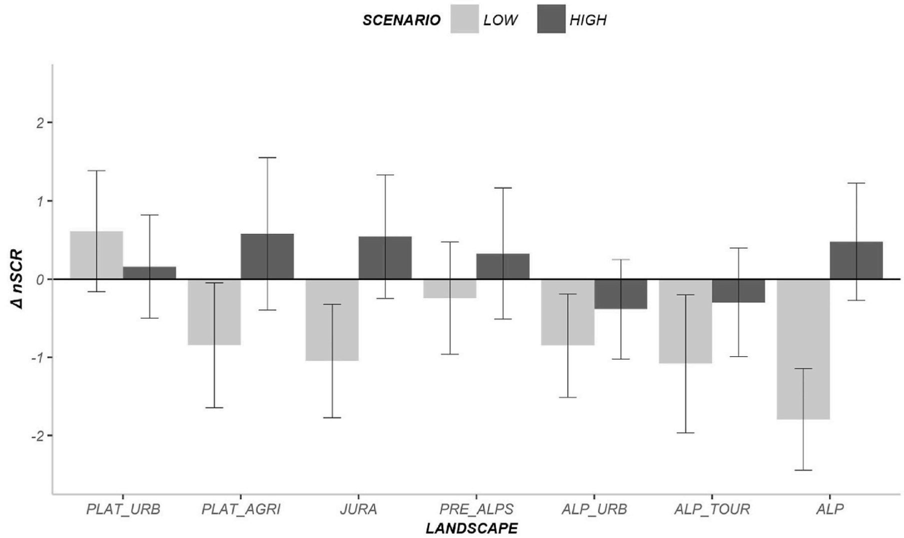
The effect of the amount of RES (SCENARIO) on changes in physiological arousal (i.e., ΔnSCR) suggests that participants were more physiologically aroused when viewing landscapes with more RES. In addition, the correlation between the visual impact of photovoltaic systems (OAISPP) and changes in physiological arousal ΔnSCR indicate that this effect may be primarily attributable to the presence of more photovoltaic systems in the landscape. This finding extends previous research that has employed questionnaires (e.g., the SAM) in order to investigate the impact of varieties of photovoltaic systems on buildings [30]. While Sanchez-Pantoja and colleagues [30] demonstrated a difference in self-reported arousal between photovoltaic systems that are either completely integrated into the building envelope or mounted using metallic supports on the roof of the building, we found a difference between different amounts of photovoltaic systems (in general) on physiological arousal. Future studies should assess in what circumstances physiological or questionnaire methods are more appropriate for landscape assessment.

Previous research has also found that wind turbines were more physiologically arousing compared to churches (but not other industrial constructions) in landscapes [36]. Moreover, Johansson and Laike [12] found that a composite measure of emotional states predicted the intention to accept wind turbines. Consistent with this research, we found a positive correlation between visual impact of wind turbines (VIWT) and physiological arousal, possibly indicating that landscapes with more wind turbines were related to higher physiological arousal. This possible correlation must be interpreted with caution because it did not survive a correction for multiple comparisons. Nonetheless, our study can motivate future evaluations of more fine-grained measures of visual impact such as the distance of wind turbines from the observer.

Notably, the relationship between RES scenario and physiological arousal was consistent across six of the seven landscape types we tested. For the urban plateau landscape (PLAT_URB), the numerical difference between high and low scenarios was in the opposite direction (i.e., higher for the low RES scenario) of all of the other landscapes tested. This trend may be attributable to the number of objects in the foreground of the PLAT_URB stimulus. In urbanized scenes, buildings and other urban infrastructure may divert attention from the renewable energy infrastructure in the landscape. It is possible that participants in the present study focused their attention on these foreground elements. According to psycho evolutionary theory [85], one would expect no difference between our low and high scenarios for PLAT_URB if participants primarily attended to unaltered infrastructure in the foreground. However, we obtained slightly higher physiological arousal for the low RES scenario of this particular landscape than the high RES scenario.

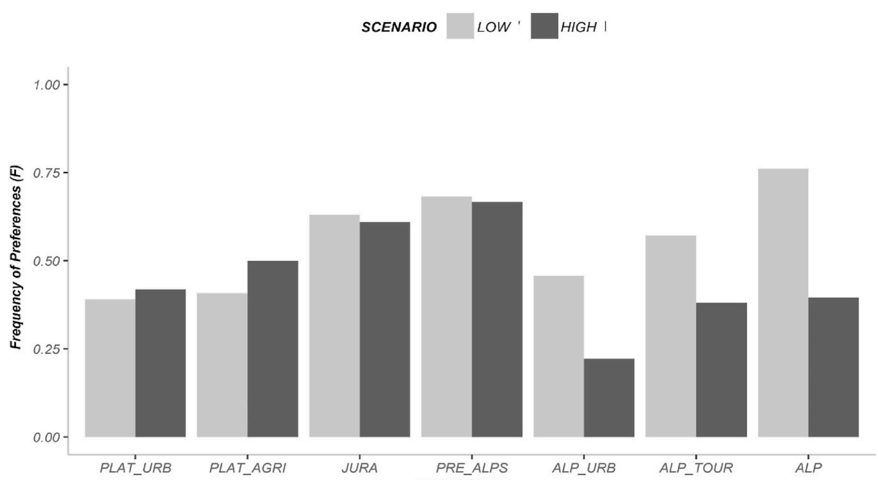
Table 2
Participants' (N = 99) SAM ratings on a 9-point Likert scale (1:9).

SAM dimension	Median	Mean	SD	5th percentile	95th percentile
Arousal	5	5.39	1.42	3	8
Valence	7	7.19	1.04	6	9
Dominance	7	7.18	1.29	5	9



	PLAT_URB LOW	PLAT_URB HIGH	PLAT_AGRI LOW	PLAT_AGRI HIGH	JURA LOW	JURA HIGH	PRE_ALPS LOW	PRE_ALPS HIGH	ALP_URB LOW	ALP_URB HIGH	ALP_TOUR LOW	ALP_TOUR HIGH	ALP LOW	ALP HIGH
M	.631	.161	-.884	.579	-1.003	.545	-.243	.325	-.849	-.386	-1.081	-.296	-1.79	.478
SE	.772	.661	.801	.974	.724	.789	.719	.839	.662	.637	.886	.695	.647	.748
N	41	43	49	38	46	41	44	33	35	54	35	50	46	38

Fig. 4. *Mean ΔnSCR (M) for each combination of LANDSCAPE AND SCENARIO. Each error bar represents the standard error of the mean (SE). N represents the number of trials in which each stimulus was presented.*



	PLAT_URB LOW	PLAT_URB HIGH	PLAT_AGRI LOW	PLAT_AGRI HIGH	JURA LOW	JURA HIGH	PRE_ALPS LOW	PRE_ALPS HIGH	ALP_URB LOW	ALP_URB HIGH	ALP_TOUR LOW	ALP_TOUR HIGH	ALP LOW	ALP HIGH
M_{Pref}	.390	.419	.408	.500	.630	.609	.682	.666	.457	.222	.571	.380	.761	.395
N_{CHOICE}	16	18	20	19	29	25	30	22	16	12	20	19	35	15
$N_{NOCHOICE}$	25	25	29	19	17	16	14	11	19	42	15	31	11	23

Fig. 5. The proportion of preferences for each combination of LANDSCAPE AND SCENARIO. Here, N represents the number of trials in which the stimulus was presented.

Because this pattern cannot be explained by any of the other high- or low-level visual features we tested, future research can employ eye-tracking studies in order to address these issues directly. With additional landscape stimuli, these studies may also have sufficient statistical power to explain these differences in terms of visual features.

There was a correlation between the low-level visual feature of subband entropy (SUB_ENTR) and physiological arousal, suggesting that higher SUB_ENTR was related to lower physiological arousal. This correlation must also be interpreted with caution because it did not survive a correction for multiple comparisons but is consistent with previous research. According to information theory [86], entropy is inversely related to redundancy. In a visual image, entropy represents difficulty in predicting particular features given their surrounds. For example, Stamps [2002] found a linear relationship between an entropy-based measure and self-reported pleasure in a landscape context. In the present study, we employed SUB_ENTR specifically as a measure of visual entropy at a particular spatial frequency. According to Rosenholtz et al. [64], lower values of the measure SUB_ENTR can be understood as more redundant information in the images [64]. For the stimuli used in the present study, images from the high RES scenario (mean = 4.079) had slightly lower mean SUB_ENTR than images from the low RES scenario (mean = 4.126), and this difference was consistent across six of the

Table 3
Correlation coefficients (r) and significance levels (p)) for the correlations between ΔnSCR/preferences and the high-/low-level visual features of the stimuli. Asterisks denote the correlation that survived a Bonferroni correction (alpha = .004) for multiple comparisons. For each correlation we report N = 14 measurements.

	Dependent variables			
	ΔnSCR		*Preferences*	
Independent variables	*r*	*p*	*r*	*p*
High-level visual features (calculated RES visual impact)				
Visual impact of wind turbines (VIWT)	.595	.024	-.390	.168
Objective Aesthetic impact assessment of solar power plants (OAISPP)	.714	.004 *	-.275	.341
Low-level visual features				
FC	-.231	.427	-.503	.067
SUB_ENTR	-.545	.044	-.202	.489
JPEG	-.232	.425	.055	.852
EC	-.175	.550	-.367	.197
FRACT	-.008	.978	.426	.129
SF_LOW	.126	.580	-.263	.364
SF_HIGH	-.253	.383	.514	.060
HUE	.445	.111	.072	.807
SAT	.037	.900	.479	.083
HUE_SD	-.237	.415	-.367	.197

seven landscapes. Therefore, lower entropy may be the result of more repetitive spatial (e.g., line orientation) and color information in the images. This trend would indicate that renewable energy infrastructure influences the aspect of redundancy in the landscapes and that this redundancy affects people's physiological reactions.

Regarding the preference data, participants tended to prefer the low RES scenarios compared to the high RES scenarios, especially for the alpine landscapes (i.e., ALP_URB, ALP_TOUR, and ALP). Notably, only the plateau landscapes (i.e., PLAT_URB and PLAT_AGRI) led to slightly more preference for the high RES scenario than the low RES scenario. These results have important implications for the addition of RES in Swiss landscapes and to support the transition towards renewable energy production worldwide. Specifically, citizens may be especially opposed to RES interventions in alpine regions. These results may appear to conflict with Michel and colleagues [57] who found that photovoltaic systems were well-accepted for high alpine regions, particularly when mounted on existing infrastructures such as avalanche barriers. However, this disparity may have resulted from our comparison of a high versus a low amount of RES with a natural landscape as the background instead of other risk protection or energy infrastructure (e.g., dam of a hydropower plant) with and without photovoltaic systems. There are two possible explanations for the landscape preferences we observed in the present study. First, alpine regions may differ from the other regions in terms of high- (e.g., VIWT) or low-level (e.g., spatial frequency) visual features. Second, there may be a particular cultural attachment to alpine regions. Future studies will need to further disentangle these possible explanations with targeted questionnaires. Since still a major portion of the global energy production comes from conventional or nuclear energy systems, we motivate other studies to specifically compare people's physiological reactions between renewable, conventional, and nuclear energy systems. This leads to a better integration and comparability of our results with other energy infrastructures which people are more familiarized compared to RES.

One potential limitation of our study was that the sample was restricted to young academics who had a political attitude that tends to be environmentally protective. We purposefully excluded older people because of decreases in the strength of their physiological signals found by previous research [87]. However, future studies can systematically assess the effects of affiliations with political and environmental groups on EDA in the context of RES visual impacts. In addition, generating our visual stimuli was time consuming compared to image manipulation based on photographs. However, with this visualization approach, we ensured that the videos were comparable among different types of landscapes. This was necessary to properly measure and analyze the physiological signal with respect to different landscape types and different levels of RES visual impacts.

5. Conclusion

The present study demonstrated that people's physiological arousal and preferences can be influenced by the visual impact of RES interventions and differences between distinct landscapes in Switzerland. For policy makers, these results may inform decisions related to the amount and placement of RES in Switzerland. However, future research is needed to elucidate the specific mechanisms underlying the relationship between emotional states and landscape preferences. For example, researchers can ask participants to rate landscape stimuli individually instead of pairwise comparisons. This approach also has the advantage of easily determining the original scale [88] but often results in higher variance, less accurate results, and more time-consuming data collection [89]. While neither preference nor arousal data necessarily indicate acceptance by the general population, the present study represents one step towards understanding landscape perception and public opinion regarding RES interventions. Future studies may extend this approach to include other dimensions of emotion (e.g., valence) and other landscapes outside of Switzerland.

CRediT authorship contribution statement

R. Spielhofer: Resources, Formal analysis, Visualization, Investigation, Data curation, Writing - original draft. **T. Thrash:** Conceptualization, Formal analysis, Writing - review & editing, Validation. **U. Wissen Hayek:** Project administration, Visualization, Investigation, Resources, Writing - review & editing. **A. Grêt-Regamey:** Funding acquisition, Conceptualization, Supervision, Writing - review & editing. **B. Salak:** Writing - review & editing, Visualization, Validation. **J. Grübel:** Methodology, Data curation, Software, Writing - review & editing. **V.R. Schinazi:** Funding acquisition, Conceptualization, Methodology, Validation, Writing - review & editing, Supervision.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2020.110410.

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