Collaborative Knowledge in Scientific Research Networks

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A volume in the Advances in Knowledge Acquisition, Transfer, and Management (AKATM) Book Series

Information Science REFERENCE
An Imprint of IGI Global

Managing Director: Lindsay Johnston
Acquisitions Editor: Kayla Wolfe
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Development Editor: Allison McGinniss
Typesetter: Kaitlyn Kulp
Cover Design: Jason Mull

Published in the United States of America by
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Collaborative knowledge in scientific research networks / Paolo Diviacco, Peter Fox, Cyril Pshenichy, and Adam Leadbetter, editors.
pages cm
Includes bibliographical references and index.
ISBN 978-1-4666-6567-5 (hardcover) -- ISBN 978-1-4666-6568-2 (ebook) -- ISBN 978-1-4666-6570-5 (print & perpetual access) 1. Knowledge, Theory of. 2. Research--Methodology. 3. Science--Methodology. I. Diviacco, Paolo.
Q175.32.K45C65 2015
001.4'2--dc23
2014029336

This book is published in the IGI Global book series Advances in Knowledge Acquisition, Transfer, and Management (AKATM) (ISSN: 2326-7607; eISSN: 2326-7615)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 4
Assessing Individual Influence on Group Decisions in Geological Carbon Capture and Storage Problems

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ABSTRACT

The inherent uncertainty in information about the Earth's subsurface requires experts to interpret and reach judgements about geological data based on their individual experience and expertise. This is particularly true for the geological storage of CO_2 in subsurface saline aquifers where the fate of the injected CO_2 needs to be predicted far into the future. In this chapter, linear modelling is used in a structured elicitation exercise to estimate the relative influence of individual experts within a group and to assess whether a group consensus reflects a genuine shared opinion or is biased towards or away from any dominant member or subgroup. The method is applied to a real expert evaluation of the carbon storage potential of a siliciclastic formation. This reveals herding behaviour amongst the experts, and levels of inter-expert influence that are undue given individual experts' levels of expertise, though neither phenomena was apparent during the meeting.

INTRODUCTION

Subsurface carbon capture and storage requires CO_2 to be stored indefinitely in the intended geological storage reservoir. However, the uncertainty associated with information about the deep subsurface makes prediction of the long term fate of the injected CO_2 difficult. The geological information on which such predictions are based is inherently uncertain, and requires individuals or groups of experts to make interpretations and judgements about the likely properties and characteristics of the reservoir, caprock and overburden layers of rock. A critical component of site evaluation

DOI: 10.4018/978-1-4666-6567-5.ch004

is the analysis of risk where risk is defined as a combination of the likelihood and the severity of impact of any event (Chadwick et al., 2008; Det Norske Veritas, 2010, Smith et al., 2010, Polson et al., 2012). As part of this process, experts are asked to assess the risk of CO_2 storage in a given site using available data, simulation results, and their experience and expertise. Uncertainty can lead to different experts forming different opinions based on the same information (Baddeley et al., 2004; Bond et al., 2007; Lowe & Lorenzoni, 2007; Polson & Curtis, 2010).

Group interactions between experts can improve the quality of decisions made as it allows knowledge and experience to be shared between experts (e.g. Phillips, 1999). All individual experts are subject to cognitive biases when making judgements in situations of uncertainty (e.g. Kahneman et al. 1982, Anderson, 1998, O'Hagan et al, 2006, Bond et al. 2012, Curtis, 2012), and evidence suggests that group interaction may help to mitigate the effects of individual bias (Sniezek, 1992, Diviacco, 2015, see chapter 1 of this book). However group interaction may lead to the introduction of other, group-related biases (Sniezek, 1992), and it is towards these that we focus attention in this chapter.

In situations where a group consensus must be reached, individual experts will exert different levels of influence on the group. In an ideal world the influence of each expert will reflect his/her relative expertise, and group performance will improve with more effective use of each additional expert (Hackman & Morris, 1975; McGrath, 1984). However other factors such as individual force of personality and confidence may bias the group decision. Also the relative influence of each expert may not be apparent from the meeting itself: while particularly dominant characters may stand out, their actual influence on the group may be lower than their dominance of the conversation would suggest. Furthermore even where no expert appears to dominate the discussions or decisions, individual experts may still have a disproportionate influence on group decisions, and on other experts.

By using a novel structured elicitation process we are able to identify when such group biases occur, for example in the assessment of geological information (Polson & Curtis, 2010). Expert elicitation theory and practice have been investigated and used in numerous studies in the earth and environmental sciences such as nuclear waster disposal (Bonano & Apostolakis, 1991), interpretation of geological data (Curtis & Wood, 2004a; Bond et al., 2007), risk and impacts of climate change (Morgan et al., 2001; Arnell et al., 2005; Lowe & Lorenzoni, 2007), hydrological modelling (Ye et al., 2008), and risk assessment connected with volcanic eruptions (Aspinall, 2006) and earthquakes (Bommer et al., 2005; Runge et al., 2013). Using a well-structured elicitation method it is possible to track the opinions and judgements of individual experts in a group environment where a consensus opinion or view is required. Polson and Curtis (2010) used this to track the influence of group discussions on the opinions of individual experts, and to compare the judgements of individual experts with the group consensus. This revealed that a variety of identifiable biases had influenced views in a real geological evaluation.

In principle such a process can also be applied to understand the relative influence of individual experts on the group consensus, and on each other. By examining in detail the judgements made at each stage of the process we may be able to identify a pattern of influence. However this analysis is complex and the results are often ambiguous. To fully understand the relative influence of each expert we need to consider each judgement made by each expert at each stage of the process within the wider context of all judgements made during the elicitation session. Even with only three experts in a group this can be a complicated and time consuming task. As the number of experts increases so does the complexity of the analysis.

Numerous studies have been conducted on influence within groups (see e.g. Kirchler & Davis, 1986; Hinsz, 1990; Laughlin, 1988, 1992; Kerr, 1992; Davis et al., 1996a, 1997; Ohtsubo et al., 2002) and on modelling the consensus forming behaviour of groups (see e.g. Lehrer & Wagner, 1981; Davis 1982, 1992, Davis et. al. 1996b). By tracking the opinions of individual members of the group it is possible to identify which experts have the most influence on the group and develop expert-weighted models (Bonner 2000, 2004).

In this chapter we use a simple linear model to characterise the relative influence of individual members of a group in a well-structured group elicitation session. This method allows us to extract the overall trends of influence quickly and without the need for the detailed individual analysis discussed above. Fitting the initial assessments of each expert at the start of the session with the final group consensus allows us to identify which expert appears to have the most influence overall on the consensus judgment. Similarly it is possible to determine the apparent relative influence of individual experts on each other by fitting the initial assessment of each individual expert with the set of individual assessments from the end of the session.

This process was applied to two group elicitation sessions to assess risks involved in a subsurface CO_2 storage project for climate change mitigation, where experts were asked to assess individually, and reach a group consensus about, the likelihood and severity of a set of Features, Event or Processes (FEPs) that might affect the project (see e.g., Maul et al., 2005; Wildenborg et al., 2004, 2005; Chadwick et al., 2008; Polson et al., 2009; Det Norske Veritas, 2010). The elicitation focused on a real onshore saline aquifer formation which was evaluated as an analogue for geological CO_2 storage in formations offshore around the UK. The results reveal which member of the group exerted the most influence, and identifies where a consensus reflected the true shared opinions of the group, and where this was not the case. In the latter situation the results should be treated with more caution than in the former.

GEOLOGICAL CONTEXT

As part of the CO_2 Aquifer Storage Site Evaluation and Monitoring (CASSEM) project (Smith et al., 2010), the region around the Ferrybridge power station in eastern England was investigated to identify a saline aquifer formation suitable for hypothetical CO_2 storage. Using available images constructed from 2D and 3D seismic data acquired for oilfield evaluation purposes in the previous decades (see Smith et al. (2010) for an example cross-section through one image that was used), and existing borehole and well data, a geological model of the subsurface was constructed for a geological area of 945 km^2, extending from Lincoln in the west to the coast in the east. A set of selection criteria were used to identify the most suitable reservoir rock formation, including but not limited to depths >800m, salinity >100 gl^{-1}, porosity >20% and permeability >500mD. The bedrock succession considered ranged in age from Carboniferous to Cretaceous. Within the Triassic strata, the Sherwood Sandstone Group was identified as the primary target aquifer with corresponding Mercia Mudstone Group caprock.

The geological context of the reservoir and caprock is described in Ford et al. (2009). The Sherwood Sandstone Group consists mainly of fluvial sandstones with occasional thin and laterally discontinuous marl seams. The Mercia Mudstone Group is predominantly red mudstones with subordinate siltstones and sandstones. The aquifer formation extends offshore from the coast at Saltfleetby to Lincoln in the west. Generally the caprock layer should provide a physical barrier to the upward migration of CO_2 to the surface. However in this case the formation is shallowly dipping, and in fact both the Sherwood Sandstone Group and Mercia Mudstone Group outcrop at the surface, far up-dip to the west of the hypothetical injection site. Thus there is a potential leakage pathway for CO_2 that may allow it to migrate to the surface. However, over long timescales (hundreds of years), CO_2 will dissolve in the brine. The density of the resulting fluid is greater than the native brine and hence the CO_2 becomes 'dynamically trapped'. Therefore the site is not necessarily ruled out for the storage of CO_2 (although to the authors knowledge there are no current plans to do so) despite the lack of complete structural closure, as the likelihood of leakage of CO_2 may still be low if the CO_2 is able to dissolve before it has time to migrate to the surface. Detailed site assessment would be required to determine the risk of leakage. Furthermore, where the aquifer is shallower in the west, it is also a source of potable water and there is the potential for the contamination by either the injected CO_2 or the saline formation fluids.

METHOD

Expert Elicitation

A project-specific risk register based on the Quintessa CO_2 FEP register (Savage et al., 2004) was constructed to assess risk for the Lincolnshire exemplar storage site (Polson et al., 2012). The register includes a hopefully exhaustive list of FEPs that define relevant scenarios and behaviour of CO_2 in the storage system which may pose risk to the project. These are assessed by experts for their likelihood (K) of impacting the project, and for the severity (S) of this impact. The full register may contain many tens or hundreds of FEPs, covering a wide range of areas of expertise. All must be assessed at multiple stages of a project by a number of experts to track any changes. In practice it is therefore only possible to complete the full risk register by using a number of experts who assess the FEPs independently, and the results of this analysis are described in Polson et al. (2012). However, it is also important to understand how the judgements of experts working in isolation might differ from those that evolve in a group environment where knowledge can be shared.

In each structured group elicitation session, three experts were asked to quantify the likelihood and severity for a subset of FEPs. The subsets of FEPs, which were ranked as moderate or high risk by the individual experts, were selected based on the similar range of expertise required to assess them. The likelihoods K are scored on a scale of 1-5 where 1 is low and 5 is high. Two separate scales for the severity S were used for each FEP: the first was for the impact on health and safety (HS), and the second for the impact on the project's financial viability, the environment, research, and industrial viability (FERI). The experts were asked to assess the lower-bound, best-guess and upper-bound for both the likelihood and severity, resulting in nine quantitative judgements per FEP (three for likelihood, and three from each of two scales for severity).

At the start of the session the experts were asked to assess each FEP independently of the other experts. These individual assessments were then shared with the group, and each expert was asked to explain their reasoning. Through subsequent discussion, the group was required to produce a group consensus assessment for each FEP which all experts could agree to. Immediately thereafter they were again required to complete individual assessments independently at the end of the session. See Polson and Curtis (2010) for more details of the elicitation methodology, and for another application in a geological asset team environment.

Two group sessions were carried out using different experts and assessing different FEPs related to a CO_2 storage project. In the first session four FEPs were assessed, resulting in a total of 36 separate judgements made by the experts at each stage of the elicitation process. This set of FEPs related to the industrial viability of CCS and included:

- (A) Construction and Site Logistics,
- (B) Construction of Pipeline,
- (C) Leakage from Pipeline,
- (D) Public Perception and Security.

In assessing the risk from these FEPs, the experts must consider the characteristics of the intended storage formation and estimate, given available information, the likelihood and severity of a negative impact related to each FEP occurring. For example, in considering public perception, the issue of the incomplete geometrical closure of the aquifer by the caprock may be an important issue; in considering the construction of pipeline, previous experience from existing CO_2 and oil and gas pipelines may contribute significantly.

In the second session three FEPs were assessed related to the transport and dynamics of CO_2 in a porous medium (the subsurface reservoir), resulting in a total of 27 separate judgments per expert at each stage of the process. The FEPs assessed were:

- (E) Advection of free CO_2,
- (F) Buoyancy-driven flow,
- (G) Water mediated transport.

For these FEPs the experts must consider the properties of the aquifer and caprock and how these will influence the transport of CO_2 in the subsurface. For example given available information about the caprock and the associated uncertainties, is CO_2 likely to migrate upwards through the subsurface to the near-surface environment?

More detailed descriptions of each FEP were given to the experts to stimulate ideas and focus attention on potential risk areas (see Appendix).

Fitting Procedure

A simple linear model is used to represent the influence of each expert on the group consensus

$$\underline{C} = \sum_{i=1}^{n} \beta_i \underline{I}_i \quad (1)$$

where $\underline{C}$ is a rank-m vector containing the consensus values (in this case it consists of blocks of three judgements $[L, B, U]$ for each FEP, where L is the lower bound score, B is the best guess score and U is the upper bound score), m is the total number of judgements made at the consensus stage, $\underline{I}_i$ is the corresponding rank-m vector of the initial or prior values for expert i, β_i is the coefficient representing the influence of expert i on the consensus, and there are n experts. Using least squares fitting to determine the values for coefficients $\underline{\beta}$, the relative influence of each expert's prior position on the final consensus can be quantified with larger values of β_i representing greater influence of expert i.

By replacing the consensus values in Equation (1) with the values from the final individual assessment of an expert, the relative influence of all experts on that individual expert can be estimated, including the influence of their own initial assessment on their own final judgments:

$$\underline{F}_i = \sum_{j=1}^{n} \alpha_{ij} \underline{I}_j \quad (2)$$

Here $\underline{F}_i$ is a rank-m vector of the final values of expert i, and coefficients α_{ij} represents the influence of the initial views of expert j on the final view of expert i.

Similarly by using just one expert's own initial assessment and the consensus assessment to fit that expert's end of session assessment it is possible to determine whether the consensus (or emergent group behaviour) has more or less influence on their final assessments than their own prior position:

$$\underline{F}_i = \gamma_i^I \underline{I}_i + \gamma^c \underline{C} \tag{3}$$

Here $\underline{F}_i$ is a rank-m vector of the final values of expert i, and γ_i^I and γ^c are the coefficients corresponding to the influence of the expert's initial values and the consensus values, respectively.

More generally it is possible to find the optimal coefficients, δ, of the equation

$$\underline{\underline{D}} = \underline{\underline{\delta}}^T \underline{\underline{D}} \tag{4}$$

where $\underline{\underline{D}}$ is the matrix containing all FEP assessments at all stages in the process, each row taking the form [L,B,U] for any one FEP, and $\underline{\underline{\delta}}$ being a matrix of mixture coefficients used to weight the various results to produce all other results. Eq. (4) is solved by $\underline{\underline{\delta}} = \underline{\underline{I}}$, the identify matrix. However this is the solution assuming that no group interaction takes place, as $\underline{\underline{\delta}} = \underline{\underline{I}}$ implies that each estimate of [L,B,U] for each FEP is influenced by nothing other than that estimate. While that may be true for the prior pdfs, it is unlikely to be true for most others. Taking the point of view that expert prior positions impact on group interaction, implies that the matrix $\underline{\underline{\delta}}$ may have certain structures imposed a priori. In this work we will use the structure described by Eqs. (1) to (3) (constructed from Eq. (4) by equating different elements of $\underline{\underline{\delta}}$ to each other or to zero), but it may be useful to note that other structures are possible.

To ensure that any distinction in the pattern of influence of individual experts was statistically significant on the consensus assessments (equation (1)), the student t-values for each coefficient were tested assuming a null hypothesis that all terms exert equal influence (i.e., that the t-values of all coefficients are equal):

$$t = \frac{\hat{\delta} - \delta_0}{SE_{\hat{\delta}}} \tag{5}$$

where t is the student t-value, $\hat{\delta}$ is the least squares estimate for a coefficient, δ_o is the specified value for δ assuming the null hypothesis is true, and SE_{δ} is the standard error for the coefficient $\hat{\delta}$. If the t-values of all coefficients do not exceed some statistically significant level (corresponding p-value < 0.05), then the linear model does not distinguish between the influence of the individual terms, and hence does not distinguish between experts. For the models described by equations (2) and (3) we test the null hypothesis that the expert is only influenced by their own original assessment.

RESULTS

Session One

Figures 1-4 show the individual and consensus scores for session 1 for FEPs A, B, C, and D respectively. Analysis and interpretation of the expert interactions exhibited within these plots is complex, requiring each to be examined individually. Figures 1-4 show no immediately obvious pattern as to which expert has the most influence on the consensus or on the other experts. Similarly it is not clear which experts tend to agree the most with the consensus. For example, initial analysis shows that the number of occasions where the consensus is closest to the individual start of session opinion of each expert is almost exactly equal for all three experts. This would suggest that they have similar levels of influence on the

Figure 1. Session 1 scores for FEP A for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Solid circles show best guesses, while horizontal lines run from lower-bound to upper-bound estimates.

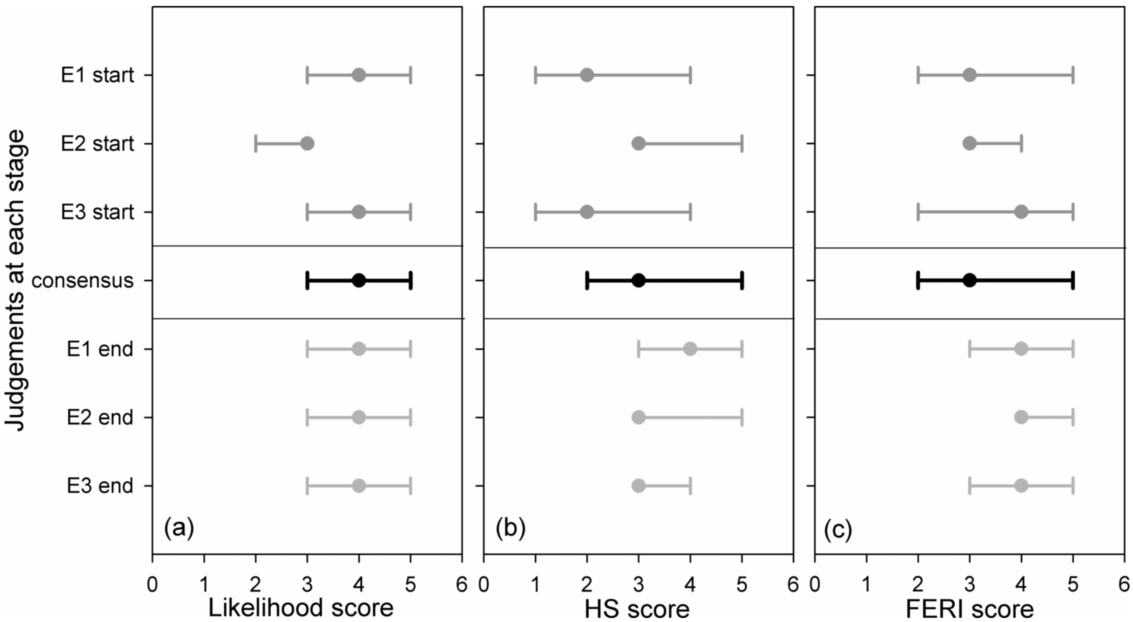


Figure 2. Session 1 scores for FEP B for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Key as in Figure 1.

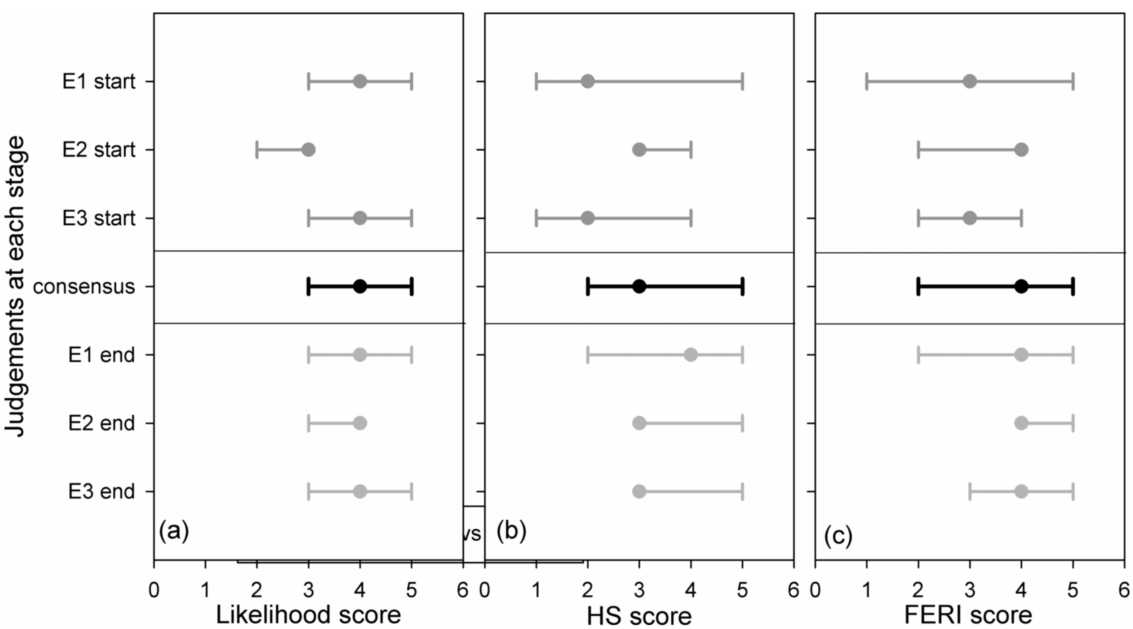


Figure 3. Session 1 scores for FEP C for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Key as in Figure 1.

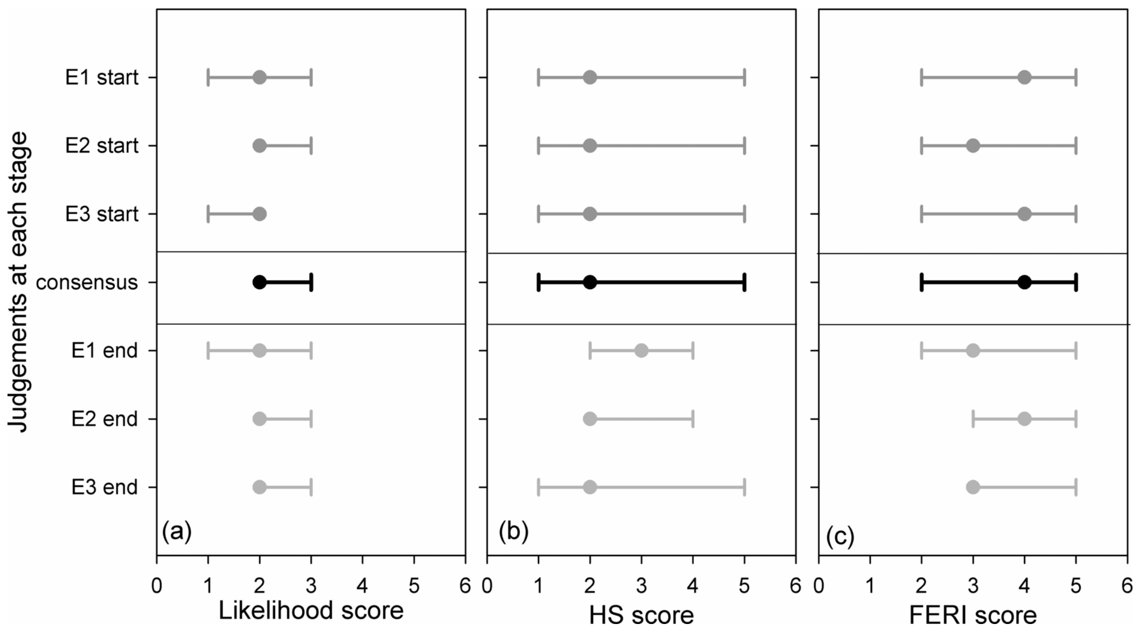
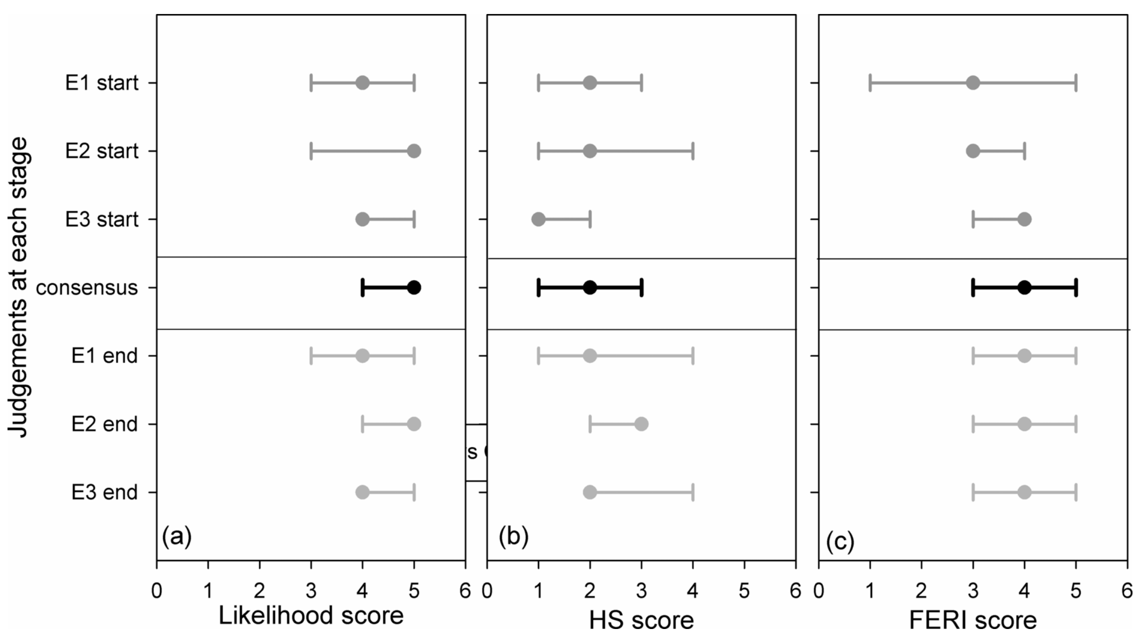


Figure 4. Session 1 scores for FEP D for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Key as in Figure 1.



group consensus. However to fully understand the patterns of influence we must consider not only which expert's individual scores tend to be closest to the consensus, but also the overall quantitative degree of similarity between each expert's individual scores and the consensus. We also need to be able to distinguish between experts who have produced exactly the same scores for a particular FEP. These figures demonstrate the complexity of the interpretation of results even with only three experts if the linear fitting technique was not used. As the number of experts grows, so the task of interpreting the results becomes increasingly difficult. Nevertheless, as we show below, the linear fitting technique offers a simple method to identify overall patterns of influence.

The coefficients for the linear models for the individual expert assessments are shown in Table 1. Here the coefficient t-values disprove the null hypothesis that each expert is only influenced by their own original opinion with p-value < 0.05. The coefficients α_{ij} suggests that expert E2 has the most influence on the other experts: the final assessment of expert E1 seems to be more strongly influenced by the initial assessment of expert E2 than by their own initial assessment (i.e., $\alpha_{21}>\alpha_{11}$). Likewise for expert E3, the initial assessment of expert E2 has the most influence on their final assessment ($\alpha_{23}>\alpha_{33}$). The final assessment of expert E2 is most influenced by their own initial assessment, with very little influence at all from expert E1.

Table 2 shows the coefficients produced by using just the expert's own initial assessment and the group consensus to fit each expert's individual assessment at the end of the session. Experts E1 and E3 are both strongly influenced by the group consensus ($\gamma^c \approx 1$), and are not strongly influenced by their own initial assessment ($\gamma_1^I \approx \gamma_3^I \approx 0$). Expert E2 is less strongly influenced by the consensus ($\gamma^c = 0.63$), however in all cases the coefficient t-values disprove the null hypothesis that the experts are only influenced by their own original assessment with $p < 0.05$, demonstrating that some interaction has taken place to significantly alter all of their positions.

The fitting procedure was also applied to the start of session assessments and the consensus assessments producing the model shown in Table 3. The coefficients β_i for the individual start of session assessments reflect the relative influence of each expert on the consensus. The coefficients are similar for all three experts implying they have similar influence as suggested above by direct examination of Figures 1, 2, 3, and 4. In fact t-values of each coefficient from equation (5) have $p > 0.05$ and hence fail to disprove the null hypothesis that all terms are equally influential.

The root mean square error (RMSE) of the experts' end of session assessments with respect

Table 1. Fitted model coefficients, α, for the individual expert (1, 2 and 3) assessments from session 1. Each coefficient α_{ij} shows the influence of each expert i on the individual end of session assessment of expert j. The coefficient showing the influence of the expert's own initial assessment on their own final judgment is in bold.

	Coefficients		
	α_{1j}	α_{2j}	α_{3j}
Expert E1	**0.39**	0.58	0.14
Expert E2	0.08	**0.69**	0.36
Expert E3	0.18	0.61	**0.33**

Table 2. Fitted model coefficients, γ, for the final individual expert (1, 2 and 3) from session 1. Each coefficient γ_i^I shows the influence of the initial assessment of expert i on their own final judgment while γ^c shows the influence of the consensus.

	Coefficients	
	γ_i^I	γ^c
Expert 1	-0.01	1.01
Expert 2	0.45	0.63
Expert 3	-0.03	1.04

Table 3. Fitted model coefficients β for the final individual expert (1, 2 and 3) assessments from the start of the session and the consensus from session 1. Each coefficient, β_i shows the influence of expert i on the consensus.

	Coefficients		
	β_1	β_2	β_3
Start	0.34	0.40	0.37

to the consensus provide a measure of the degree to which the experts tend to disagree with the consensus at the end of the meeting. For experts E1, E2 and E3 the RMSE values are 0.60, 0.69 and 0.53 respectively. This shows that expert E3 tends to agree with the consensus the most and expert E2 agrees with the consensus the least.

Figure 2(c) shows an example of individual start and end of session assessments, and the consensus assessment, which exhibit the effects identified by the linear fitting algorithm. Here we can see that at the start of the session the scores of expert E2 are closest to the consensus scores that the group reached with the same best-guess and lower bound. By the end of the session the assessments of experts E1 and E3 both more closely match the consensus assessment than the assessment of expert E2. Expert E1 gives the same scores as the consensus while expert E3 has the same best guess and upper bound with a slightly higher lower bound. Expert E2 has not changed his/her assessment of the best-guess, however he/she has increased his/her upper bound but also increased his/her lower bound so that he/she is now less in agreement with the consensus of the three experts.

In an earlier assessment, the experts were asked to rate their expertise on a scale of 1 to 5 for each FEP where 1 = novice and 5 = expert. Expert E1 consistently ranked his/her expertise above the other 2 experts as shown in Table 4. However expert E1 has similar levels of influence overall on the consensus as experts E2 and E3, and has the least influence on the final assessments of the other two experts. Expert E2 on the other hand has the most influence on the final assessments of the other two experts even though on one occasion he/she went as far as saying that for one FEP he/she was not particularly knowledgeable in that area. Despite the difference in expertise, expert E2 shows the most influence on the group while being the least influenced by it.

Session Two

A second elicitation session was carried out for three different experts and a different set of FEPs. Figures 5-7 show the individual assessments of each expert at the start and end of the session and the consensus assessment for FEPs E, F, and G respectively. As with Figure 1-4 it is not immediately obvious which expert tends to exert the most influence overall; detailed analysis of each plot would be required to extract this information. One pattern that does emerge is that expert E4 tends not to change his/her views from the start to the end of the session, reproducing exactly the same scores in 7 out of 9 occasions. This suggests that the other two experts in the group have little influence on this expert. In order to better understand the overall trends of influence we use the same linear fitting technique as above.

The coefficients for the linear models produced for each individual expert are shown in Table 5. In this case all three experts are most influenced by their own original assessment from the start

Table 4. Self rated expertise of each expert for each FEP from session 1. Expertise scale 1-5 where 1 = novice and 5 = expert.

FEP	Expert 1	Expert 2	Expert 3
A	4	3	2
B	4	2	2
C	4	2	2
D	3	3	2

Figure 5. Session 2 scores for FEP E for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Key as in Figure 1.

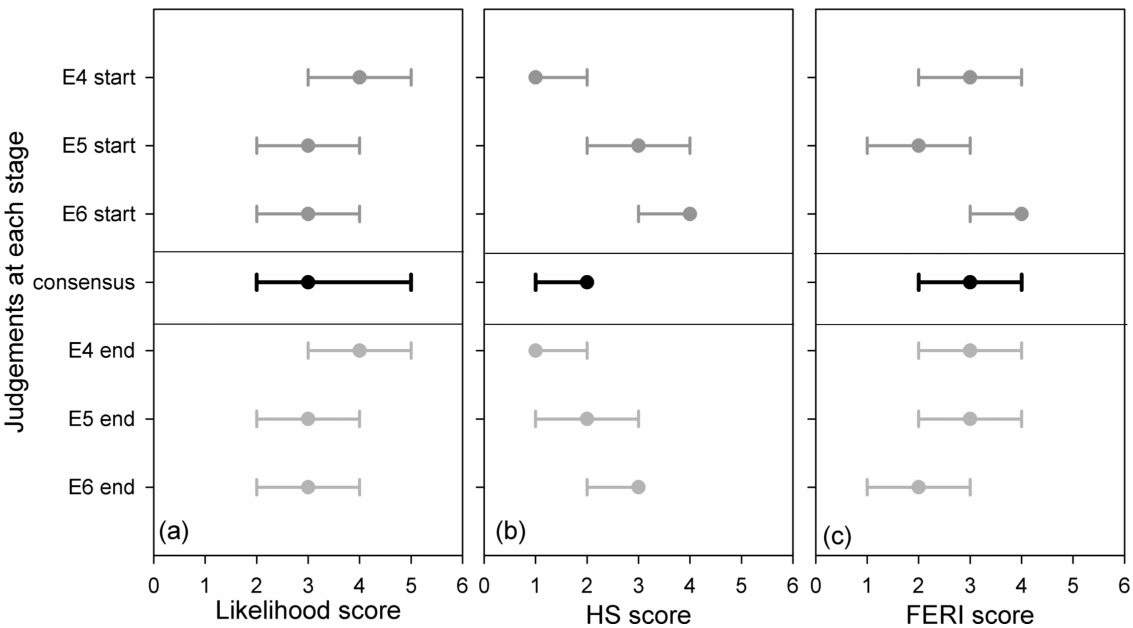


Figure 6. Session 2 scores for FEP F for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Key as in Figure 1.

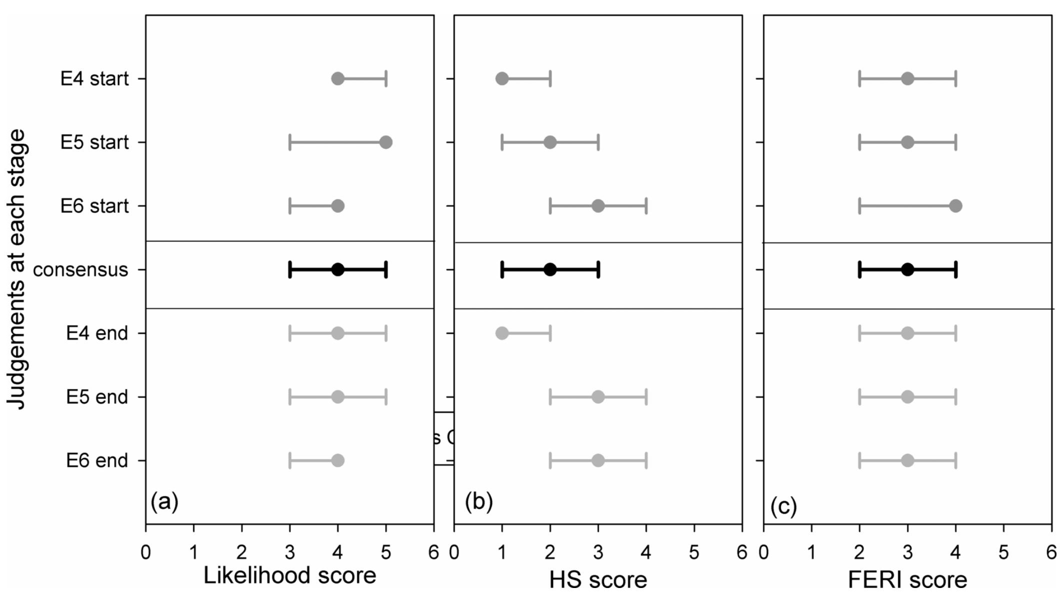
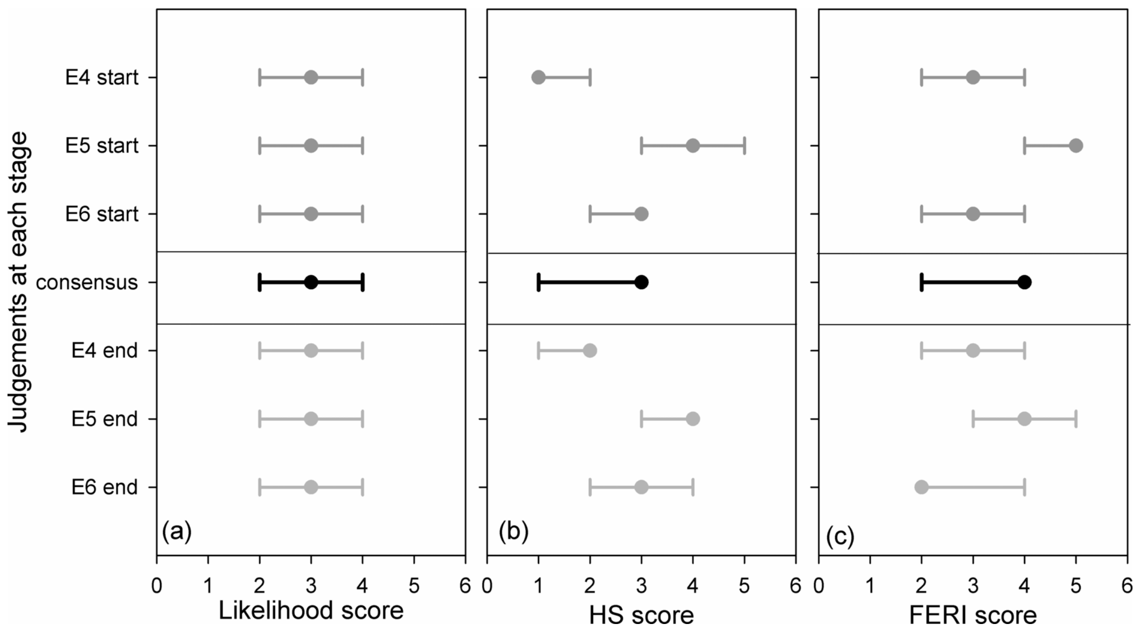


Figure 7. Session 2 scores for FEP G for individual start and end of session (grey) and consensus (black) assessments for (a) likelihood, (b) health and safety (HS) severity and (c) financial, environmental, research and industrial viability (FERI) severity. Key as in Figure 1.



of the session. As identified in the examination of Figures 5, 6, and 7, expert E4 in particular exhibits little influence from the other two experts with $\alpha_{44} \approx 1$ and $\alpha_{54} \approx \alpha_{64} \approx 0$. Experts E5 and E6 are more influenced by the other experts, but the influence of their own prior opinion still dominates with corresponding coefficients of ~ 0.5. Here the t-values for the model for expert E4 fail to disprove the null hypothesis that the expert is only influenced by their own original opinion. For experts E5 and E6 the t-values are statistically significant and hence show that these two experts have been influenced to some degree by the interaction with the other experts, even though they are most influenced by their own opinion.

Table 6 shows coefficients for the linear models produced for fitting the individual end of session opinions to their own start of session assessments

Table 5. Fitted model coefficients, α, for the individual expert (4, 5 and 6) assessments from session 2. Each coefficient α_{ij} shows the influence of each expert i on the individual end of session assessment of expert j. The coefficient showing the influence of the expert's own initial assessment on their own final judgement is in bold.

	Coefficients		
	α_{4j}	α_{5j}	α_{6j}
Expert 4	**0.95**	0.02	0.02
Expert 5	0.20	**0.52**	0.29
Expert 6	0.08	0.33	**0.50**

*Table 6. Fitted model coefficients, **γ**, for the final individual expert (4, 5 and 6) from session 2. Each coefficient γ_i^I shows the influence of the initial assessment of expert i on their own final judgment and the $\boldsymbol{\gamma}^c$ shows the influence of the consensus.*

	Coefficients	
	γ_i^I	γ^c
Expert E1	0.87	0.11
Expert E2	0.48	0.55
Expert E3	0.58	0.35

and to the consensus assessments. Of the three experts, expert E4 is the least influenced by the consensus assessment with their start of session assessment coefficient $\gamma_4^I = 0.87$ compared to the consensus assessment coefficient $\gamma^c = 0.11$, though the t-value for γ_4^I is statistically significant with $p < 0.05$ and hence in this case shows that expert E4 is not solely influenced by their own original opinion. Both experts E5 and E6 are more strongly influenced by the consensus with $\gamma_5^I = 0.48$ and $\gamma^c = 0.55$ for expert E5 and $\gamma_6^I = 0.58$ and $\gamma^c = 0.35$ for expert E6, where the t-values are statistically significant. This again suggests that expert E4 is very confident in his/her original assessment and is the least swayed by the other experts in the group.

Table 7 shows the coefficients β_i for the linear model between the consensus and start of session individual assessments. The coefficient t-values in this case disprove the null hypothesis that all terms are equally influential and hence we can distinguish a pattern of influence. Expert E4 exerts the most influence on the consensus with $\beta_4 = 0.58$ compared to $\beta_5 = 0.22$ for expert E5 and $\beta_6 = 0.18$ for expert E6. Clearly in this instance expert E4 has significantly more influence on the group consensus than the other two experts whose influence seems to be approximately equal. The RMSE values for the experts' end of session assessments and the consensus are 0.54, 0.69 and 0.79 for experts E4, E5 and E6 respectively. This suggests that at the end of the elicitation session, the assessment of expert E4 is closest to the consensus while the assessment of expert E6 is furthest from the consensus.

An example of this is shown in Figure 5(b) where the individual scores from the start of the session show that the consensus is very similar to assessment of expert E4. At the end of the session expert E4 does not change his/her assessment, while experts E5 and E6 do change theirs towards the consensus but are still partly anchored to their assessments from the start of the session. Indeed, expert E6 does not agree with the consensus at all.

The self-assessed expertise of the expert for each FEP are shown in Table 8. From this we can see that experts E4 and E6 consider themselves to have equal expertise for all FEPs while expert E5 considers his/her expertise to be lower. As with the previous session, this was not reflected in the relative influence that each expert had on the group, with expert E4 exerting considerably more influence on the consensus than expert E6. The result is that the consensus closely reflects the start of session assessment of expert E4. This expert is influenced little by the other experts with the result that they change their start of session assessment little when asked to reassess the likelihood and severity at the end of the session. The other two experts have agreed to the consensus of expert E4 but they are less influenced by this expert in their individual assessments. Despite agreeing to a consensus that strongly reflects the start of session assessment of expert E4, personally they still tend to anchor most strongly to their own initial assessments at the end of the session.

Table 7. Fitted model coefficients, β, for the final individual expert (4, 5 and 6) assessments from the start of the session and the consensus from session 2. Each coefficient, β_i shows the influence of expert i on the consensus.

	Coefficients		
	β_4	β_5	β_6
Start	0.58	0.22	0.18

Table 8. Self rated expertise of each expert for each FEP from session 2. Expertise scale 1-5 where 1 = novice and 5 = expert.

FEP	Expert 4	Expert 5	Expert 6
E	4	2	4
F	4	2	4
G	4	1	4

CONCLUSION

From the range of opinions presented in the elicitation sessions, it is clear that experts can reach differing and even contradictory conclusions from the same geological data. To reconcile these differences experts are often asked to reach some consensus position requiring detailed group discussions. However, as this work and other studies have shown, this group consensus may not only reflect the range of opinions of all experts present in the meeting but can also be influenced by the social dynamics in the meeting.

Using simple linear models to represent the behaviour of the group we can begin to understand the relative influence of individual members and the dynamics of the group interactions without the need for complex recording and analysis of group behaviour, nor the complicated detailed analysis of the opinions and judgements of individual experts at each stage of the elicitation process. However, caution must be shown in interpreting these results as this does not conclusively show which expert exerts the most influence. For example, a high value coefficient may simply reflect that the initial assessment of a particular expert is coincidently closer to the final assessment of the group. In addition, as a least squares (L2 norm) fit is used, more emphasis will be placed on choosing coefficients that reduce large differences in individual scores rather than smaller differences. For example, an expert who disagrees with the lower bound of the consensus by two units will tend to be found to be less influential than an expert who disagrees with the consensus lower bound by one unit and the best-guess by one unit. This could of course be altered by using a different norm for the measurement of misfit, such as an L1 norm instead of L2. Repeating the analysis using an L1 norm produces largely similar results. The only notable change of influence is for expert E5, who in Table 5 is identified as most influenced by their own initial opinion using the L2 norm. When we use the L1 norm this expert is equally influenced by their own initial opinion and the opinion of expert E6 and is not longer influenced at all by expert E4; in all other cases, the identity of the most influential expert is unchanged.

In the first session, the start of session opinions of expert E2 are consistently the most influential in the linear models of the individual experts' opinions at the end of the session. This suggests that this expert did indeed have the most influence overall in the group discussions with the other two experts changing their initial assessments to more closely reflect the original assessment of expert E2. In addition, expert E2 is also the least influenced by the group consensus when making his/her individual assessment at the end of the session. Experts E1 and E3 are both primarily influenced by the group consensus suggesting they generally agree with the group judgement. Expert E2 is influenced by the group consensus but less than experts E1 and E3. This suggests that at the end of the session, expert E2 tended to be least swayed by the group. Somewhat paradoxically, it was found that post-consensus expert E2 tended to be furthest from the group consensus position despite apparently having the most influence in the group.

The paradox can be resolved by reasoning that despite his strong influence on the other experts, and his relative intransigence with respect to his personal opinion during the discussion, he was nevertheless willing to sign up to a consensus position that was farthest from his own opinion. This is a complex pattern of behaviour which could have other causative interpretations: for example, it could be that while he presented persuasive evidence, his manner dissuaded the others from agreeing publicly. Either way, we might be reasonably confident that in this case the consensus is relatively conservative in the sense that it has not obviously been dominated by the most influential individual.

For session 2 a different picture emerges. In this session expert E4 seems to exert the most influence on the group with the consensus assessment tending to most closely match the initial assessment of this expert. However, unlike in session 1 where one expert appeared to exert greatest influence over other members of the group, in session two, the experts all seemed to be more influenced by their own initial assessments than by other members of the group. They also tended to be less influenced by the group consensus when making their end of session assessments than the experts in session 1. For example in Figure 7(b) we see that expert E5 agreed to a consensus that is contradictory to (does not agree with) either their initial or final opinions.

From the RMSE of the end of session assessments and the consensus, the expert who appears to most closely agree with the consensus is expert E4. Here the expert who exerted the most influence on the consensus tended to agree with it most strongly. This implies that he/she was more successful at persuading the other experts in the group to agree with his/her opinion during the consensus-reaching part of the discussion. It appears that experts E5 and E6 exhibit herding behaviour: they converge around expert E4 during discussions and diverge immediately thereafter. The consensus should therefore not be regarded as the group's shared opinion in session 2.

Comparing the coefficients for the start of session assessment with the RMSE at the end of the session for session 1, we see that the expert who exerted the greatest influence on the group was the least likely to agree with the group consensus at the end of the session. However in session 2 we see the expert who has exerted the greatest influence on the consensus also agrees with it the most. Thus, by careful elicitation and simple analysis of the results of the various linear models, we can begin to distinguish the different individual and group dynamics that have produced different kinds of results for the two sessions.

The relative influence of individual experts on the group might be expected to correlate with experience or expertise, with the most expert member exerting the most influence on the group and being the least influenced by other members of the group. However, the experts ranked their expertise for each FEP, and this ranking was shown not to be correlated with relative influence in either session. This either indicates that expertise does not correlate with influence, or that experts are poor at assessing their own expertise.

It was not apparent during the group discussions for either sessions 1 or 2 that any one expert was dominating the group, or that any expert was tending to be overruled. Nevertheless the results suggest that in both cases, a single expert has exerted significantly more influence than the other experts despite having less or equivalent relevant expertise to other experts in the group. This was also not obvious from the results by direct inspection. By using a simple linear model we are able to better understand the behaviour of individual experts and the group dynamics, helping to identify where a single expert may be dominant or where bias such as herding and divergence occurs. In this case we are able to identify that in one of the two sessions the consensus position should *not* be used as a fair representation of the group's combined uncertainty or opinions, and either the post-session individual opinions might need to be somehow combined to synthesise a fair post-session group position (see O'Hagan (2006) for a discussion of the difficulties of carrying this out), or another elicitation session, perhaps using a different mode of communication between experts, might be necessary. This method of structured elicitation and linear modelling can be applied to any group decisions where experts are asked to reach a quantitative consensus judgement of some uncertain property (e.g. in an asset team in an oil company). While herding is always likely to be a problem in such situations, this method makes it possible to identify some situations in which the consensus decision is likely to be biased and as such provides a test of the reliability of the final group decision. When bias is identified, it gives the decision makers the opportunity to reassess the outcome of group discussions. Alternatively, the results may provide reassurance that a consensus judgement fairly reflects the opinions of the individual experts. Appropriately communicating the results of this type of analysis may provide greater confidence in expert decisions and help with public acceptance of new technologies like carbon capture and storage.

The results of such risk assessments are critical to evaluating the suitability of a potential subsurface CO_2 storage site. They inform decision makers of areas of high risk, help to prioritise and plan future activities and allocation of resources, and ultimately may lead to rejection or acceptance of a site. It is therefore critical that methods are found to reduce the bias in such assessments and improve the decisions made by groups. The method described in this chapter combined with the elicitation procedure of Polson and Curtis (2010) provides an efficient and easily applied means to understand the dynamics within a group and identify potential bias within group decisions. Crucially, by comparing the influence of individual experts with their level of expertise, we can assess whether the group is making the optimum use of the available personnel's knowledge and experience when making such critical decisions. In this study it was shown that influence does not correlate with expertise, and that herding of opinion towards a consensus position followed immediately by divergence of opinion occurred. For the robust use of group opinions in geological problems it will therefore be important that future research identifies robust strategies for remedial action in cases where biases such as herding and undue influence are detected.

ACKNOWLEDGMENT

The authors wish to acknowledge the support of, the UK Technology Strategy Board (TSB) and the Engineering and Physical Sciences Research Council (EPSRC), and of the project industry partners AMEC, Marathon, Schlumberger, Scottish Power, and Scottish and Southern Energy and the academic partners; the British Geological Survey, Heriot-Watt University, University of Edinburgh, and of the University of Manchester. The research related to this chapter has been carried out within the CO_2 Aquifer Storage Site Evaluation and Monitoring (CASSEM) project, which is a project supported by the UK TSB. We also thank the anonymous reviewers for their useful contributions.

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APPENDIX: DETAILED DESCRIPTION OF EACH FEP GIVEN TO THE EXPERTS IN EACH SESSION

The detailed description of each FEP given to the experts in session 1 are shown below (these are from the Quintessa CO_2 FEP register [Savage et al., 2004]).

Construction and Site Logistics (Non-Pipeline): Construction and site logistics issues can affect the timescale, financial, safety and viability of the project. There are issues surrounding the ability to build on existing sites and the resources available to build carbon capture facilities.

Failures and delays in construction and logistical aspects of the project may have significant impact on viability of the project through impacts on timescale, finance or safety. Site logistics may require compromises in construction and/or retrofitting of carbon capture facilities to existing sites. If many sites decide to introduce carbon capture at the same time, this may lead to a shortage of skills, labour and possibly materials which will likely increase the cost of construction. As well as restricted supplies, more inflexible time slots amongst suppliers may impact the project.

Construction of Pipeline: The construction of the pipeline will be affected by a number of factors. Many of these will not be unique to CO_2, however the pipeline route will be affected by regulations particular to CO_2 such as distance from populated and ecologically sensitive areas. The composition of the CO_2 will affect corrosion rates and therefore impact on the design of the pipeline as will the need for isolation points. In addition the pipeline design and construction will also be affected by the injection pressure which will determine whether it is more cost efficient to have onshore or offshore compression.

Planning and regulations will affect the route pipeline can take with minimum distances from sensitive areas; this affects the length and therefore the cost of the construction. Planning regulations may cause particular difficulties near to the plant or coast where potential routes are restricted. In addition isolation points will be required more frequently near populated areas where the health effects of potential leaks need to be considered. Also the injection pressure required for the aquifer will affect whether it is more cost efficient to compress the CO_2 onshore and transport the CO_2 at higher pressures or to transport the CO_2 at lower pressures and use offshore compression near the aquifer.

Leakage from Pipeline: Onshore, accidental damage to the pipe by works unrelated to the project could potentially produce a CO_2 release resulting concentrations in nearby areas (over 10%) that could have major health implications due to the asphyxiation effects of CO_2. There is also the potential for small undetected leaks from the pipe that could result in the accumulation of CO_2 in low lying areas (e.g. basements). Small undetected leaks could also potentially impact the local ecology both through increased CO_2 concentrations and potential acidification of ground water and through release of contaminants (e.g. heavy metals). Offshore the potential impacts to human health are reduced however small undetected leaks could impact the marine ecology due to acidification or release of contaminants. In areas where trawler fishing or the navy are active, damage to the pipeline due to collisions may result in large scale release. In addition to potential health or ecological impacts, leakage may also result in negative public perceptions which could have a negative impact on future projects.

Leakage from the pipeline provides a potentially important pathway for CO2 to enter the environment with impacts on human health, the environment, public perception and cost.

Public Perception and Security: Public perception could have negative or positive impacts on planning applications. In addition negative public perception may lead to increased security risks with onsite protests and potentially sabotage.

Public perception and security could impact the project in cost, time delays and where public opposition is extreme, potentially hinder or prevent the completion of the project.

The description of the FEPs given to the experts session 2 are shown below (these are from the Quintessa CO_2 FEP register (Savage et al., 2004)).

Advection of Free CO_2: Advection of free CO_2 occurs in response to differences in pressure. The pressure difference may be due to differences in the pressure of injected CO_2 and formation pressures. The rate and direction of advection is affected by the physical properties of the rock, such as porosity and permeability. Advection may also occur though fractures. Fracture flow will be episodic with high transport efficiencies. Resealing of fractures (for example by cementation) will reduce and ultimately block fluid flow.

This includes Fault Valving a process resulting from gradual build up of pore pressure due to fluid generation, causing the subsequent opening of a fault along with fluid escape towards surface. This mechanism has been recognised as causing earthquakes in many parts of the world, as a result of hydrocarbon generation or infiltration of other fluids.

Advective flow is a key transport process for migrating CO2, and associated contaminants, in the geosphere (reservoir, surrounding and overlying rock), near-surface and surface environments. Large releases of pore fluids may occur during fault valving episodes.

Buoyancy-Driven Flow: Different relative densities of fluids in a geological system will result in buoyancy-driven flows as less dense fluids will have a tendency to flow upwards. The density of fluids will depend on their temperature and pressure.

Carbon dioxide can be less dense than water, which may cause injected CO_2 to flow upwards and accumulate above the water phase below the cap rock of a reservoir. Water with dissolved CO_2 is more dense than water, which can result in stratification of water bodies into which CO_2 may leak, if conditions are suitable.

Water Mediated Transport: Processes related to transport of CO_2, and associated contaminants, in ground and surface water, include advection, dispersion and molecular diffusion. Advection is the process by which CO_2, and associated contaminants, are transported by the bulk movement of water in which they are dissolved. Advective groundwater flow can occur along connected porous regions, such as fractures and faults. Processes that affect the movement of groundwater, such as fault valving, will also affect the migration of dissolved CO2, and associated contaminants. Dispersion is the collective name for the consequences of a number of processes that cause ‘spreading-out’ of CO_2, and associated contaminants, dissolved in water in all directions, superimposed on the bulk movement predicted by a simple advection model. It results in a spatially distributed contaminant plume. Spreading of the solute plume can occur in the direction of advection, in which case it is known as longitudinal dispersion, or it can occur perpendicular to the direction of advection, in which case it is known as transverse dispersion. Diffusion is the process whereby chemical species move under the influence of a chemical potential gradient (usually a concentration gradient). In the storage domain, diffusion of CO_2 might be significant in the cap rock and low permeability sedimentary host rock environments where advective transport is absent or limited, and diffusion of other chemical species may give rise to chemical regimes in parts of the system that inhibit or enhance the transport of CO_2.

The transport of CO_2, and associated contaminants, within groundwater is likely to be a key migration process and therefore an important consideration in determining performance and safety.