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Research

Emotionally augmented mental models, connectivity and beaver reintroduction in Southwest England

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ABSTRACT. Understanding the psychology of human-wildlife interactions has grown beyond cognitive frameworks to include appreciation of roles played by emotion in human responses to wildlife. From its beginnings as an essentially cognitively framed proposition, mental modeling has been shown readily applicable to representing and interpreting stakeholder perspectives on combined social and natural systems, but lacks an integrated approach to emotion. This is an important knowledge gap. To commence an investigation into the relationship focused on the requirements of wildlife conservation, we carried out a case study of perspectives toward a free-living Eurasian beaver (*Castor fiber*) reintroduction in Southwest England, ecologically significant as a generator of high-value wetland habitat while interacting strongly with local human interests. Using fuzzy cognitive mapping techniques, we report predictive relationships between model measurements and subjective emotional valence elicited in relation to stakeholder conceptual content. Significant interactions were identified between three measures of concept connective influence within mental models and associated emotional valence intensity: single model concept connective salience, aggregated model concept connective salience, and aggregated model predictive inferences made by dynamic analysis. A possible explanation for these findings is outlined in which we propose that criteria-based evaluations suggested by appraisal theory of emotion are sensitive to the strength and distribution of connective influences within mental models. Apart from its theoretical significance, the evidence presented in this paper highlights the importance of attending to conservation stakeholder emotional experiences, and may assist in new approaches to mitigation where conservation objectives require human adjustment.

Key Words: *Castor fiber; conservation; fuzzy cognitive maps; emotion; human-wildlife interactions; mental models*

INTRODUCTION

Emotion and wildlife

As the ecological impact of human activity has become increasingly critical, so human-wildlife interactions and their psychological basis in conservation have attracted increasing research interest. Investigations exploring human dispositions with respect to conservation have tended to concentrate on cognitive variables and their influence on human-wildlife conflict (Fulton et al. 1996, Manfredo and Dayer 2004, Teel et al. 2010, Johansson et al. 2016), while the role of emotion has been relatively neglected (Manfredo 2008, Jacobs 2012, Zainal Abidin and Jacobs 2019). This is paradoxical because emotion defined as "episodic, relatively short-term, biologically based patterns of perception, experience, physiology, action and communication that occur in response to specific physical and social challenges and opportunities" (Keltner and Gross 1999:468) is clearly central to day to day human experience; emotions signify value and influence memory, motivation, decision making, and perception pertinent to human-wildlife interactions (Jacobs and Vaske 2019). Emotional responses are therefore a crucial feature of human-wildlife coexistence, and research exploring emotion in social-ecological systems is viewed as increasingly important (Glikman et al. 2019, Jacobs and Vaske 2019).

In this paper we set out to investigate and offer explanations for possible regularities between human emotion and cognitive perspectives on "how things work" represented by connected concept arrays known as mental models typically underpinning human understanding and reasoning, taking as a conservation case example a large-scale wildlife reintroduction.

Mental models

The pioneer psychologist Kenneth Craik first proposed that people model real-world processes as subjective concept networks in order to infer predictions, make decisions, and guide actions, in work dating from the mid-20th century (Craik 1967). More recent interest building on Craik's original ideas has stimulated research into the structure and properties of mental models, showing that human perspectives in environmental science can be explored as two-dimensional cognitive maps applicable to natural resource and wildlife conservation, especially useful in complex and data-poor social-ecological systems (Biggs et al. 2011, Jones et al. 2011, Lynam et al. 2012, Moon et al. 2019).

A particularly fruitful elaboration of this approach contending with sometimes imprecise knowledge contained in mental models has made use of "fuzzy logic" to generate semi-quantitative fuzzy cognitive maps, FCMs (Kosko 1986, Özesmi and Özesmi, 2004), which can be used both to analyze reasoning processes and to infer knowledge about the external world. FCMs comprise nodes or concepts that can show varying levels of activity, and inter-nodal connections with given directions, signs, and weights, representing causal influences. In FCM format, mental models can be analyzed and compared, and their dynamic behavior simulated to show variation in concept activation and therefore some measure of model output (Özesmi and Özesmi 2004, Jetter and Kok 2014, Yoon and Jetter 2016).

To date, a systematic explanation of how the cognitive conceptual content of mental models interacts with emotion is conspicuously absent. Despite a paucity of research, in an environmental study of direct conservation relevance, Biggs et al. (2008:7) propose an

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explicit role for emotion in their descriptive working definition of mental modeling: "(psychological) representations of objects, their relationships and dynamics as well as the attributes or characteristics of these and the person's valence (cognitive and emotional) to the objects, relationships, and dynamics." From this insight, we suggest that understanding how emotion and cognitive factors interact within mental models in conservation requires further elucidation.

Emotion and mental models

Represented in an environmental mental model, emotion can be framed as part of a model's conceptual content; so, for example, "stakeholder emotional satisfaction," a concept describing emotion, may be shown as part of a conceptual network alongside other cognitive concepts. An alternative approach might be to consider an additional layer of subjective emotional feeling mapped on to the cognitive conceptual content of the mental model and corresponding to variations in facial expression, autonomic and hormonal activity as part of the organism's psycho-social adjustment (Izard 2007). However represented, failure to account for emotion in the structure of reasoning and decision making is psycho-biologically incomplete (Damasio 1994).

In relation to evolved capacity to generate and make use of mental models, emotion serves as an adaptive survival mechanism by linking to social and ecological stimuli; for example aspects of emotional response may focus individual attention, elicit memories, and regulate decision making (Niedenthal and Ric 2017a), and when shared with others extending to reinforced social group coherence, coordination, and collective action (Niedenthal and Ric 2017b).

According to evidence supporting appraisal theory of emotion, translation of environmental stimuli into emotional responses is accomplished by evaluative mechanisms comprising commonly cited appraisal criteria including qualities of novelty, desirability, goal conduciveness, agency, and norm compatibility (Moors et al. 2013). Criteria-based concept-stimuli evaluations vary between individuals, denoting what matters, or perceived personal significance and qualitative variation of emotional responses (Ellsworth 2013).

In mental models, connections between concepts represent beliefs infer what is likely to happen, and therefore what matters predictively, corresponding to aspects of appraisal criteria-based assessments of personal significance. For example, in an environmental context, a concept appraised by a human stakeholder matters not only as an isolated stimulus but because of its known and quantitative connective influence on ecological, social, cultural, and economic outcomes perceived to be important within a given domain by the subject.

How stimulus (concept) activation relates to intensity of associated emotional responses is unclear, but it has been suggested that perception of stimulus change as opposed to absolute value carries special significance, hence "the greater the change, the stronger the subsequent emotion" (Frijda 1988:353). In selecting what aspect of emotion to measure, a dimensional evaluation of core emotional valence (like/pleasure–dislike/displeasure) is a reasonable candidate, influential as a basic psychobiological function in emotion theory (Russell 2003, Barrett 2006) and amenable to psychometric evaluation in a research interview (Broekens and Brinkman 2013).

Mental models and connectivity

In this paper the generic term "connectivity" is used to refer to connective properties of mental models whether relating to the influence of single concepts or the model as a whole, in which connections between concepts represents beliefs, translated into causal influences in FCMs. Standard measurements based on connectivity have been described in environmental mental modeling (Özesmi and Özesmi 2004), and widely used in network analysis. Mental model and FCM metrics have subsequently been applied in a wide variety of conservation-related fields including hydrology (Bracken and Croke 2007), resource pathways in ecology, and relationships in human social networks, where numbers and types of connections can predict system stability and properties such as emergence within system modeling (Fletcher et al. 2011, Daigle et al. 2020).

Yoon and Jetter (2016) describe commonly applied FCM model parameters sensitive to the number, direction, and strength of connective influences between concepts. In this paper the following are considered: (i) degree centrality, concerning individual concepts to determine how connected a concept is to other concepts, (ii) whole model connective density, to determine how connected or sparse FCMs are, and (iii) dynamic analysis of FCMs in which connective influences between concepts are played out in repeated iterations until the resulting concept states arrive at a stable output activation profile, thus showing the (future) response of the cognitive system.

As overall connectivity in mental models represents causal belief strengths linking concepts, measurements of concept degree centrality, model density, and dynamic analysis of perceived changes to concept activity offer some quantifiable means of assessing how people perceive an ecosystem of interest, conceptually important to stakeholders themselves, managers, and research theorists (Özesmi and Özesmi 2004, Gray et al. 2013, Turnbull et al. 2018).

Group (social) mental models

An important development of mental model theory concerns the notion of shared mental models held within social groups, relevant to team work and thought to form a basis for trust and cooperation in effective group function (Jonker et al. 2010, Gray et al. 2014). To infer shared features sets of individual mental models can be aggregated, retaining the most frequently mentioned concepts and connections by combining them to represent shared knowledge structures (Özesmi and Özesmi 2004). Stakeholder groups with sectional interests identified in relation to natural resources are known to develop distinctive shared mental models (Aminpour et al. 2020), which function to minimize within-group conflict (Evans et al. 2019) comparable to accounts of group-based emotion aligning and regulating individual responses in groups seeking to address shared priorities (Kuppens and Yzerbyt 2014).

Hypotheses

Possible interactions between concept centrality, model density, and dynamic concept activation metrics described by Yoon and Jetter (2016) on the one hand, and attributions of personal significance derived from appraisal theory of emotion on the other, suggest value in searching for predictive regularities in linked sets of data. In this paper the proposition is addressed by considering both individual and aggregated stakeholder mental models elicited in relation to an important large-scale wildlife conservation reintroduction project set up to monitor and manage a free-living Eurasian beaver, *Castor fiber* population in Southwest England. Beaver conservation is especially pertinent because as a species, beavers have a transformative impact on their environment, generating significant human-wildlife interactions and making it more likely that a wide range of stakeholders will develop both strongly connected and emotionally engaged mental models.

Hypothesis 1: Stakeholder mental model analysis will show predictive correlations between measurements of emotional valence and individual mental model (a) concept centrality and (b) density.

Hypothesis 2: Aggregated (shared) stakeholder group mental models will show predictive correlations between measurements of emotional valence and concept centrality.

Hypothesis 3: Aggregated (shared) stakeholder group mental models will show predictive correlations between measurements of emotional valence and predicted concept activation (dynamic analysis).

Case study: beaver reintroduction

The Eurasian beaver (Fig. 1) is an important European conservation species (Campbell-Palmer et al. 2016), which narrowly avoided extinction in the early 20th century as the culmination of a long history of hunting and habitat loss, including complete extirpation in Britain during the early modern period (Halley and Rosell 2003, Coles 2006). Throughout former European range, including recent projects in Scotland, protection and where absent reintroductions have led to successful recovery associated with improvements in ecosystem health and biodiversity (Law et al. 2016, Puttock et al. 2017, 2018). In England, a government decision formally approved a small population of breeding beavers found to be living on the River Otter in Southwest England and subject to the five-year River Otter Beaver Trial (ROBT), which reported in early 2020 (Brazier et al. 2020). In addition to ecological changes, the ROBT undertook assessments of direct and indirect human factors and outcomes, authoritatively defined elsewhere as “socio-economic circumstances, community attitudes and values, motivations and expectations, behaviours and behavioural change” (IUCN/SSC 2013:11), criteria that do not explicitly consider the influence of emotional responses.

Highly valued, high use locations typically found in lowland English landscapes such as the Otter valley carry multiple stakeholder interests, and make the ROBT an excellent opportunity to examine individual and group stakeholder emotional responses alongside conceptual perspectives.

METHOD

Geographic area

The study focuses on the ROBT reintroduction area, based on the River Otter, of which the mainstem runs 32 km into the western English Channel, with a catchment of 250 km² and total watercourse including tributaries of 594 km. The catchment includes two conservation “Areas of Outstanding Natural Beauty,” an estuarine “Site of Special Scientific Interest,” and 46 km of accessible riverside paths. By completion of the ROBT in 2020, it was estimated that up to 18 beaver family groups were resident within the project area (M. Elliott, Devon Wildlife Trust, *personal communication*), creating patches of rapidly changing, typical beaver wetland habitat (Fig. 2). A quarter of the riparian margin is arable, the rest pasture plus localized forestry, orchards, and small settlements (Brazier et al. 2020).

Fig. 1. Eurasian beaver (*Castor fiber*) on the River Otter (ROBT site). One of the first free-living English populations of beavers to be restored after a centuries-long absence. Photograph by kind permission of Mr David R. White

Fig. 2. Developing beaver landscape showing new wetland features; lower River Otter, Southwest England. Photograph by the first author, with kind permission of Clinton Devon Estates.

Stakeholder sampling

A total of 48 stakeholder participants were recruited on the basis of (i) one or more criteria of residence, work, conservation, academic or leisure participation in the ROBT area, (ii) an occupational or self-declared interest in the trial in the five-year period up to expected completion in 2020, and (iii) self-defined identification with key group labels derived from discussion with the ROBT project manager and a reading of annual ROBT reports later summarized by Brazier et al. (2020). These comprise general public (GP), conservation and environmental scientist (CES), landowners and manager (LM) stakeholder groups, and small numbers of farmers, fishers, and regulators (Others) not specifically considered in this paper.

Mindful of the need "not to obtain a representative sample of a population but to represent different knowledge areas" (Olazabal et al. 2018:800), purposive sampling recruited approximately half of participants via community social media advertising, while most specialist occupational participants were sought out by direct approach or snowballing.

It was planned that sample size would be determined by concept saturation (Özesmi and Özesmi 2004). Interviewing coupled to progress in recruitment continued beyond the anticipated plateau phase because of slow recruitment of specialist stakeholder groups, however accumulation analysis showed that 89% concept saturation was achieved by 25 of 48 interviews.

Stakeholder interview procedure

All interviews by the first author took place between October 2018 and May 2019, averaging 149 (range 70–270) minutes, conducted in people's homes or workplaces. In situ interviewing in the presence of relevant environmental cues is considered preferable (Jones et al. 2014) but judged impractical for mostly evening meetings and winter weather conditions.

Interviews commenced with a semi-structured explanation of procedure, academic affiliation, ethical standards, collection of individual identifier data, and finally sharing photographs of a beaver, the river, and a map of the trial area. Participants were given one mandatory concept subsequently retained as a concept-category, "Beaver presence" and invited to write their own terms considered mental model concepts onto Post-its displayed however preferred on a 120x90 cm board, according to three a priori framing categories determined by the first author as reasonable ecosystem parameters: "beavers and a) wildlife & vegetation, b) river & physical environment, c) people & human activities." Participants were instructed to consider effects over the next five years, creating a reasonable time frame to enable participants to express their understanding and expectations of emergent or fluctuating and periodic events such as accentuated peaks and troughs in rainfall.

To minimize potential interviewer influence, interviewees were asked to lead in generating a list of positive terms, e.g., "tolerance" not "intolerance." Participant stress meant that more process support was required and a conversational method was adopted instead, in which the first author noted participant terms shared back for accuracy. Participants then wrote and displayed their own terms as a network, following which they were asked to consider each term in turn, in their preferred order, adding signed direct (+) or inverse (-), and fuzzy-weighted (Very Strong, VS; Strong, S; Moderate, M; and Weak, W) causal arrows to represent perceived influences between concepts, until satisfied with the overall outcome.

Finally, participants scored emotion responses using the AffectButton facial expression icon (Broekens 2014) to consider "how you feel when thinking about (each concept in turn)," identifying the expression best representing subjective emotional response or feeling. AffectButton automatically rates scores for emotional valence, termed "pleasure" on a dimension (-1, 1) representing subjective maximal displeasure (frowning and unhappy) through a neutral response to maximal pleasure (smiling and happy) indicated by the coordinates of the selected facial expression within the "affect space" of the visual icon.

AffectButton is based on the linear non-verbal Self-Assessment-Manikin scale (Bradley and Lang 1994), chosen for its representation of core affect scales, reliability, and validity including strong correlation with verbal emotion scales, and ease of use (Broekens and Brinkman 2013). Scores associated with each term and visible to the investigator were noted on the relevant Post-it.

Although AffectButton scores dimensions of arousal and dominance with respect to the environment, only emotional valence is considered further, justified by the fundamental nature of emotional valence and additional analysis revealing minimal differences between predictive effects seen for emotional valence and the other two dimensions (A. Blewett, *unpublished data*).

Mental model elicitation and FCMs

Methods for elicitation of mental models (Axelrod 1976, Jones et al. 2014) and conversion to FCMs as a graphical technique for mental model representation (Gray et al. 2014) follow previous environmental studies (Özesmi and Özesmi 2004, Obiedat and Samarasinghe 2016, Olazabal et al. 2018). The procedure is summarized as follows: (i) standardization and reduction of raw interviewee terms, condensed into semantically equivalent FCM concept-categories, (ii) conversion of FCMs into square adjacency matrices populated with numerical connection values attributed to fuzzy semantic terms: very strong, 0.8; strong, 0.6; moderate, 0.4; weak 0.2, and (iii) in the case of combined models, concatenation to multiple values in each equivalent cell averaged to produce a mean weight (Abel et al. 1998, Cannon-Bowers and Salas 2001, Gray et al. 2014), (iv) dynamic analysis to calculate concept activation values.

The raw sample of 48 models initially comprised 657 interviewee terms (mean per model 13.3, range 8–24), each with a matched emotional valence score. Initial data cleansing reduced the sample of terms to 600 by (i) merging 16 pairs of duplicated terms and 1 set of triplicated terms into one each within their mental models, and (ii) inverting 22 individual terms plus two of the merged duplicated terms so as to express their meaning positively for consistency. In both sets of cases, attached valence data was discarded from further analysis.

Mental model aggregation

Aggregating stakeholder mental models to facilitate analysis of stakeholder group FCMs was done by aligning the terms used by each participant in rows headed by 53 concept-category labels forming columns defined by semantic equivalence emerging on inspection by the first author as accumulation proceeded. For example, four raw participant tourism terms: "Tourism," "Beaver tourism," "Hospitality/Hotel sector," and "External tourism" were merged into a single concept category "Nature tourism." In the case of the 16 pairs and 1 group of three replicated terms dealt with initially by merging, the most strongly weighted connection was retained for the subsequent connection merging procedure required prior to dynamic analysis of aggregated models.

Model aggregation procedures are not standardized in the literature; methods advocated include assembling all concepts with retention of the strongest summated connections (Özesmi and Özesmi 2004) or inclusion by weighting for expert credibility (Obiedat and Samarasinghe 2013). In this study, model aggregation was accomplished by retaining information from concepts and connections mentioned most frequently within the sample of mental models composing the whole sample and each stakeholder group, to represent a face-value shared model in each case.

In practice, retaining concepts above the median quartile threshold from each group concept list ranked by frequency generated model sizes deemed ideal for interpretation (Özesmi and Özesmi 2004). Model aggregation also requires thresholds for connection inclusion. This was done based on (i) frequency of a connection arising, and (ii) causal sign agreement (i.e., direct or inverse). Stakeholder group connection thresholds were selected to balance exclusion of less-shared information while minimizing orphan concept loss as follows: (i) GP; at least three same-signed connections, or four connections with no more than one contrary signed connection, which was removed before calculating the mean, (ii) CES; as GP, (iii) LM; at least two same-signed connections, otherwise as GP. Once the threshold was applied, any unconnected "orphan" concepts were excluded from analysis.

FCM analysis

FCM analysis measures essential properties of mental models as networks. Typically, measurements are arrived at by computer-based calculations based on the number, location, and weights of connecting relationships between concepts. Correlations between connectivity and emotion were studied at the level of (i) the entire sample of terms, n = 600, (ii) individual FCMs, n = 48, and (iii) aggregated FCMs for general public (GP), landowners and managers (LM), and conservation and environmental scientists (CES) stakeholder groups.

In this study, connectivity data shown in FCM matrices were analyzed with free-to-use, publicly available FCMappers software (Wildenberg et al. 2010). FCMappers calculates concept in-degree and out-degree from the summed weighted values of all in-connections and out-connections respectively, for each concept. The sum of each concept's absolute in-degree and out-degree values, termed concept degree centrality and abbreviated to "centrality" is a measure of each concept's influence or significance within the model (Eden et al. 1992, Özesmi and Özesmi 2004, Yoon and Jetter 2016; Table 1).

Model density D was calculated by dividing the actual number of connections by the maximum number of connections possible (the square of the number of concepts adjusted to account for a no self-loop rule preventing concepts from connecting directly back onto themselves in participant elicited raw mental models):

$$D = \frac{N_c}{N_n(N_n - 1)} \quad (1)$$

Table 1. Mental model parameter definitions.

Model Parameter	Definition
Concept degree centrality	Sum of (absolute) in-degrees and out-degrees, indicating overall influence of a concept within a model
Concept in-degree	Sum of inputting weighted concept connections
Concept out-degree	Sum of outputting weighted concept connections
Density	Ratio of actual connections to all possible connections, where higher density may indicate greater resilience and perceived management opportunities

Emotion and connectivity

Identification of relationships between emotional valence and metrics for concept centrality, density and deductively inferred dynamic analysis, as three possible indicators of greater perceived connectivity-linked personal significance, underpin the hypotheses.

In this study, AffectButton emotional valence scores in range (-1,1) are converted to an absolute value (0,1), because the focus is on intensity of emotional response, not its direction.

Specific correlations were calculated for the following:

(i) Emotional valence and centrality for the whole sample of cleaned terms (n = 600); centrality values were normalized (0 to 1) in each model to account for variation in model sizes given that all paired centrality-emotional valence data was analyzed as a single data set,

(ii) Mean emotional valence for concepts calculated within each of the n = 48 models, and the corresponding n = 48 model densities relying on an assumption that a net overall emotional response can reasonably be inferred from each mental model,

(iii) Mean emotional valence and centrality considered separately for the aggregated Whole Sample group and each of the aggregated GP, CES, and LM stakeholder group models.

(iv) Mean emotional valence and stable activation values determined by dynamic analysis for concepts in the aggregated Whole Sample group model, and for each of the aggregated GP, CES, and LM stakeholder group models.

Dynamic analysis of individual and aggregated FCM concept activation values was done using the dynamic function in publicly available software FCMappers (Wildenberg et al. 2010). In dynamic analysis, concepts are given values representing activity or activation level permitted to change under the influence of inputting weighted connections, hence dynamic activation values. The resulting set of concept values undergoes the same procedure and so onwards iteratively, until the whole set of concepts arrives at stable final activation outcomes (Stylios and Groumpos 2004, Kok 2009, Singh and Chudasama 2017).

Mathematically, initial concept activation values form state vector A (a_1, a_2, ..., a_n) where, for example, a_1 is the activation value of concept c_1 from the set C of a given model, is multiplied by the c_n x c_n adjacency matrix W with cells populated by connection weights in range (-1 to 1), including zero where there is no

Table 2. Research sample stakeholder groups and demographics.

	General Public (GP)	Landowners & Managers (LM)	Conservation & Environmental Scientists (CES)	Others
Number of Mental Models in each category	21	7	9	11
F: M	13: 8	0: 7	4: 5	0: 11
Modal age group (range)	26–40 (26–61+)	41–60 (26–61+)	41–60 (18–61+)	41–60 (18–61+)

connective influence. Iterative progression from A^t to A^{t+1} mediated by a normalizing transformation function *f* is repeated until *A* stabilizes, represented in summarized algebraic format as outlined by Groumpos (2010):

$$A^{t+1} = f\left(A^t W + A^t\right) \tag{2}$$

In FCMappers dynamic analysis, (i) all initial activation values A^t are granted a baseline value of 1 representing “fully active” in the context perceived by the interviewee to avoid altering outputs sensitive to varying initial conditions (Knight et al. 2014), including driver concept activation stability maintained by researcher attributed self-loops of value “+1,” (ii) the previous iteration of “memory” values A^t are added to *W*-factored values of A^t prior to normalization, designed to replicate temporal continuity in ecological and social systems, and (iii) positive normalization (0 to 1) at each iteration is accomplished with the sigmoid squashing function *f* (Equation 3), judged most appropriate compared to alternatives that introduce discontinuities unsuitable for r calculation, or hyperbolic tan function, which has equivalent suitability for correlation purposes (Bueno and Salmeron 2009), but is not readily available via accessible software,

$$(f)\alpha = \frac{1}{1 + e^{-\lambda\alpha}} \tag{3}$$

Variable α is the value to be normalized, *e* is Euler’s number, and λ = 1 (W. Bachhofer, *personal communication*). The low λ value selected for FCMappers determines a shallow curve approximating a linear function for non-extreme values

In the correlation analysis, any data pairs comprising concept activation values and emotional valence values where the latter is fixed for a driver concept were excluded from subsequent calculations for Hypothesis 3, however sensitivity testing not shown here determined that this made no meaningful difference to r values.

In calculating correlation values, effect sizes for Pearson’s r values are applied as follows: r = 0.10, small effect; r = 0.30, medium effect; r = 0.50, large effect (Cohen 1992).

RESULTS

Demographics

The total sample of n = 48 participants was majority male with modal age 41–60, notably in landowning and management roles plus farming, fishing, and regulatory roles in “Others.” Mostly younger women participated more frequently in the GP and CES groups (Table 2).

Emotion and connectivity

Hypotheses are addressed at the level of (i) individual concept connectivity, (ii) an overall connectivity metric for individual mental models, and (iii) aggregated mental model concept connectivity.

Hypothesis 1

Analysis of the raw set of 600 concepts linked to emotional valence scores showed a small but significant predictive relationship between emotional valence and concept centrality (r = 0.16, P < 0.01). For the sample of 48 FCM models there was also a small effect, insignificant for this sample, between mean model emotional valence and mental model density (r = 0.13, P > 0.05), shown in Table 3.

Hypothesis 2

Analysis of the whole sample (WS) aggregated group model representing a shared perspective reveals a strong and highly significant predictive relationship between emotional valence and aggregated concept centrality (0.60, P < 0.01). Analysis of aggregated stakeholder shared group model data also revealed large significant effects for the GP (r = 0.63, P < 0.05) and LM (r = 0.56, P = 0.05) groups, and a small non-significant effect for CES (r = 0.17, P > 0.05).

Hypothesis 3

Dynamic analysis results (Method, Equation 2) of aggregated FCM data show consistent positive predictive relationships between concept emotional valence and stabilized dynamic concept activation values, with significant strong effects for WS (r = 0.56, P < 0.05), GP (r = 0.52, P < 0.05), and CES (r = 0.60, P < 0.05). Analysis of the smallest stakeholder group, LM, revealed no significant relationship.

Aggregated WS and stakeholder group data including concept descriptors, centrality, and emotional valence are shown in Table 4. Conceptual content distributed between the aggregated stakeholder models consists of six ecological variables including the mandatory “Beaver presence,” and 17 human-centric variables in some way deriving from these including material and cultural ecosystem services, social-economic factors, beaver acceptance and beaver-applicable wildlife/nature finance, policy, and management.

DISCUSSION

Emotion predicts connectivity

The findings support presence of predictive relationships between measures of emotional valence and a selection of FCM

Table 3. Correlations; valence and model connectivity metrics. WS, whole sample; GP, General Public; LM, Landowners and Managers; CES, Conservation and Environmental Scientists.

	r	2 tailed P
Valence v. Centrality (600 concepts in 48 individual models)	0.16	< 0.01
Valence v. Centrality (Aggregated WS)	0.60	< 0.01
Valence v. Dynamic concept values (Aggregated WS)	0.56	< 0.05
Valence v. Centrality (Aggregated GP)	0.63	< 0.05
Valence v. Dynamic concept values (Aggregated GP)	0.52	< 0.05
Valence v. Centrality (Aggregated LM)	0.56	0.05
Valence v. Dynamic concept values (Aggregated LM)	0.31	Not Significant
Valence v. Centrality (Aggregated CES)	0.17	Not Significant
Valence v. Dynamic concept values (Aggregated CES)	0.60	< 0.05
Valence v. Density (n = 48 mental models)	0.13	Not Significant

parameters determined by various aspects of mental model connectivity. For our samples, emotional valence shows a small significant predictive effect in relation to individual model concept centrality indicating concept influence within mental models, and strongly positive predictive effects for both centrality and dynamic analysis for most but not all aggregated stakeholder groups. A small insignificant effect for model density possibly reflects an inadequately powered study, limiting further discussion.

Centrality and dynamic analysis are both derived from model connectivity, thus expected to correlate as structure necessarily predicts function, however the two sets of findings convey different types of information. Support for all three hypotheses invites explanations drawing on connectivity representing beliefs about causal influence, and emotion denoting personal or social significance of concepts and their causal relationships.

Centrality as a connectivity measurement is important because it highlights which drivers are believed to "make things work" and contribute to outputs of interest. For example, in beaver habitat damming connects to flow and storage of water, nutrient cycling, biodiversity, and human fulfilment; outputs valued or dis-valued by stakeholders with varying priorities.

Emotional signaling

Emotions function as internal individual and interpersonal social signals (Levine et al. 2018), in this case it is suggested responding to perceived connectivity within mental models. Because connectivity mediates dynamic outputs, emotional signaling is likely to be adaptive as an indicator for where and whether important social and ecological outputs increase or decrease (Norberg and Cumming 2008, Turnbull et al. 2018). For example, in the perceived River Otter beaver-system, change might conceivably result from the influence of "Government policy/ finance for nature," pressure exerted on politicians and decision makers in relation to expanding "Beaver presence" in the post-ROBT phase, or through wider public impact of emergent "Beaver persecution," all concepts shown in Table 4. This study's findings suggest that such developments will excite emotional responses consistent with connective influence acting on or from the concept. For example, "Beaver persecution" is a potentially controversial topic that perhaps counterintuitively currently features only weakly for both influence and emotional valence, and only for the CES group.

How mental model connectivity might generate stakeholder emotion is considered in relation to appraisal theory of emotion in Table 5, showing possible interactions between appraisal theory criteria indicating "significance of the environment for well-being" (Moors et al. 2013) and perceived connectiveness, with reference to possible features of the ROBT.

Appraisal theory of human emotion proposes various patterns of dimensional criteria that either determine or recursively interpret specific emotions (Scherer 2009). Appraisal criteria may be fundamental and automatic, or involve complex cognitive processing with greater social evolutionary and cultural specificity (Scherer 2001). For example, the illustrative beaver-specific judgments outlined represent interpretations that might weigh differently according to stakeholder and cultural context, and may be more strongly shaped by learning through experience and education.

The role of appraisal criteria might be further illustrated by our finding that GP and LM group memberships align for both connective salience and emotional valence intensity, respectively for "Beaver acceptance - General public" and "Beaver acceptance - Farmer, landowner, forestry" (see Table 4). In both cases, signaling emotional response to peer opinion may serve a purpose in affirming stakeholder affiliation, identity, and group security.

Aggregation and emotion

Increases in predictive correlation of emotion-connectivity associated with aggregation is notable, although interpretation of this finding has to be considered alongside consideration of what shared mental models really represent. Gray et al. (2014) distinguish social models in teams whose members have close knowledge of each other's mental models from social models arising in looser associations characterized by broadly common worldviews. Emotion for the latter might still signal important badges of shared group identity. The groups studied here seem likely to fall into the loose association category, with the possible exception of the CES group, some but not all of whom have professional links but nevertheless show weaker emotional correlations with perceived model connectivity. This apparent anomaly is unexplained but may reflect less need for peer emotional reinforcement, possibly reflecting group heterogeneity hence less prominent normative group identity. The aggregation effect shown exemplifies properties of scale; data showing large scale processes generally exhibit greater regularity in social, economic, and ecological systems, and are less vulnerable to chance disruption (Levin 1999).

Table 4. Aggregated stakeholder models for GP, General Public; LM, Landowners and Managers; CES, Conservation and Environmental Scientists; WS, Whole Sample: concepts and data parameters (EV†, mean absolute Emotional Valence; C‡, Concept degree Centrality; DA§, Dynamic Analysis - concept value)

Aggregated Stakeholder Groups; GP, LM, CES, WS - Concept values	EV† GP	C‡ GP	DA§ GP	EV† LM	C‡ LM	DA§ LM	EV† CES	C‡ CES	DA§ CES	EV† WS	C‡ WS	DA§ WS
Beaver presence (given)	0.85	8.70	0.94	0.81	4.98	0.94	0.86	7.53	0.93	0.85	13.28	0.99
Riparian woodland - vegetation health	0.70	1.42	0.84	0.73	1.68	0.80	0.66	0.50	0.78	0.72	1.78	0.85
Nature tourism	0.53	2.22	0.92				0.83	0.60	0.79	0.66	3.88	0.96
Beaver flooding/ impact on productive land	0.41	1.07	0.76				0.42	1.32	0.66	0.45	2.68	0.85
Beaver acceptance - Farmer, landowner, forestry	0.55	1.95	0.37	0.70	3.58	0.90	0.72	2.99	0.61	0.68	8.58	0.84
Holistic enrichment through valuing nature	0.76	0.55	0.66									
Sense of place/ specialness	0.86	2.73	0.95							0.81	3.45	0.96
Beaver acceptance - General public	0.66	4.32	0.98	0.67	2.96	0.91	0.72	4.53	0.89	0.71	8.96	1.00
Biodiversity - General	0.81	5.32	0.98	0.85	4.27	0.96	0.98	2.22	0.86	0.86	10.59	1.00
Making space for wilder nature	0.71	2.31	0.81				0.90	1.20	0.79	0.84	5.22	0.96
Beaver acceptance - Anglers							0.60	1.28	0.74	0.64	2.99	0.88
Science, education & knowledge	0.57	2.47	0.87				0.93	0.80	0.83	0.77	5.01	0.94
Monitoring & mitigation				0.65	1.80	0.77						
Wildlife NGO - Effective leadership	0.72	1.45	0.66	0.53	0.70	0.66	0.42	2.93	0.66	0.60	6.44	0.94
Conflict - public and private property/ amenity										0.49	1.25	0.80
Business generation	0.56	0.60	0.79							0.66	3.60	0.95
Flow rate/ Problem flooding in lower reaches	0.41	1.08	0.38							0.52	0.70	0.47
Conflict & distress - Natural resource stakeholder							0.40	0.53	0.78	0.58	1.63	0.86
Beaver damming and impoundment of water	0.72	3.05	0.83	0.75	1.42	0.82				0.78	4.19	0.82
Government policy/finance for nature				0.67	4.30	0.96	0.52	1.08	0.78	0.62	5.88	0.98
Water retention - Upper catchment	0.53	1.42	0.77	0.57	2.77	0.90				0.61	4.17	0.89
Wetland - Ecosystem health & services	0.53	1.24	0.80	0.85	2.78	0.83	0.90	1.79	0.78	0.75	4.92	0.98
Beaver persecution							0.35	1.80	0.51			

Table 5. Appraisal criteria (Moors et al. 2013) and adaptive social-ecological connectivity.

Appraisal criteria	Illustrative example of linked connections
Novelty	Emergence of influential concepts with strong driving inputs, for example an officially sanctioned beaver release
Desirability	Valuing sustainable causal origins of sought-after outputs
Conduciveness	Alignment with personal objectives including cultural and economic gains
Agency	Recognizing the role of (for example) beavers in maintaining ecosystem services
Norm-compatibility	Peer and social esteem represented by linkage to stakeholder acceptance concepts

Dynamic analysis and emotion

In the ROBT sample, emotion-connectivity correlations observed when models are run to simulate the dynamic outcome of concept interactions infer a "person's valence (cognitive and emotional) to the objects, relationships, and dynamics (of the model)" (Biggs et al. 2008:7), stressing both emotional valence and dynamics. The five-year time parameter for mental models in this study does not imply that dynamic analysis confers a regular time dimension, but does provide a frame within which change is envisaged with a perspective on before and after, for example, modulation of (unwanted) flooding downstream of beaver activity. A capacity to judge dynamic concept interactivity is likely to be adaptive. Dynamic analysis of concept activation shows how the mental model logic delivers expected change. Humans do not generally conduct complex calculations to anticipate outcomes, but it has been proposed that internally generated "as if" outcomes and emotional responses as suggested from mental models may act as feedback mechanisms underlying decision making (Damasio 1994, Lerner et al. 2015).

Dynamic analysis has a further important theoretical application in social-ecological scenario studies considering alternative futures modeled by adding or changing experimental weighted concepts to FCMs (Kok 2009, Jetter and Kok 2014). Exploring adjustments to signed emotional valence associated with variation in activation levels of critical outcomes has potential to deliver insights into likely stakeholder responses to conservation policy or land use.

Emotion-connectivity and conservation

Buijs and Lawrence (2013) argue that emotion needs to be acknowledged as essential to understanding human engagement with nature. The findings of this paper show an important aspect of how this relationship might function. For conservationists embarking on projects such as the ROBT, emotionally charged controversy between stakeholders may indicate a requirement to re-set the debate if interests are to be reconciled, requiring clarity about connections and outputs valued by different actors (Blicharska and Angelstam 2010). Reflecting on high intensity emotional valence may help focus on under-appreciated connections made by stakeholders, and a more informed approach to diagnosis and management of conflict and conservation such as proposed by Madden and McQuinn (2014).

Mental modeling with selected stakeholders may also add to understanding of the connective basis for conflict where emotional significance signals appear to diverge and risk undermining social feasibility, considered essential for successful wildlife reintroductions or similar conservation actions (IUCN/SSC 2013). We envisage that this could be done using pre-identified lists of key concepts identified from preliminary stakeholder interviews or expert workshops, making elicitation of perceived connectivity and emotional hot spots within mental models for affected individuals or community groups a more straightforward practical public engagement procedure. Where appropriate, designing psychological mitigation as tailored information to influence perceived connective salience and emotive responses offer a potential corollary to ecological mitigation in holistic stakeholder-sensitive conservation.

Stronger predictive relationships at aggregate scale suggest a direction for conservationists to focus on social group and community effects, including strategic interventions with large scale cross community effects such as pro-nature economic policy.

Associated and future research questions

1. We measured concept salience by “Degree Centrality.” Obiedat et al. (2011:1086) review alternative centrality constructs; (a) “Betweenness Centrality,” “determined by summing the proportion of shortest paths between node (concept) pairs that go through that node,” and (b) “Closeness Centrality,” which “measures how close a node (concept) is to all other nodes in the graph,” based on work by Freeman (1977, 1978). Intriguingly, an earlier investigation showed a relationship between the emotional quality of satisfaction from “real life” task accomplishment and “Betweenness Centrality” (Leavitt 1951). To our knowledge, possible relationships between emotion and either formulation, or how any such relationships compare with “Degree Centrality” remain unexplored.
2. Thagard (2006) outlines a decision-making framework relying on coherence within a network of positive or negative value-laden constructs such as concepts, beliefs, and goals. The network can be presented visually as a “Cognitive Affective Map” construed as an inferential reasoning mechanism (Thagard 2011). Thagard’s maps are not directed graphs showing mental models of “how things work,” but they do suggest ways in which emotions attached to concepts might interact directly. Our method could be adapted using Thagard’s insights to look for evidence of emotionally determined relationships between neighboring concepts, for example, whether concept closeness correlates with emotional intensity independently of perceived strength and direction of connections indicating causal influence.
3. Sensitivity analysis of the relationship between emotional valence and connectivity expressed through dynamic concept activation identified in our sample, done by real-time dynamic scenario-testing and repeat emotional valence testing for concepts would offer support for our findings. Practical scenario applications might include examining the emotional response to variations in perceived connectivity linked to modeling economic policy designed to increase farmland biodiversity or simpler practical conservation measures such as warning-notices designed to introduce conflict-aversive linkages into the mental models of visiting dog walkers.
4. Our study did show an emotional signal for overall model density, but the relationship was weak and did not reach conventional significance. There may be value in examining potential emotional responses to dense clusters of mutually connected concepts nested within mental models, termed “subgraphs” (Harary et al. 1965). Future findings of valance-discontinuity between subgraphs and less connected concepts may shed light on attribution of charismatic species status or wildlife hostility where high levels of connectivity suggest a meeting of criteria such as either extreme desirability and strong norm-compatibility, shown in Table 5. Shared possession of internally connected charismatic subgraphs might also help to explain the phenomenon of species-specific conservation group-identity.

CONCLUSIONS

Individual and group stakeholder mental models for a restored English beaver population show correlations between emotion and perceived concept connectivity and dynamics. Thus, emotional valence may be signaling functional influence attributed to concepts, as well as sensitivity to altered concept states, as perceptions of change in ecosystems unfold. It is proposed that criteria specified in appraisal theory of emotion plausibly account for human sensitivity to connectivity within their mental models. Because the linkages between emotional responses and mental models are likely to have roots in ecological and social adaptiveness and to be expressed in the outcomes of decision making, there is a rationale for paying attention to the role of human emotion in conservation practice. This study shows how emotional responses to an important conservation species such as beaver, compounded by rapid change following reintroduction into high-usage domesticated landscapes common to developed countries such as England, can be considered an important and inevitable aspect of stakeholder participation in a large-scale conservation project, for good or ill. These findings invite further investigations into likely mechanisms underlying the complex relationship between emotion and mental modeling of human-wildlife interactions, and suggests a rationale for conservation planners and managers to recognize and work directly with stakeholder emotional responses, as well as recognizing differing perceptions of connectivity that may be revealed by emotional conflict.

Responses to this article can be read online at:
https://www.ecologyandsociety.org/issues/responses.php/12823

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Data Availability:

All data that support the findings of this study are available on request from the principal author. Raw data is stored on a drive held within the Cultural Geography Chair Group, Department of Social Science, Wageningen University & Research, (WUR) NL and accessible to academic staff. Following departmental policy, all data will be moved to a publicly accessible Dutch national archive accessible on publication. Ethical approval for this research study was granted by internal procedure of the Cultural Geography Chair Group operational at the time the project was initiated, and confirmed in writing by the relevant Departmental Ethical Committee for research involving human subjects.

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