Shedding light on the usability of ecosystem services–based decision support systems: An eye-tracking study linked to the cognitive probing approach

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Graphical abstract

Abstract

The requirements for communicating ecosystem services (ES) information often are not considered in operationalizing ES concepts. In particular, the heterogeneous uses of ES require different functionalities and qualities for the information provided, which must be considered when processing ES data into different types of information. The relevant factors that influence the usability of ES information include the users' knowledge and cognitive ability as well as case study-specific factors. This missing knowledge can affect the transformation of the ES concept into practice, thus preventing the use of ES for further development or for transformation to sustainable management. Providing information that is relevant and useful for decision-making thus depends on understanding potential users' demands and their cognitive processes involving the information in making decisions.

In this contribution, we present the evaluation of specific design features of a prototype ES decision support system assessed in an eye-tracking experiment. The study was conducted with more than 100 participants who were split into two groups. The participants in both groups had a background in spatial planning but differed in their connection to the case study region. The tool presented various GIS-based modeled land-use scenarios driven by a new spatial planning policy recently adopted in Switzerland that lead to various impacts on ES in the region. The ES information was shown with additional land-use indicators as well as information about the landscape aesthetic in landscape visualizations. The results show that there were significant differences between the participants in the way they perceived, interpreted and used the information for ES-based decision-making tasks. We also identified critical key factors defining the types of representation of the information that influence perception and cognitive processes.

In summary, the results of the study provide design recommendations for representing ES information based on the intended use and identify critical representation features that could potentially influence the perception of ES information.

1. Introduction

In 2011, the European Commission (EU) adopted the EU biodiversity strategy to halt the loss of biodiversity and Ecosystem Services (ES) in the EU by 2020 (European Commission, 2012). The EU strategy targets public awareness of ES issues in addition to establishing education and communication campaigns as well as developing instruments for more effective ES management and providing information on ES. These targets are crucial elements of sound decision-making and therefore call for an improvement in and implementation of ES information in spatial planning tools and processes to provide ES-based reasoning and communication to stakeholders and the public. At the same time, the existing working group on Mapping of Ecosystems and their Services in the EU and its Member States (MESEU) has been investigating the best practices for supporting the improved implementation of ES information in policy and decision-making (MESEU, 2014). To achieve the strategy targets by 2020, information on the ES provided at the local scale is indispensable for implementing the information in spatial planning. In terms of communication strategy, ES information can be provided in a wide range of different types and scales, but clear guidelines on which types or scales are suitable for conveying this information to various types of users is lacking (Klein et al., 2015).

A new trend is to provide the public with spatially explicit environmental information—for instance, information on provision of ES—via streamlined, easy-to-use and often web-based GIS platforms (e.g., www.ecometrica.com). Some of

these platforms are specifically designed to provide relevant information in decision-making processes or to allow exploration of future scenarios (e.g., Wissen Hayek et al., 2015; Grêt-Regamey et al., 2013). Such platforms are also known as planning support systems or decision support systems (DSSs). In landscape and urban planning such DSS can contribute to support sound decisions that account for sustainable use of ecosystems and their providing services. The trend of such DSS emergence has been stimulated by modern information and communication technologies and policy strategies, such as worldwide access to broadband Internet (also an EU initiative; European Commission, 2015a). Furthermore, EU policy aspires to provide cross-national spatial information: For example, the EU's *Infrastructure for Spatial Information in the European Community* (INSPIRE) aims at establishing common data typologies for transnational environmental assessments and environmental policies (European Commission, 2015b). In addition, national laws for the provision of and public access to spatial information were passed in recent years, for example, in Germany (BMUB, 2012) and Switzerland (GeolG, 2007). With these regulations, access to environmental and ES information can also be enabled, allowing potentially easier use and implementation of administrative information in a DSS, which would facilitate transparency, credibility and legitimacy, as previous studies have shown (e.g., Wissen Hayek et al., 2015; Ruckselshaus et al., 2015; Pettit et al., 2011; Cash et al., 2003).

Empirical studies in spatial decision-making have shown that the amount of information affects the quality of the decisions (e.g., Jankowsky and Nyerges, 2001; Jelokhani-Niraraki and Malczewski, 2014). For example, as the number of alternative locations or criteria available in the decision-making process increases, stakeholders also need an increasingly deeper understanding of the relations and dependencies of the locations or criteria to assess and prioritize them (Jelokhani-Niraraki and Malczewski, 2015). Furthermore, recognition of relations and dependencies becomes more difficult, and users then tend to simplify their decision-making processes to avoid high cognitive demands for examining the information. Consequently, low-quality decision-making and a low level of consensus between decision-makers frequently occur (Jelokhani-Niraraki and Malczewski, 2015). Although the relevance of information integrated in a DSS facilitates the transparency, credibility and legitimacy of decision-making (Ruckselshaus et al., 2015), the best methods for representing information so that the users' decision-making process is most effectively supported and the level of information required for high-quality decisions remain unclear.

In general, to communicate is to transmit information so that it is understood and, typically, used to guide action. For environmental information, the relation and interaction between different environmental criteria make successful communication a complex, multifaceted task. This complexity is further increased by spatial information, which makes comprehensive understanding and, therefore, effective communication more difficult (Mors et al., 2010). The initially communicated environmental information hinders easy information transfer because of the multifaceted effects on other environmental criteria. Especially, the communication of combined environmental and spatial information can lead to complex socio-psychological interactions (Mors et al., 2010), including emotional reactions if recipients are personally affected or have a relation to an affected place (e.g., Veríssimo and Campbell, 2015; Rogge et al., 2011). As previous studies have shown, recipients can often cognitively link the communicated environmental criteria to landscape aesthetics (e.g., Junker and Buchecker, 2008). Such an extended perspective of non-DSS-included information (as they would be supported by landscape visualizations) can be based on either experience or knowledge of the place. These reactions can be identified over the course of participative landscape planning approaches in which stakeholders react and interact with provided information (e.g., Celio et al., 2014; Höppner et al., 2007). In contrast, a lack of information or criteria that are used for reasoning can affect the trust or confidence in a DSS, as there is a lack of completeness. Disinterest in participation or dissatisfying communication might be the consequence (Höppner et al., 2007). Most notably, not only the detail, comprehension and amount of information (e.g., indicators, criteria and localities) influence user emotions and behavior, but also the design of the presented information affects cognition and therefore the reasoning processes (Russo et al., 2014). Consequently, understanding the information requirements of DSS users can result in more comprehensive and improved communication and thus more effective and efficient decision-making due to the transparency, credibility and legitimacy of the information integrated in a DSS (Wissen Hayek et al., 2015; Ruckelshaus et al., 2015; Pettit et al., 2011). In summary, to determine how to provide the most effective and efficient information for users, two main aspects must be addressed: how to communicate environmental and ES information comprehensively and how to represent such information. Knowledge of these aspects can avoid negative effects such as a loss of trust and confidence, or emotional reactions that prevent an objective examination of the information (Pettit et al., 2011). Especially for DSSs, appropriate communication and presentation of information are important to support users with relevant and needed information in their personal decision-making strategy (Jelokhani-Niraraki and Malczewski, 2015; Vessey, 1991; Vessey and Galletta, 1991).

Novel techniques such as eye tracking (ET) make it possible to record humans' gaze and, thus, to research visual behaviors in a natural setting. With this technique, we can investigate how DSS users use information and apply a DSS. ET has been proven to be a helpful technique in user research, especially for the evaluation of visual stimuli in practical applications. With ET, the length and frequency that users look or gaze at particular areas of interest (AOIs) can be determined (Duchowski, 2007; Holmqvist et al., 2011). The position of the gaze is typically expressed using screen coordinates (i.e., pixels). From these basic screen coordinate measurements, various gaze metrics are derived in relation to the stimuli (screen display), such as the fixation duration or dwell time (i.e., how long a gaze is fixed on a certain AOI), fixation count (i.e., how often the gaze revisits an AOI), number of revisits of the AOIs and scan-path characteristics (e.g., length and speed of eye movements; Ooms et al., 2014). Although a new technique, ET has already been applied in many research fields, such as software engineering (e.g., usability tests; e.g., Jacob and Karn, 2003; Nivala et al., 2001), marketing (e.g., advertising placement, webpages, product label design; e.g., Goldberg et al., 2002; Pieters, 2008; Pieters and Wedel, 2004; Poole and Ball, 2006), psychology (e.g., reading, scene perception, visual search; e.g., Rayner, 1998, 2009; Recarte and Nunes, 2000) and landscape perception and design (Dupont et al., 2013; Duchowski, 2007). However, gaze behavior does not provide feedback about why DSS users focus on specific information. In other words, ET cannot be used to

determine whether the visually perceived information is relevant for reasoning or decision-making. However, a combination of ET and cognitive interviewing enables an investigation of usability of provided information. To understand this interaction between the use of information integrated in a DSS and cognitive processes, cognitive interviewing, which has been designed to capture cognitive processes and is supported by a large body of methodological research, must be applied (Campanelli, 1997; Campanelli et al., 1991; De Maio and Rothgeb, 1996; Dipbo, 1989; Esposito and Hess, 1992; Jabine et al., 1984; Jobe and Mingay, 1991; Jobe et al., 1993; Lessler and Sirken, 1985; Royston et al., 1986; Sirken et al., 1999; Willis et al., 1999; Willis and Schechter, 1997). Thus, by linking information provided by ET with knowledge of cognitive processes, users' manner of perceiving information provided by a DSS can be investigated.

With this study, we shed light on the usability of an ES-based DSS. We investigated what information is used and how this information affects users' cognitive processes and reasoning in decision-making. We designed a DSS that displayed ES information in various types of representation. Further, we developed an experimental design based on *functions in application* of ES information (Klein et al., 2015) to identify key types of representation for communicating ES information. Various functions in application and various experimental tasks were defined that prompted users to apply the information integrated in the DSS in various contexts. These functions in application describe the differences between the purposes the users were applying ES information. Klein et al.'s (2015) results showed that users demand or prefer specific display types or types of representation depending on the intention for using the ES information and thus on the specific function in the application. In the present study, during the experimental runs, the users' gaze behavior was measured with eye tracking to identify which ES information was used. We also developed a set of cognitive probing questions to investigate users' reasoning based on perceived information. Finally, to understand how users' attachment to a location influences their use of information, reasoning and decision strategy, we applied a split-sample design that separated users with and without connections to the region.

2. Methods

In the following section, we describe (1) how the ES information was presented by various types of representation integrated in the DSS and (2) how we determined specific user behaviors on the intention of applying the ES information. For the latter, we used ET parameters to analyze the participants' gaze characteristics in information use and cognitive interviewing to identify relevant information for certain decision-making and reasoning. To combine the methodologies, we developed a set of probing questions, specifically tailored to the study's tasks. Further, information on the participants' connections to the case study region were also collected to investigate whether familiarity with the region affects reasoning and use of the ES information. The measured ET parameters were analyzed with a repeated-measures analysis of variance (ANOVA) and linked to feedback from the cognitive interviews.

2.1. DSS content and case study region characteristics

The region is characterized by increasing settlements in total area through an expanding secondary sector (+87 ha) and higher average spatial demand per person (+18% on average; BFS, 2015). The resulting land-use conflict between fertile farming land and suitable settlement areas has led to a loss of ES and original landscape characteristics in the region, a development that could cause loss of attraction as a tourist destination (Brand et al., 2013). The landscape is further structured in small and often badly accessible or badly cultivable agricultural areas, especially in more remote areas. The most fertile and most accessible farming land is located at the bottom of the main valley directly adjacent to the city of Visp, which also recorded the highest increase in settlement area within the region (BFS, 2015; VSGIS, 2015). In the peri-urban to rural surroundings of Visp, the primary sector is still the most important source of income other than tourism (Brand et al., 2013).

The case study region in the Canton of Valais, Switzerland, covers a total area of 348.8 km² and is home to 16,021 residents (as of 2013; BFS, 2015). The largest city, Visp, is located in the main valley, to which the valley of Saas is connected in the south and the valley of Baltschieder in the north (Fig. 1). The valleys are surrounded by alpine terrain. The Rhone River flows through the main valley. Twelve municipalities are located within the region, all within the Visp district: Baltschieder (658 m a.s.l.), Eisten (1,086 m a.s.l.), Saas-Balen (1,483 m a.s.l.), Saas-Fee (1,798 m a.s.l.), Saas-Grund (1,559 m a.s.l.), Saas-Almagell (1,672 m a.s.l.), Stalden (795 m a.s.l.), Staldenried (1,052 m a.s.l.), Visp (658 m a.s.l.), Visperterminen (1,378 m a.s.l.) and Zeneggen (1,370 m a.s.l.). The one exception is the village of Eggerberg (846 m a.s.l.), which is in the neighboring Brig district.

Fig. 1. Case study region, Visp district. The profile shows the bottom of the valley starting at the counter-slope in Eggerberg, down to Visp and upstream to Saas-Fee.

The DSS shows changes in land use and ES under various socio-economic and climate scenarios in the region. Mountain cultural landscapes that developed during centuries and millennia are undergoing rapid transformation, leading to a growing loss of the ecosystem services (e.g. food production by agriculture) demanded by people living in and outside these areas. Whereas settlement expansion is nurtured by a better transportation infrastructure and the expansion of service and manufacturing industries, structural changes in the agrarian sector have led to an intensification of agricultural land-use practices and the associated decline in semi-natural habitats. The content is based on model outputs generated by a modeling framework consisting of a spatially explicit agro-economic optimization model linked with a cellular automata based settlement allocation model. The GIS model couples agro-economic land allocation modeling and settlement expansion modeling to explore the effects of spatial planning instruments on ES provision. The modeling framework links two models: a recursive-dynamic agent-based land-use model (the Alpine Land-Use Allocation Model, ALUAM) and an automated settlement transition model (the Dynamic Settlement Allocation model, DSA). Both models are spatially explicit with a resolution of 100 m x 100 m per raster cell. Based on a land-use map as well as agro-economic input data, the ALUAM simulates land-use changes and ES provision in agriculture and forestry under different scenarios by maximizing the aggregated income of farmers and foresters in the region. The resulting land-use map was subsequently transferred to the settlement allocation model DSA. The DSA then calculated the demand for new settlement area in the region and allocated the required number of settlement cells based on the location factors and the ES. The scenarios demonstrate that spatial planning is key for shaping mountainous landscapes and supporting ES. Cooperation among municipalities and an explicit consideration of ES can inform ES trade-off decisions under the pressing demand for land.

For this study, two scenarios were selected and visualized on the DSS. In scenario A, new settlement cells can be allocated freely adjacent to existing settlements, and municipalities are cooperating to distribute the new settlement cells. In scenario B, new settlement cells are allowed only in designated building zones.

2.2. DSS integrated types of representation

Based on Klein et al.'s (2015) work, an experimental design was developed to identify types of representation for communicating ES information. The method builds on analyzing participants' behavior while they use ES information. Fig. 2 shows the DSS on a display monitor, which was used as the DSS user interface for the experiment.

Fig. 2. Decision support system with ecological services information provided by various types of representation.

All ES information in the DSS was available in more than one representation; thus, the participants could prioritize which representation type they want to use for different tasks. *Table 1* shows how the information of the various types of representation was linked. *Direct information* (grey cells, *Table 1*) means that the specific information could be read out directly from a representation type, *whereas linked information* (yellow cells, *Table 1*) means that the same information content was also represented by another representation type. *Potentially linked information* (blue cells, *Table 1*) means that information can be connected to information from other types of representation in a more inferable way. Last, *inferable information* (green cells, *Table 1*) indicates that a deeper understanding of the data was required for further information gain. For example, by switching between the two scenarios the participants could have read that the settlement area was constant over the area but varied among the municipalities. Such varying settlement area deployment on municipal level also affected potentially different increases in noise stemming from increased traffic because of additional settlement areas in peri-urban municipalities. However, this information was not shown in the DSS, and participants had to be aware of the potential consequences of peri-urbanization to draw such a conclusion.

Table 1

Links and interdependencies between types of representation and the information content.

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direct information

linked information

potentially linked information

inferable information

All information describing or resulting from a scenario (e.g., scenario definition and constraints, ES loss and land-use impacts) was grouped as AOIs, which were used as the units for the ET experiment (Fig. 3). The AOIs corresponded to the main representation categories identified in Klein et al.'s (2015) demand analyses. The AOIs were comprised of visual and non-visual representations and covered similarly sized areas on the DSS screen, which consisted of eight AOIs. A *realistic landscape visualization* (R0) showed a view of a settlement area in the municipality of Visp in 2034. In addition to changes in the number of buildings, the visualization showed agricultural changes with different types of meadow (intensive vs. extensive use) varying in growth height and vegetation composition. Information on land uses over time from 2014 to 2034 in 5-year increments was provided by a combined *bar and pie chart* (R1). This information was available at the municipal and regional levels. Additionally, this representation allowed the participants to investigate either the total area of the land-use type per time step or the proportions per year. Using this representation, the participants related information from finer scales (e.g., municipality) to the entire region. In a *thematic 2D map* (R2), land-use information was presented as a raster map, which showed intensive and extensive meadows and pastures, as well as settlement areas, forest and uncultivated land on top of aerial images and thematic map layers. The participants interacted with this thematic 2D map by zooming and panning, for detailed inspection of the sites (e.g., investigate the location of the municipalities). In the *photorealistic landscape visualization* (R3), the municipality Saas-Fee in 2034 was shown. Between the scenarios, the number of buildings in this visualization changed. A short scenario description was provided as a *text/abstract* (R4) that contained information about the scenario preconditions. Additionally, scenario constraints were shown with *icons* (R5) for quick identification of the differences between the scenarios. The various icons were explained at the beginning of each trial. Furthermore, mouse-over tool tips were available for the icons. The potential loss of various ES (noise emission (recreation/quietness), visual vulnerability (aesthetics), demand on free space (recreation nearby), ecological connectivity (habitat function), agricultural production (food production) and ground water (protection, ground water recharge) in 2034 was displayed as a *stacked bar chart* (R6) by municipality. The settlement area in 2014 and 2034, again differentiated by municipality, was also displayed as a *stacked bar chart* (R7). A *grouped bar chart* (R8) was used to depict the development of agricultural production in 5-year increments for various agricultural products (i.e., meat, crop, milk and total).

Fig. 3. Various types of representation (R0–R8) defined as the areas of interest (AOIs).

Data from the modeling framework was provided as an ASCII table. These data were either converted to a Key Markup Language (KML) map presented by Google Maps API (<http://developers.google.com/maps>) or linked to various chart visualization libraries using various D3js JavaScript libraries (www.d3js.org). KML and Google Maps were used for the *thematic 2D maps* (R2), whereas the diagrams (R1, *pie and bar chart* for the whole study region land-use information; R6/R7, *stacked bar charts* for the potential ES loss, and current and new settlement area; R8, *grouped bar chart* for agricultural production) were generated with JavaScript. Both *landscape visualizations* were created separately with a photo montage in Adobe Photoshop (R3: *photorealistic landscape visualization*) or with 3dnature VNS software (www.3dnature.com), (R0: *realistic landscape visualization*). In addition, both landscape visualization types represented the land-use characteristics of the modeled scenario data. The user interface was programmed in web-based HTML language. HTML-based tags contained the various types of representation.

2.3 Study sample

The participants (n = 101) were university students who received invitations to participate in their classes and by e-mail. The study lasted from March to May 2015. The study participants were subdivided in two user groups: The first group (n =

50) had no direct connection to the region and consisted of spatial planning or environmental science students from the Federal Institute of Technology (ETHZ) in Zurich, and the second group (n = 51) consisted of persons with a direct connection to the study region or the region of Valais and were tourism students at the Haute école spécialisée de Suisse occidentale (HES-SO) Sierre. Both student groups had a common background in sustainable planning. All participants were undergraduates or had received a bachelor's degree; 62.7% (n = 64) of the participants were female, and 37.3% (n = 38) were male. Most participants were between 21 and 30 years old (82.4%, n = 84); only 6.9% were 20 years or younger (n = 7). More than half (56.9%; n=58) of the participants had previous personal experience with the topic, and 52% (n = 53) had worked on the topic as part of their occupation or studies. Nearly a quarter of the participants in the second group (24.5%; n = 25) indicated that they personally or their family members or friends would be directly affected by the impacts of the scenarios.

2.4 Experimental design

To cover a broad set of *functions in application* (i.e., the intention to use the information as described by Klein et al., 2015), a set of nine tasks (nine stimuli) was defined to analyze how users applied the ES information integrated in the DSS when they faced a question to which the answer could be derived from the information. The definitions of the possible basic functions of ES information in the DSS are based on Brömmelstroet's (2013) work and consist of informing about, communicating and analyzing content, which also describes the intention to use the information integrated in a DSS. In a previous study (Klein et al., 2015), we developed a more detailed set of these *functions in application* to differentiate among the detailed properties of various demands (e.g., *exploration of content*, *spatial analysis*, *support of assessment*, Table 2). With these more concrete *functions in application*, it becomes possible to understand the relevant stages of individual reasoning and decision-making processes (Klein et al., 2015; Keller, 1997; Simon, 1960; Sugumaran and de Groote, 2011). Table 2 shows the tasks participants were exposed to with the related *functions in application*.

Table 2
Definitions of tasks based on the functions in the applications.

ID	Function in application	Task	Time	Scenario number ****
Task 1 (T1)***	Content information	What information can be extracted or inferred from the DSS? What might the overall topic of the information?	4'	1
Task 2 (T2)**	Communication of content	Please describe the scenario characteristics.	2'	1
Task 3 (T3)*	Exploration of content/ support of analyses	Please show how the scenarios vary. How do you interpret this difference(s)?	2'	2
Task 4 (T4)*	Support for spatial analyses	In which locations are the biggest difference(s) between the scenarios?	2'	2
Task 5 (T5)*	Support for estimates/ scenario development	Please estimate how the scenarios would result if there were no new settlement area in the municipality of Visp in 2034.	2'	2
Task 6 (T6)*	Support for assessment	Please assess the impacts of the new settlement areas in 2034 on the municipalities of Saas-Fee and Visp.	2'	2
Task 7 (T7)*	Support for aesthetic assessment/decision-making	Please assess and decide which scenario provides the most beautiful landscape.	2'	2
Task 8 (T8)*	Support for decision-making	Please assess and decide for this scenario which one is the most ecologically sustainable.	2'	2
Task 9 (T9)****	Support for aesthetic assessment/decision-making	Please assess which of the scenarios provide the most beautiful landscape.	30"	2

* Randomly deployed in the experiment sequence between T1 and T9

** The participant was asked to explain simultaneously while the information was shown the scenario characteristics to the study attendant.

***	Introduction function to allow participants to initially identify what the topic is about with the information
****	Control function to identify differences in application characteristics between realistic and photorealistic landscape visualizations. Only representation type R0 (the realistic landscape visualization) and R3 (the photorealistic landscape visualization) were shown on the screen; they showed the same perspective of a settlement area of municipality Visp. For this task, both types of representation (R0 and R3) were displayed at the same time for both scenarios.
****	Fig. 4 shows the two scenarios in different types of landscape visualization that varied in the level of realism next to each other.

Fig. 4. Controlling task (Task 9) for identifying possible bias through the level of realism of the landscape visualizations.

All participants were shown a sequence of web-based HTML screens starting with a welcome site, an ET calibration site, and a thematic introduction, followed by experiment instructions and background information on the information by types of representation. The participants started each task whenever they were ready. As a reminder, the tasks were presented at the top of the DSS screen. The information was shown for only a limited time. During these time sequences of 2 to 4 minutes (depending on the task), the participants were asked to derive the answer for a task by concentrating on the information without talking to the study attendant (with exception of Task 2). After the set amount of time, the DSS and its information panels disappeared, the task or question was repeated and the participant was asked to answer. In addition to the main question of the task, two to three questions were asked to identify the participants' cognitive processes and to understand their reasoning (see *section 2.5.2*). Depending on the specific task, information on a second scenario was also available on a second screen, and the participants were allowed to switch between the screens. The task sequence was randomized, with the exception of Tasks 1 and 9 (Table 2). The data gathered in Tasks 1 and 9 were not considered for the ANOVA, because these data had either an introductory or control function. The complete study required 40 to 60 minutes per participant, depending on the rate and complexity of the answers. The total time that the information screens were presented to the participants was 18 minutes 30 seconds (Table 2).

2.5. Data acquisition, processing and analysis

2.5.1. Eye tracking

In the study design, the participants were asked to wear mobile SMI ET glasses (www.smivision.com) to capture gaze behavior when they looked at the DSS information on a 24 inch 16:9 monitor display with a resolution of 1920 x 1080 pixels. The ET glasses were a binocular eye tracker, which captured both eyes and computed the gaze position in a scene image. The scene image was captured by a scene camera located in the center of the glasses. To obtain accurate gaze positions, each participant had to perform a system calibration. The ET glasses measured the gaze pointer for both eyes with automatic parallax compensation with 30 Hz. Gaze pointer accuracy of 0.5° to 1.0° and a tracking range of 80°/60° horizontal/vertical assured the precise localization of the participant's gaze on the 1280 x 960 pixel scene video with 24 fps that was captured by the ET unit.

BeGaze™ analysis software by SMI (www.smivision.com) was used to process the raw ET data generated in the experiment. With BeGaze™, we calculated the variables *dwelt time*, *fixation count* and *revisits* of the AOIs, which were also used in the statistical analyses as suggested by Ooms et al. (2014), Dixon et al. (2014) and Vidal et al. (2013). The number of revisits of an AOI indicates its complexity: Users have to revisit the AOI repeatedly to link, analyze or compare the presented information together with other information. Dwell time and fixation count quantify the use of AOIs for the task at hand and identify the potential relevance of the information for answering the task question.

2.5.2. Cognitive interviewing

Cognitive interviewing is a general method that critically evaluates the transfer of information (Willis, 2005). So that respondents understand the questions correctly, technique and question design are important for cognitive interviewing. Think-aloud and verbal probing approaches assume that participants can report and even evaluate their own cognitive processes (Willson and Miller, 2014). However, the think-aloud method in combination with ET has been criticized (Oh et al., 2013). Verbal probing uses an afterwards/debriefing survey design that is more suitable in combination with ET and is appropriate for cognitive and decision process investigations (Caspar et al., 1999; Willson and Miller, 2014). Therefore, we decided to apply the verbal probing method.

In the debriefing survey, we included the four questions presented in *Table 3*. In the *recall and construct strategy* question, we asked for an explanation. To identify the overall ability and experience of using ES information to fulfill a task, in the *comprehension question* the participant was asked whether completing the task or answering the question was difficult and to identify his or her overall ability and experience. The participant rated the question on a binary scale ranging from *difficult* to *easy*. The *confidence identification* question was posed to identify the participant's confidence to investigate if and potentially why there were issues in fulfilling the task. The participants answered according to a 4-item Likert scale: *not at all sure*, *not sure*, *sure* and *very sure*. When the task included special terms (e.g., Tasks 7 and 8), we used another question to investigate the participant's term comprehension interpretation to identify whether there was bias through an incorrect definition or even a misunderstanding.

The participant's answers to the *recall and construct strategy* question were recorded in a protocol. In this protocol, all rationales by participants were collected and assigned to types of representation (AOIs) or further categories. For example, if the participants reasoned concretely by AOI assignable information, indicators or characteristics or stated therefore that he or she perceived this information by a specific AOI, the reasons were linked to these AOIs within the protocol. Furthermore, the various characteristics, elements and scales of the information provided by the different types of representation were protocolled (e.g., buildings, trees). We added a group of *other scales* that included *extended region*, if the participant wanted to reason by facts of outside the region at a larger spatial scale. We also added a group of *specific other locations*, if the reasoning was related to specific locations outside or inside the region. Other scales were *elevation-based location*, if the participant's rationales were based on altitude, and *thematic-based location*, if the participant related the location to specific areas that were defined by another topic (e.g., "everywhere there, where..."). These additional scale categories seemed necessary to compare the participant sample groups, as the participants with connections to the region could potentially have based their rationales on their knowledge of the place. Another category *other rationales* was added, if the participant's reasoning was not based on the DSS information or indicators.

2.5.3. Statistical analysis

For each of the ET parameters *dwel time*, *fixation count* and *revisits*, we compared the average value per representation type and task. We used a repeated-measures ANOVA with IBM SPSS Statistics version 22 (www.ibm.com/spss), in which the participants were entered as random effects, because repeated measures were performed per participant (i.e., each participant fulfilled all nine tasks by using the types of representation). Additionally, we compared differences in the average ET parameters between the groups with and without a connection to the region. To determine the attractiveness of the types of representation, we also investigated the cognitive interview protocols with a descriptive analysis.

Table 3.

Cognitive probing question set by tasks (stimuli). Translated from German.

ID	Recall and construct strategy (1)	Comprehension identification (2)	Confidence identification (3)	Term interpretation (4)
Task 1	Why do you think this is the topic described by the information?	Was the question easy or difficult to answer and why?	How certain are you that this is the topic for which the information is provided?	-
Task 2	-	Was the question easy or difficult to answer and why?	How certain are you that you have communicated the scenario correctly?	-
Task 3	Why did you interpret the differences in this way?	Was the question easy or difficult to answer and why?	How certain are you that you interpreted the differences correctly?	-
Task 4	Why do you think that the biggest changes or impacts can be found specifically in these locations?	Was the question easy or difficult to answer and why?	How certain are you that you identified the locations with the biggest changes or impacts?	-

Task 5	Why exactly do you think that these would be the impacts?	Was the question easy or difficult to answer and why?	How certain are you of your estimates that these would be the consequences?	-
Task 6	Why exactly do you think that these would be the impacts?	Was the question easy or difficult to answer and why?	How certain are you about your assessments that these would be the impacts?	-
Task 7	Why do you think that the chosen scenario provides the most beautiful landscape?	Was the question easy or difficult to answer and why?	How certain are you that you have really chosen for the scenario the most beautiful landscape?	What do you understand under “beautiful landscape”?
Task 8	Why did you think that the chosen scenario is ecologically sustainable?	Was the question easy or difficult to answer and why?	How certain are you that you really have chosen the most ecologically sustainable scenario?	What do you understand under “ecologically sustainable landscape”?
Task 9*	Why do you think that the chosen scenario provides the most beautiful landscape?	-	-	-

* Task 9 is defined as a control task to identify potential bias of the landscape visualization types (realistic vs. photorealistic) (see Table 2, Fig. 4)

3. Results

The results show that there are specific preferences in using ES information provided by types of representation. This user behavior depends on the *function in application* of the ES information. In other words, the intention of information use determines the preference for a certain representation type. For example, visual information in general was more preferred compared to texts or abstracts. To answer general questions, information presented on a small scale was preferred to large-scale information. However, information on a large scale and therefore more detailed information could improve the quality of the answers. The participants’ connection to the site often influenced their reasoning and therefore the use of the scale of information. Such effects depend on the information depth and detail provided by a representation type and on the experience that participants have with specific types of representation, as well as the availability to link their knowledge of the place to the information provided. Participants with a connection to the region for which the ES information was provided exhibited other behavior than participants without a connection to the region. This effect was also identified in the cognitive interviews.

3.1. Eye tracking

Depending on the information necessary to solve a certain task, participants exhibited different strategies for acquiring relevant information, by using the various types of representation. Fig. 5 shows this different use of the types of representation by task. This behavior varied for all tasks, and strong diversity in the preferred information by types of representation existed. Knowledge of place further affected the participants’ reasoning and decision-making strategy. The ET data showed a significant relationship between tasks and types of representation (Fig. 5; Huynh-Feldt’s sphericity test (dwell time: $p = 0.363$; fixation count: $p = 0.398$; revisits: $p = 0.487$). The univariate analysis results for the ET parameters of the types of representation (AOIs) showed high dependencies on tasks and therefore preferences depending on the intention to use ES information (dwell time: $p = 0.000$, $F = 26.888$, $df = 17.410$; fixation count: $p = 0.000$, $F = 27.757$, $df = 19.117$; revisits: $p = 0.000$, $F = 22.093$, $df = 23.385$). Because the results for the ET parameters dwell time and fixation count (Table A2 and A3) were almost identical, we focus on dwell time in the following paragraphs.

The value of revisits of an AOI can be seen as an indicator of the complexity of a representation type. It can be inferred that if a representation type contains either comprehensive information or the information is difficult to remember, participants revisit a representation type more often. However, it is remarkable that types of representation with a high revisit count were preferred for specific tasks although the required information was available from other types of

representation with a lower revisit value (i.e., types of representation that were easier to read). Consequently, it seems that the complexity of the ES information does not discourage participants if it is in line with their intention to apply the DSS (*function in application*).

The following results indicate that the participants also made assumptions about the effectiveness of the types of representation. This was particularly influenced by titles of types of representation, from which the participants interpreted their relevance for the tasks. For example, the titles for R0 and R3 were about landscape scenery, but R6 included information about landscape aesthetics. In contrast, R0 and R3 were limited by their information but were preferred for Task 7. This behavior seems to have been based on experience or expectations of representation type's title or even characteristics. The participants reported afterward that they had estimated, because of the time limitation, from which representation type they could receive the most supportive ES information to answer a task-specific question. Especially, such behavior was identified for Task 4 and Task 7, where *thematic 2D map* (R2) for a spatial analysis and *landscape visualizations* (R0 and R3) for an aesthetic assessment/decision-making were mostly used. The most supportive information for both tasks was provided by the *stacked bar chart* (R6) that contained the indicator about the visual vulnerability, whereas the information content of the preferred types of representation used for the tasks was either limited to a location (R0 and R3) or consisted of generic land-use information (R2).

Further, interactive types of representation, for example, provided by *interactive pie and bar chart* (R1) and *thematic 2D map* (R2), were not used above-average. The interactive functionality of these two types of representation was used only if the participants recognized the relevance for specific tasks, as it was given by Task 4 (*support of spatial analysis*).

Fig. 5. Estimated mean dwell times [ms] for the types of representation separated by tasks, $n = 101$ ($n = 50$ without/
 $n = 51$ with a connection to the case study region).

Finally, texts/abstracts were the most unappealing types of representation. R4 and R5 consisted of texts or abstracts, and we observed that specifically for these types of representation the dwell times were shorter than average (Fig. 5). However, in this study both types provided important information about the scenario conditions; the texts explained the scenarios (R4) and therefore provided easy differentiation between the scenarios. Even in Task 2 (*support of communication*), in which the participants were asked to communicate the scenario story face-to-face while the information was displayed, the text was mostly ignored. The same occurred for Task 3 (*exploration of content*), on which the participants had to explain the differences between the scenarios: R4 and R5 offered the required information but were mostly ignored.

For all tasks with the exception of Task 7, significant differences in the dwell times of the types of representation between the sample groups were identified (Fig. 6). For face-to-face communication (Task 2), participants without local knowledge used significantly more generic information provided by the types of representation on a small display scale (R1, R4, R5, R6). In contrast, the participants with a connection to the region preferred types of representation that provided location-specific ES information (R0, R3, R2). For scenario exploration or analysis (Task 3), participants with no connection to the region and therefore without local knowledge used the scenario descriptions (R4) and information about the potential ES loss (R6) to a significantly higher degree than the participants with local knowledge. This user behavior seemed to be contradicted by the data on spatial analysis in Task 4. However, this behavior can be explained by a lack of local knowledge: Participants without local knowledge spent more time with the map (R2) overall as they first needed to locate the municipalities before proceeding with information required to solve the original task (R7, R6). This effect can be also identified for Task 6 and the impact assessment of two municipalities (Task 6). The participants without knowledge of the location were required to initially locate both municipalities in the region before they performed a comprehensive assessment. A similar effect can be identified for the estimates of the indicators that were not represented and scenario development (Task 5), where participants without a connection to the region relied significantly more on information about the current and future sizes of the settlement areas within the municipalities (R7), as it explains a triggered event for potential ES loss (R6). In addition to the map (R2), landscape visualizations (R0, R3) were preferred by the participants without knowledge of place, whereas participants with a connection to the region used information that was not provided by the DSS significantly more (R8). At least for decision-making (Task 8), participants with a connection to the region also considered aesthetic information (R3) significantly more than participants without a connection. Thus, participants with a connection to the region tried to more comprehensively use the information and included rationales that were not

provided by the DSS triggering a comprehensive and more complex cognitive process (compare Task 2) than participants without a connection. This characteristic of task-specific preferences in ES information emphasizes the heterogeneous user demands due to their knowledge of place and therefore the resulting reasoning or decision-making strategy (see section 3.2.).

We also identified that participants generally spent more time on the *photorealistic landscape visualizations* than on the realistic landscape visualizations as identified by Task 9 (Fig. 6, see also Fig. 2). The reason for this participant behavior was the level of detail in the visualizations and therefore the number of visualized landscape elements and the time required to identify them. However, landscape visualizations with a higher level of detail supported improved landscape recognition as the participants with a connection to the region more easily identified the location presented by the photorealistic landscape than by the realistic landscape as was reported in the cognitive interviews.

More details about the differences between the participant groups and the ET variables are given in the tables in the Appendix.

Fig. 6. Differences in using [dwell times in ms] landscape visualization types (R0 and R3) and therefore preferences in level of detail between the participant groups.

Fig. 7. Differences between the dwell times [ms] of the participant groups by type of representation and tasks. Significant differences are highlighted in yellow ($p \leq 5\%$) and orange ($p \leq 1\%$).

3.2. Cognitive interviews

Results of the cognitive interviews showed that the participants' reasoning strategy was task specific. As with the eye-tracking study, in the interviews, we found that certain types of representation were preferred for specific tasks, because the participants reasoned by concrete information characteristics that were provided by only a single type of representation. Rationales brought up in the interviews often related to the scale of the preferred information. Interestingly, especially participants with knowledge of the location reasoned about the scales and with information/indicators that were not provided by the DSS although relevant information was provided to answer the question. Such a deviation from the provided information reflects that integrated ES information in the DSS potentially triggers the direction of the cognitive process and shows simultaneously that not all relevant topics were or even could be provided by the DSS that are required by participants for reasoning or decision-making.

Results of the cognitive interviews supported the results provided by the ET experiments; participants with a connection to the region generally reasoned more often with information not provided by the types of representation (12.66% of the total reasoning was based on other information) than the participants who had no connection to the region (only 4.2% of their total reasoning was based on information not provided in the DSS). In addition, the scale selected by the participants varied. Participants with local knowledge preferred the municipality scale (59.62% of reasoning) and other scales (6.69%). Participants without a connection to the region reasoned less about these scales in total (municipality scale: 54.33%, *other scales*: 3.91%) but used more general information about the total region as scale of reasoning (32.98% of total reasoning, compared to participants with connection: 25.11%).

The reasoning for aesthetic assessment and aesthetic decision-making (Task 7) varied considerably between the participant groups. Participants without a connection to the region reasoned more based on aesthetic values provided by the landscape sceneries (R0, R3), whereas participants with local knowledge used the potential loss of ES in municipalities (R6) for reasoning. This reasoning strongly varied between the two participant groups by non-explicit aesthetic decision-making for selecting the more sustainable scenario (Task 8). Here, participants with a connection to the region reasoned about the municipality scale in combination with scenario description (R5) and about indicators that were not presented, whereas participants without a connection to the region based their reasoning on the potential loss of ES (R6).

Using cognitive probing questions, diversity in knowledge/experience (comprehension identification) and understanding (confidence identification) were identified between the participant groups. Statistically significant differences existed between the participants' ratings for the level of difficulty for fulfilling a task, as well the belief in their reasoning. For example, in Task 2 (communication of content) both groups rated their confidence in their reasoning. Participants without a connection to the region considered this task to be easier than participants with local knowledge (mean value difference = 0.304, $p = 0.027$, $t = 2.237$). Task 4 (support of spatial analysis) also showed very significant differences between the groups in the difficulty of fulfilling the task. Participants with a connection to the area rated this task as easier than participants without (mean value difference = 0.268, $p = 0.004$, $t = 2.947$). Both significant differences can be explained by differences in local knowledge: In Task 2, participants with local knowledge exhibited more complex thinking and tried to consider other aspects than those provided by the DSS. However, they struggled to communicate about the scenario and their thoughts. This changed in Task 4, where local knowledge helped the participants directly analyze and infer spatial differences more comprehensively and complexly with *other rationales*, as opposed to participants who had no connection to the study area who had to spend time locating the municipalities first.

An investigation of the ET results compared with participant reasoning determined by cognitive probing (compare Fig. 7 and Fig. 8) illustrates that types of representation that showed information on a smaller scale were generally used to answer general questions about the region. For example, charts with information about the total region were preferred instead of information grouped by municipality, or to define the ecologically more sustainable scenario in Task 8, participants compared the total land-use information with potential ES loss by municipalities. More details about the differences between the participant groups and cognitive protocols are given in the tables in the Appendix.

■ users without connection to case study region
□ users with connection to case study region

Fig. 8. Bar plots showing the percentage of times that participants indicated which representation type (R1-R8) and additional factors were reasoned to solve certain tasks (Tasks 1 to 8).

4. Discussion

We found heterogeneous participant preferences for ES information presented in various types of representation. The specific demands for ES information to solve certain tasks—and therefore the ES information's function in application (Klein et al., 2015), as defined in our study—reflect the complexity of providing (decision) supportive information. However, a combination of various types of representation allowed the participants to customize the ES information in such a way that their personal preferences were met. This potentially led to a bias in using types of representation that were personally preferred but actually provided less supportive information for the task at hand. Participants may even have relied more heavily on less relevant information for decision-making because they chose the representation type based on its visual attractiveness instead of information relevance. Specific types of representation were preferred for certain tasks.

In particular, participant preferences for relying on types of certain ES information were context sensitive. Aspects that influenced participants' preferences and how they applied the available information included the topic of information, the reason why it was provided, the presented indicators and the details and scale of the information. Participants recognized situations in which needs and interests were not fully and clearly identified (e.g., Pettit et al., 2011; Bartke and Schwarze, 2015). If the ES information was not considered supportive, the participants ignored it for reasoning and decision-making. Instead, they relied on their experience and knowledge to bring in additional information that was not provided in the DSS. This effect was also described by Coussement et al. (2015); they concluded that a DSS that does not fully exploit all available information and neglects relevant information is unlikely to lead to optimal decisions. The authors also concluded that the opinions of experts, who are often the end participants in a DSS, must be heard during the design of the DSS to ensure that their needs are met. However, omission of information is not entirely inevitable and reflects the individuality of cognitive processes (Caspar et al., 1999). As our results show, there was no total individuality in the participants' cognitive processes. We identified differences between the participant groups and their reasoning as dependent on the participants' connection to the region. In addition, the availability of local knowledge seemed to affect decision-making. Participants with knowledge of the location based their rationales more on information not provided by the DSS, scales and even political issues, while using the ES information integrated in the DSS as a trigger to think or discuss about further impacts in the region. Natarajan (2015) emphasized the ways participants bring in this local knowledge for reasoning in participatory spatial planning. This reasoning of locals is often very detailed and explanatory based on personal experience (Natarajan, 2015). Thus, the cognitive processes and reasoning of the participants with a connection to the region were often more complex or included political rationales.

The visual complexity and therefore the reading, understanding and remembering of the information provided by the representation type also influenced its uses. Studies have shown that visual complexity and design influence participants' perception, preference and behavior (e.g., Machado et al., 2015; Quispel and Maes, 2014). In the present study, graphical information was used more than non-graphical information (for instance, text information). Although the text elements contained important information about the scenario, participants mostly ignored the text. With this behavior, scenario descriptions in R4 and R5 by DSS participants were ignored and therefore mostly not considered for reasoning, which shows that the participants were not able to weigh the importance of the information. This behavior likely was based on retrospection, which means that visual information, for example in charts, is easier to remember and to compare than text and numbers. Dilla and Raschke (2015) concluded that specifically graphical representations are more efficient and effective for spatial tasks (i.e., assessing relationships among data), while textual representations are more efficient and effective for symbolic tasks (i.e., extracting individual data values). Depending on the intention of the applied information, scaling, categorization and filtering of information clearly affect the frequency of use of a certain representation type. This behavior can be explained by cognitive cost-benefit theory, which poses that more efficient and effective decision-making results are accomplished when the problem representation matches the task (Vessey, 1991; Vessey and Galletta, 1991). Participants make compromises either in the complexity of reasoning or in the spatial scale of their reasoning, if the information does not entirely meet their demands. This behavior shows that DSS users are biased by the display scales of information. Thus, they find thinking on other scales or even "outside the box" by extrapolating or transferring information limited to municipalities and their characteristics to correlated indicators or dependent place specifications difficult. However, information about the region on a small display scale was used to analyze the proportions of the ES information by municipality in a larger scale context. For example, the participants struggled with the overall statements about the ES loss for the region, because this information was provided only by municipality, not in total for the region. Therefore, they reasoned only on a municipality scale about ES loss or instead used information provided on a regional scale. If they used other information for reasoning about ES loss, they often failed to infer and consequently link this information to ES, though. This behavior was also observed in the use of complex types of representation. If these types of representation comprised indicators that matched the information requirements for the specific task, they were used although they were more complicated to read. For example, the information about ES loss was, compared to the other types of representation, more difficult to read and to compare to the other information. Nevertheless, the participants employed this information because they had recognized its importance, and this was the only representation type that displayed the required information directly. Otherwise, if the participants did not want to refer to this representation type, they were forced to infer information about ES loss from other types of representation, which required a more complex cognitive process. Such user behavior supports Vessey's (1991) cognitive fit theory, which is a special case of the cognitive cost-benefit theory in which it specified that decision makers choose strategies that trade off the effort required to make a decision versus outcome accuracy (Beach and Mitchell, 1978; Payne, 1982).

The results showed that the participants used varying behaviors when they applied the ES information. These behaviors were mostly identified by the DSS participants with knowledge of the location. This local expertise led to alternative decision-making by using the information provided as a trigger while basing their reasoning on other information.

Identifying or existing knowledge consequently influenced this decision-making strategy. Fig. 9 shows the decision-making model based on the results in combination with the cognitive fit and cognitive best-fit theories (Vessey, 1991; Vessey and Galletta, 1991) and alternative decision-making strategies. Depending on additional constraints (e.g., time pressure to accomplish a task/making a decision), the participants chose between accuracy-optimized and effort-optimized decision-making. It seems that users depended their type of decision-making on their expertise, difficulty of tasks, or knowledge where to find the relevant information in DSS. Due to these factors, users were potentially stressed (i.e. effort-optimized) because of limited time frame and choose the type of decision-making individually. However, if the provided information did not match the cognitive notion, the participants mostly tended to develop an alternative decision-making strategy (non-solid arrow, Fig. 9). Finally, there was still the possibility that the participants did not want or were not able to make a decision due a lack of information, which led to inconclusiveness.

Providing additional supportive information could avoid precarious user reasoning and consequently support better decision-making. Although the amount of provided information may not be the critical factor in decision-making, an increase in information could influence the evaluation process (with more demand on time) and could therefore influence cognitive loops during decision-making (Jelokhani-Niaraki and Malczewski, 2014).

The amount of information in general influences a user's gaze. Results of other eye-tracking studies showed that fixation count and dwell time increased strongly with the number of AOIs (Vu et al., 2015; Horstmann et al., 2009; Lohse and Johnson, 1996; Reutskaja et al., 2011). In addition, the amount of information is a critical aspect that could lead to an overload of information in a DSS and consequently overstrain participants. In fact, it is unclear how the gaze data were biased in this study, because not all provided information was directly relevant or further used for reasoning. Additionally, time pressure (as was the case in this study) affects gaze behavior and therefore decision-making (Reutskaja et al., 2011). To avoid biased results through time pressure, we randomized the order of the tasks, and the AOIs were identical for all tasks. However, despite the unclear effects of time pressure, the results still show a diversity of participants' preferences in using ES information. The information provided did not change with the tasks, and Task 1 allow the participants to become acquainted with the information.

Fig. 9. Extended model of a representation-based decision-making process with alternatives strategies based on Vessey's (1991) and Vessey and Galleta's (1991) cognitive fit and cognitive best-fit theories, respectively.

The present study underlines the complexity of environmental communication and information provision. Especially for setting up a DSS, consideration of user demands is crucial, and relevant information must be integrated. For identifying and understanding these heterogeneous user demands and behaviors, requirement engineering approaches such as usability tests with ET are important and helpful (Klein et al., 2015). A demand analysis should be performed initially to identify user-relevant information, especially if there are heterogeneous user groups. Otherwise, DSS users are likely to ignore the provided information and not use it for reasoning. Instead, they use the provided information only as a trigger for accessing their own knowledge and experience and therefore do not work with the provided information. As a consequence, the DSS fails as a tool: Decisions are made without consideration of the provided information and are based solely on personal experiences and preferences. Consequently, there is a high risk that participants will be frustrated about the DSS or even ignore the provided information, because they cannot find common sense and reasons for common decision-making.

5. Conclusions

This study investigated user behaviors and cognitive processes while applying ES information integrated in a DSS. These results are information and user-group sensitive and do not necessarily support general statements about demands on ES information. Further, the results do not describe ES specific requirements. Instead, the study outlined the complexity of providing DSS and ES or environmental information as well as the relevance of user demands. The results of the ET approach show that the use of ES information by representation type depends on the intention of use. Further, cognitive processes varied among the participants. These results indicate the importance of multiple types of representation and the option of combining them to provide ES information.

Making general recommendations on how ES or environmental information should be represented and communicated is difficult. The information framework seems to be heavily context and user sensitive. In particular, the user behaviors and demands could vary among information content, region and reason or purpose why information is provided. This makes it challenging to meet all user demands. However, a good approach for covering such unpredictable user behaviors and demands is to provide a large set of types of representation that vary in visualization style, display type and scale. This allows users to filter and select the information they deem most supportive and relevant.

Furthermore, results show how the representation type characteristics of ES information influence the behaviors of users. Especially, detail and scale between applied information and reasoning is correlating, which describes the power of information provision and therefore the key for its operationalization. This could mean also in case of ES concept operationalization, tiered approaches are required as well as a variety of representing ES data to provide supportive information at different scales and for heterogeneous user groups.

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APPENDICES

Table A1

Overview of the types of representation (AOIs) with their characteristics (AOI coverage in DSS, interactive functionality), and information content.

(AOI)	Representation type	Information	Interactive	Time series*	AOI coverage**
R0	Realistic landscape visualization	Landscape scenery of municipality of Visp that shows a settlement area in 2034	no	no	7.4%
R1	Pie and bar chart	Land-use information for study region with additional time behavior for 2014, 2019, 2024, 2029, 2034	yes	yes	9.3%
R2	Thematic 2D map	Land-use information for study region in 2034	yes	no	11.9%
R3	Photo-realistic landscape visualization	Landscape scenery of municipality of Saas-Fee that shows a settlement area in 2034	no	no	10.6%
R4	Text/abstract	Short abstract about scenario preconditions and the general behavior	no	no	3.5%
R5	Icons	Scenario preconditions	yes	no	1.0%
R6	Stacked bar chart	Potential of ecosystem services loss for each municipality in 2034	no	no	10.6%
R7	Stacked bar chart	Settlement area in 2014 and 2034 for each municipality	no	yes	10.0%
R8	Grouped bar chart	Total agricultural production with the food products milk, meat and crop for 2014, 2019, 2024, 2029, 2034	no	yes	10.0%

* Information is provided for multiple years

** 25.80% of DSS coverage consist of background, task information, button to switch between scenarios, institute icons that was measured as “white space” and was not further considered in the analysis

Table A2

Mean values and standard deviations (SDs) of dwell times (DTs) in milliseconds for each representation type by task. Per task highest mean value for participant groups (Hypothesis 2) is marked in bold as well the three most used types of representation in total. Highlighted colors for types of representation correspond to the AOIs.

Task	Region*	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2	no	3.255	2.966	12.939	11.225	7.615	6.280	4.493	4.023	4.318	6.510	1.728	3.168	22.107	12.263	15.907	7.633	10.189	6.830
	yes	3.722	4.746	8.961	8.201	9.518	9.844	6.039	7.095	1.751	3.224	488	1.256	16.989	10.437	17.553	10.638	12.710	9.338
	total	3.493	3.962	10.911	9.954	8.585	8.306	5.281	5.820	3.009	5.241	1.096	2.461	19.498¹	11.600	16.746²	9.279	11.475³	8.263
3	no	3.538	3.260	12.344	12.125	9.698	9.861	2.977	2.929	8.833	15.361	5.564	8.797	18.748	14.268	14.570	7.842	7.173	6.038
	yes	4.615	8.080	9.340	10.282	8.905	9.380	5.204	8.054	3.583	8.717	1.829	4.037	17.650	12.522	16.968	11.528	6.879	6.533
	total	4.087	6.198	10.812³	11.269	9.293	9.579	4.113	6.178	6.156	12.641	3.660	7.021	18.189¹	13.351	15.793²	9.919	7.023	6.266
4	no	4.941	8.173	5.188	7.674	36.034	28.843	3.766	5.000	1.107	3.012	966	2.747	19.137	16.658	16.900	15.457	2.728	3.982
	yes	4.170	7.778	6.581	8.301	20.965	25.176	3.799	6.074	1.252	3.912	482	1.413	21.562	20.986	20.901	17.982	3.047	3.646
	total	4.548	7.944	5.898	7.991	28.352¹	27.946	3.783	5.546	1.181	3.484	720	2.174	20.373²	18.934	18.940³	16.830	2.891	3.799
5	no	4.872	5.690	7.215	8.337	12.639	14.361	3.297	4.057	4.296	7.632	2.358	4.121	20.857	12.593	20.435	12.495	4.762	5.191
	yes	4.679	5.043	9.553	10.921	13.381	15.985	4.169	7.680	2.765	4.312	1.834	3.647	17.961	12.559	15.401	9.773	5.817	5.587
	total	4.773	5.344	8.407	9.764	13.017³	15.140	3.741	6.161	3.516	6.184	2.091	3.876	19.380¹	12.597	17.869²	11.418	5.300	5.396
6	no	6.827	9.982	5.303	8.478	14.608	17.498	6.447	7.417	3.283	7.134	1.633	4.488	32.432	19.294	13.178	10.210	2.774	3.512
	yes	3.374	4.570	7.369	8.292	6.503	7.934	3.970	4.959	2.521	6.782	1.142	2.112	33.722	20.730	13.203	8.599	4.431	4.621
	total	5.067	7.867	6.356	8.406	10.476³	14.032	5.184	6.377	2.895	6.933	1.383	3.476	33.090¹	19.950	13.191²	9.376	3.618	4.178
7	no	17.492	11.275	8.062	10.361	15.654	15.485	17.136	11.339	2.910	5.202	2.321	4.663	13.819	15.708	5.670	5.937	3.286	3.720
	yes	17.663	16.337	6.539	6.860	17.570	16.419	13.957	10.871	1.497	3.841	1.296	2.907	10.465	12.262	6.492	6.342	3.386	4.169
	total	17.579¹	14.016	7.286	8.742	16.631²	15.918	15.515³	11.162	2.190	4.591	1.799	3.883	12.109	14.088	6.089	6.130	3.337	3.936
8	no	2.406	1.751	14.764	12.446	9.262	10.344	2.228	2.291	4.314	8.216	2.979	5.923	39.227	23.291	7.451	5.144	5.312	5.373
	yes	3.799	5.233	12.257	10.276	8.013	8.699	4.388	4.797	3.264	7.328	1.736	3.077	30.351	18.858	8.640	7.445	6.731	6.070

total	3.116	3.976	13.486²	11.404	8.625³	9.514	3.329	3.917	3.778	7.755	2.345	4.711	34.702¹	21.509	8.057	6.417	6.035	5.755
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* between-subjects factor variable: *participants' relation to the region* (Hypothesis 2)

¹ = type of representation with the longest dwell time, ² = type of representation with the second longest dwell time, ³ = type of representation with the third longest dwell time

Table A3

Mean values and standard deviations (SD) of fixation counts (FC) for each representation type by task. Per task highest mean value for participant groups (Hypothesis 2) is marked in bold as well the three most used types of representation in total. Highlighted colors for types of representation correspond to the AOIs.

		R0	R1	R2	R3	R4	R5	R6	R7	R8							
Task	Region*	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2	no	13,50	11,77	47,14	37,57	29,86	22,56	18,02	14,59	16,82	23,11	6,18	9,72	83,54	41,25	63,24	27,03
	yes	15,92	18,36	35,77	29,38	39,19	36,75	25,00	26,15	7,35	12,67	2,21	5,45	68,50	40,22	72,02	39,97
	total	14,74	15,46	41,34	33,96	34,62	30,84	21,58	21,46	11,99	19,04	4,16	8,05	75,87 ¹	41,23	67,72 ²	34,36
3	no	13,14	11,06	42,74	38,91	30,06	27,32	9,86	8,68	32,80	56,64	19,48	29,68	69,02	47,12	53,62	27,16
	yes	17,44	24,60	34,58	32,74	32,88	29,51	18,54	24,78	14,44	33,96	7,50	14,71	70,17	45,18	66,87	41,61
	total	15,33	19,23	38,58 ³	35,95	31,50	28,35	14,28	19,12	23,44	47,16	13,37	23,93	69,61 ¹	45,92	60,37 ²	35,73
4	no	17,28	24,54	18,80	25,93	107,54	84,17	11,96	14,70	4,60	12,67	2,98	8,93	65,36	51,18	59,54	51,60
	yes	16,42	27,18	24,12	28,17	71,79	77,95	14,87	22,26	5,33	15,41	2,02	5,78	79,19	70,97	78,63	61,70
	total	16,84	25,79	21,51	27,10	89,31 ¹	82,63	13,44	18,90	4,97	14,07	2,49	7,47	72,41 ²	62,15	69,27 ³	57,50
5	no	15,82	16,90	26,06	24,90	40,28	43,51	10,36	10,79	16,72	29,84	8,96	15,16	76,22	42,96	74,18	40,81
	yes	18,21	19,02	35,63	36,66	48,15	51,00	14,98	22,77	11,33	17,28	7,15	13,57	69,65	45,04	61,12	33,74
	total	17,04	17,96	30,94	31,66	44,29 ³	47,41	12,72	17,99	13,97	24,29	8,04	14,33	72,87 ¹	43,94	67,52 ²	37,76
6	no	19,66	24,33	19,32	27,39	43,92	47,34	18,50	17,13	13,04	28,14	5,76	13,28	112,02	62,49	47,82	33,79
	yes	13,50	16,47	28,87	29,04	25,10	26,90	15,17	17,74	10,52	27,74	5,02	9,11	126,06	65,56	53,08	29,55
	total	16,52	20,83	24,19	28,51	34,32 ³	39,27	16,80	17,44	11,75	27,83	5,38	11,30	119,18 ¹	64,14	50,50 ²	31,65
7	no	55,82	34,97	28,84	34,85	47,26	39,62	49,66	36,32	11,86	20,45	8,18	15,85	48,66	46,01	22,72	20,33
	yes	60,79	47,05	26,27	25,61	60,63	50,83	46,40	32,71	6,25	14,93	5,25	11,54	43,15	48,67	26,35	23,94

8	total	58,35 ¹	41,44	27,53	30,37	54,08 ²	45,95	48,00 ³	34,39	9,00	17,98	6,69	13,83	45,85	47,23	24,57	22,21	14,10	15,47
	no	9,28	6,22	49,68	39,89	31,16	33,44	7,58	6,97	16,54	30,38	9,94	17,37	133,00	68,60	29,64	18,76	19,24	18,06
	yes	14,73	18,63	44,79	34,95	30,27	31,17	16,25	15,63	13,73	29,38	7,44	12,39	117,50	71,93	34,46	27,22	26,69	23,36
	total	12,06	14,20	47,19 ²	37,35	30,71	32,14	12,00	12,88	15,11	29,76	8,67	15,02	125,10 ¹	70,40	32,10 ³	23,47	23,04	21,16

* between-subjects factor variable: *participants' relation to the region* (Hypothesis 2)

¹ = most fixated representation type, ² = second most fixated representation type, ³ = third most fixated representation type

Table A4

Mean values and standard deviations (SD) of revisits (RV) for each representation type by task. The per-task highest mean value for subject groups (Hypothesis 2) is marked in bold as well the three most used types of representation in total. Highlighted colors for types of representation correspond to the AOIs.

Task	Region*	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2	no	3,64	3,38	5,86	4,47	7,34	5,79	4,28	2,96	1,74	2,08	0,92	1,38	10,78	6,66	11,22	6,01	5,78	3,32
	yes	3,23	3,60	5,29	3,89	9,02	6,72	5,13	5,23	1,25	2,09	0,35	0,81	8,44	5,85	11,04	6,64	6,52	3,63
	total	3,43	3,48	5,57	4,17	8,20 ³	6,31	4,72	4,27	1,49	2,09	0,63	1,16	9,59 ²	6,34	11,13 ¹	6,31	6,16	3,49
3	no	3,48	2,75	6,00	3,52	6,20	3,30	2,46	2,10	3,10	4,67	3,04	4,74	11,64	7,06	12,12	7,27	4,46	2,77
	yes	4,23	3,57	5,29	3,76	7,67	5,48	3,87	4,03	1,60	2,93	1,42	3,18	12,31	7,34	13,73	7,45	4,85	3,89
	total	3,86	3,20	5,64	3,64	6,95 ³	4,58	3,18	3,29	2,33	3,93	2,22	4,08	11,98 ²	7,18	12,94 ¹	7,37	4,66	3,38
4	no	3,30	3,79	3,84	5,04	8,96	5,02	2,40	2,73	0,54	1,20	0,38	1,34	10,24	7,65	10,32	8,49	2,30	2,90
	yes	3,15	3,59	3,81	4,32	7,77	6,19	3,15	4,12	0,69	1,38	0,33	0,88	9,56	6,62	11,21	6,51	2,85	3,70
	total	3,23	3,67	3,82	4,66	8,35 ³	5,65	2,78	3,51	0,62	1,29	0,35	1,12	9,89 ²	7,12	10,77 ¹	7,52	2,58	3,33
5	no	4,20	4,18	5,28	3,93	7,64	5,07	2,62	3,06	2,52	4,98	1,88	3,74	13,40	8,36	15,26	8,59	4,12	4,16
	yes	3,60	3,55	5,17	4,02	8,35	5,53	3,31	3,65	0,79	1,16	1,13	2,47	11,17	6,43	12,29	7,00	4,96	3,59
	total	3,89	3,87	5,23	3,96	8,00 ³	5,30	2,97	3,38	1,64	3,67	1,50	3,16	12,26 ²	7,48	13,75 ¹	7,92	4,55	3,88
6	no	3,24	3,08	3,26	3,06	6,00	4,80	3,64	3,39	1,32	2,64	0,90	1,80	12,24	7,28	10,78	6,91	2,50	2,60
	yes	2,92	3,20	4,38	3,86	5,46	5,01	3,06	3,44	1,08	2,50	1,04	2,34	13,31	8,39	11,33	6,93	3,29	2,91

7	total	3,08	3,13	3,83	3,52	5,73 ³	4,89	3,34	3,41	1,20	2,56	0,97	2,08	12,78 ¹	7,85	11,06 ²	6,89	2,90	2,78
	no	9,86	5,23	4,82	4,94	8,96	5,33	7,88	5,18	1,34	2,20	1,18	1,66	7,94	5,27	6,04	4,48	2,88	2,86
	yes	9,60	5,18	5,31	4,30	9,35	4,61	8,44	4,68	0,73	1,60	0,63	1,51	7,48	6,16	6,25	5,11	2,92	2,90
	total	9,73 ¹	5,18	5,07	4,61	9,16 ²	4,95	8,17 ³	4,91	1,03	1,93	0,90	1,60	7,71	5,72	6,15	4,79	2,90	2,86
8	no	2,66	2,17	5,72	4,67	5,10	3,54	1,92	1,96	1,68	2,58	1,44	2,42	12,12	5,63	6,98	3,58	3,02	2,43
	yes	3,79	3,24	6,23	4,34	5,73	4,48	4,00	3,42	1,52	2,28	1,25	2,09	12,46	6,32	8,12	5,58	4,08	2,64
	total	3,24	2,82	5,98 ³	4,49	5,42	4,04	2,98	2,98	1,60	2,42	1,34	2,25	12,29 ¹	5,96	7,56 ²	4,72	3,56	2,58

* between-subjects factor variable: *participants' relation to the region* (Hypothesis 2)

¹ = most revisited representation type, ² = second most revisited representation type, ³ = third most revisited representation type

Table A5

Estimated ET variable measures.

		95% Confidence Interval			
		Mean	Std. Error	Lower Bound	Upper Bound
Dwell Time (DT)	R0	6096,658	415,118	5273,076	6920,240
	R1	9029,566	391,375	8253,088	9806,043
	R2	13597,474	764,503	12080,721	15114,226
	R3	5847,798	364,093	5125,448	6570,148
	R4	3263,900	407,929	2454,580	4073,220
	R5	1882,673	223,079	1440,091	2325,255
	R6	22502,088	782,258	20950,111	24054,066
	R7	13805,064	538,464	12736,767	14873,361
	R8	5658,932	242,629	5177,563	6140,300
Fixation Count (FC)	R0	21,537	1,319	18,920	24,154
	R1	33,043	1,276	30,511	35,575
	R2	45,579	2,357	40,902	50,255
	R3	19,797	1,176	17,464	22,129
	R4	12,952	1,601	9,776	16,127
	R5	7,005	,786	5,445	8,566
	R6	83,004	2,694	77,658	88,349
	R7	53,091	1,944	49,234	56,949
	R8	22,967	,944	21,095	24,839
Revisits (RV)	R0	4,350	,202	3,950	4,750
	R1	5,019	,236	4,551	5,486
	R2	7,396	,317	6,768	8,025
	R3	4,012	,211	3,594	4,429
	R4	1,421	,157	1,109	1,733
	R5	1,135	,138	,861	1,410
	R6	10,935	,445	10,053	11,817
	R7	10,477	,397	9,689	11,266
	R8	3,894	,172	3,553	4,236

Table A6

Test of within-subjects contrasts of dwell times.

Tests of Within-Subjects Contrasts

Source				Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Task_* Representation Type_	Dwell Time_	Level 1 vs. Level 7	Level 1 vs. Level 2	884994183,364	1	884994183,364	3,632	,060	,035	3,632	,471
			Level 2 vs. Level 3	631762259,411	1	631762259,411	1,797	,183	,018	1,797	,264
			Level 3 vs. Level 4	419753106,775	1	419753106,775	2,628	,108	,026	2,628	,362
			Level 4 vs. Level 5	749850027,798	1	749850027,798	7,429	,008	,069	7,429	,770
			Level 5 vs. Level 6	25011970,192	1	25011970,192	,302	,584	,003	,302	,085
			Level 6 vs. Level 7	19959097418,362	1	19959097418,362	34,594	,000	,257	34,594	1,000
			Level 7 vs. Level 8	58364478509,730	1	58364478509,730	82,645	,000	,452	82,645	1,000
			Level 8 vs. Level 9	1081062205,315	1	1081062205,315	6,637	,011	,062	6,637	,723
	vs.	Level 2	Level 1 vs. Level 2	1352541196,914	1	1352541196,914	4,837	,030	,046	4,837	,586
			Level 2 vs. Level 3	1132245183,282	1	1132245183,282	2,495	,117	,024	2,495	,346
		Level 7	Level 3 vs. Level 4	1438525,482	1	1438525,482	,007	,932	,000	,007	,051
			Level 4 vs. Level 5	273100738,452	1	273100738,452	1,388	,242	,014	1,388	,215
			Level 5 vs. Level 6	118944729,127	1	118944729,127	,613	,436	,006	,613	,121
			Level 6 vs. Level 7	32774443182,962	1	32774443182,962	43,697	,000	,304	43,697	1,000
			Level 7 vs. Level 8	60273965699,261	1	60273965699,261	72,168	,000	,419	72,168	1,000
			Level 8 vs. Level 9	4603453984,099	1	4603453984,099	29,409	,000	,227	29,409	1,000
	Level 7	Level 3	Level 1 vs. Level 2	8403791863,289	1	8403791863,289	38,427	,000	,278	38,427	1,000
		vs.	Level 2 vs. Level 3	77042787551,107	1	77042787551,107	68,568	,000	,407	68,568	1,000
			Level 3 vs. Level 4	38325954189,193	1	38325954189,193	49,039	,000	,329	49,039	1,000
			Level 4 vs. Level 5	969601769,044	1	969601769,044	12,562	,001	,112	12,562	,939
			Level 5 vs. Level 6	97155191,242	1	97155191,242	1,744	,190	,017	1,744	,258
			Level 6 vs. Level 7	16721825823,459	1	16721825823,459	19,965	,000	,166	19,965	,993
			Level 7 vs. Level 8	65237489947,010	1	65237489947,010	57,224	,000	,364	57,224	1,000
			Level 8 vs. Level 9	19953644967,582	1	19953644967,582	66,799	,000	,400	66,799	1,000
	Level 7	Level 4	Level 1 vs. Level 2	4713585768,626	1	4713585768,626	22,644	,000	,185	22,644	,997
		vs.	Level 2 vs. Level 3	9200151030,167	1	9200151030,167	18,842	,000	,159	18,842	,990
			Level 3 vs. Level 4	1589054243,967	1	1589054243,967	4,546	,035	,043	4,546	,560
			Level 4 vs. Level 5	47497717,721	1	47497717,721	,370	,544	,004	,370	,092
			Level 5 vs. Level 6	1180,481	1	1180,481	,000	,997	,000	,000	,050
			Level 6 vs. Level 7	23306241830,180	1	23306241830,180	35,704	,000	,263	35,704	1,000
			Level 7 vs. Level 8	65020986089,822	1	65020986089,822	92,091	,000	,479	92,091	1,000

Level 8 vs. Level 9		11465287654,710	1	11465287654,710	54,100	,000	,351	54,100	1,000
Level 5	Level 1 vs. Level 2	8578449907,883	1	8578449907,883	30,715	,000	,235	30,715	1,000
vs.	Level 2 vs. Level 3	8429780696,293	1	8429780696,293	16,863	,000	,144	16,863	,982
Level 7	Level 3 vs. Level 4	32695,935	1	32695,935	,000	,992	,000	,000	,050
	Level 4 vs. Level 5	791662658,569	1	791662658,569	6,197	,014	,058	6,197	,693
	Level 5 vs. Level 6	707856,006	1	707856,006	,008	,931	,000	,008	,051
	Level 6 vs. Level 7	56116385,075	1	56116385,075	,064	,801	,001	,064	,057
	Level 7 vs. Level 8	4794142218,002	1	4794142218,002	4,978	,028	,047	4,978	,599
	Level 8 vs. Level 9	5834525312,014	1	5834525312,014	36,141	,000	,265	36,141	1,000
Level 6	Level 1 vs. Level 2	43624889214,822	1	43624889214,822	101,804	,000	,504	101,804	1,000
vs.	Level 2 vs. Level 3	20515434297,527	1	20515434297,527	36,065	,000	,265	36,065	1,000
Level 7	Level 3 vs. Level 4	1853330877,254	1	1853330877,254	3,974	,049	,038	3,974	,506
	Level 4 vs. Level 5	19483929542,677	1	19483929542,677	74,364	,000	,426	74,364	1,000
	Level 5 vs. Level 6	109564693,148	1	109564693,148	1,150	,286	,011	1,150	,186
	Level 6 vs. Level 7	49792363772,781	1	49792363772,781	74,717	,000	,428	74,717	1,000
	Level 7 vs. Level 8	43616704272,361	1	43616704272,361	57,302	,000	,364	57,302	1,000
	Level 8 vs. Level 9	53048130,133	1	53048130,133	,649	,422	,006	,649	,125

a. Computed using alpha = ,05

Task-Levels: 1 = Task 2, ..., 7 = Task 8

Representation-Levels: 1 = R 0, ..., 9 = R 8