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Visualizing Uncertainty in Dispersion Forecasting: Effects on User Perceptions and Communication

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ABSTRACT

Operational dispersion forecasts have traditionally been produced deterministically, producing a single best estimate of the situation despite inherent uncertainty. Recently, there has been a paradigmatic shift toward providing uncertainty information as part of operational aviation forecasts. Yet, little is currently known about how exactly this information should be presented or about its effects on understanding and perceptions (vs. purely deterministic information). Using an ensemble of dispersion forecasts (produced using varying inputs) allows visualization of some of the dispersion uncertainty. Here, we compared how deterministic versus ensemble visualizations affected the graphical and written guidance provided. Across two scenarios featuring volcanic eruptions, 30 participants working in atmospheric dispersion were asked to produce an advisory graphic (a polygon encompassing an area of volcanic ash) and a written statement, as well as to rate the visualizations for utility, clarity, and importance. Overall, we find that participants drew bigger polygons (encompassing a larger geographical extent) in the uncertain, ensemble condition, though these were more consistent than those in the deterministic condition. Advisory statements in the ensemble condition also reflected greater uncertainty. Broadly, perceptions of the uncertainty information were neutral to positive, though graphics where less ash was shown were perceived as less useful. Our findings indicate that the presence of uncertainty information can influence communication products generated, underlining the importance of testing ensemble visualizations with users.

1 | Introduction

Uncertainty is an inherent feature of any scientific endeavor. The importance of recognizing the existence of uncertainty is undisputed, but despite its ubiquity, the extent to which uncertainty is (and should be) communicated and incorporated into decision-making remains a sizeable challenge for scientists, particularly within the realm of natural hazards (Doyle et al. 2023). Computational modeling offers the ability to integrate many types of uncertainty to inform decision-making, with high-profile examples including those used as part of the UK's COVID-19 pandemic response (Brooks-Pollock et al. 2021) and by the Intergovernmental Panel on Climate Change (2023). Indeed, the use of uncertainty analyses in modeling in an environmental science context has proliferated in recent years, for example, in flood modeling, where more data can be acquired to validate results (Lim et al. 2016).

This complexity is compounded by the very nature of uncertainty, often categorized on the basis of where the uncertainty derives from, which can be epistemic (relating to incomplete, missing knowledge/information) or aleatory (relating to chance, natural variability, or stochastic processes) (Fox and Ulkumen 2011; Hacking 2006). In the current paper, we focus on the context of atmospheric dispersion, specifically volcanic ash, where both epistemic and aleatory uncertainty are always present

All authors contributed equally to this work

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(Rao 2005). In the context of atmospheric dispersion modeling, the relative contributions to model uncertainty that arise from data/parameter uncertainty (from errors in the data), model uncertainty (from inaccurate treatment of processes), and stochastic uncertainty (from atmospheric processes) vary in each situation, resulting in spatial uncertainty which is generally, but not always, dominated by epistemic uncertainty (Leadbetter et al. 2020; Wellings et al. 2018). The need for atmospheric dispersion models to identify and estimate such uncertainties has long been recognized, with a trend away from deterministic (single best estimate) predictors toward incorporating probabilistic methods, via ensemble models (Dabberdt and Miller 2000; Rao 2005).

One of the predominant concerns with systematically incorporating uncertainty into modeling pertains to how well it is understood and the effects on decision-making. The concerns over both communicating uncertainty and incorporating it into decision-making are well documented in the literature (e.g., Pappenberger and Beven 2006). One of the most commonly cited concerns is that uncertainty will be misunderstood (Johnson and Slovic 1995) or perceived as vague and ambiguous, making decision-making difficult (Lim et al. 2016) and leading to a loss of trust (Frewer et al. 2003). Others have suggested uncertainty presentation can lead to unintentional biases (Bonneau et al. 2014) or take too long to digest in fast-paced operational settings (Mulder et al. 2017). Further complicating matters is that precisely how best to visually communicate spatiotemporal uncertainty associated with the use of ensemble models is not yet fully established (French et al. 2019). Indeed, it has not been the focus of large amounts of research attention (though see Liu et al. 2019; Padilla et al. 2017, for exceptions). There is, however, a growing body of evidence regarding the understanding and visual presentation of uncertainty from other contexts, which we move on to consider.

1.1 | Understanding and Visual Communication of Uncertainty

Studies focusing on the effects of presenting visualizations of uncertainty, such as amount of rainfall or profitability of stocks, have found that, in comparison to textual, numerical, or deterministic presentations, providing uncertainty visualizations can be beneficial for outcomes such as understanding, decision-making, and task performance (Bisantz et al. 2005; Cheong et al. 2016; Fernandes et al. 2018; Greis et al. 2018) as well as trust (e.g., Joslyn et al. 2013). However, the advantages are often situation-specific, with some biases observed (Joslyn and Savelli 2021; Mulder et al. 2020; Padilla et al. 2018, 2020), such as the deterministic construal error (DCE), in which uncertainty information is interpreted as representing deterministic information. An example of this comes from the "cone of uncertainty" visualization, used by the US National Hurricane Center to depict the potential path of a hurricane. Broad et al. (2007) found the middle line was often interpreted as the main path of the hurricane, with other misunderstandings including interpreting the diameter of the cones as depicting growth or intensity of the storm. Difficulties with uncertainty visualizations are not just limited to nonexperts—Padilla et al. (2015) found that expert users often used decision-making strategies that ignored the uncertainty information, or when it was factored in, were biased toward lower variability. The mixed picture of evidence may in part result from how visualizations have been evaluated in the literature (for instance, geared toward a small set of metrics, such as performance and accuracy; Hullman et al. 2019) and the types of uncertainty depicted.

In their review of geodata uncertainty visualization and decision-making research, Kinkeldey et al. (2017) make a distinction between studies of three different categories of uncertainty—attribute, positional, and temporal—noting that the majority examined the first. They found that most studies indicated evidence of a positive effect of visualizations on decision accuracy, though there was less clear evidence for such an effect on decision speed. They also note differences in effects depending on the precise nature of the representation of uncertainty. Kinkeldey et al. (2017) echo the words of MacEachren et al. (2005, 155) in stating: "we cannot yet say definitively whether decisions are better if uncertainty is visualized or suppressed, or under what conditions they are better; nor do we understand the impact of uncertainty visualization on the process of analysis or decision making." They attribute this to the difficulty in generalizing results, owing to the different measures and contexts used in research. This statement underlines the importance of considering context when evaluating the effects of visualizations. Much visualization research has either been in the context of weather or climate, and/or has not always explicitly addressed spatial uncertainty, making it less directly relevant to the visualizations used in the current study. We therefore consider the (comparatively smaller) body of evidence in atmospheric dispersion and ensemble modeling.

1.2 | Ensemble Modeling

The use of ensemble modeling has burgeoned in recent years (Lim et al. 2016). Here, models are run multiple times, using different parameters (Brodlie et al. 2012), leading to different results each time. Uncertainty of the model can then be estimated on the basis of these outputs. Some research has examined the visualization of uncertainties based on ensemble models, albeit with nonexpert participants. Set in the context of flood modeling, Lim et al. (2016) compared two types of graphical representations: an uncertainty map (aggregating across ensemble results) and performance bars (representing individual results), testing their effects on user performance, as well as perceptions. Participants thought that the inclusion of uncertainty information was essential, and generally rated uncertainty as useful and important to their decision-making, though the extent to which this was the case depended on the format of the information and how it was understood, with performance worse for the uncertainty map.

Despite the numerous sources of uncertainty inherent in atmospheric dispersion models, most operational dispersion forecasts are still deterministic. However, increases in computational power have lessened barriers to running ensemble dispersion models, and as such, there has been a growing recognition of the utility of providing uncertainty information alongside model predictions (Jones et al. 2023; Leadbetter et al. 2022). This has

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prompted a shift in thinking as to how best to communicate ensemble outputs.

Nagy et al. (2020) explored the effect of visualization of uncertainty on interpretations of radiation dispersion maps using a mixed-method approach, finding that these maps were often a source of uncertainty in and of themselves, associated with misinterpretations and problematic for communication. In a similar context—a nuclear accidental release scenario—the introduction of visual uncertainty information was associated with difficulty reaching a decision (Duranova et al. 2020).

Mulder et al. (2017) explored the question of how Volcanic Ash Advisory Center (VAAC) forecasts and additional Met Office forecasts of ash concentration are interpreted by both the aviation industry and researchers responsible for creating these. This included interpreting forecast information to approve flight paths (from three different graphic types [polygon, filled contour, satellite]), considering the effects of conflicting forecasts, as well as drawing a no-fly zone. Participants also rated familiarity, trust, and preferences for the different types of representation. The provision of ash concentration information was concluded to improve decision-making (in terms of flights canceled/diversions followed, etc.). A further effect observed was that respondents were typically conservative, in (a) not approving flight paths, even when these went through safe concentration levels, and (b) in drawing no-fly zones larger than the areas of unsafe ash concentration. Participants were risk-averse for high-risk decisions, and risk-seeking for low-risk decisions. Participants who were operational did not want uncertainty information and preferred deterministic forecasts, a pattern also observed in flood managers (Nobert et al. 2010). Participants also showed evidence of inferring uncertainty in the deterministic forecast.

Notably, much of the aforementioned research has either focused on nonexperts or the decision makers, rather than the interim user. While some dispersion products are transferred directly to the end user, for others there are multiple stages of information transfer: the dispersion model is run, the expert interim user receives the model outputs, adds interpretation, and then conveys the information to decision makers. The multistage nature of this information dissemination underlines the importance of understanding exactly how uncertainty information is assimilated and integrated in a communication (Golding 2022).

The 2010 Eyjafjallajökull eruption was a turning point in the atmospheric dispersion modeling community, as well as for the public, who suddenly had a deepened understanding of the widespread consequences of volcanic eruptions. Even relatively low concentrations of ash are associated with significant damage to jet engines and are avoided by aircraft to prevent damage, while high concentrations can result in complete engine failure. As a result, in 2010, volcanic ash avoidance caused widespread disruption for over 10 million passengers, with over 100,000 flight cancellations at a huge economic cost of £3 billion (Budd et al. 2011; Clarkson et al. 2016). A large part of the disruption was attributed to the fact that it happened within extremely busy airspace over Europe and the North Atlantic.

Under the International Airways Volcano Watch (1987), the International Civil Aviation Organization established the global network of VAACs to provide forecast advice on the presence of ash to enable aviation regulators and operators to manage the risk that would result from flying through those areas. As a result of the 2010 Eyjafjallajökull eruption, the VAAC advisory, which comprises the Volcanic Ash Graphic (VAG) and Volcanic Ash Advisory (VAA), has become the most high-profile example of a multistage information transfer within the atmospheric dispersion modeling community. To produce a VAAC advisory, experts first generate a source term for the modeling based on a notification from a volcano observatory. They then use dispersion model outputs to produce a five-point polygon forecasting the extent of the ash cloud (VAG) and a written description of the area affected (VAA). This polygon corresponds to what is discernible from satellites and other agreed instruments (Prata and Prata 2012), which is commonly taken to be ~200 $\mu g/m^3$ (International Volcanic Ash Task Force 2012; Witham et al. 2012). These outputs are then provided to a range of aviation service providers, who make additional products, and to aviation decision makers (Lechner et al. 2018).

Taken together, there is clear value in developing better ensemble dispersion models, which integrate the various sources of uncertainty (Leadbetter et al. 2022), so as to minimize the financial and social costs to society. We carried out a pilot study (S. J. Leadbetter, personal communication 2020) to investigate how experts (scientists and meteorologists) use spatial uncertainty information in the context of a hypothetical volcanic eruption. The results demonstrated that the ensemble output influenced the VAG polygon drawn, but there was little consensus on which products were most useful. These results indicated that presentation of uncertainty information led to larger locations of predicted ash, but the pilot study did not include a sufficient uncertainty-absent (deterministic) condition for comparison.

In the present study, we build on these past findings and systematically compare the difference between ensemble and deterministic forecasts in the context of volcanic ash dispersion to examine whether concerns over the presentation of uncertainty information are substantiated. The VAAC advisory process has a high profile in the atmospheric dispersion community due to the Eyjafjallajökull eruption and its open-access nature. As such, most atmospheric dispersion scientists have a familiarity with the process, making it an excellent choice of task for understanding expert interpretation of uncertainty rather than interpretation of task instructions.

While the VAAC advisory process is being updated to remove the expert interpretation step in creating the VAG (International Civil Aviation Organization 2022), the general awareness in the community of the VAAC process, coupled with the fact that similar workflows exist for other dispersion products, means the research has implications for many contexts within the wider atmospheric dispersion modeling community. The study therefore focuses on how information from ensemble dispersion models (a) is communicated to users and (b) is subsequently perceived, noting that this is only one element of what is a complex, nonlinear communication process (Fischhoff 1995; Warren and Duckett 2026). Given the exploratory nature of the study, we did not make a priori hypotheses.

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1.3 | Research Questions

Research Question 1. How does the presentation of uncertainty information affect the graphical and written guidance provided during a volcanic eruption?

Research Question 2. Which presentations of uncertainty information do users find most useful?

2 | Methods

2.1 | Participants

A total of 30 individuals participated in the study. Fifteen participants were recruited as part of the NAME User Workshop organized by the Met Office in June 2023, bringing together academic, industry, and research users of the NAME atmospheric dispersion model. After the workshop, we also collected data from six participants working as meteorologists in the London VAAC, based at the Met Office, and nine participants from the Atmospheric Dispersion and Air Quality (ADAQ) group at the Met Office. Participation was on a voluntary, non-compensated basis. The research was conducted in line with relevant guidelines and regulations, including the Declaration of Helsinki, and all participants provided informed consent. For participant characteristics, see Table 1.

TABLE 1 | Demographic characteristics of the sample.

Demographic	*N* (%)
Age	
22–64 (Mdn = 34)	20 (66.6)
Not given	10 (33.3)
Gender	
Male	10 (33.3)
Female	11 (36.7)
Not given	9 (30.0)
Sector	
University	7 (23.3)
Government agency	16 (53.3)
Not given	7 (23.3)
Role	
Research	14 (46.7)
Operations	5 (16.7)
Management	2 (6.7)
Specified "Student"	2 (6.7)
Not given	7 (23.3)
Experience of ensemble information	
< 6 months	4 (13.3)
6–12 months	1 (3.3)
1–2 years	4 (13.3)
2–5 years	3 (10.0)
> 5 years	11 (36.7)
Not given	7 (23.3)
Experience in dispersion modeling	
< 6 months	4 (13.3)
6–12 months	1 (3.3)
1–2 years	0
2–5 years	5 (16.7)
> 5 years	13 (43.3)
Not given	7 (23.3)

2.2 | Design

A 2 (uncertainty: present [hereafter, ensemble]/absent [hereafter, deterministic]) × 2 (scenario: Katla/Hekla) was manipulated within participants (see Figure 1). Participants were initially randomly assigned to Route A or B, and the number of participants in each route was monitored during data collection, which took place over a period of weeks. After 28 respondents, assignment was modified to Route A to try to balance numbers in each condition, after which a further two respondents completed the study. Crucially, the map that participants drew their polygons on differed according to scenario. In the Katla scenario, for both uncertainty conditions, participants drew on the map that was the control of the ensemble (although participants in the deterministic condition were told that it was the deterministic forecast). In the Hekla scenario, in the ensemble condition, participants drew on the map that was the control of the ensemble, whereas in the deterministic condition, they drew on the deterministic map—a situation closer to what would occur in operational practice.

2.3 | Materials and Procedures

Meteorological fields from the Met Office Unified Model were used to drive the atmospheric dispersion model NAME (Jones et al. 2007) to simulate volcanic ash clouds from hypothetical eruptions of Katla and Hekla volcanoes. Focusing on one flight level (FL200–350; a typical cruising altitude for short-haul flights), NAME was run separately with the deterministic global numerical weather prediction configuration (Walters et al. 2019) to produce the uncertainty-absent conditions, and with each of the 18 members of the Met Office global ensemble numerical weather prediction, MOGREPS-G (Inverarity et al. 2023), to create nine graphics for the uncertainty-present condition:

- The prediction of ash concentrations from the control run,
- A map of the mean ash concentrations predicted by the ensemble members,
- A map of the maximum ash concentrations predicted by all ensemble members,
- Maps of the 5th, 50th, and 95th percentile of the ash concentrations, and
- Maps of the number of members exceeding thresholds of 200, 2000, and 4000 μg/m^3 volcanic ash (the graphic for 200 μg/m^3

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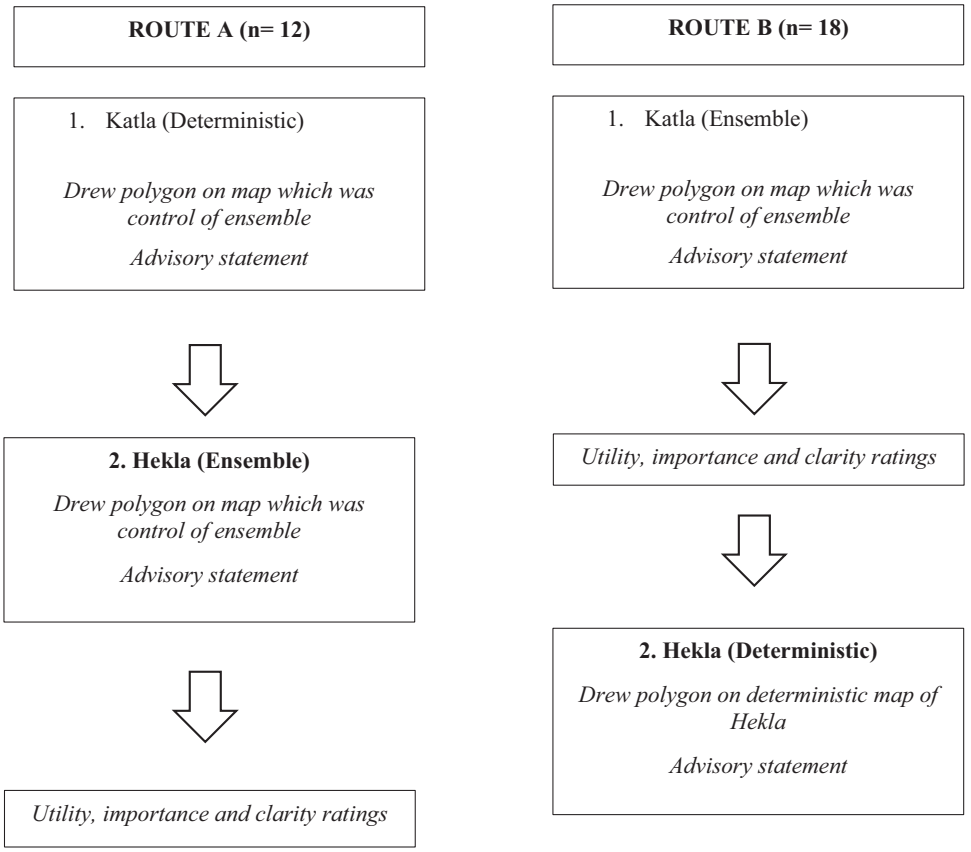


FIGURE 1 | Route through task.

is issued by the VAAC; the other thresholds are currently used by the Met Office in their supplementary concentration charts [Beckett et al. 2024])

For further information on scenario generation, see Supporting Information S1.

Participants were first asked to indicate their age, their gender, which sector their job was in (university, government agency [response/nonresponse, other—please specify]), the area of their primary role (research, operations, management, market/customer engagement, other—please state), and their level of experience with (a) ensemble information and (b) dispersion modeling, both on a scale of < 6 months, 6–12 months, 1–2 years, 2–5 years, and > 5 years. They then began the main task, in which they were asked to issue an advisory for an eruption, in the form of a VAG and supplementary text guidance.

Participants were provided with information about the eruption, eruption height, eruption duration, and the current date and time (for the complete text/setup, see Supporting Information S1). Those in the ensemble condition were also presented with nine different representations of the output, and those in the deterministic condition were presented with only a single output (see Figure 1). They were then asked to produce the forecasted location of the ash (> 200 μg/m^3) at a specified flight level of FL200–350, 18 h into the future—the same time as the model output they were shown. In line with operational constraints due to data transfer limits, participants drew a polygon with no more than five vertices to encompass the region where they expected ash to be located. On the next screen, they were then asked to write an advisory statement—a text-based description of the VAG in two to four sentences—while able to refer back to their drawn polygon.

After drawing their polygon, participants in the ensemble condition were shown the nine graphical representations and asked to rate them according to (a) how useful they found the graphic, (b) how important it was in the creation of the VAG, and (c) how clear they found the graphic, all on a 7-point Likert Scale, ranging from *Not at all useful/important/clear* to *Extremely useful/important/clear*. For those in the deterministic condition, after drawing the polygon, participants were asked to type in a free-form box what other information they would have liked to help draw the polygon.

The process was then repeated, but for a different eruption scenario (in the opposite uncertainty condition). Finally, participants were thanked and debriefed, as well as given the option to leave their name and contact details if they wished to take part in further research.

3 | Results

All analyses were run using R (R Core Team 2024) in RStudio (Posit Team 2024), version 4.2.2 (October 31, 2022). Given the differences in the maps participants were asked to draw polygons

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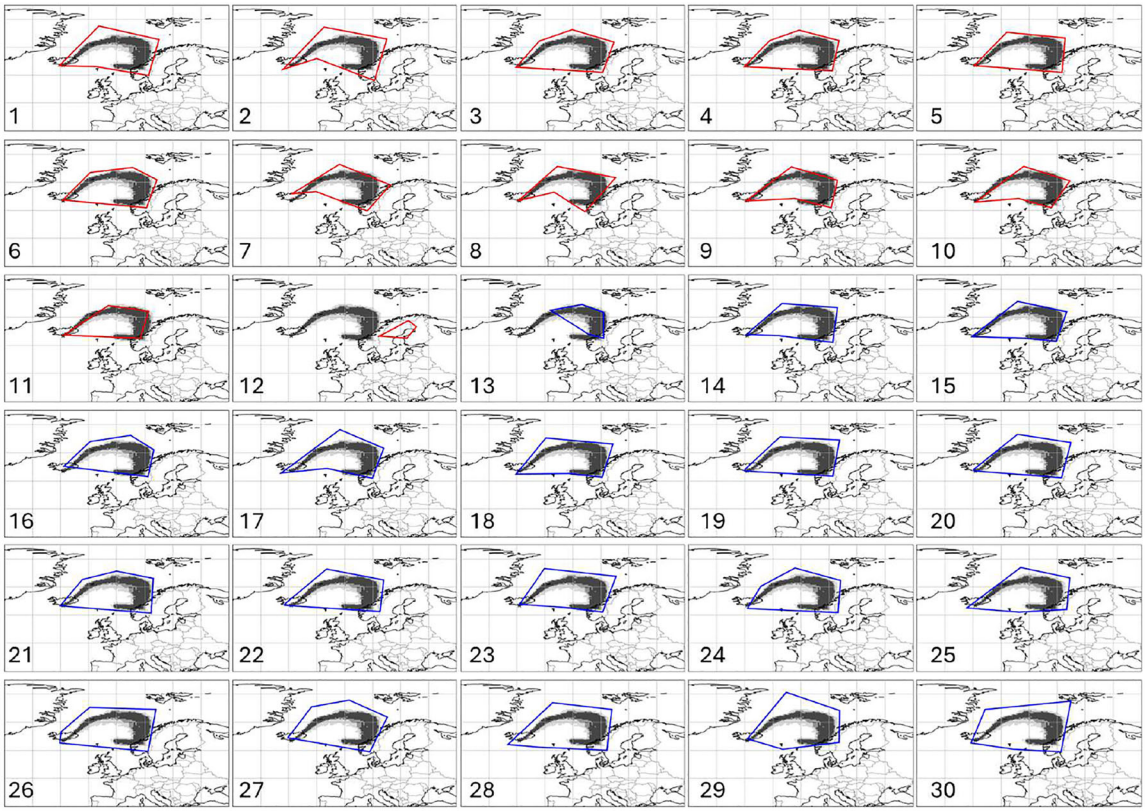


FIGURE 2 | Polygons drawn by respondents in the Katla scenario for both conditions. Polygons are labeled by participant number. Participants 1–12 were in the deterministic condition (red), and Participants 13–30 in the ensemble condition (blue). Participant 12 was excluded from the analysis. All participants were presented with the same graphic; see Supporting Information S1.

on in the two scenarios, the following polygon analyses are conducted separately for Katla and Hekla.

3.1 | Polygon Size

Figures 2 and 3 depict the location of polygons drawn by participants for each scenario. One participant appeared to interpret the task as predicting the location 18 h after the modeling shown, rather than at the same time as the modeling. This participant drew areas that were much smaller than those of other participants (< 14% of the mean area of other responses for these scenarios) for both scenarios; one polygon did not contain any of the modeled ash, and the other only a very small concentration. As such, this participant's responses were removed from the analysis[1] of polygon data for both scenarios. Heat maps of the polygons drawn for each scenario and condition with this participant removed are shown in Figures 4A,B and 5A,B.

For the Katla scenario, all participants drew their polygon on the same graphic, which was the control of the ensemble, such that the results are directly comparable in units of degree^2. However, for the Hekla scenario, participants in the two conditions drew polygons on different graphics where the extent of volcanic ash concentrations exceeding 200 μg/m^3 was different. To control for this, we normalized the polygon areas by dividing by the exact area of volcanic ash exceeding 200 μg/m^3 in the NAME output graphic the participant drew upon (113.7 degree^2 for the deterministic condition and 130.4 degree^2 for the ensemble condition). We thus perform comparative analysis on the normalized areas.

For Katla, there was a marginally significant difference between the mean area (M) of the polygon drawn in the ensemble condition ($M = 356.07$ degree^2, SD = 77.8 degree^2), and that drawn in the deterministic condition ($M = 304.77$ degree^2, SD = 53.73 degree^2), $t(27) = 1.92$, $p = 0.07$, $d = 0.73$ (95% CI: 0.05, 1.50), $BF_{10} = 1.34$, with slightly larger polygons in the ensemble condition (see Figure 4C).

For Hekla, there was no significant difference between the average normalized area of the polygon drawn in the ensemble condition ($M = 2.48$, SD = 0.73), and that drawn in the deterministic condition ($M = 1.87$, SD = 1.00), $t(27) = 1.75$, $p = 0.09$, $d = 0.67$ (95% CI: 0.11, 1.44), $BF_{10} = 1.09$ (see Figure 5C).

Given concern over the relatively small sample size for each condition and thus the potential implications for statistical power, we additionally analyzed the data together using polygon areas normalized by the area of the 200 μg/m^3 contour in the NAME output graphic drawn upon. Using the lme4 package (Bates et al. 2015), we fitted a linear model, with individual as a random effect, to predict normalized area from scenario and condition, and their interaction.[2] We observed a significant effect of condition ($\beta = 0.61$, $t(45.66) = 2.32$, $p < 0.05$, $\eta_p^2 = 0.26$, 95% CI: 0.03, 0.50) and no significant effect of scenario ($\beta = -0.34$, $t(45.66) = -1.27$, $p = 0.21$, $\eta_p^2 = 0.33$, 95% CI: 0.07, 0.55). Crucially, there was no significant interaction between the two ($\beta = -0.36$, $t(27) = -0.80$,

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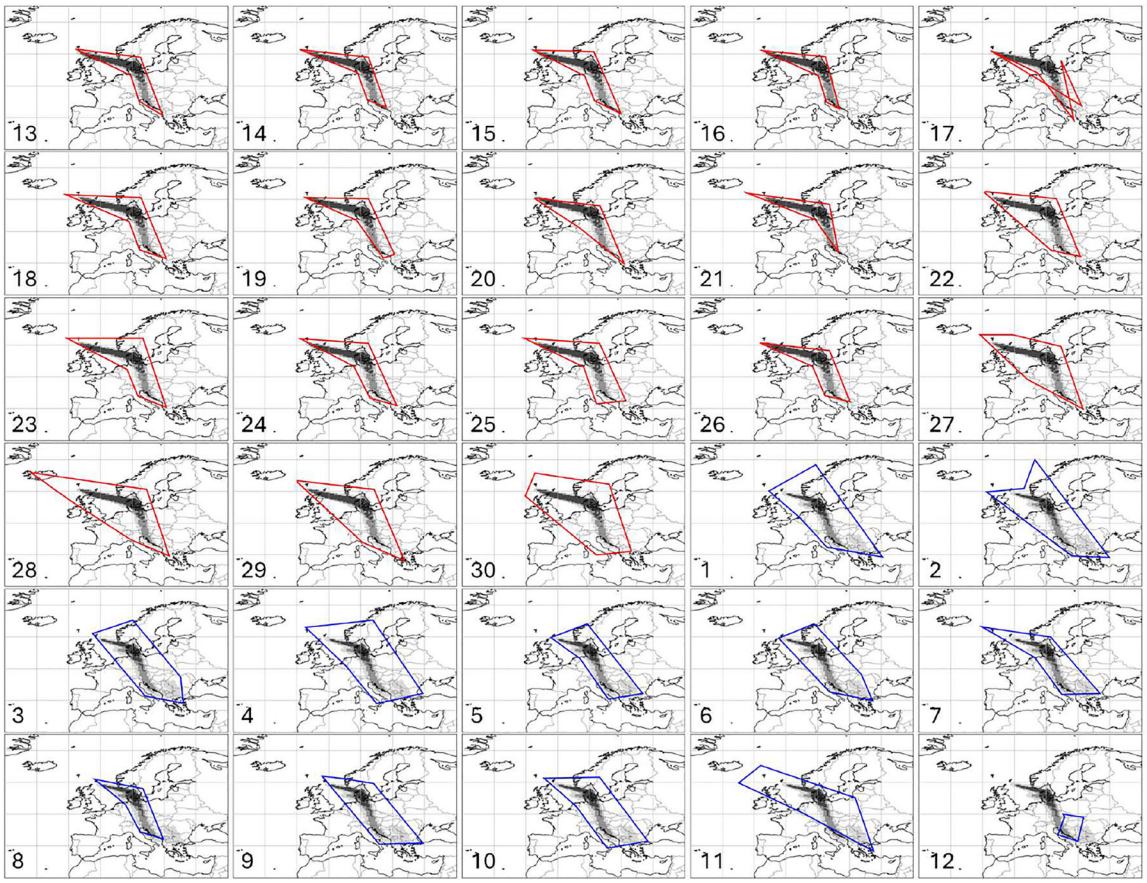


FIGURE 3 | Polygons drawn by respondents in the Hekla scenario for both conditions. Polygons are numbered by participant. Participants 13–30 were in the deterministic condition (red), and Participants 1–12 were in the ensemble condition (blue). Participant 12 was excluded from the analysis. Participants in the two conditions were presented with different graphics; see Supporting Information S1.

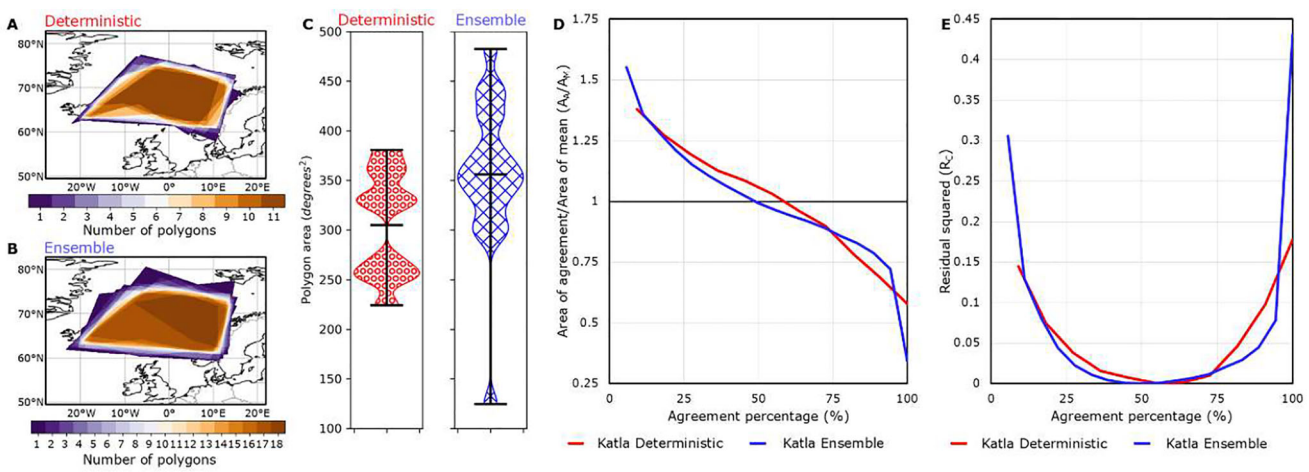


FIGURE 4 | Results for the Katla scenario—all participants. (A, B) Heat maps of participants' polygons for the deterministic and ensemble conditions, respectively. Color scales depend on the number of participants in the condition: brown indicates regions where more polygons overlap, while purple indicates less overlap with other polygons. (C) Violin plots of the distribution of polygon area (degree^2) drawn in the deterministic and ensemble conditions; bars show the mean and range. (D) Ratio of area of agreement to area of mean (A_A/A_M) for varying agreement percentages; 100% agreement percentage corresponds to regions where all polygons overlap (dark brown in A and B); perfectly consistent polygons will produce a horizontal line through one. (E) R_C (residuals squared) values for varying agreement percentages calculated from (D). In (C–E), deterministic participants are shown in red, and ensemble participants are shown in blue.

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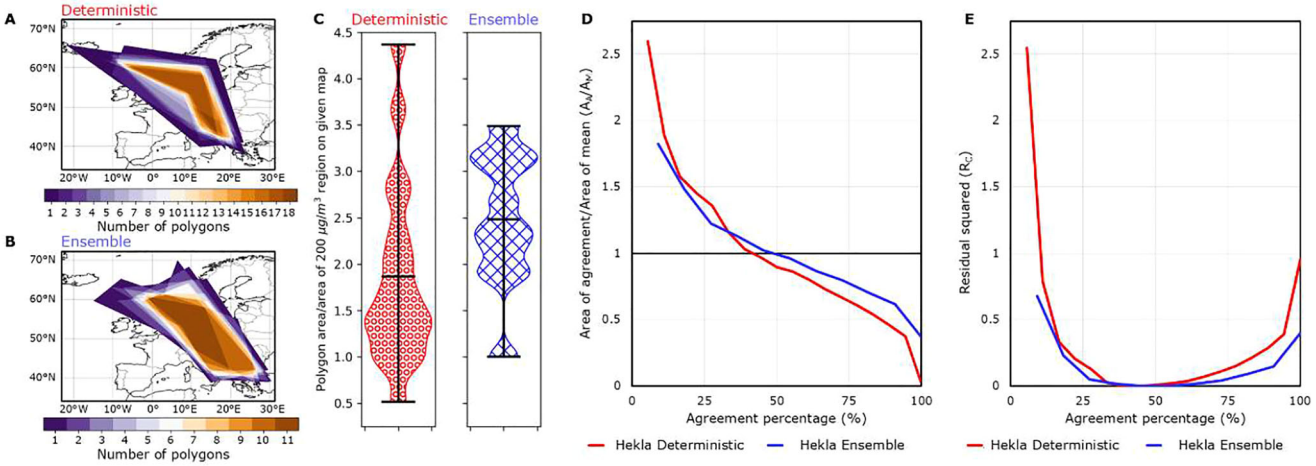


FIGURE 5 | Results for the Hekla scenario—all participants. Panels and colors as described in Figure 4, except (C): violin plots of the distribution of polygon areas drawn divided by the area of the graphic drawn upon (no units) in the deterministic and ensemble conditions; bars show the mean and range.

$p = 0.43$, $\eta_p^2 =$, 95% CI: 0.00, 0.22). This indicates that the effect of condition was the same across both scenarios, with polygons drawn with a larger normalized area in the ensemble ($M = 2.05$, SD = 0.63) versus the deterministic condition ($M = 1.74$, SD = 0.82).

We fitted another linear model to predict normalized area, as before, but this time including expertise (binary predictor: "expert" vs. "nonexpert/not stated") as an additional predictor. However, both the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) were higher than those of the previous model, indicating a worse model fit, and thus we retained the original model above. Further analyses concerning ensemble experts can be found in Supporting Information S2.

3.2 | Polygon Consistency

In an operational context, updated volcanic ash forecasts are issued at least every 6 h, and it is desirable for changes in the polygons drawn to reflect updates to the forecast data, rather than a difference in the on-duty forecaster interpreting them. As such, we suggest that it is desirable for respondents within the same condition to draw polygons that are similar to each other, as this reduces variability between outputs caused by user interpretation. We define "consistency" in this context as polygons drawn by different respondents having the same size and shape and being in the same location. Descriptively, the heat maps of the polygons for the ensemble condition seem to suggest a higher similarity of responses compared to the deterministic condition (Figures 4A,B and 5A,B), due to the appearance of the gradient between the purple and brown regions of the heat map. We follow these differences up systematically, extending the concept of the Figure of Merit in Space (FMS).

The FMS has been used in the atmospheric dispersion community to compare a single forecast prediction with measurements, for example, tracer detections or satellite images of volcanic ash location (Mosca et al. 1998; Wilkins et al. 2016). The FMS is an example of a Jaccard index; in this measure, the area of intersection of the observation and forecast data is divided by the area of the union of the observation and forecast data. Jaccard indices are usually compared to one, but the FMS is often multiplied by 100 to give a percentage. This results in an FMS that is 100% when the forecast and observation agree exactly, with lower values indicating a larger discrepancy in at least one of the size, shape, and location of the forecast and observation.

In the present study, to compare the varying numbers of polygons for each condition, we extend the concept of the FMS. To do this, we define the "agreement percentage," where the area common to all polygons is agreement at the 100% level, the area common to at least half of the polygons is agreement at the 50% level, and so on. In our measure, for each condition, we calculate the area at each agreement percentage (A_A), and divide these values by the area of the mean (A_M). The mean was selected after examining the violin plots of polygon size and wishing to avoid undue influence of extreme responses; division considers the size of the variation compared to the mean, enabling us to compare consistency for polygons with different mean areas. For perfectly consistent polygons, a value of unity would be found at every agreement percentage; in reality, values can be larger or smaller, so we calculate and plot the square of the residual from unity, R_C:

$$R_C = \left(1 - \frac{A_A}{A_M}\right)^2$$

Figures 4D and 5D depict the fraction A_A/A_M and Figures 4E and 5E depict R_C versus the agreement percentage. Returning to our definition of consistency, for a set of polygons of identical size, shape, and in the same location, we would expect the plots of R_C to be a horizontal line through one—the larger the deviations from this, the less consistent the polygons drawn by individual participants are.

Since particularly large or small polygons will tend to cause high squared residuals at both ends of the R_C plot, it is instructive to look at the central region. We define the area under the residuals squared (AURS) as a measure of the consistency between data

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TABLE 2 | Area under the residuals squared (AURS) values for all scenarios and ensemble/deterministic conditions.

Scenario	AURS 10%–90%	AURS 25%–75%
Katla deterministic	2.662	0.584
Katla ensemble	2.014	0.366
Hekla deterministic	11.685	2.323
Hekla ensemble	7.119	1.021

Note: Lower AURS values indicate higher consistency of responses.

of different sample sizes. We consider two illustrative ranges to apply AURS to (bearing in mind our sample size): 10%–90% and 25%–75%. Figures 4E and 5E use the trapezoidal rule to calculate the area under the curve. In both figures, we see that the ensemble curves lie closer to the axis than the deterministic curves through the central range. Lower AURS values are found in the ensemble condition in both illustrative percentage ranges, indicating more consistency in the ensemble condition in both scenarios (see Table 2).

3.3 | Advisory Statements

The length of the VAA statements, that is, the textual descriptions of the drawn polygons, did not vary significantly between conditions (see Supporting Information S3), unsurprisingly given the instructions for participants were the same: write a VAA of two to four sentences.

The statements from both scenarios were collated, and we took a data-driven approach to create a coding structure. Author X initially summarized each advisory statement and categorized these summaries into a set of qualitative codes, representing six key themes of the dataset. Subsequently, Author Y coded all responses using the same coding scheme. In total, 86% of responses were coded identically by the coders, though Author Y suggested an additional theme of "weather." The 14% that were not coded identically were resolved through discussion.

Table 3 demonstrates the final themes extracted from the data, and examples that fit with these, alongside the frequency of the themes by uncertainty condition. We found that advisory statements in the ensemble condition mentioned probability/conditionality and confidence more often than in the deterministic condition.

3.4 | Perceived Utility of Information

To investigate which of the ensemble graphics were most useful to the respondents, they were asked to rate each graphic for usefulness, importance, and clarity. The scale showed high internal consistency (Cronbach's $\alpha = 0.88$). For each type of rating (see Figure 6), we conducted a two-way ANOVA, applying a Bonferroni correction. Results include all participants.

For usefulness ratings, there was a significant effect of graphic $F(8, 198) = 4.35$, $p < 0.001$, $\eta_p^2 = 0.15$, but no effect of scenario $F(1, 198) = 0.03$, $p = 0.87$, nor an interaction $F(8, 198) = 1.55$, $p = 0.14$. Follow-up post hoc Tukey HSD tests revealed that the fifth percentile graphic ($M = 3.54$) was perceived as less useful than the exceedance of 200 μg/m^3 ($M = 6.04$, $p < 0.001$) graphic. The control ($M = 4.26$) was also perceived as significantly less useful than the exceedance of 200 μg/m^3 graphic ($M = 6.04$, $p < 0.01$).

For importance ratings, there was a significant effect of graphic $F(8, 189) = 3.89$, $p < 0.001$, $\eta_p^2 = 0.14$, but no effect of scenario $F(1, 189) = 1.25$, $p = 0.27$, nor an interaction $F(8, 189) = 1.69$, $p = 0.10$. Follow-up post hoc Tukey HSD tests showed that the fifth percentile graphic ($M = 3.69$) was perceived as less important than the exceedance of 200 μg/m^3 graphic ($M = 6.00$, $p < 0.01$). Similar to usefulness, the control ($M = 4.36$) was also perceived as significantly less important than the exceedance of 200 μg/m^3 graphic ($M = 6.00$, $p < 0.01$).

For clarity ratings, there was a significant effect of graphic $F(8, 189) = 3.92$, $p < 0.001$, $\eta_p^2 = 0.14$, but no effect of scenario $F(1, 189) = 2.81$, $p = 0.10$, nor an interaction $F(8, 189) = 0.30$, $p = 0.97$. Follow-up post hoc Tukey HSD tests revealed the fifth percentile graphic ($M = 4.17$) was perceived as less clear than the exceedance of 200 μg/m^3 ($M = 5.92$, $p < 0.01$) graphic.

3.5 | Requests for Additional Information

Requests for additional information could be categorized according to three main themes: general information/observations, information on certainty/confidence, and specific task-related information. A similar number of people requested observations and task information, regardless of which order they completed the ensemble and deterministic conditions. Participants who had already completed the ensemble condition (Route B) were more likely to ask for uncertainty information or specific uncertainty graphics, with 66% ($n = 10$) requesting these. In contrast, only 44% ($n = 4$) of respondents who had not yet seen the ensemble information asked for uncertainty information.

4 | Discussion

Across two volcanic eruption scenarios, we investigated the effects of presenting uncertainty information on the interpretation of volcanic ash dispersion maps. We found that participants given uncertainty information in the ensemble condition (on average) drew larger polygons, which were more consistent in terms of their size, shape, and location. Advisory statements in the ensemble condition included more caveats and references to confidence compared to those in the deterministic condition.

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TABLE 3 | Themes identified in advisory statements.

Final theme	Initial coding definition	Example	Proportion (by condition)
Probability/conditional	What is predicted or likely to happen	"Ash is likely to extend across large parts of continental Europe impacting air space in many European countries"	Det = 32.1% Ens = 58.6%
Certainty/definitive	Statements about event (e.g., what will be/is affected)	"Area affected is due E of volcano as far as W coast of Norway and extending to around 75N"	Det = 57.1% Ens = 41.4%
Confidence	As stated	"There is reasonably high confidence in the area identified"	Det = 3.6% Ens = 24.1%
Geographical	Explicit mention of areas	"Area east of Iceland, north of Scotland, west of Norway"	Det = 92.9% Ens = 82.8%
Relevance to UK	Explicit mention of areas relating to the UK	"could impact northern UK" "possibly far north of UK"	Det = 60.7% Ens = 27.6%
Limitations	Mention of constraints of task, data, etc.	"Due to the limitations imposed by the 5 vertex points, some parts of the area to the SW of the identified area may be clear of ash"	Det = 7.1% Ens = 6.9%

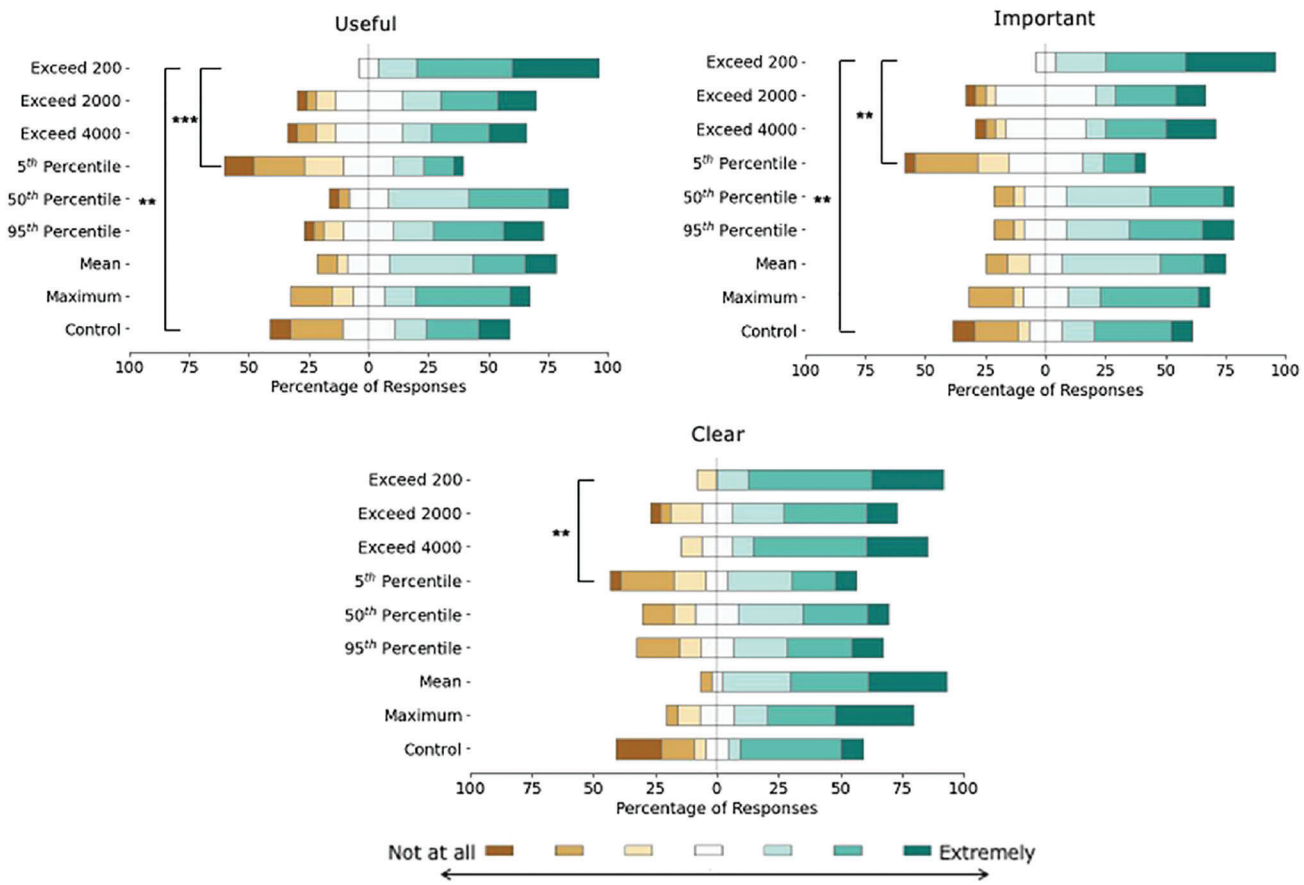


FIGURE 6 | Perceptions of usefulness, importance, and clarity for each ensemble graphic and all respondents. $^{**}p < 0.01$ level; $^{***}p < 0.001$ level.

Uncertainty graphics where there was little ash shown (control and fifth percentile) were perceived to be less useful.

The finding that the presence of uncertainty information influenced the size of polygons is in keeping with existing literature, which found uncertainty was linked with wider ranges (Dieckmann et al. 2010) and increased risk perceptions (Han et al. 2011). This result, coupled with the finding that advisory statements in the ensemble condition included more mentions of probability and hedging, suggests participants themselves did not fall prey to

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the DCE. However, it remains an open question as to whether a recipient of this polygon would interpret it similarly. These findings, at first glance, might be taken to align with concerns raised elsewhere that uncertainty information will be perceived as ambiguous or vague (Lim et al. 2016). We caution against drawing the conclusion that presentation of uncertainty information is bad (and thus undesirable), for three main reasons. First, we observed that the polygons drawn in the ensemble condition were more consistent than those in the deterministic condition. Second, research has indicated that a level of uncertainty is often expected in some contexts (Joslyn and Savelli 2010; Padilla et al. 2015) and inferred, even given deterministic presentations (Mulder et al. 2017). Finally, as well as being more transparent and increasing perceptions of credibility (Jenkins 2020), we suggest explicitly communicating uncertainty gives the communicator more control over inferences drawn from the visualization. Rather than solely focusing on the debate between the relative (dis)advantages of communicating uncertainty, we argue the focus should shift to how to effectively design a visualization to depict task-relevant uncertainties, which will differ depending on the decision maker's role (French et al. 2019).

Given experts' concerns that the provision of uncertainty information could be perceived unfavorably (e.g., Frewer et al. 2003) and as a constraint to making decisions (Deitrick and Wentz 2015), as well as the complexities of ascertaining a "correct" interpretation of the information, we opted to study perceptions of uncertainty information. Contrary to concerns cited in the literature, utility, clarity, and importance ratings were generally positive (i.e., above the midpoint) for the majority of the graphics. Specifically, we found that the exceedance of 200 $\mu g/m^3$ graphic was considered a particularly useful, clear, and important graphic versus the control and fifth percentile graphics. While this could be partially attributed to task instructions (i.e., participants being asked to draw the polygon where the forecasted location of the ash would exceed 200 $\mu g/m^3$), the instructions cannot explain why the control and fifth percentile would be perceived more negatively in comparison. It is possible that the more negative ratings for the control graphic were due to the fact that it was not explicitly stated in the graphic title that it was the control.

The negative ratings observed for the fifth percentile graphic could indicate a lack of familiarity or knowledge regarding its relevance. The 5th and 95th percentile graphics can be thought of as showing the statistical range between ensemble members, which could be thought of as indicative of uncertainty. Perceptions could conceivably differ according to context. For an ensemble with little spread and similar model outputs for all ensemble members, the 5th and 95th percentile graphics will be similar to/consistent with other graphics and thus could be perceived as more fluent (Unkelbach and Greifeneder 2013), in turn increasing confidence in the forecast (Alter and Oppenheimer 2009). However, for ensembles with high spread, the 5th and 95th percentile graphics are likely to show significant discrepancies from the mean and exceedance graphics. While this is important for conveying model confidence, perceptions and, indeed, integration of uncertainty information could be influenced by the risk appetite of the decision maker (British Standards Institute 2022), who might choose to focus on one graphic or the other, leading to anchoring effects (Cho et al. 2017; Valdez et al. 2018). Alternatively, the contrasting appearances of the graphic could be perceived as dissonant by the viewer, leading to selective exposure effects, in which participants avoid and thus discount dissonant information entirely (Cotton 2013; Festinger 1957). In the present study, we only had two scenarios and did not seek to specifically manipulate ensemble spread, underlining the importance of further testing graphics across contexts and participants. This is particularly pertinent to explore with those who have varying degrees of familiarity with ensemble output. It is possible that those who are familiar with ensemble outputs, and indeed the task, will be more versed in both the nuances (for instance, identifying which type of uncertainty was driving the spread of the ensemble they saw) and the consequences associated with communicating it.

When looking at the requests for additional information, some of the requests pertaining to scientific uncertainties chimed with gaps identified within the literature (Nagy et al. 2020). Notably, however, most requests for uncertainty information came from those who had already participated in the ensemble condition, indicating more of an influence of context (e.g., attributable to the task), rather than an unprompted, intrinsic desire for such information. This suggests that training in both the interpretation of the uncertainty products *and* their utility will be important as more atmospheric dispersion products move to presentation of ensemble information.

4.1 | Implications for Operational Decision-Making

The areas of polygons drawn by respondents to the ensemble information were larger than those drawn by respondents to the deterministic condition. Once ensemble volcanic ash forecasts are used by the aviation industry to determine regions where flight should be avoided, such findings could indicate that more airspace might be avoided in the event of a real volcanic eruption happening rather than when purely deterministic data is used. While it is clearly desirable to reduce the likelihood of false negatives in such a context (i.e., in not avoiding an area hazardous to both planes and humans), a greater polygon area also increases the likelihood of false positives (i.e., unnecessary airspace closures). A decision maker must make a trade-off between these two elements. Given the high-stakes context of the task in terms of public safety, and following Mulder et al. (2017), we suggest the larger polygons reflect more conservative judgments, where the costs of missing a hazard outweigh the costs of unnecessary disruption. However, we recognize this interpretation depends on the precise decision context and the cost–benefit trade-offs involved; for some decision makers, the costs of being under-conservative could be greater than the costs of being overconservative, in organizational, political, or financial terms. More broadly, effects of uncertainty might also reflect other factors such as institutional dynamics (e.g., norms, values, and actor responsibilities; Renn 2008; van Asselt and Renn 2011) or the desire to avoid blame, a factor informally mentioned by participants in the workshop (see also Juanchich et al. 2012, in relation to verbal probability expressions for communicating uncertainty).

In this study, we used a task familiar to many in the atmospheric dispersion community to quantify how ensemble information is interpreted, but our findings have broader implications for inter-

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pretation of ensemble and deterministic atmospheric dispersion modeling outputs in a myriad of applications. Indeed, advisory statements, similar to those we asked participants to produce for volcanic ash, are produced for many other dispersion applications, such as chemical accidents and biological and radiological events. In these scenarios, one might predict an even bigger influence of uncertainty information, given the change from consideration of primarily financial impacts on private companies to health impacts on a population (whether human or animal). As well as impact severity, these domains also differ in the temporal framing of the decision; volcanic ash advisories typically inform decisions about future flights, whereas responses to radiological and chemical incidents concern an event that has occurred or is unfolding (French et al. 2019). The costs of over- versus underwarning may differ depending on whether a decision maker is acting preemptively to prevent future harm, or acting to minimize current harm, further complicating a straightforward comparison of the influence of uncertainty across domains.

As individual atmospheric dispersion modeling applications move from using a single model run to incorporating ensembles in both the meteorology and the source term, it is important to understand the implications of this change in output on the interpretation provided to, and performed by, users. Currently, polygons supplied to the aviation industry via the VAACs are generated by both experts and an algorithm; in the future, only algorithm-generated polygons will be supplied, removing individual expert area selection and thus reducing variability of outputs. However, decisions have yet to be made for other dispersion products in alternative contexts. Our results suggest that, in general, providing uncertainty information from ensembles of model runs could yield higher consistency between individual interpretations, but also inadvertently lead to an increase in larger estimations. It is an open question as to whether this would translate to more conservative decisions by recipients of this information.

4.2 | Implications for Presenting Uncertainty Information

The current study presented participants with nine different visual displays, which would have been both cognitively and perceptually demanding. Padilla et al. (2021) suggest that when reasoning with uncertainty, individuals will often substitute hard mental computations for easier ones, using a variety of heuristics. Rather than assimilating across all nine graphics, we suggest participants may have used one graphic as an anchor to guide their decision-making (Cho et al. 2017; Valdez et al. 2018), as indicated in the pilot study (S. J. Leadbetter, personal communication 2020). We speculate the choice of graphic used as a basis could be influenced by factors such as familiarity (Gigerenzer and Goldstein 2011; Goldstein and Gigerenzer 1999, 2002) and similarity (Medin et al. 1995). Use of such a strategy could be problematic in certain contexts where reference to multiple graphics would be advantageous, for instance, should individual visualizations from an ensemble depict conflicting information. In such an instance, one might expect additional requests to other sources for information (see Mulder et al. 2017).

Given the cognitive complexity of integrating across graphics, we are therefore sympathetic to Nagy et al.'s (2020) suggestion that uncertainty should be indicated within a single visualization where possible. Of course, no one visualization will be able to meet the needs of all users (Thompson et al. 2015) and thus in some instances it might be appropriate to use multiple visualizations, ensuring that adequate explanatory text is provided (an element we did not include in the current study). The question of how best to communicate ensemble model output is therefore not going to be answered with a single, standardized solution across contexts. Visualizations should be appropriately tested with users and evaluated (Padilla et al. 2021; Thompson et al. 2015); studies such as this one represent initial steps toward the empirically informed design of volcanic ash dispersion maps.

4.3 | Limitations and Future Directions

The present study was designed as a scoping exercise to better understand how ensemble information is integrated and used within a task by stakeholders familiar with this context. We examined one element of a complex, dynamic communication process, and thus can only conclude that the provision of uncertainty information influenced outputs, rather than evaluating the relative success (or otherwise) of communication. Relatedly, our task design was not intended to capture participants' reasoning, including their communicative goals or how they anticipated another user would interpret the information. Our future research seeks to elucidate the mechanisms behind the larger polygons by incorporating an experimental manipulation of consequence severity alongside more open questions concerning participants' reasoning.

Inevitably, due to the specialist nature of the sample, the sample was small and not evenly distributed in terms of characteristics such as training and expertise. Expertise could conceivably play a role in interpretations and use of ensemble model information, in that greater levels of expertise/experience could be associated with integration of more decision-relevant information, such as the typical exceedance thresholds for volcanic ash. Nevertheless, expertise does not always equate to improved performance, with experts still demonstrating similar biases to novices (e.g., Hegarty et al. 2012; Nadav-Greenberg et al. 2008). Furthermore, we recognize the limitations associated with the design of the Hekla scenario, such that participants in the two uncertainty conditions drew the polygons on different maps. Although this reflects the way that polygons are typically drawn within an operational context, it meant that we had to apply an additional transformation to enable comparison across scenarios.

In addition, the current experiment was set within the context of a volcanic eruption with participants specifically asked to identify low levels of volcanic ash (~200 $\mu g/m^3$). At this level, the implications of the ash dispersion predominantly relate to financial loss, for instance, those arising from damage to aircraft engines and flight cancellations. Here, the precise size and location of a polygon might arguably have different consequences versus a situation in which participants identified an area of a higher volcanic ash concentration, which is associated with immediate engine failure. Similarly, participants' risk appetite may be different in a radiological context where human health and life might be the primary risk; in general, people perceive

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higher risks for radiological hazards (Slovic 2012), which evoke strong emotional responses (Krieger et al. 2014). In the latter context, the presence of uncertainty information could have greater effects on interpretations and decision-making, such that larger estimates of affected areas are given, with potentially greater attention paid to contextual information such as urban conglomerations and airports, where there would be greater consequences. Provision of larger estimates in such contexts is akin to a severity effect, observed in weather forecasters' (hypothetical) warnings (Liefgreen et al. 2024) and is in line with an asymmetric loss function account (Harris et al. 2009; Weber 1994), where the costs of under-warning are greater than those of over-warning. Notably, even though ensemble track visualizations of a hurricane's path were linked with increased performance versus other types of visualizations (Liu et al. 2019), such a format was still vulnerable to contextual influences (e.g., if the hurricane was shown as impacting a particular point of interest; Padilla et al. 2017, 2020). Future research should therefore consider the potential influence of context, both broadly at a domain level, as well as more specifically in relation to landmarks.

5 | Conclusion

Overall, we found that participants presented with uncertainty information drew larger polygons, though there was evidence indicating that these were more consistent in terms of shape, size, and location. Participants found the 200 $\mu g/m^3$ exceedance graph most useful, and the fifth percentile and the control the least useful. Our results indicate that while presenting uncertainty information is not negatively perceived, its presence can influence how modeling output is assimilated and subsequently communicated for decision-making. Given the move toward communicating ensemble modeling outputs across various contexts, including meteorology, radiological, biological, and chemical settings, it is vital to continue investigating the effects of such presentations.

Author Contributions

Helen Miller: software, formal analysis, investigation, writing – original draft, writing – review and editing, visualization. **Susan Leadbetter**: conceptualization, methodology, software, formal analysis, investigation, writing – original draft, writing – review and editing, visualization. **Sarah C. Jenkins**: conceptualization, methodology, formal analysis, writing – original draft, writing – review and editing.

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The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] A significant effect of the uncertainty condition is found when this participant is included in the analysis of area for the Katla scenario ($p < 0.03$, $d = 0.88$) and a marginally significant effect for Hekla ($p = 0.05$, $d = 0.75$).

[2] Again, this analysis was conducted with the participant who misunderstood the task removed.

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