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Short Communication

A test of the use of computer generated visualizations in support of ecosystem-based management

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ABSTRACT

Systematic scenario analysis is increasingly being used as an approach to evaluate ecosystem-based management options, often using “storylines” communicated through computer-generated (CG) images or visualizations. To explore potential issues associated with using CG imagery for conveying scenarios of habitat restoration we performed experiments in the Puget Sound, Washington region in which we asked whether respondents could differentiate among images of varying seagrass density and spatial extent, and if the presence of humans in the images affected these assessments and their perceptions of ecosystem health. Respondents were able to grossly determine relative seagrass density in the images, but only about 50% of them were able to determine this perfectly. Most errors occurred when the difference in density was small: approximately 20 shoot m^{-2}. The ability to correctly distinguish among images was inversely correlated with educational level. The presence or absence of people in the imagery did not influence the ability of respondents to correctly sort images, nor did it affect perceptions of ecosystem “health”. Taken together, the results suggest that such imagery can be useful as basis for communicating large differences in ecological conditions, but may be less informative as means to convey marginal changes in ecological structure. This work begins to highlight some of the pitfalls, but also the promise, of the use of CG visualization in marine resource management.

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1. Introduction

Following the publication of the Millennium Ecosystem Assessment [1], systematic scenario analysis is increasingly being used as an approach to evaluate ecosystem-based management options e.g., [2]. Scenario analysis generates multiple alternative descriptions of potential outcomes, including processes of change, thresholds and uncertainties [3]. Scenarios explore alternative perspectives about underlying system processes and can illuminate key issues by using a consistent set of assumptions about the system state to broaden perspectives [4,5]. As such, they generate alternative, internally consistent, logical descriptions of the future. Scenarios can be qualitative, in which “storylines” are developed, or quantitative, in which the outcomes of numerical models are explored [4,5].

An important attribute of scenarios is that they acknowledge the interdependencies of system components. However, communication of these sometimes complex and nuanced connections can be challenging. Computer-generated (CG) visualizations offer an effective means for visualizing complex systems [6,7] and informing environmental policy [8]. Such visualizations are powerful because they can integrate scientific information and intuition, engage the lay public, enhance personal salience, and are flexible [9]. Indeed, in normative research, computer generated images are a common tool for illustrating different states of nature in normative surveys [10,11].

There are a number of pitfalls in generating images for environmental policy [12], including issues such as exaggeration of landforms, viewpoint selection, coloring and lighting of the landscape [13], and cultural differences in perception of images [14]. As examples: 1) creation of imagery and visualizations remains highly subjective and expert-oriented, and does not generally involve users in its preparation [13]; 2) interpretation of imagery depends as much on viewers′ prior perceptions, experiences, attitudes and social background as on the physical visual stimulus [15]; 3) responses to images are not always rational, but may have an emotional component [16].

As a consequence to the potential issues associated with using CG visualizations, it is crucial that initial analyses be conducted that establish biases, misinterpretation or other issues associated with imagery. As part of the ongoing work on restoration of nearshore habitats in Puget Sound, Washington, CG images were developed of seagrass (*Zostera marina*) beds varying in density and

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spatial extent. Here, results are reported from experiments which tested whether respondents accurately differentiated among CG images of seagrass beds that differed in density of seagrass shoots, and if accuracy was associated with educational background or demographic attributes. Secondly, the hypothesis that the presence of humans in visualizations influenced the ability of respondents to accurately determine relative seagrass densities or affected their perceptions about the health of the ecosystem was tested.

2. Methods

Computer-generated seagrass visualizations were evaluated by individuals attending the 2011 annual meeting of the Western Society of Naturalists (WSN, westsocnat.com). Volunteers were solicited at the WSN poster session and varied in levels of experience (i.e., education obtained), demographic traits (i.e., gender and age), and area of expertise (Table 1).

Each volunteer participated in three exercises. First, respondents were provided with six randomly sorted images that differed in seagrass shoot density (ranging from 0 to 150 shoots m^{-2}) and seagrass bed area (Fig. 1). The seagrass densities were selected based on a gradient from degraded to restored levels of the seagrass, *Z. marina*, documented in Puget Sound [17–19]. About half of the respondents ($N=33$) were provided with images that included people along the shore, and ca. half ($N=27$) were provided images without people.

A Spearman's rank correlation procedure was used to assess how well the participants were able to sort the imagery, and chi-square analyses were used to test the hypotheses that the ability of respondents to correctly sort seagrass images was independent of the presence of people in the images, gender, and level of education.

In the second exercise, participants were provided with pairs of images and asked to identify the image with a higher density of seagrass. For this exercise, images with 90 shoots m^{-2} and 110 shoots m^{-2} were used and people were asked to evaluate the following pairs: 1) 90 shoots m^{-2} without people versus 90 shoots m^{-2} with people; 2) 90 shoots m^{-2} without people versus 110 shoots m^{-2} with people; and 3) 110 shoots m^{-2} without people versus 90 shoots m^{-2} with people. Chi-square analyses were used to test whether there was a difference between the ability of participants to differentiate between: 1) images with the same level of seagrass with and without people; and 2) images with different levels of seagrass with and without people.

In a third exercise, using these same pairs of images used in exercise 2, respondents' perceptions about ecosystem health were assessed by asking them which image depicted a "healthier" ecosystem. Chi-square analyses were used to test whether images with more seagrass and higher water clarity were considered healthier and whether the presence of people influenced respondents' perception of ecosystem health.

Table 1
A breakdown of the participants ($n=60$) in the exercises by gender, level of education, and age (*Note*: one respondent did not provide age information).

Gender		
Male	28	47%
Female	32	53%
Education		
High School	1	2%
Bachelor's	23	38%
Master's	10	17%
Ph.D.	15	25%
Post-Doc	11	18%
Age		
22–27	19	32%
28–36	17	28%
37–45	13	22%
46–54	5	8%
55–64	5	8%

3. Results

3.1. Experiment 1 – seagrass image ranking

When participants were asked to sort six seagrass images from lowest to the highest shoot density, about half (32/60) of the respondents correctly completed the task. Images with people were correctly sorted by 64% of the respondents, while 41% of respondents correctly sorted the image-set without people (Table 2); however, this difference was not statistically significant (χ^2 (1, $N=60$)$=3.210$, $p>0.05$). In other words, the ability to correctly sort the imagery was not significantly influenced by the presence or absence of people in the visualizations. The ability to correctly sort images also did not significantly vary between genders (χ^2 (1, $N=60$)$=0.067$, $p>0.05$). However, the ability to correctly sort images did vary among participants of different education levels (χ^2 (3, $N=60$)$=17.281$, $p<0.05$), with participants with Bachelor's degrees performing better than those with higher levels of education.

While only half the respondents perfectly completed the sorting task, 82% of respondents who made an error still sorted the images in a manner that was correlated at an $R>0.80$ with the correct order. Not surprisingly, vast majority of the participants were able to differentiate between no seagrass and 150 shoots m^{-2} (Table 3). However, a substantial minority of respondents had difficulties distinguishing among images that differed by 20 shoots m^{-2} (Table 3). In cases in which a participant could select an image with 20 shoots m^{-2} above or below the correct answer (i.e. 70, 90, 110; 90, 110, 130; and 110, 130, 150 shoots m^{-2}), respondents made an error on an average of 23% (SD 4%) of the time (Table 3). When the difference between images was 40 shoots m^{-2}, an average of 3.5% (SD 1.1%) of the responses were incorrect, and when the difference was ≥ 70 shoots m^{-2} only an average of 1.2% (SD 0.9%) of responses were incorrect (Table 3).

3.2. Experiment 2 – pairwise comparison of seagrass images.

Overall, the presence of people in images did not significantly affect respondents ability to distinguish between pairs of seagrass images (χ^2 (1 d.f., $N=60$)$=1.51$, $p>0.05$), nor did gender (χ^2 (1 d.f., $N=60$)$=0.051$, $p>0.05$). However, the ability to correctly rank the pairs did vary between participants of different levels of education (χ^2 (3 d.f., $N=59$)$=20.831$, $p<0.05$), with participants with Bachelor's degrees again performing better than those with higher levels of education.

When participants were given paired images with identical seagrass shoot densities (90 shoots m^{-2}) with one image containing people and the other without people, 80% of respondents correctly determined that the seagrass shoot densities were equal. Of those that incorrectly thought the images portrayed different seagrass densities, about twice as many participants thought the images without people had greater seagrass than the images with people (13% of respondents selected the image without people; 7% chose the image with people).

When participants were asked to distinguish between images with 90 and 110 shoots m^{-2}, with the higher density image containing people, 83% of respondents correctly identified the image containing more seagrass. However, 13% incorrectly selected that "neither" image had more seagrass, 3% of respondents incorrectly chose the image with less seagrass as having a higher seagrass density.