Recognizing societal influences in earthquake geohazard risk perception with explainable AI while mitigating risks through improved seismic interpretation

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Abstract

As public awareness of climate-change-related weather events and temperature anomalies increases in the United States, citizens' attitudes toward climate change should be studied, including the effects of climate mitigation strategies and their associated risks such as induced seismicity. Using social survey data and earthquake records, an explainable artificial intelligence method (SHAP) is employed to investigate factors that are important in explaining individual perceptions and assessments of future induced seismicity. Focusing on Oklahoma, where the majority (greater than 75%) of earthquakes are induced, SHAP reveals that personally experiencing earthquakes is a significant factor in the respondents' past and future perception of earthquake frequency. Realizing that induced seismicity plays a strong role in individual perceptions of earthquake frequency, it is increasingly important to mitigate this geohazard, which is expected to increase with climate mitigation strategies, whether they are carbon capture and sequestration or geothermal in nature. To this end, seismic attribute methods to improve subsurface characterization, particularly for fluid migration pathway identification, are examined using data from a carbon sequestration project in northwest Montana in the Kevin Dome area. While broadband and multispectral coherence do not improve the identification of faults and fractures, in this case, aberrancy (the third derivative of structure) successfully highlights lineations because it is more susceptible to detecting flexures in seismic data. Based on this result, we strongly encourage interpreters to include aberrancy in their reservoir analysis to identify and mitigate fluid migration that may result in induced seismicity.

Introduction

Carbon reduction techniques, such as carbon sequestration and geothermal energy, require fluid injection into the subsurface. This creates changes in the rock stress field that can induce seismicity (Ellsworth, 2013; Grigoli et al., 2017). If the seismicity is significant, the climate solution techniques may encounter pushback from the local population. This particular geohazard risk requires analysis of multiple factors, from geomechanical, hydraulic, and thermal properties to geologic formation characteristics and orientations (Vilarrasa et al., 2019). In this two-part study, we introduce explainable artificial intelligence (AI) techniques to analyze the population's perception of seismicity (part 1). We also demonstrate techniques to help reduce potential seismicity through enhanced fault imaging by using seismic attribute analysis (part 2).

In part 1, explainable AI is applied to survey data. The survey included questions regarding people's experience with earthquakes. Many social science studies investigating environmental concerns note that beliefs about climate change only changed slightly over the course of this century (Deeg et al., 2019; Saad, 2019). Those beliefs are often firmly rooted in an individual's political and ideological views (Hornsey et al., 2016; McCright et al., 2016). Recent work (Jenkins-Smith et al., 2020; Goldberg et al., 2021) demonstrates that conservative-leaning individuals report greater fluctuations in their beliefs over time compared to liberal-leaning individuals. This suggests that overall attitudes toward climate change are slowly shifting, albeit asymmetrically. Investigations into which factors trigger changes in attitudes are plentiful, including those that focus on economics (Mildenberger and Leiserowitz, 2017), politics (Dunlap et al., 2016; Palm et al., 2017), media coverage (Goldberg et al., 2021), cultural worldviews (Goebbert et al., 2012; Kahan, 2012), cultural theory (Douglas and Wildavsky, 1983), informational messaging (Spampatti et al., 2022), and temperature anomalies (Akerlof et al., 2013; Borick and Rabe, 2014; Moore et al., 2019). These interdisciplinary insights are essential as we focus on energy challenges (Trutnevyte et al., 2019). To gain a more holistic understanding of the various factors at play, our analysis uses an explainable AI method called SHapley Additive exPlanations (SHAP). This method was originally developed using game theory for economic analysis in the 1950s (Shapley, 1951). We analyze responses from an Oklahoma survey (Jenkins-Smith et al., 2017) to assess the relative importance of various sociodemographic, political, cultural/psychological, and experiential factors in the strength of individual belief regarding induced seismicity. Uniquely, we also analyze respondent experiences with earthquakes. This work is one of the first to tie in experiences, perceptions, and attitudes regarding seismicity. In Oklahoma, these are primarily the result of subsurface fluid injection related to hydraulic fracturing (Skoumal et al., 2018; Ries et al., 2020).

In part 2, we introduce seismic attribute methods to provide geophysical solutions to improving the imaging of fluid migration pathways. These methods are applicable in any well-imaged seismic data set, regardless of the purpose of hydraulic-fracturing wastewater injection or fluid injection for carbon capture or geothermal purposes. In this demonstration, we test these methods on data collected by the Big Sky Carbon Sequestration Partnership (BSCSP) project in the Kevin Dome region of the Sweetgrass Arch region of Toole County, Montana. Kevin Dome

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is a large structural closure that naturally traps CO_2. It was identified as an ideal site to study underground carbon storage. The Devonian Dolomite Duperow Formation (Zaluski, 2018) was identified as a potential CO_2 storage formation. Although EPA regulations did not allow for the storage of anthropogenic CO_2 in Duperow, BSCSP altered the focus of the project to collecting data that aid in characterization of the reservoir (from well logs to cores) along with seismic data. Seismic attribute analysis is performed to create a workflow that optimizes the visualization of faults in the Duperow Formation. This aids in the analysis of migration pathways for injected fluids. Identifying potential migration pathways is a critical step in the risk analysis of carbon storage reservoirs because CO_2 injection into the subsurface may induce seismicity, which could alter public opinion and acceptance of carbon mitigation projects.

Part 1: Explainable AI for earthquake perceptions

Machine learning has existed since the 1940s (McCulloch and Pitts, 1943) and is employed in a wide range of disciplines. The data patterns that machine learning methods detect are often complex and nonlinear. This introduces doubt on the validity of the algorithm and results, particularly when introduced into a new subfield. If properly designed, integrated, and tested, the statistics behind machine learning can be insightful. This would reveal relationships in data sets that have previously remained hidden, allowing researchers to develop new hypotheses and quickly sort through big data. This could provide promising applications in a variety of disciplines. If collected, scaled, and merged properly, data can be an insightful tool for interdisciplinary research.

As machine learning becomes popular in understanding large data sets, methods to peer into the black box of machine learning (Molnar, 2020) have been developed, tested, and employed under the umbrella of explainable AI algorithms such as individual contribution expectation (Goldstein et al., 2015), SHAP (Lundberg and Lee, 2017), and SHAP Flow (Wang et al., 2021).

Explainable AI. SHAP (Shapley, 1951) excels in explaining the internal structure of nonparametric nonlinear variables. It is well suited for the current study because social science survey data commonly include both linear and nonlinear variables. In this analysis, there is no predictive machine learning algorithm that we seek to explain. Instead, we examine the black box, which is the complicated interplay of the human experience and value systems, from demographics to political, ideological, and religious dimensions as well as individual perceptions and experiences regarding earthquakes. Given that SHAP evaluates every variable's contribution and considers all of the correlations and interactions between variables, the SHAP method (Lundberg and Lee, 2017) is ideal for social science survey data analysis. This is because it is not sensitive to the independent variables' levels of measurement (e.g., categorical, binary, and linear). The result is a SHAP value for each variable that represents the relative importance of the variable in predicting variation in the dependent variable.

The concept behind SHAP is visually represented in Figure 1, where the relationship between the independent variables of a single individual respondent and their resultant perception of earthquake frequencies f(x) as compared to the entire population's opinion E[f(x)] is unclear. After calculating the relative importance of all independent variables by iterating through all combinations of variables, leaving one variable out at a time, the relative importance of that single variable to the model is calculated. This is achieved by assuming a data set with n features that attempt to predict an output. SHAP calculates the contribution of each feature to the model output based on that feature's marginal contribution (Shapley, 1951). The marginal contribution of each feature can then be represented as the SHAP value, relaying the impact of that feature on the prediction.

Looking at a case in the waterfall plot on the right-hand side of Figure 1, it is clear that this individual has a higher belief in the certainty of climate change than the general population (f(x) > E[f(x)]). The two most impactful variables that contribute to the relative difference in their belief is that they are liberal and Democrat, both of which increase the SHAP value, pushing their individual score to the right in the window on the right side of Figure 1. The same individual, however, has not noticed any changes in extreme temperatures recently. This shifts their SHAP value more to the left, meaning that this experience (or lack thereof) slightly attenuates their belief. Education also has a negative effect on the SHAP value. The results of each

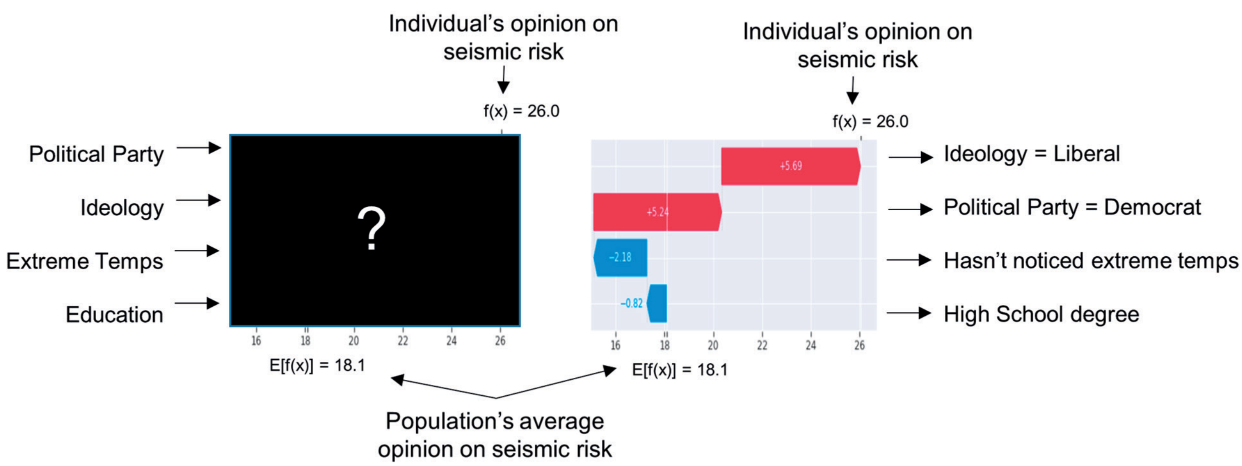

Figure 1. Schematic explanation of the SHAP method for analyzing survey data.

individual are analyzed at the population level to determine the global feature importance.

Data. Because the majority (greater than 75%) of recent seismicity in Oklahoma is linked to water injection for hydraulic fracturing (Skoumal et al., 2018), and Oklahoma has not had an active history prior to the mid-2000s, Oklahoma is an ideal case study to examine individual perceptions and attitudes regarding induced earthquakes. Oklahoma is also an ideal state to study because residents are evenly split in their climate-change beliefs (Howe et al., 2019), and Oklahoman climate-change beliefs are consistent with those of the United States (Jenkins-Smith et al., 2020). This study analyzes 2018 survey data that were collected by the Oklahoma Meso-Scale Integrated Socio-Geographic Network on a random sample of 1657 respondents, administered either online or by phone. A summary of independent and dependent variables is presented in Table 1.

In addition to demographics and underlying belief system questions, there were three questions related to the respondents' earthquake experience and perception. The first question, Q1 (Table 1), is an indicator of the respondents' recent experience with earthquakes. Q2 measures the respondents' perception of changes in earthquake frequency in the recent past. Because most seismicity in Oklahoma is human derived, this question of perception was compared to measured earthquake data.

We use the earthquake catalogs compiled, examined, and maintained by the Oklahoma Geological Survey for seismicity. To align the earthquake record with the survey questions, we focus on earthquakes that were likely to have been felt. Because these are mostly shallow earthquakes, the catalog is filtered to those of magnitude 2.5 and greater occurring from May through September. The survey collected only the zip code of the respondents, and we do not have information about where the respondents work or may have traveled. So, we compare the respondents' county from the survey with the count of earthquake occurrences in the respondents' home county during the summers of 2013–2017 ("previous summers" in Q2) and the summer of 2018 ("this summer" in Q1). We then calculate a variable that compares the respondent's perception of earthquake frequency in 2018 compared to earlier years to the actual recorded earthquake to assess if that individual tends to recall seismicity and whether they under- or overpredict earthquake frequency in their area.

Methodology. After the listwise deletion of nonresponses, the multicollinearity of features was tested using Pearson's correlation coefficient to investigate the relationship between two variables. The only correlation of note, 0.6, is between party lean and ideology. Due to their inextricable relationship, these variables are left in the model. Because these data are used to generalize inferences about the population, the calculated poststratification weights were used for sample replication. Moving forward, the SHAP analysis contains independent variables from demographic, religious, political, and cultural worldviews along with experiential factors and social capital. All of these features are examined to understand their relative importance in the respondents' perceptions of past seismicity, future seismic risk, and risk of climate change to harm people and the environment. The independent and dependent variables are defined in Table 1.

Results. The global ranking and spread of SHAP values related to future seismic risk (Figure 2a) and the perception, or recall accuracy, of past seismic frequency (Figure 2b) reveal that a respondent's recent earthquake experience [evntexp_ethqk] is the most important feature in explaining past or future earthquake beliefs and how they relate to an increased belief that earthquakes will increase in frequency (a positive SHAP value or impact on model output). In this initial result, we note that the experiential factor of recently experiencing an earthquake is the largest factor in the belief that more earthquakes will continue to happen. This ties in with construal level theory (Trope and Liberman, 2010), in which events become less abstract to a person once they experience them. It also perhaps ties in with the psychology-based terror management theory (Solomon et al., 1991), in which humans tend to group together based on similarities in the face of threat. These SHAP results suggest that this relationship can also be extended to the occurrence of earthquakes. We validate the SHAP result that a recent earthquake experience is a significant factor in both past and future cases through a traditional social science methodology by conducting an ordinary least squares (OLS) regression, which is a linear regression that can describe the relationship between independent and dependent variables (Table A1). The

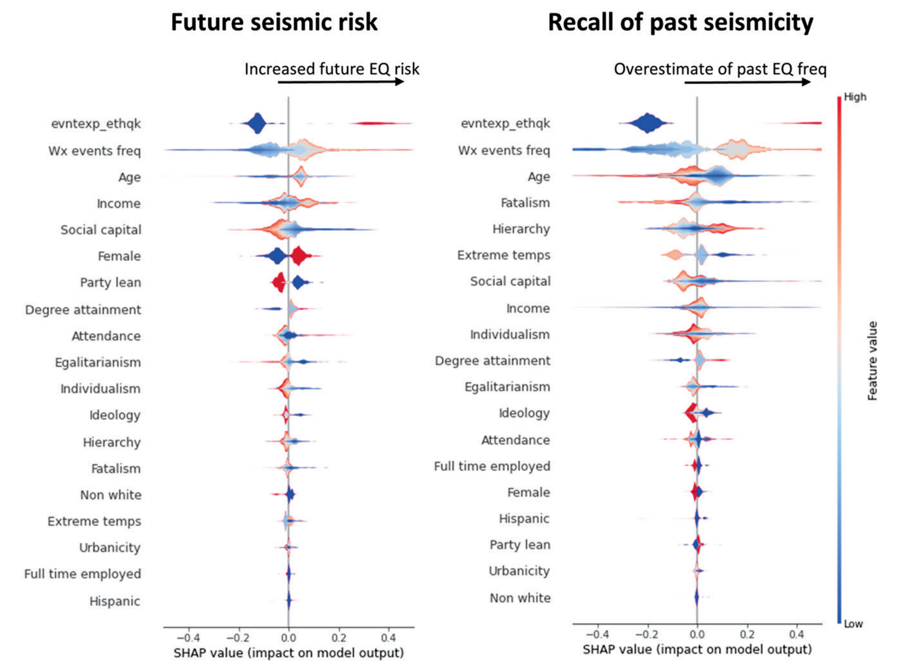

Figure 2. SHAP feature importance. More important features are plotted at the top. Each feature is colored by its value, and the impact of that feature is plotted on the horizontal axis.

Table 1. Variables, definitions, and answer scaling used in the SHAP analysis.

Event/climate perceptions		
Experienced earthquake [evtexp_ethqk]	Have you experienced an earthquake in the area around where you live?	0 = no; 1 = yes
Extreme temps	Would you say that overall, extreme high and/or low temperatures have occurred more often or less often in the past three years as compared to previous years?	1 = less often; 2 = with about the same frequency; 3 = more often
Weather events frequency	In the area around where you live, would you say that the following kinds of events (wind, rain, tornadoes, wildfires, heat, hail) have happened more frequently or less frequently this summer as in previous summers?	1 = less frequently; 2 = with about the same frequency; 3 = more frequently
Political/civic variables		
Party lean	With which political party do you lean toward and identify?	1 = Democrat; 2 = Independent; 3 = Republican
Ideology	On a scale of political ideology, which of the following categories best describes your views?	1 = liberal; 2 = moderate; 3 = conservative
Social capital	Do you have strong connections and depend on and help your neighbors?	scale of 1 (weak) to 7 (strong) relationship
Cultural worldview		
Hierarchy	I am more comfortable when I know who is and who is not a part of my group, and loyalty to the group is important to me. I prefer to know who is in charge and to have clear rules and procedures.	scale of 0 (not at all) to 10 (completely)
Individualism	Groups are not all that important to me. I prefer to make my own way in life without having to follow other people's rules. Rewards should be based on initiative, skill, and hard work, even if that results in inequality.	scale of 0 (not at all) to 10 (completely)
Egalitarianism	My most important contributions are made as a member of a group that promotes justice and equality to combat unfairness and corruption in society.	scale of 0 (not at all) to 10 (completely)
Fatalism	Life is unpredictable, and I have very little control. I tend not to join groups, and I try not to get involved because I can't make a difference anyway.	scale of 0 (not at all) to 10 (completely)
Demographic variables		
Age	What is your age?	age
Female	Are you female?	0 = no; 1 = yes
Non-white	Is your race best described as non-white?	0 = no; 1 = yes
Hispanic	Do you consider yourself to be Hispanic, Latino, or Spanish?	0 = no; 1 = yes
Degree attainment	What is the highest level of education you have completed?	1 = less than high school; 2 = high school/GED; 3 = some college; 4 = Bachelor's degree or higher
Full-time employed	Are you employed full time?	0 = no; 1 = yes
Income	What is your annual household income	log linear value of income
Rurality	Which of the following best describes your property?	1 = urban; 2 = suburban; 3 = rural
Religious service attendance	Apart from occasional weddings, baptisms, or funerals, how frequently do you attend religious services?	0 = never; 1 = only for religious holidays; 2 = few times a year; 3 = once or twice a month; 4 = almost every week; 5 = every week; 6 = more than once per week
Dependent variables		
Q1: Future seismic risk	Looking to the future in the area around where you live, what do you think about the frequency of earthquake occurrences over the next few summers compared to this summer?	1 = less frequently; 2 = with about the same frequency; 3 = more frequently
Q2: Recall of past seismicity	In the area around where you live, what is the frequency of earthquakes comparing this summer to previous summers?	1 = less frequently; 2 = with about the same frequency; 3 = more frequently
Q3: Certainty of global climate-change risk	How certain are you that global climate change poses a risk to humans and the environment?	Scale of −50 (high certainty that climate change is not a risk) to +50 (high certainty that climate change is a risk)

OLS regression shows that the average level of future seismic risk for those who have recently experienced an earthquake is significantly higher than the average perceived risk of future seismicity for those who have not recently experienced an earthquake. In the case of seismic recall, the OLS regression results lined up with SHAP results.

Next, in terms of feature importance, is the respondents' perception that extreme weather events are happening more frequently. In both cases of past and future seismicity, those who noticed weather events (hail, lightning, flood, and drought) are happening as often or with increased frequency compared with the past are also concerned about an increase in seismicity in the future and are overestimating seismicity in the past.

The age of the respondent is the third most important feature. Note that younger people tend to overestimate past seismicity and believe that earthquakes will be less frequent in the future. On the other hand, middle aged and older people tend to expect a higher risk of earthquake occurrence in the future while underestimating seismicity in the past. Rounding out the top five for the increased risk of future seismicity is higher incomes and a lower feeling of social capital. This may suggest a concern that governing entities are not concerned for an individual's interests. In terms of accurate recall of past seismicity, cultural theories of fatalism (believing that humans have no influence over nature) and hierarchy (where nature will be stable within limits) are significant factors. Those with a lower fatalistic attitude (who believe humans can influence the environment) overestimate past seismicity, as do those with stronger hierarchical beliefs.

We further explore the relationship of the features by employing a SHAP interaction plot. These plots highlight the interaction effects between two features. As observed in Figures 3a and 4a, there is a high level of interaction between the variables of age, weather events frequency, and individualism with evntexp_ethqk (red boxes). From these observations, we can plot the two features against one another to understand how that feature contributes to the SHAP value (Figures 3b–3d and 4b–4d). Note that in both future seismic risk and seismicity recall, the younger and older respondents tend to predict and recall less seismicity (lower SHAP values on the vertical axis). Those who have experienced less extreme weather events also tend to predict and recall less seismicity, especially those who did not experience an earthquake (blue dots). Looking at the individualistic scale of respondents, those who identify as less individualistic (less than 5) and did experience a recent earthquake tend to overpredict future seismic risk and overestimate past seismicity.

Next, we investigate the link between seismic experience and the belief in the risk of climate change harming humans and the environment (Figure 5). SHAP identifies that politics and ideology play a lesser role in individuals who recently experienced an earthquake, while experiential environmental factors play a larger role. We validate the SHAP result that a recent earthquake experience is a significant factor in the belief that climate change is a risk to humans and the environment through an OLS regression (Table A1). Note that the average level of climate-change risk for those who have recently experienced an earthquake is significantly higher than the average perceived risk of those who have not recently experienced an earthquake.

Discussion. Taking into account survey results regarding past recall, future seismic risk, and the belief in the risk of climate change, this analysis suggests that as people begin to experience and notice seismicity, their awareness of seismic events and concern about increasing future seismicity becomes elevated, as does their concern of global climate risk. This observation in the data is in line with construal level theory (Trope and Liberman, 2010), which relates a person's proximity to an event to their perception of that event. This suggests that when a person is in close proximity to an event or object, they perceive it as more concrete, perhaps even as an impending threat that requires action, whereas those at a distance perceive it as more abstract. Previous studies demonstrate a clear relationship between the psychological distance to a climate event, such as temperature change or the occurrence of droughts, and an individual's increasing concern regarding the

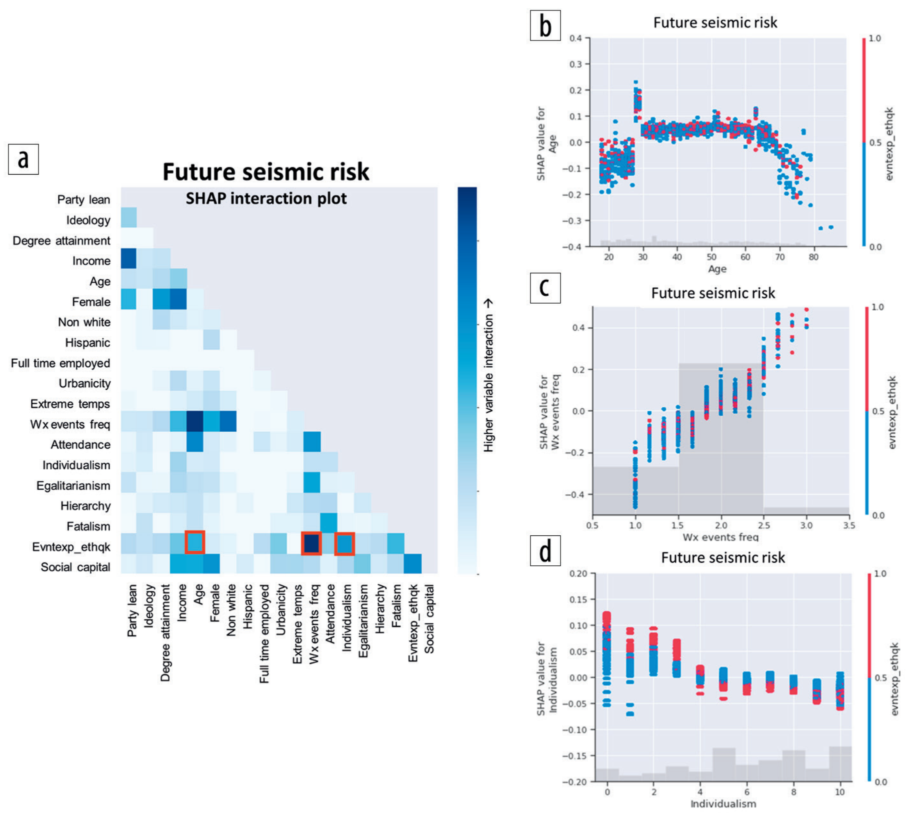

Figure 3. SHAP dependence plots for the recall of past seismicity. (a) SHAP interaction plot demonstrates interactions between pairs of variables. These highlight potentially significant interactions, as demonstrated in the SHAP dependence plot for an individual's earthquake experience with (b) age, (c) experience with severe weather events, and (d) individualistic worldview.

topic of climate change (Akerlof et al., 2013; McDonald et al., 2015; van der Linden, 2015). Our SHAP analysis extends construal level theory to earthquake experiences and possibly geohazard risk as the result of human-induced seismicity. Although there is no scientific link between induced seismicity and climate risk, the SHAP analysis reveals changes in severe weather event frequency as the second most important feature (Figure 2) in explaining attitudes toward induced earthquakes. It is likely that experiencing an earthquake is priming people to notice changes in the natural world, potentially related to human activity. The link between these two factors by survey respondents is likely spurious: (1) human activity is increasing seismicity and causing climate change, and (2) even though they have no relationship to one another, the connection to human activity is likely connecting them in the minds of those most affected by seismicity. These findings align with construal level theory, furthering the idea that living through natural events may increase an individual's awareness and change their perception of what is occurring in the natural world.

Partisan politics and ideologies play less of a role in individual beliefs about seismicity in the presence of experiencing seismic events. This societal pattern needs to be emphasized as carbon mitigation methods that may further increase seismicity are deployed. Increased seismicity could increase risk awareness and reduce public support for these carbon mitigation efforts. This finding is particularly important given recent increases in political polarization. The notion that the perception of natural phenomena can override hyperpartisan divisions could signal that the shared experiences of natural phenomena such as earthquakes may be a pathway to greater political unity on other issues including climate change and environmental degradation.

As researchers move toward climate mitigation and new energy solutions that involve the injection of fluids, seismic attributes will play a critical role in identifying fluid migration pathways. These fluid migration pathways will be important to map before injection is initiated and to monitor changes in migration pathways during injection as pressures change in the reservoir. These attribute methods can be applied throughout the reservoir management monitoring phase if additional seismic data are acquired, with the goal of improving fluid migration pathways to reduce induced seismicity.

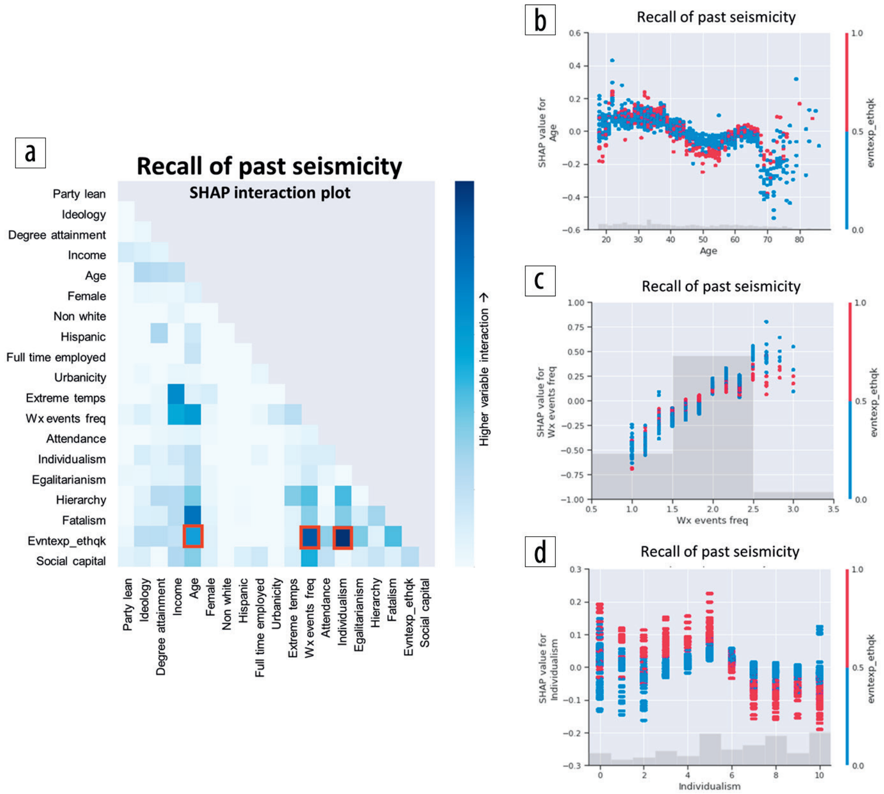

Figure 4. SHAP dependence plots for the recall of past seismicity. (a) SHAP interaction plot demonstrates interactions between pairs of variables. These highlight potentially significant interactions as demonstrated in the SHAP dependence plot for an individual's earthquake experience with (b) age, (c) experience with severe weather events, and (d) individualistic worldview.

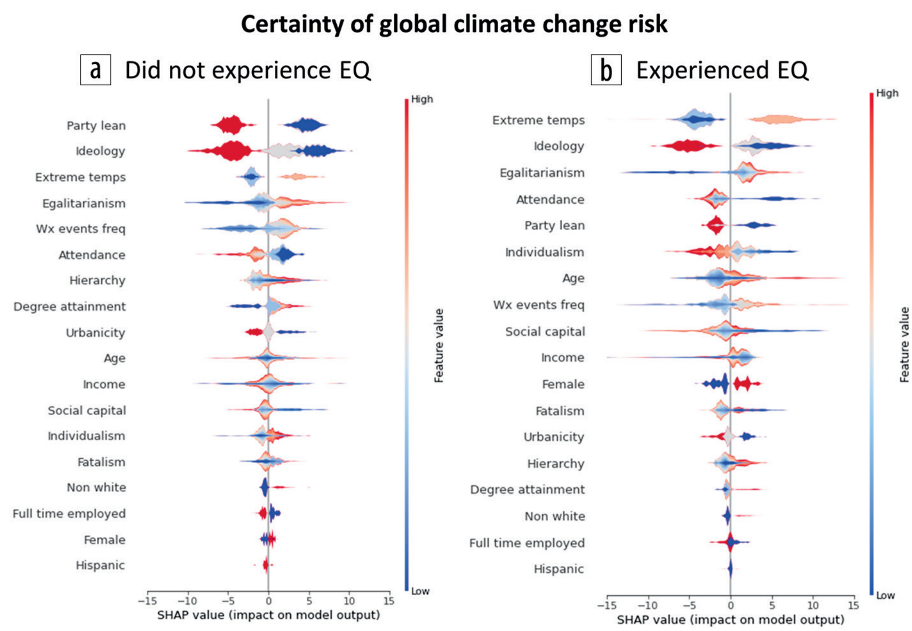

Figure 5. SHAP results for the subpopulations of those who (a) did not experience seismicity in the months before the survey and (b) those who did recently experience seismicity.

Part 2: Imaging fluid migration pathways

Seismic attributes have been widely applied for structural and stratigraphic interpretation. The most common seismic attributes applied for structural interpretation are coherence and curvature. As presented here, we also suggest including multispectral coherence and aberrancy. All of these attributes fall into the geometric category, which is based on the spatial relationships between the seismic traces instead of the amplitude.

Coherence is well known for mapping faults and edges of different types of architectural elements. However, coherence fails when the offset of a discontinuity in the rock is below seismic resolution because the seismic reflector appears continuous (Gao, 2013). In some cases, this can be addressed by applying different approaches such as spectral decomposition and spectral voice analysis. Multispectral coherence, for example, has proven to be a great tool to delineate discontinuities lost due to tuning effects and enhance fault visualization (e.g., Lyu et al., 2020; Mora et al., 2022).

Curvature attributes are able to map subseismic faults when they appear as folds adjacent to faults (Chopra and Marfurt, 2011). However, faults with low bending may still not be discernible, making it necessary to apply complementary attributes such as aberrancy (Gao and Di, 2015). Mathematically, curvature is the second derivative of the structure; therefore, it measures dip changes and highlights upward or downward concavity. Because geologic features may have curvature at different scales, it can also be calculated as long or short wavelength (Al Dossary and Marfurt, 2006; Chopra and Marfurt, 2011).

Aberrancy is the third derivative of the structure. Therefore, it measures the flexures (the location at which curve shapes change the most). For this reason, aberrancy is able to map planes of potential subseismic faults, whose seismic expression is a subtle flexure of the reflector (Gao and Di, 2015; Qi and Marfurt, 2018; Bhattacharya and Verma, 2019).

Data. The Kevin Dome data set (Figure 6) includes a 3D nine-component seismic survey, but we focused only on the primary P-wave prestack time migrated seismic volume. There are three main faults that clearly cut the seismic reflectors below the target Duperow Formation. However, reports that integrate all available information into a static model indicate these faults are sealing faults that do cut the injection interval (Zaluski, 2018). For this reason (the lack of clear fault imaging in a target injection interval), we choose to investigate this data set to identify techniques to improve fault imaging.

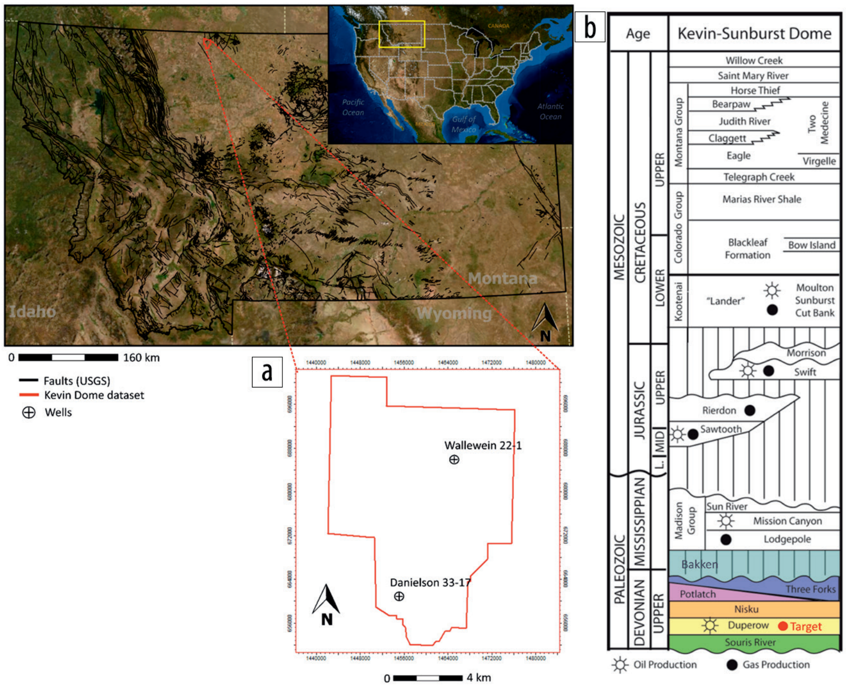

Figure 6. (a) Location of Kevin Dome seismic data set within the state of Montana. (b) Stratigraphic column in the Kevin Dome area (modified from Clochard et al. [2018]).

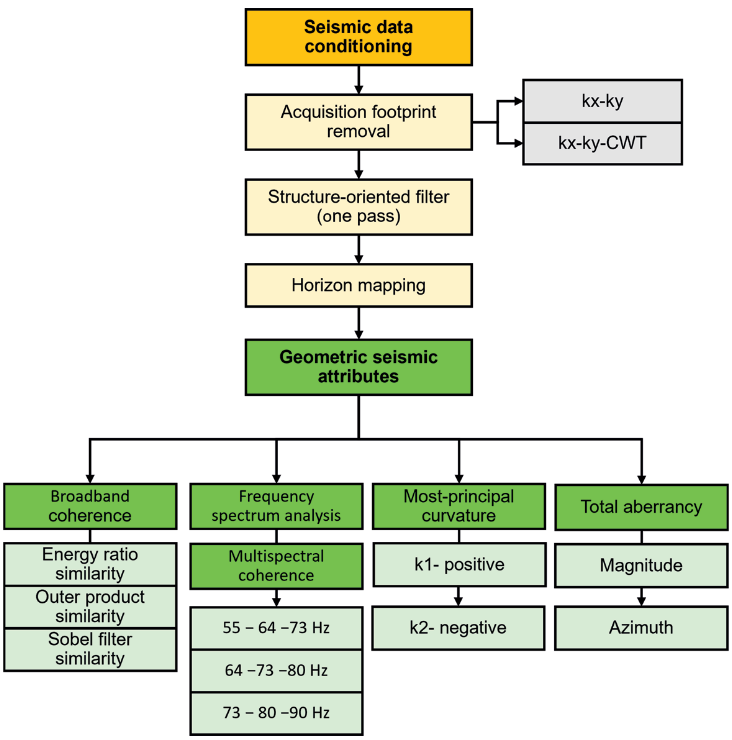

Figure 7. Seismic attribute analysis workflow.

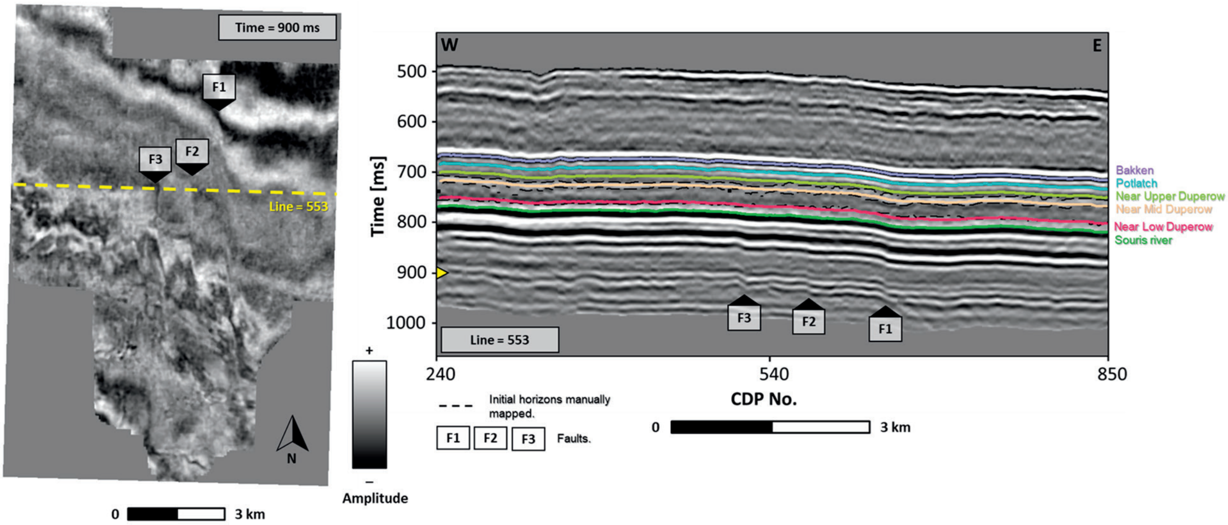

Figure 8. Stratal mapping of surfaces compared to mapped horizons of Zaluski (2018). Note the faults (F1, F2, F3) below the target zone.

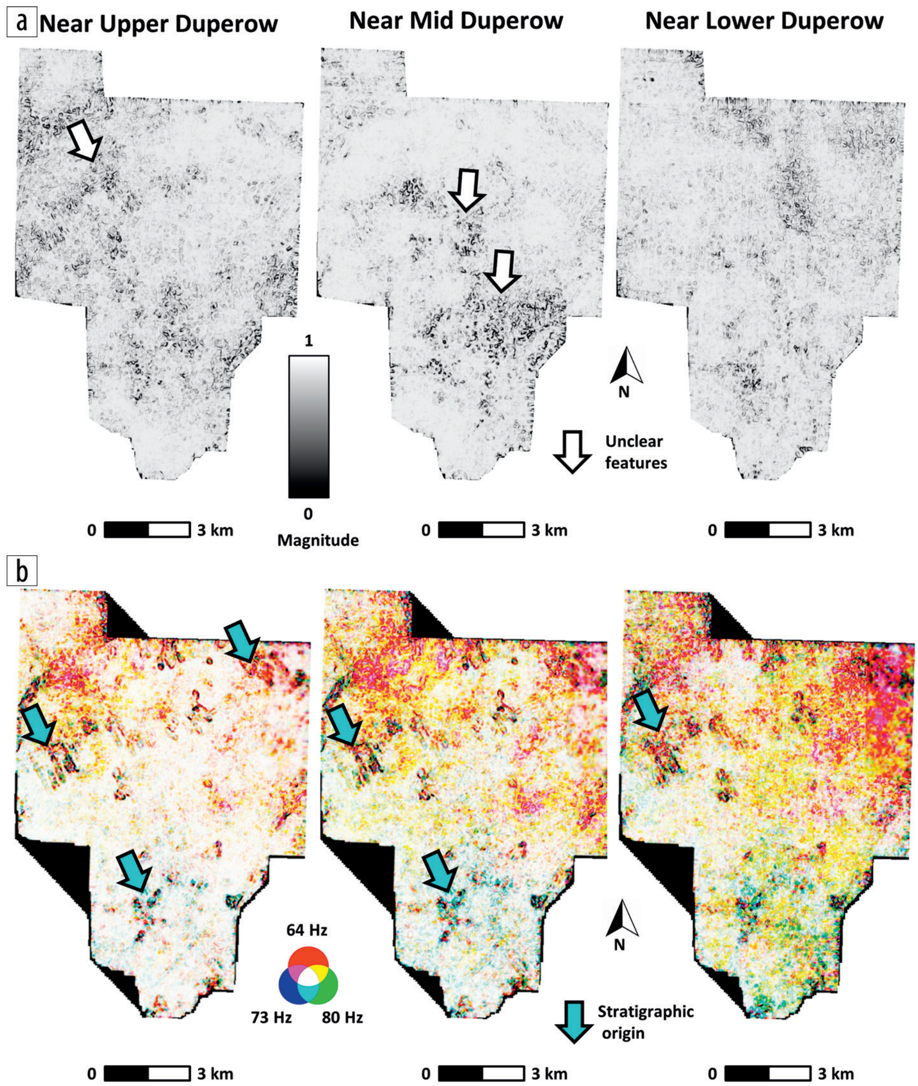

Figure 9. (a) Sobel filter similarity broadband coherence. (b) Multispectral coherence for the upper, mid, and lower Duperow.

Methodology. Before calculating any seismic attribute, we applied two data conditioning steps to the seismic volume (Figure 7). Acquisition footprint removal was implemented to decrease the footprint pattern seen in the Kevin Dome data set that could potentially lead to incorrect interpretations. Two workflows were attempted (kx-ky and kx-ky-cwt). The first showed the best results by deleting acquisition-related patterns while preserving stratigraphic-related features. A structure-oriented filter was applied to delete random noise and enhance the edges of structures, as well as smooth the seismic reflectors.

As an additional step, we mapped the horizons of interest to allow more geologic interpretations. Because the reflectors within the Duperow Formation were not fully continuous, any approach of manual or automated interpretation was either difficult or not accurate (dotted black lines in Figure 8). Thus, we created stratal slices by using the more continuous reflectors of the Bakken and Souris River formations as inputs (Figure 8). Notice that there are three clear faults in the deeper reflectors that are not easy to continuously map within the target formation (Figure 8).

For coherence, we tested three different algorithms (energy ratio, outer product, and sobel filter similarity) and determined the sobel filter to be optimal because it had the best signal-to-noise ratio. For this reason, the sobel filter was also employed when calculating multispectral coherence. An initial step for the calculation of multispectral coherence was frequency spectrum analysis to determine the frequencies that can possibly better highlight small discontinuities. In case of curvature and aberrancy, both long and short wavelengths were also tested. However, long wavelengths displayed clearer results, highlighting both structural and stratigraphic features.

Results. While coherence reveals interesting features in the northwest near the upper Duperow horizon and southeast near mid Duperow, it is not clear whether they are stratigraphic or structurally related (Figure 9a). With the multispectral coherence approach (Figure 9b), some features are better delineated and indicate a stratigraphic origin. Nonetheless, fluid migration pathways, such as the faults observed below the Duperow in the amplitude volume, remain absent. As we analyze the faults' seismic expression, we note that despite clearly cutting the reflectors below the Duperow Formation, within it they appear as continuous subtly folded reflectors. Therefore, it is logical that any discontinuity-based attribute may fail.

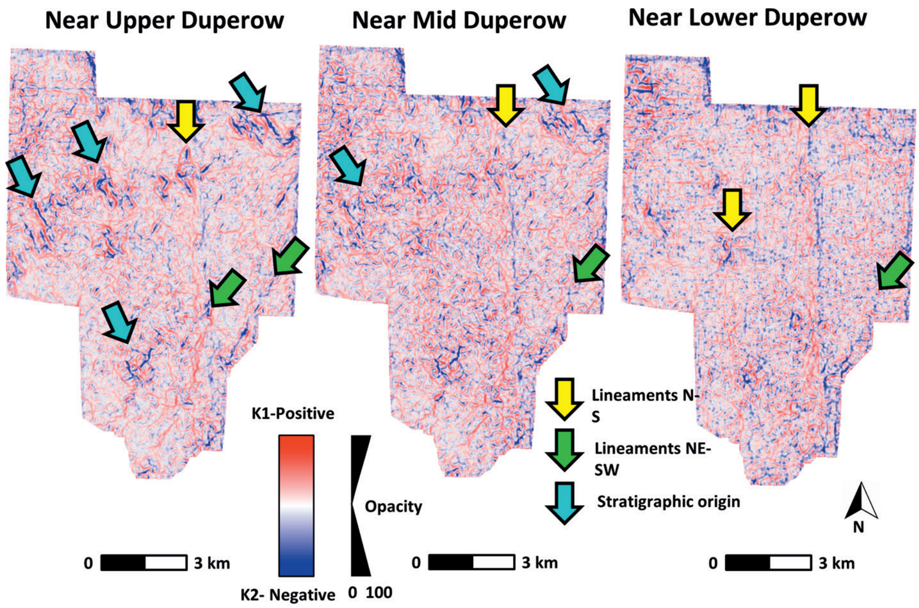

Figure 10. Corender of K1 most positive curvature and K2 most negative curvature.

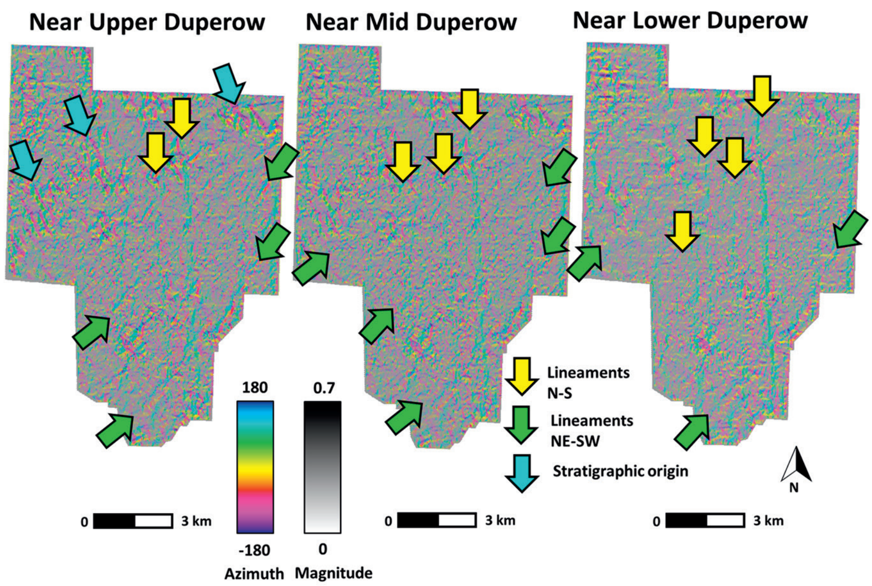

Figure 11. Corender of total aberrancy azimuth and magnitude.

On the other hand, curvature highlights one of the main faults (yellow arrows in Figure 10) in the three horizons. In the near lower Duperow, it shows a subtle positive curvature response probably related to a second fault. Moreover, curvature gives a better idea of the features seen in the northwest zone of near upper and mid Duperow horizons, which appear as elongated stratigraphic features that are probably karstic related (cyan arrows). Additionally, curvature highlights another lineament with a northeast-southwest trend (green arrows) in the southwest of the three horizons that could be related to a previously undetected fault.

The best results, in terms of structural interpretation, are provided by aberrancy (Figure 11). Because aberrancy is able to map the moment of maximum curvature change (flexure) whether the bend is subtle or prominent, these attributes succeed in mapping all three main faults (yellow arrows) with near north-south trend within the target zone. Additionally, it highlights other lineaments with northeast-southwest trend. This also correlates with the feature seen within the curvature attribute. These lineaments serve as references for further analysis to confirm their structural origins. Thus, while coherence and curvature remain critical tools in the seismic interpreter's toolkit, the addition of aberrancy further enhances the ability to detect subtler faulting and possibly fracture zones that act as fluid migration conduits. We emphasize here that these subtle features may be best imaged in seismic volumes, where processing steps aim to remove noise.

Discussion. Well-tested attributes such as coherence and curvature work for identifying many of these features but are not always ideal for smaller-offset faults and fractures, as demonstrated in this data set. Multispectral coherence appears to be a slightly better approach than coherence when analyzing intervals of clearly faulted strata, such as those presented by Mora et al. (2022). However, in this case of subseismic resolution faulting, multispectral coherence does not reveal the faults, similar to broadband coherence. In the case of the Kevin Dome data set, we clearly demonstrate the need for the addition of aberrancy to standard

Appendix

Table A1. OLS regressions on variable significance. The β values are the standardized regression coefficient, which allows comparison of variable rank importance, where the most important variable has the highest absolute value.

Dependent variable	Model 1 β	Model 2 β	Model 3 β	Model 4 β
Event/climate perceptions				
Experienced earthquake	.308***	.316***	--	--
Extreme temps	–.077**	–.004	.119***	.171***
Weather events frequency	.194***	.172***	.122***	.047
Political/civic variables				
Right party lean	.020	–.062*	–.179***	–.086
Right ideology	–.041	–.037	–.199***	–.227***
Social capital	.015	–.075**	–.057*	–.070
Psychology/cultural variables				
Hierarchy	.041	–.020	.047	.010
Individualism	–.032	–.051*	.043	–.140
Egalitarianism	–.013	–.052	.134***	.165
Fatalism	–.082**	–.022	–.003	.021
Demographic variables				
Age	–.080**	–.017	–.016	.094
Female	–.010	.094***	.040	.119**
Non-white	–.009	–.045	.060*	.097*
Hispanic	–.001	–.014	–.030	–.041
Degree attainment	.055*	.082**	.094**	.008
Full-time employed	–.044	.007	–.046	–.025
Income	–.006	.034	.023	.041
Rurality	.014	.012	–.099***	–.039
Religious service attendance	–.015	–.021	–.129***	–.155***
Adjusted R-squared	.150	.169	.289	.311

Model 1: DV = Overproduction of earthquakes
Model 2: DV = Belief in future earthquake frequency
Model 3: DV = Climate risk (subsample has not experienced earthquake)
Model 4: DV = Climate risk (subsample has experienced earthquake)
Note: Data are weighted to adjust for oversampling of nonrespondents
*p ≤ .05
** p ≤ .01
*** p ≤ .001 (two-tailed test)

migration pathway mapping workflows because it is more sensitive to small flexures that could be related to subseismic faults where fluids could travel, increasing the chance of induced seismicity.

Conclusions

SHAP analysis is applied to social survey data to elucidate insights into Oklahomans' experience, perception of future and past earthquake events, and belief in climate-change risk to humans and the environment, particularly in relation to induced seismicity. The SHAP analysis reveals that as Oklahomans experience seismicity, they overestimate the frequency of previous seismicity and expect more earthquakes in the future, as compared to Oklahomans who did not recently experience an earthquake. This is of particular note because some carbon mitigation efforts are expected to increase the frequency of induced seismicity. Based on the SHAP results, as more Oklahomans experience earthquakes, their perceptions of the earthquakes and acceptance of climate mitigation techniques may be affected.

In light of this attitudinal awareness, seismic attributes are investigated in the Kevin Dome area where a carbon sequestration subsurface characterization project is located. We note that without clear-cutting faults, neither broadband nor multispectral coherence is able to detect small faults and fractures that may act as fluid migration pathways. Curvature is able to detect some faults and aberrancy performs well, suggesting that this seismic attribute should be added to every seismic interpreter's toolkit when characterizing carbon storage and even geothermal reservoirs. TLE

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Data and materials availability

Data associated with this research are available and can be accessed at https://edx.netl.doe.gov/.

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