

# *Characterising the atmospheric conditions leading to large error growth in volcanic ash cloud forecasts*

Article

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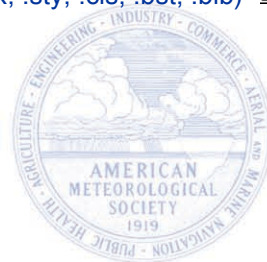
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1 **Characterising the atmospheric conditions leading to large error growth in**  
2 **volcanic ash cloud forecasts**

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## ABSTRACT

11 Volcanic ash poses an ongoing risk to the safety of airspace worldwide. The  
12 accuracy to which we can forecast volcanic ash dispersion depends on the con-  
13 ditions of the atmosphere into which it is emitted. In this paper we use mete-  
14 orological ensemble forecasts to drive a volcanic ash transport and dispersion  
15 model for the 2010 Eyjafjallajökull eruption. From analysis of these simu-  
16 lations we determine why the skill of deterministic-meteorological forecasts  
17 decrease with increasing ash residence time, and identify the atmospheric con-  
18 ditions in which this drop in skill occurs most rapidly. Large forecast errors  
19 are more likely when ash particles encounter regions of large horizontal flow  
20 separation in the atmosphere. Nearby ash particle trajectories can rapidly di-  
21 verge leading to a reduction in the forecast accuracy of deterministic forecasts  
22 which do not represent variability in wind fields at the synoptic-scale. The  
23 flow separation diagnostic identifies where and why large ensemble spread  
24 may occur. This diagnostic can be used to alert forecasters to situations in  
25 which the ensemble mean is not representative of the individual ensemble  
26 member volcanic ash distributions. Knowledge of potential ensemble outliers  
27 can be used to assess confidence in the forecast and to avoid potentially dan-  
28 gerous situations in which forecasts fail to predict harmful levels of volcanic  
29 ash.

## 30 **1. Introduction**

31 Volcanic ash poses a significant hazard to aircraft. It can cause both temporary engine failure  
32 and permanent engine damage (*Guffanti et al. 2005*). Flights are therefore restricted in ash con-  
33 taminated airspace, which disrupts air traffic leading to the potential for large financial losses. For  
34 example the 2010 Eyjafjallajökull eruption grounded over 95,000 flights, costing the airline in-  
35 dustry over 1 billion pounds. Analysis of the 1900-2010 Icelandic historical records shows that a  
36 volcanic eruption of the size of the 2010 Eyjafjallajökull eruption has a repeat period of between  
37 5 and 10 years (*Thordarson and Larson 2007*). Worldwide, volcanic eruptions 10 times the size  
38 of the 2010 Eyjafjallajökull eruption have repeat periods on a decadal timescale (e.g. Mount St  
39 Helens 1980, Hudson 1991, Puyehue 2011). Given the ongoing risk of volcanic eruptions it is  
40 important to continually evaluate and improve the accuracy of volcanic ash forecasts to ensure  
41 safe and optimised flight operations during future volcanic eruptions.

42 The volcanic ash advisory centres (VAACs) are responsible for producing volcanic ash cloud  
43 analysis and forecasts to assist the aviation community in planning their operations and minimis-  
44 ing risks. There are currently 9 VAACs that together provide a comprehensive global modelling  
45 and warning system for the aviation community. These 9 VAACs use 6 different volcanic ash  
46 transport and dispersion (VATD) models to to produce volcanic ash charts showing the forecast  
47 location of volcanic ash in the atmosphere at different flight levels and out to forecast lead-times  
48 of 24 hours. VATD models are initialised using data about the location of the eruption, the time  
49 at which the eruption started and, if available, information about the plume rise height, vertical  
50 profile of volcanic ash and ash size distribution (known collectively as eruption source parameters,  
51 ESPs). They also use 3-D winds as input from numerical weather predictions to transport volcanic  
52 ash away from the source. Typically the meteorological input used has a horizontal resolution of

53 between 10 and 50km. To represent dispersion on scales smaller than this horizontal diffusion  
54 is applied. The diffusion represents the dispersion by unresolved eddies and acts to increase the  
55 vertical and lateral spread of volcanic ash clouds (*Dacre et al. 2015*). This approach assumes  
56 that the small-scale dispersion processes are of an eddy viscosity character and thus can be repre-  
57 sented using a Gaussian description (*Pasquill and Smith 1983*). The simulated ash cloud therefore  
58 represents the time mean of an ensemble of realisations.

59 At larger scales however, individual realisations can often display considerable deviations from  
60 the ensemble mean (*Mylne and Mason 1991*). The scale at which this occurs depends on the  
61 size of the dispersion processes relative to the width of the time averaged ash cloud. For aver-  
62 aging periods of a few hours, this scale is typically greater than 500 km. Variability on synoptic  
63 scales however differs for different atmospheric circulation patterns, meaning that the traditional  
64 Gaussian diffusion approach used for small-scale dispersion processes cannot be used. Current  
65 operational VATD models do not represent variability at the synoptic scale. They use meteorolog-  
66 ical input from a single realisation of the flow field to produce a volcanic ash forecast (referred  
67 to as *deterministic-met volcanic ash forecast* in this paper). The aim of this paper is to identify  
68 the atmospheric conditions in which there is a higher chance that deterministic-met volcanic ash  
69 forecast skill may rapidly decrease and to discuss the potential use of ensemble meteorological  
70 input to VATD models as a method to address the missing synoptic-scale variability in volcanic  
71 ash forecasts (referred to as *ensemble-met volcanic ash forecasts* in this paper).

72 Several studies have investigated the space and time-dependent skill of deterministic-met vol-  
73 canic ash forecasts. For example, *Stunder et al. (2007)* analysed the forecast skill for 7 different  
74 volcanic eruptions by comparing deterministic-met volcanic ash forecasts with satellite observa-  
75 tions. They showed that these forecasts were generally good for short-term (18 hours from start  
76 of the eruption) forecasts but that forecast skill appeared to decrease at longer lead-times. This

77 relationship between volcanic ash forecast skill and forecast lead-time is due to (i) increasing er-  
78 rors in the forecast wind fields and ESPs at longer forecast lead-times and (ii) longer lead-time  
79 forecasts include particles with longer residence times. These particles experience an accumula-  
80 tion of errors in the wind field leading to larger positional errors on average than particles with  
81 shorter residence times. *Dacre et al. (2016)* examined the second of these sources of error by per-  
82 forming hindcast simulations of the Eyjafjallajökull eruption (using analysis wind fields). They  
83 showed that generally skill decreases as the residence time of ash increases but that the rate of  
84 skill decrease depends on the meteorological situation. In some situations only the position of ash  
85 particles with residence time less than 24 hours are correctly simulated whereas in other situations  
86 the position of ash particles with residence times longer than 72 hours can be accurately simulated.  
87 Other studies have shown that the inclusion of buffer zones, to account for positional errors in the  
88 deterministic-met volcanic ash clouds, can lead to significant improvement in the agreement with  
89 observations (*Webster et al. 2012; Grant et al. 2012*). These buffer zones are a simplistic attempt  
90 to account for uncertainty in the synoptic-scale wind fields.

91 For some time the use of ensemble-met volcanic ash forecasts has been advocated by the wider  
92 volcanic ash community (*Bonadonna et al. 2012*) as a more rigorous way of accounting for uncer-  
93 tainty in large-scale wind field. *Stefanescu et al. (2014)* and *Madankan et al. (2014)* include both  
94 ensemble meteorology and an ensemble of ESPs in their study to quantify overall uncertainty in  
95 volcanic ash forecasts. They demonstrate that the range of predicted concentrations can be large  
96 at forecast lead-times of 48 hours. Similarly *Vogel et al. (2014)* performed time-lagged ensemble  
97 simulations of volcanic ash dispersion from the Eyjafjallajökull plume and found that for some  
98 times the spread in ensemble-met forecasts is small but at others it is large. They attribute this to  
99 the nonlinear behaviour of the atmosphere. *Dare et al. (2016)* performed a comparison of both  
100 deterministic and ensemble-met volcanic ash forecasts for the 2014 Kelut eruption. They found



101 that both showed good agreement with satellite observations for the first 12 hours from the start  
102 of the eruption. However, for longer lead-times (18-24 hours) the ensemble-met forecast showed  
103 better agreement with observations than the deterministic-met forecast.

104 While all these studies demonstrate that ensemble-met forecasts show better agreement with  
105 observations than the deterministic-met forecasts, particularly at longer lead-times, the dynamical  
106 reasons why they perform better has not been explored. The aim of our study therefore is to  
107 illustrate why the skill of deterministic-met forecasts decreases with increasing ash residence time,  
108 and furthermore to identify the atmospheric conditions in which this drop in skill occurs most  
109 rapidly. These conditions are identified using ECMWF meteorological ensembles as input to the  
110 NAME VATD model to simulate an ensemble of particle trajectories.

## 111 **2. Methodology**

### 112 *a. Meteorological fields*

113 In order to determine the uncertainty associated with the synoptic scale meteorological flow  
114 field an ensemble of meteorological forecasts are used. Each forecast is produced from perturbed  
115 initial conditions that represent the likely initial analysis error distribution. In this paper the Eu-  
116 ropean Centre for Medium Range Weather Forecasting (ECMWF) Integrated Forecasting System  
117 (cycle 41r1) has been used to create bespoke ensemble forecasts of the meteorological conditions  
118 during the 2010 eruption of Eyjafjallajökull. Global forecasts are initialised every 12 hours be-  
119 tween 00 UTC on 1 May - 12 UTC on 8 May 2010. Each forecast is 42 hours long and has  
120 20 ensemble members. Data is archived every 6 hours on 26 levels and at T639 spectral trunca-  
121 tion (approximately 32km horizontal grid spacing). Initial perturbations are constructed using the  
122 singular-vector approach (*Buizza and Palmer 1995*) and model uncertainty is taken into account

123 through the use of a simple stochastic physics scheme (*Buizza et al. 1995*). Data is extracted from  
124 the ECMWF archive at  $0.25^\circ \times 0.25^\circ$  on a regular lat/lon grid and several fields (surface stresses,  
125 sensible heat flux and precipitation fields) are post-processed as data extracted from the ECMWF  
126 archive cannot be used directly as input to the VATD model described in section b.

### 127 *b. NAME dispersion simulations*

128 The VATD model used in this study is the Numerical Atmospheric-dispersion Modelling Envi-  
129 ronment (NAME). NAME is used by the London Volcanic Ash Advisory centre to forecast the  
130 spatial distribution of volcanic ash following an eruption. In this study we use NAME III (version  
131 6.3) and ECMWF numerical weather prediction meteorological data to disperse particles released  
132 into the atmosphere at the position of the Eyjafjallajökull volcano in Iceland. The dispersion of  
133 volcanic ash by small-scale three-dimensional atmospheric turbulence and unresolved mesoscale  
134 motions are parametrized within NAME using random-walk techniques. The aim of the random-  
135 walk dispersion is to compute an ensemble of random trajectories of Lagrangian particles through  
136 a flow field whose statistics are based on observations of vertical and horizontal velocity variances  
137 and diffusivities (*Thomson and Wilson 2013*). The position of the particles is tracked for 42 hours  
138 to create particle trajectories. The volcanic ash density is assumed to be  $2300 \text{ kg m}^{-3}$  based on the  
139 value used in the operational version of NAME (*Leadbetter and Hort 2011*) and the particle size  
140 is assumed to be  $2 \mu\text{m}$  based on in-situ observations of the ash cloud by the FAAM aircraft over  
141 and around the UK in the Eyjafjallajökull ash cloud (*Johnson et al. 2012*). Particles are subject to  
142 removal processes including sedimentation, wet and dry deposition (*Jones et al. 2007*). Note that  
143 the choice of particle size does not affect the conclusions reached in the paper.

144 *c. SEVIRI satellite observations*

145 To qualitatively evaluate the performance of the NAME forecasts we compare simulated ash  
146 cloud distributions with data from the Spinning Enhanced Visible and Infrared imager (SEVIRI).  
147 SEVIRI volcanic ash retrievals are calculated using brightness temperature difference measure-  
148 ments (see *Francis et al. (2012)* for more details). The advantage of using volcanic ash retrievals  
149 from an instrument onboard a geostationary satellite is that they are available at high temporal res-  
150 olution, every hour, allowing us to track the evolution of the volcanic ash cloud and to interpolate  
151 between timesteps when water or ice clouds obscure the volcanic ash. Following the method of  
152 *Harvey and Dacre (2016)* we composite satellite observations over a 5 hour time window. This has  
153 been shown to be sufficient to create a continuous time series while remaining highly correlated  
154 with the noncomposited fields. The satellite volcanic ash retrievals are averaged onto a  $0.5^\circ \times 0.5^\circ$   
155 latitude/longitude grid to allow direct comparison with the NAME output.

156 *d. Ensemble spread and flow separation diagnostics*

157 One measure of the uncertainty in meteorological flow conditions is the time evolution of spatial  
158 spread in particle trajectories. In this paper the ensemble spread is calculated using the root-  
159 mean-square (*RMS*) distance between individual ensemble particle positions (1 particle from each  
160 ensemble simulation),  $(\mathbf{x}_i)$ , and the mean position of the particles,  $(\bar{\mathbf{x}}_i)$ , summed over all  $N$  particles  
161 (thus  $N$  equals 20 as there are 20 ensemble simulations). The distance is measured perpendicular  
162 to the mean direction travelled by the particles during the previous 10 minutes to capture lateral  
163 spreading of the trajectories only.

$$RMS = \sqrt{\frac{1}{N} \sum_i^N (\mathbf{x}_i - \bar{\mathbf{x}}_i)^2} \quad (1)$$

164 The diagnostic used to characterise the synoptic-scale flow conditions is the 2-D horizontal flow  
165 separation diagnostic introduced in *Dacre et al.* (2016). This flow separation is calculated as the  
166 velocity gradient perpendicular to the flow.

$$\frac{\partial \mathbf{v}}{\partial n} = \frac{1}{q^2} \left[ v^2 \frac{\partial u}{\partial x} - uv \left( \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) + u^2 \frac{\partial v}{\partial y} \right] \quad (2)$$

167 where  $\mathbf{v}$  is the velocity vector,  $q$  is the wind speed,  $n$  is distance in the direction perpendicular to  
168 the flow, and  $x$  and  $y$  are distances in longitude and latitude directions, respectively. Where this  
169 diagnostic is positive, the atmospheric flow separates, and where it is negative, the flow contracts.  
170 Thus it is a good diagnostic for identifying where particle trajectories will spread apart. The flow  
171 separation diagnostic is related to the 3-D Lyapunov exponents used by *Legras et al.* (2005) and  
172 *Pisso and Legras* (2008) to characterise the rate of separation of infinitesimally close trajectories  
173 in phase space.

### 174 3. Results

#### 175 a. Satellite-detected ash clouds

176 Figure 1(a) and (b) show the ash cloud from the Eyjafjallajökull eruption, as detected by the  
177 SEVIRI instrument. At 12 UTC on 7 May (figure 1(a)) the ash was detected in a coherent plume  
178 extending southward from Iceland to the west of the UK. The ash cloud exhibits an anticyclonic  
179 curvature as ash particles were transported anticyclonically around a high-pressure centre in the  
180 North-Atlantic. At around 50°N the ash cloud has started to bifurcate with one branch of volcanic  
181 ash continuing to follow an anticyclonic trajectory whilst another branch was advected cycloni-  
182 cally towards southern Europe. This cyclonic branch reaches the coast of Portugal at 00 UTC  
183 on the 8 May (figure 1(b)) whilst the majority of the volcanic ash continues to travel anticycloni-  
184 cally. The ability of VATD models to capture this complex ash cloud bifurcation is dependent on

185 the accurate representation of the input meteorological wind fields. For example, *Wilkins et al.*  
186 (2016) showed that their NAME deterministic-met volcanic ash forecast was not able to capture  
187 the structure the thin filament of ash extending over northern Spain on 8 May 2010.

### 188 *b. Ensemble member forecasts*

189 Figures 1(c),(d) and (e),(f) show two volcanic ash forecasts using different ECMWF ensemble  
190 member flow fields, both initialised at 00 UTC on 6 May 2010. Particles are released at the loca-  
191 tion of Eyjafjallajökull volcano at a rate of 3600/hr. All of the particles were released at a height  
192 consistent with the maximum observed plume height at that time. It can be seen that close to the  
193 volcano the volcanic ash distribution for both forecasts is very similar, with both forecasts pro-  
194 ducing an ash cloud extending southward from Iceland to the west of the UK, consistent with the  
195 satellite detected ash cloud location. However, at 50°N the forecasts start to diverge. In figures 1(e)  
196 and (f) the majority of the volcanic ash is transported cyclonically and is advected towards Europe.  
197 In contrast in figures 1(c) and (d) the majority of the volcanic ash cloud continues to travel anticy-  
198 clonically and is advected into the North Atlantic. For this example, the deterministic-met forecast  
199 shown in figures 1(c) and (d) would be considered a good forecast as it closely matches the evo-  
200 lution of the ash cloud seen in the satellite observations. However the deterministic-met forecast  
201 shown in figures 1(e) and (f) would be considered a poor forecast as it does not forecast the ob-  
202 served ash in the North Atlantic. This is despite both forecasts using equally plausible realisations  
203 of the flow field. This example highlights the danger of using a single deterministic-met flow field  
204 as input to a VATD model to forecast the ash cloud distribution. These 2 ensemble members are  
205 chosen because they exhibit very different volcanic ash cloud evolutions, the other 18 ensemble  
206 members result in ash distributions which resemble a mixture of the two extremes.

207 *c. Flow separation*

208 In this section we explain why the ensemble member forecasts differ so much from each other.  
209 In order to do this we examine the flow pattern at approximately 50°N and 15°W, the location at  
210 which the ash particle trajectories show an increase in spread.

211 Figures 2(a) and (b) shows the streamlines and flow separation at 12UTC and 18UTC on 6 May  
212 respectively, for a single deterministic-met ensemble member forecast. The streamlines evolve  
213 over time but broadly show a low pressure to the west of the domain, a large region of high  
214 pressure in the centre of the domain and low pressure in the east of the domain. Figures 2(a) and  
215 (b) also show the flow separation diagnostic averaged over 100hPa at the release height of the ash  
216 particles. The flow separation is positive in regions where the streamlines spread apart and negative  
217 where the streamlines contract. For the purposes of illustrating why different ensemble members  
218 diverge and under what conditions, it is not feasible to visualise the trajectories of thousands of  
219 particles. Therefore, for simplicity, we have chosen to visualise a single particle trajectory (that is  
220 not subject to stochastic motions) from each ensemble member. The thick black trajectory shown  
221 in figures 2(a) and (b) is a single 42 hr particle trajectory from the same ensemble simulation shown  
222 in figure 1(e) and (f)). This particle was released from the volcano source at 06 UTC and is subject  
223 to the flow field shown in figures 2(a) and (b). In order to isolate transport by the resolved-scale  
224 flow it is not subject to perturbations representing unresolved eddies, hence its smooth trajectory.  
225 The black star indicates the location of the particle at the time of the flow separation field. 12 hours  
226 after the particle is released into the atmosphere (figure 2(a)) the particle is at 57°N, 13°W where  
227 the streamlines are roughly parallel to one another and hence flow separation is small. 24 hours  
228 after the particle is released into the atmosphere (figure 2(b)) the particle is at 51°N, 17°W and is

229 in a region of strong positive flow separation. The streamlines spread apart as they approach the  
230 point of intersection between the trough and ridge region (known as a col or saddle point).

231 It is difficult to analyse the along-trajectory flow separation in this Eulerian framework, therefore  
232 figure 2(c) shows the flow separation extracted at the relevant time along the Lagrangian particle  
233 trajectory. This Lagrangian analysis demonstrates that the particle advected in this deterministic-  
234 met forecast enters a region of strong flow separation at  $52^{\circ}\text{N}$ ,  $17^{\circ}\text{W}$ . In order to determine whether  
235 this is specific to a single ensemble-met member forecast or to all of the meteorological ensemble  
236 forecasts initialised at 06UTC on 6 May the along-trajectory flow separation has been calculated  
237 for each of the meteorological ensemble forecast members. Figure 2(d) shows the evolution of  
238 flow separation along 20 particle trajectories released at the same time, a single particle trajectory  
239 in each ensemble-met forecast. The flow separation in each ensemble-met forecast is very similar  
240 up until the point at which the trajectories start to diverge. This is expected since the regions of  
241 positive and negative flow separation are spatially coherent. It also illustrates how the trajectory  
242 separation rapidly increases after the point at which the trajectories encounter the region of positive  
243 flow separation. Performing an ensemble-met volcanic ash forecast for this case accounts for the  
244 variability in the synoptic flow field and is necessary to fully encompass the ash cloud distribution  
245 uncertainty due to the flow field.

#### 246 *d. Trajectory spread*

247 To establish if trajectory spreading always rapidly increases after trajectories encounter regions  
248 of positive flow separation similar experiments were performed for meteorological ensemble fore-  
249 casts initialised at 06UTC on the 15 April - 7 May 2010. For each of these ensemble forecasts a  
250 single particle were released at a height corresponding to the observed plume top from the Eyjaf-  
251 jallajökull volcano. It is well known that in low wind-speed conditions wind direction can vary

252 significantly in a short period of time causing particle trajectories can rapidly diverge (*Venkatram*  
253 *et al.* 2004). In this paper we choose to focus on the less well studied uncertainty occurring in  
254 moderate-strong wind conditions and thus only analyse the situations in which the wind speed at  
255 the release height was greater than  $10\text{m s}^{-1}$ . Figure 3 shows the ensemble-met member forecasts  
256 with the 4 highest (figures 3(a)-(d)) and 4 lowest (figures 3(e)-(h)) trajectory spreads. Individual  
257 particle trajectories correspond to a single particle released at the same time in each ensemble-met  
258 member forecast. It can be seen that on some days, figures 3(a)-(d), the trajectories diverge after  
259 encountering regions of positive flow separation, consistent with the analysis for the 6 May 2010  
260 (figures 2(d)). By comparison on other days, figures 3(e)-(h) the trajectories remain close together  
261 for 42 hours.

262 Figure 4 quantitatively describes the relationship between residence time and ensemble-met  
263 forecast trajectory spread (measured using the RMS perpendicular distance described in section d).  
264 As observed in figure 3 trajectory spread generally increases with residence time but not always at  
265 the same rate. The rate of trajectory spread depends on the synoptic situation. Figure 4 also shows  
266 the maximum along-trajectory flow separation from each ensemble-met forecast, accumulated  
267 over 42 hours for each set of simulations. The simulation with the smallest trajectory spread after  
268 42 hours residence time corresponds to the 3 May 2010 (figure 3(h)) and the along-trajectory  
269 accumulated flow separation is small at all points along the trajectory. By contrast the simulation  
270 with the largest trajectory spread corresponds to the 19 April 2010 (figure 3(a)) and the along-  
271 trajectory accumulated flow separation is neutral or positive at all points along the trajectory. Thus,  
272 these simulations suggest that trajectories that experience large along-trajectory accumulated flow  
273 separation are more likely to spread apart than trajectories that experience no large along-trajectory  
274 flow separation, potentially leading to large error growth for a single deterministic forecast (as  
275 shown in figure 1)



## 276 **4. Discussion and Conclusions**

277 In this paper we examine the atmospheric flow characteristics that lead to volcanic ash cloud  
278 bifurcation and a reduction in forecast skill. We performed multiple forecasts using the UK Met  
279 Office volcanic ash transport and dispersion model (NAME) and input from ensemble meteorological  
280 flow fields from the ECMWF ensemble prediction system.

281 In moderate to strong wind situations the atmospheric conditions leading to large variability  
282 in volcanic ash particle positions are associated with large flow separation. When ash particles  
283 encounter regions of large horizontal flow separation their future trajectories are very sensitive  
284 to their position at that time. Nearby ash particle trajectories can rapidly diverge leading to a  
285 reduction in forecast accuracy for deterministic-met volcanic ash forecasts. Potentially leading to  
286 predictions of ash-free airspace in regions that are in-reality contaminated with ash or vice versa.

287 In order to fully represent the synoptic-scale meteorological uncertainty ensemble-met volcanic  
288 ash forecasts are needed. When volcanic ash clouds encounter regions of large flow separation the  
289 individual ensemble-met members may display considerable deviations from the ensemble mean.  
290 2-D fields of positive flow separation could be used as a flag to alert forecasters to this potential  
291 risk and the individual ensemble-met member forecasts analysed. A combination of the flow  
292 separation diagnostic and ensemble volcanic ash forecasts will help to identify where and why  
293 large uncertainty in the forecast occurs and provide an estimate of the confidence of the forecast.  
294 For example, a forecaster could reduce the size of the hazardous area whenever high confidence  
295 in the ash cloud forecast was indicated. Reductions in the hazard area would avoid unnecessary  
296 disruption to airspace.

297 In this paper we have only considered the uncertainty in the horizontal wind fields. Uncertainty  
298 also exists in the magnitude and location of precipitation which leads to wet-deposition of volcanic

299 ash. This uncertainty may also cause large errors in the magnitude of volcanic ash forecasts as  
300 precipitation is a very efficient removal mechanism. We have also not considered the uncertainty  
301 associated with the volcanic eruption source parameters (ESPs). The best way to combine the  
302 meteorological and ESP uncertainty and effective ways of communicating this uncertainty with  
303 users is the subject of future work.

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311 <http://dx.doi.org/10.5072/uor-data-00000000>. Further information about the data supporting these  
312 findings and requests for access to the data can be directed to [h.f.dacre@reading.ac.uk](mailto:h.f.dacre@reading.ac.uk).

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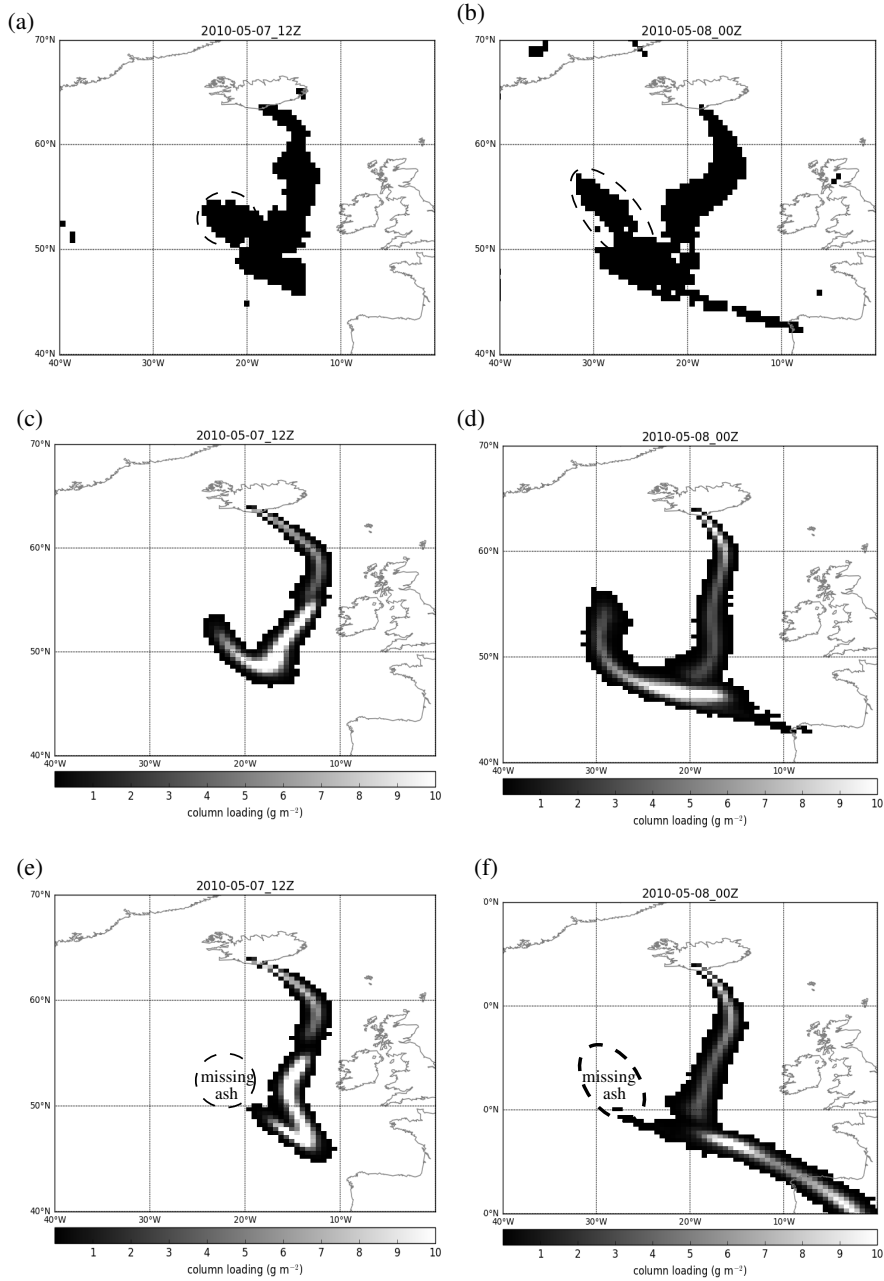
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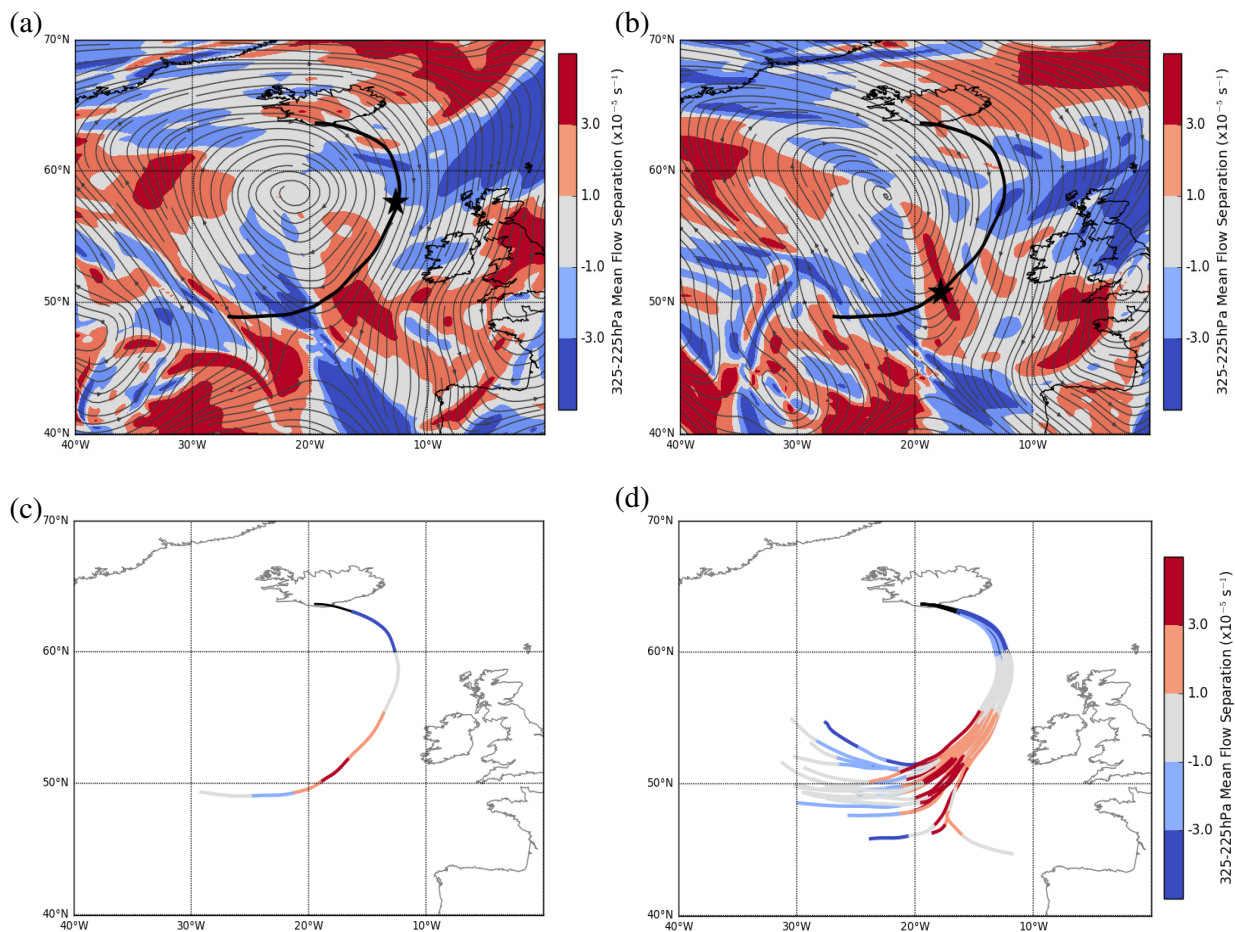
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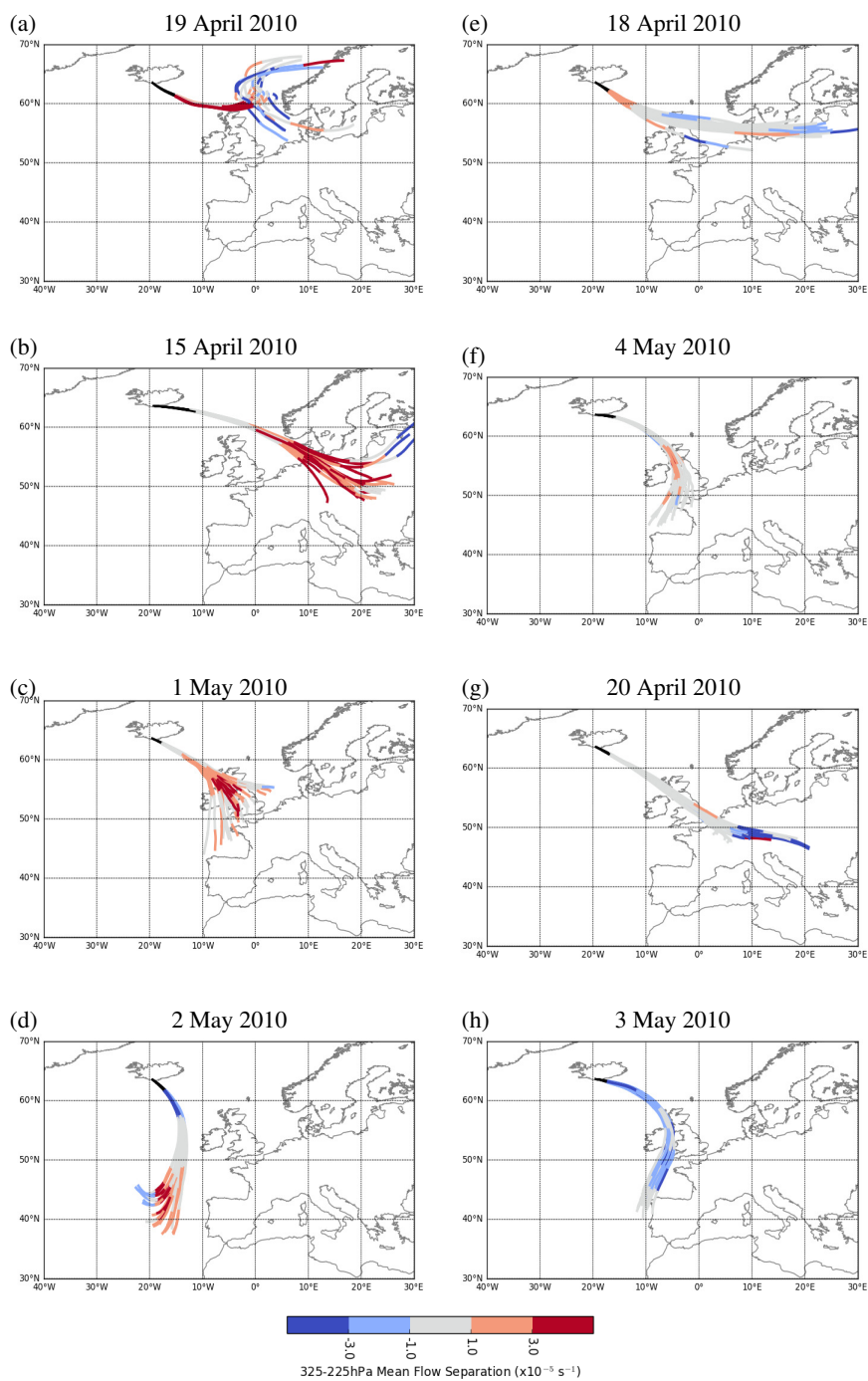


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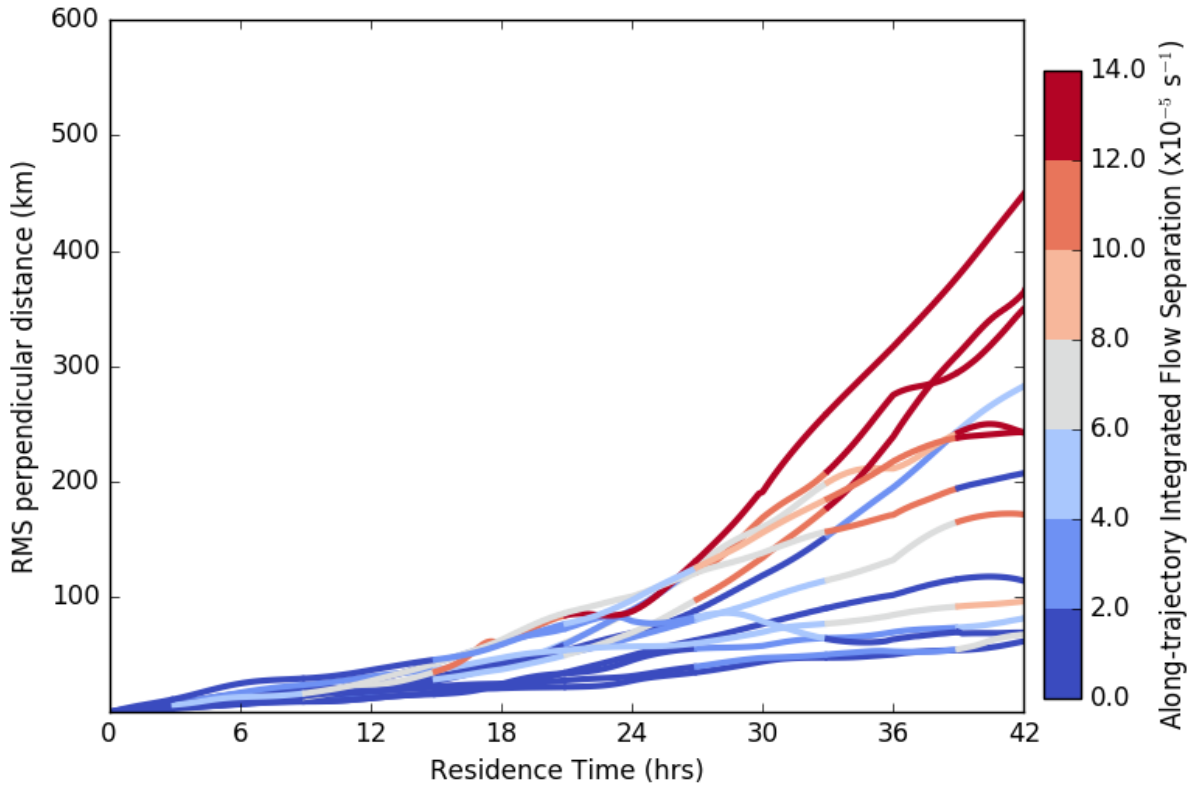




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