

# Scenario based volcanic hazard assessment from ash dispersion

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**Abstract.** Before the eruption of Eyjafjallajökull in 2010, the aviation disasters in such an enormous scale have not realistically been expected. Volcanic eruptions and earthquakes are not only rare but also very sudden events of which prediction and preparedness are often impossible. This study present a scenario based strategy to assess the hazard from the volcanic ash dispersion by combining computational simulation of the ash dispersions and ensemble method to reduce the uncertainty. Due to lack of information in advance, a scenario is designed to consider a range of parameters of the eruption such as particulate volume and eruption strength. The meteorological data are generated over past thousands days by numerical weather forecasting model in this study. With the given conditions in each scenario, the volcanic ash dispersion is simulated using Eulerian based scalar transport model. Once the large amount of the results from ash dispersion simulations are compiled, the meteorological conditions are classified to several groups according to meteorological similarity using K-mean method. Since tens of days are grouped to each similar weather condition, a set of ash dispersion results corresponding to a specified similarity group then is ensemble averaged to generate the representative hazard.

**Keywords:** Volcanic ash, Dispersion, Eruption scenario, Meteorological conditions, Computational simulation, Ensemble method, Similarity

## 1. Introduction

Since aviation disaster triggered by the eruption of Eyjafjallajökull in 2010, the volcanic ash dispersion has been of high interest. And recent activities of volcanoes in Northern Pacific also indicate potential disaster in the coming future. In 2016, following the volcanic eruption of Mt. Pavlof in Alaska on March 27th, Mt. Kliuchevskoi in Russia on July 24, the Mt. Swanose in Japan on Aug. 1 and Mt. Aso in Japan on Oct. 8 have revealed potential threat to the surround area. Korea is not free of volcanic disaster, too, because it is located very close to the ring of fire and Mt. Beakdu had shown active precursors during 2002 to 2005.

Among many aspects of volcanic hazard, the long range transport of ash is one of the global interests and subsequently the numerical prediction methods have been extensively investigated, including PUFF-UAF [1-3], FALL3D [3-5], HYSPLIT [6] and CMAQ [7,8]. Research on atmospheric diffusion problems such as diffusion is also actively underway.

However, the analysis model of volcanic ash diffusion takes longer than a day to calculate and it is difficult to cope immediately after volcanic eruption.



In addition, another difficulty of inevitable uncertainty lies in the process of ash dispersion model since every dispersion model is based on various assumptions on physical conditions and numerical algorithms. Similar difficulty is found in numerical weather predictions and climatological analysis, which employed ensemble analysis to reduce the uncertainty. In the meteorological field, Simple Model Averaging (SMA) [9], Reliability Ensemble Average (REA) [9], and Bayesian A multi-model averaging technique such as Bayesian Model Averaging (BMA) [10] is used. SMA is a method of averaging models using equal weights whereas REA is a method of weighting by comparing different models, in which the average value is determined and the weight is determined by using the difference from the average value for each model. Then, the average value is calculated, and the average value is recalculated until the weight is determined by using each model difference and converged. BMA calculates the probability of how accurately an individual model will yield a predicted value, generates a model using the predicted values of the estimated individual models, which are more accurate in estimating uncertainty and performing reliable prediction [10-12]. However, most of the ensemble methods, including BMA, regard the field observations as the main data, but field measurements of the volcanic ash are difficult to obtain in most cases. Therefore, in this study, we propose a modified REA which can use only the results of volcanic ash diffusion without application of field observation data. REA is often employed to determine how well GCM (Global Climate Model) scenarios simulate and how GCM scenarios compare to future prospects for future GCM scenarios [13].

## 2. Ash Dispersion Simulation

### 2.1. Numerical Model for Ash Dispersion

In this study, FALL3D, developed at the Supercomputing Center in Barcelona, Spain, was used as a numerical model for the dispersion of volcanic ash. The Fall3D model uses the Eulerian approach and is a program that models the movement of particles and gases in the atmosphere, in which the diffusion is calculated according to the size, density and shape factor of each particle [3-5].

*2.1.1. Governing Equation.* The major factors controlling the atmospheric transport of ash are wind migration, turbulent diffusion and gravity sedimentation of particles. Ignoring the interaction effects such as collision and aggregation between particles and particles, the Euler form of the governing equation used in the general coordinate system is as follows [5].

$$\begin{aligned} & \frac{\partial C}{\partial t} + V_x \frac{\partial C}{\partial X} + V_y \frac{\partial C}{\partial Y} + (V_z - V_{sj}) \frac{\partial C}{\partial Z} \\ & = -C \nabla \cdot V + C \frac{\partial V_{sj}}{\partial Z} + \frac{\partial}{\partial X} \left( \rho K_X \frac{\partial C / \rho_*}{\partial X} \right) + \frac{\partial}{\partial Y} \left( \rho K_Y \frac{\partial C / \rho_*}{\partial Y} \right) \quad (1) \\ & \quad + \frac{\partial}{\partial Z} \left( \rho K_Z \frac{\partial C / \rho_*}{\partial Z} \right) + S_* \frac{\partial}{\partial Y} \end{aligned}$$

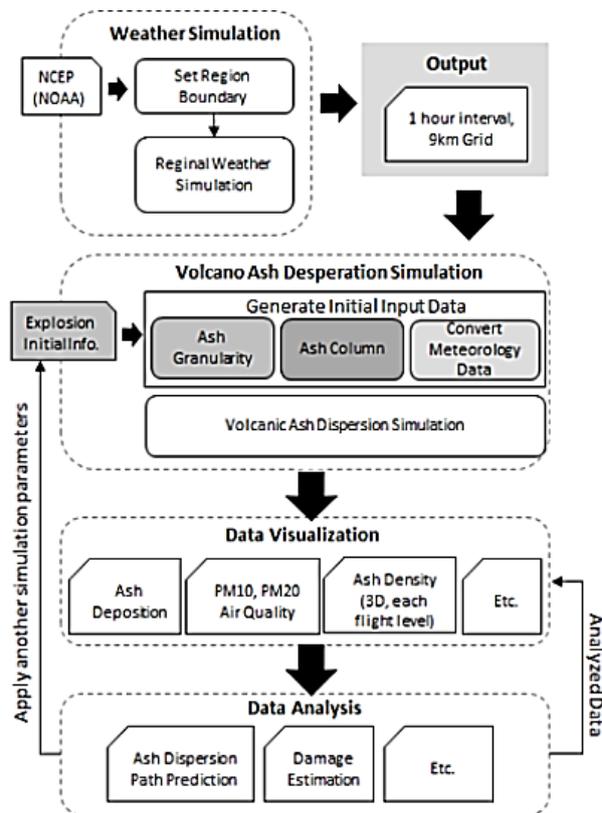
where  $C$  is the scaled average density,  $V = (V_x, V_y, V_z)$  is the scaled air velocity,  $K_x, K_y$  and  $K_z$  are the diagonal terms of the scaled vortex diffusion tensor,  $\rho_*$  is the scaled atmospheric density and  $S_*$  is the expanded source term. FALL3D calculates equation (1) for each particle using the terrain-following coordinate system. Table 1 shows the scaling factors of the terrain tracking coordinate system. Normal particles  $j$  are determined by  $(d_p, \rho_p, F_p)$ , that is, diameter, density and shape factor. And the spherical surface  $\varphi$  which is the ratio of the surface area of the sphere to the surface area of the particle with respect to the shape coefficient  $F_p$  is selected. Equation (1) solves independently for each particle velocity. In other words, it is assumed that there is no interaction between particles during transport. For the simplicity of the calculations, particle agglomeration in the transmission process is not considered, and the particles are assumed to be on the ground at the termination speed. It is also assumed that the effect of the earth curvature is negligible.

**Table 1.** Scaling factors for a terrain-following coordinate system.  
(h: topographic relief, J: the determinant of the Jacobian of the coordinate system transformation)

| Parameter              | Scaling                                                          |
|------------------------|------------------------------------------------------------------|
| Coordinates            | $X=x, Y=y, Z=z-h(x,y)$                                           |
| Velocities             | $V_x = v_x, V_y = v_y, V_z = v_z J^{-1}, V_{sj} = v_{sj} J^{-1}$ |
| Diffusion Coefficients | $K_X = K_x, K_Y = K_y, K_Z = K_z J^{-2}$                         |
| Concentration          | $C = cJ$                                                         |
| Density                | $\rho_* = \rho J$                                                |
| Source Term            | $S_* = SJ$                                                       |

*2.1.2. Numerical Weather Simulation Model.* As the input data of FALL3D, we can use the weather data (GFS) and WRF (weather research and forecasting model) [14] model data as input data. WRF was developed at the American Institute of Atmospheric Research and is a proven model of computational stability and accuracy of the output data. It is based on nonhydrostatic equations. On the other hand, Korea Meteorological Agency is using the UM (Unified Model) model as a working model. Another meteorological data source is the meteorological reanalysis data provided at the global level of the National Center for Environmental Prediction (NCEP), which provides a 6-hour interval of predictions with a grid resolution that divides the space by 0.5 degree. In this case, the resolution of the weather input data is low and the WRF model is used to enhance the spatial and temporal resolution and this method is used in this study.

*2.1.3. Simulation Process.* Simulation of diffusion of volcanic ash consists of three steps as shown in Fig. 1. Step 1 generates weather data, and Step 2 predicts the diffusion path of volcanic ash using the ash diffusion model by inputting the first stage meteorological data and volcanic eruption information. Finally, the simulation results of volcanic ash produced in Step 3 are analysed.



**Figure 1.** Process for volcanic ash dispersion simulation

2.2. Eruption Scenario and Similarity Analysis

The hypothetical eruption from Mt. Aso was calculated using the volcanic ash diffusion model as the first step for the ensemble analysis, and the differentiation conditions are shown in Table 2. VEI means the volcanic explosion index [15] and VEI = 4 means the ejection volume is about 0.1km<sup>3</sup>.

**Table 2.** Condition of hypothetical eruption

|                      |       |
|----------------------|-------|
| VEI                  | 4     |
| Ash column height    | 11 km |
| Duration of Eruption | 24 hr |

In general, the ensemble method is a tendency to use an ensemble prediction system (EPS) using multiple models to reduce the uncertainty of long-term forecast by the numerical weather prediction model of wind forecast [16]. This method complements the limitations of deterministic predictions of single predictions by combining a number of independent initial conditions, boundary conditions, or physical processes [17]. In this study, the date of the volcanic eruption was used as the basis of the volcanic eruption, not the ensemble of the future numerical data, and the results of the volcanic ash diffusion model. This method was developed to predict the diffusion and migration path of the ash immediately based on the volcanic ash diffusion data constructed using the flue gas at the time of the eruption.

Similar weather events were evaluated using spatial correlation analysis of meteorological conditions such as pressure and fossil record, and the K-mean algorithm was used for the clustering method. The climatic variables used were high pressures of 300, 500 and 850 hPa, which have the greatest effect on the diffusion pattern of volcanic ash, a relative humidity of 850 hPa affecting deposition of ash, and a vertical wind speed of 500 hPa [18, 19]. In this paper, the similar weather date

of meteorological data on October 8, 2016 was selected, on which Aso volcano, one of the active volcanos in Japan erupted, and April 22 and 29, October 16 and October 18, 2010 were extracted.

### 2.3. Representative Results for Ash Dispersion Simulation

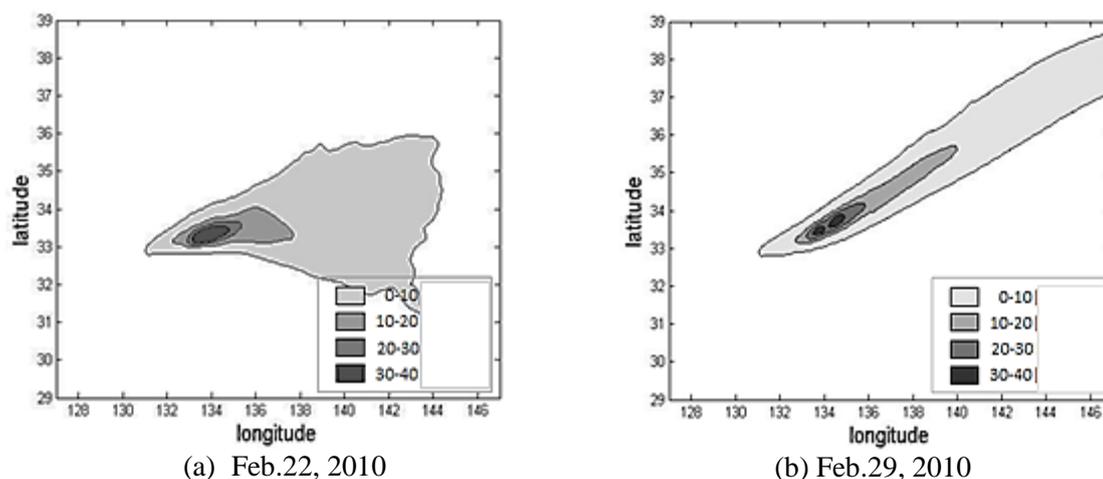
The distribution of volcanic ash concentration is shown in Fig. 2 as the result of the dispersion simulation of volcanic ash using the FALL3D model. It is diffused from the altitude of 8.5km to the northeast direction from Mt. Aso at the latitude of 32.884 and the longitude of 131.104 at the 24th hour.

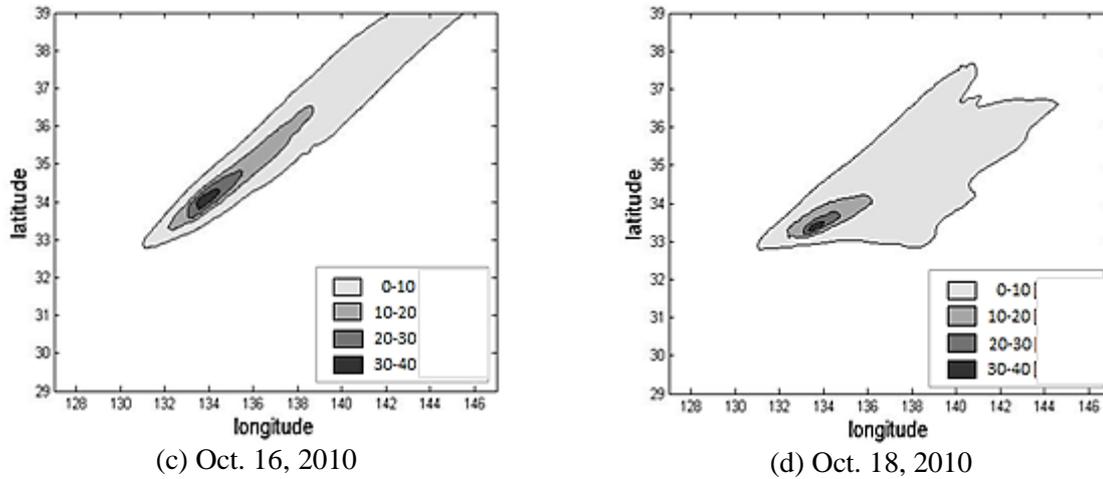
The concentration of the volcanic ash column is the highest at  $30 \sim 40 \text{ mg/m}^3$  and the concentration decreases as the distance from the center increases. It is also explained that the area distant from the crater was damaged by ash because it was stretched to the northeast by the southwest wind. The lightest part is  $0\text{-}10 \text{ mg/m}^3$ , and it can be seen that air navigation in the area can be restricted considering  $4 \text{ mg/m}^3$  as the ash safety limit of the aviation operation recommended by ICAO [20]

### 3. Modified REA Method

In the meteorological studies, multi-model averaging techniques such as SMA (Simple Model Averaging), REA (Reliability Ensemble Averaging), and BMA (Bayesian Model Averaging) are used to minimize the uncertainty of the climate change model and to improve the limitations of a single model.

Since REA has been proven efficient to reduce the uncertainty [13], this study employed and modified the reliability ensemble averaging method, which can derive the mean of each model with uncertainty supplemented without observation data. In our REA method, the average change,  $\tilde{X}$ , is given by a weighted average of the ensemble, that is,





**Figure 2** Horizontal distributions of ash concentration ( $mg/m^3$ ) from the hypothetical eruptions from Mt. Aso on four days

$$\tilde{X} = \frac{\sum_i R_i X_i}{\sum_i R_i} \tag{2}$$

where the  $R_i$  is a model reliability factor defined as

$$R_i = \left[ (R_{B,i})^m \times (R_{D,i})^n \right]^{1/(m \times n)} \tag{3}$$

Here  $R_{B,i}$  is a measure of the model performance criterion while  $R_{D,i}$  is a measure of the model convergence criterion and the parameters  $m$  and  $n$  can be used to weigh each criterion. For most calculations in this work,  $m$  and  $n$  are assumed to be equal to 1, which gives equal weight to both criteria. In this,  $R_{B,i}$  can be expressed by the follows;

$$R_{B,i} = \frac{\epsilon}{abs(B_{X,i})} \tag{4}$$

$$B_{X,i} = \widehat{X}_{p,t} - X_p \tag{5}$$

$$R_{D,i} = \frac{\epsilon}{abs(D_{X,i})} \tag{6}$$

$$D_{X,i} = X_i - \bar{X} \tag{7}$$

$D_{X,i}$  represents the difference between the SMA(Simple Model Average) value  $\bar{X}$  and the  $i$ -th future scenario variable value, and  $\bar{X}$  is again as follows.

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N \Delta X \tag{8}$$

The distance  $D_{X,i}$  is calculated using an iterative procedure. A first guess of  $D_{X,i}$  is the distance of each  $D_{X,i}$  from the ensemble average change  $\Delta X$  of Eq. (8), that is,  $[D_{X,i}]_1 = [X_i - \bar{X}]$ . The first guess values are then used in Equations (2) and (3) to obtain a first-order REA average change  $[\tilde{X}]_1$ , which is then used to recalculate the distance of each individual model as  $[D_{X,i}]_2 = [X_i - [\tilde{X}]_1]$  and repeat the iteration. Typically, this procedure converges quickly after several iterations.  $R_{D,i}$  are set to 1 when  $D$  are smaller than  $\epsilon$ , respectively. Essentially, Equation (3) states that a model projection is ‘‘reliable’’ when both its bias and distance from the ensemble average are within the natural variability, so that  $R_{D,i} = R = 1$ . As the bias and/or distance grow, the reliability of a given model simulation decreases. Note that, for  $R_{D,i}$  lower than 1,  $\epsilon$  cancels out in the REA operator and the reliability factor effectively reduces to the reciprocal of the product of bias and distance [13].

In this study, since the number of models is small, the weight is always 1 when the maximum value and the minimum value are used. Therefore, we define  $\epsilon = \widetilde{\delta}_X$  and apply  $\widetilde{\delta}_X$  which differs every iteration.  $\delta_X$  is the uncertainty of the SMA, and  $\widetilde{\delta}_X$  is the uncertainty of the REA as follows.

$$\delta_X = \left[ \frac{1}{N} \sum_{i=1}^N (X_i - \bar{X})^2 \right]^{1/2} \quad (9)$$

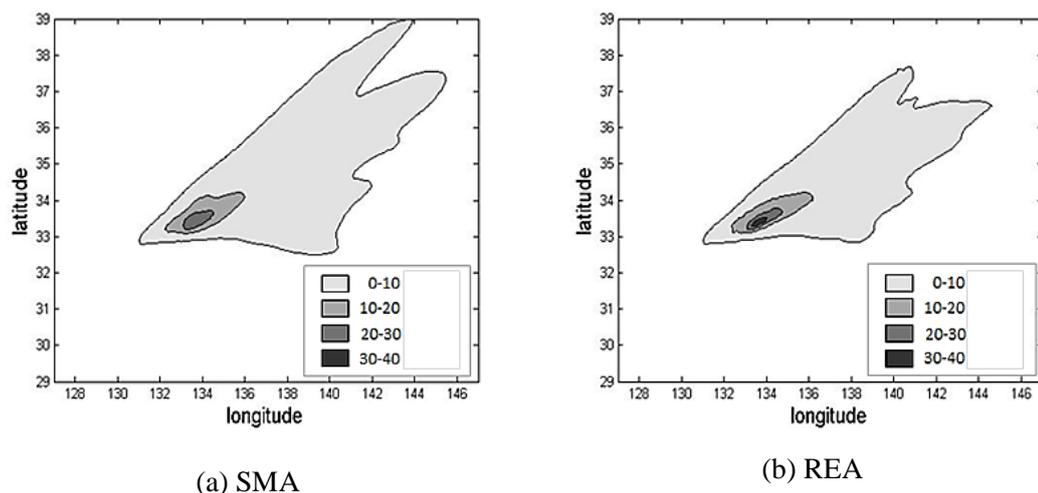
$$\widetilde{\delta}_X = \left[ \frac{\sum_{i=1}^N R_i (X_i - \bar{X})^2}{\sum_{i=1}^N R_i} \right]^{1/2} \quad (10)$$

#### 4. Result from Ensemble Analysis

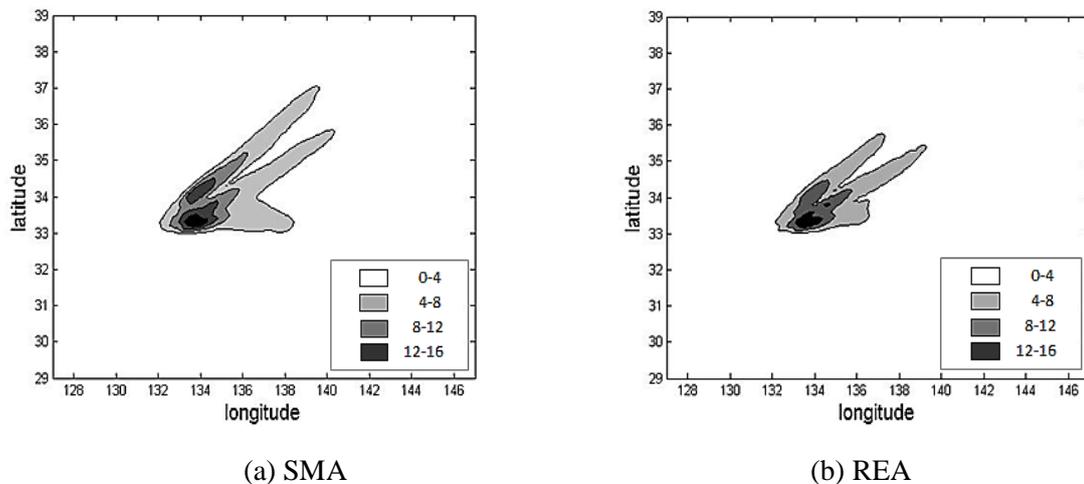
In this study, as mentioned in the previous section, the ensemble analysis uses the results of the volcanic ash diffusion analysis of four cases selected according to the similarity of the meteorological field. The resulting ensemble concentration distribution is shown in Fig. 3. Fig. 3 (a) shows the results of the simple model average analysis and (b) shows the results of the reliability ensemble average analysis.

When the reliability analysis ensemble average analysis result is compared with the simple model average analysis result, the range of 1-10  $mg/m^3$  concentration is decreased. Concentration 30-40  $mg/m^3$  is not revealed in the simple model average analysis result, but appears as a small area in the reliability ensemble average analysis.

In ensemble analysis, it is very important to quantify uncertainty in a reliable way by ensemble results. The uncertainty of the simple model average method and the reliability ensemble averaging method is shown in Fig. 4 using Equations (9) and (10). The uncertainty in the vicinity of the minutiae was large in both the simple model averaging method and the reliability ensemble averaging method because the position of the minutiae concentration was not coincident due to the minute difference of the wind direction after 24 hours. However, when compared with SMA, REA shows a significant reduction in the range of uncertainty, which means that the reliability is higher.



**Figure 3** Comparison of horizontal distributions of ash concentrations ( $mg/m^3$ ) ensemble averaged by SMA and REA from the hypothetical eruptions from Mt. Aso on four days



**Figure 4** Comparison of horizontal distributions of uncertainty by SMA and REA

## 5. Conclusion

In this study, we propose a modified reliability ensemble averaging method that can perform ensemble analysis with only the results of volcanic ash diffusion analysis of past days except actual volcanic ash diffusion data.

(1) In the first step, the WRF is maintained daily, and k-means clustering is performed using climatic variables such as painting, relative humidity and vertical wind speed to obtain the similar weather day of October 8, 2016.

(2) The second stage is the Fuller3D model based on the Eulerian method. As a result, it was confirmed that the volcanic ash was spread toward the NE direction in all four days.

(3) Finally, the simple model average analysis and the reliability ensemble average analysis were performed using the concentration distribution which is the result of the volcanic ash diffusion analysis of the four days

(4) Confidence ensemble averaging method as a result of the research. The results show that the uncertainty is reduced and the reliability is higher than the simple model averaging method.

In this way, using the ensemble analysis method to reduce the uncertainty of the model by using the past similarity model of single or multiple models, it will be helpful to predict the diffusion of volcanic ash during volcanic eruption.

Finally, the method used in this study is based on the extraction of the similar weather date rather than the meteorological field at the time of volcanic eruption, and therefore the uncertainty due to the difference in the date of the differentiation date and the similar weather day is inherent. Therefore, this method should be used for immediate response at the early stage of differentiation, and it would be better to obtain more accurate results by simultaneously analysing the diffusion of volcanic ash using the meteorological field at the time of differentiation.

## Acknowledgment

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## References

- [1] Searcy, C., Dean, K., Stringer, W., "PUFF: A high-resolution volcanic ash tracking model", J. Volcanology and Geothermal Research, Vol.80, pp.1-16, 1998.
- [2] Daniele, P., Lirer, L., Petrosino, P., Spinelli, N. and Peterson, R., "Applications of the PUFF model to forecasts of volcanic clouds dispersal from Etna and Vesuvio", Computers & Geosciences, 35, 5, 1035-1049, 2009.

- [3] Lee, J. Y., Lee, S., Son, H. A., Hwang, S. T., Heo, D. Y., “Probabilistic estimation of spatial distribution of volcanic ashes from Mt. Baekdu and Mt. Aso”, *Journal of the Wind Engineering Institute of Korea*, Vol.21(3), 2017
- [4] Folch, A., Jorba, O. and Viramonte, J., “Volcanic ash forecast-application to the May 2008 Chaiten eruption”, *Nat. Hazards Earth Syst. Sci*, Vol.8(4), pp.1334-1342, 2009.
- [5] Folch, A., Costa, A. and Macedonio, G., “Fall3D: A computational model for transport and deposition of volcanic ash”, *Computers & Geosciences*, Vol.35(6), pp. 1334-1342, 2009.
- [6] Drxler, Roland R. and Hess, G. D., “An overview of the HYSPLIT\_4 modelling system for trajectories.” *Australian meteorological magazine*, Vol.47(4), pp.295-308, 1998.
- [7] Byun, D. W. and Ching, J. K. S., “Science algorithms of EPA Models-3 community multiscale air quality (CMAQ) modeling system”, Washington, DC: US Environmental Protection Agency, Office of Research and Development, 1999.
- [8] Byun, D., and Kenneth L. S., “Review of the governing equations, computational algorithms and other components of the Models-3 Community Multiscale Air Quality (CMAQ) modeling system” *Applied Mechanics Reviews*, Vol.59(2), pp.51-77, 2006.
- [9] Lee, J. K., “Scenario Selection and Uncertainty Quantification”, Ph.D. dissertation, Univ. Seoul, 2013.
- [10] Miao, C., Duan, Q., Sun, Q., Huang, Y., Kong, D., Yang, T., Ye, T., Di, Z. and Gong, W., “Assessment of CMIP5 Climate Models and Projected Temperature Changes over Northern Eurasia”, *Environmental Research Letters*, Vol.9, pp.1-12, 2014.
- [11] Duan, Q., Philips, T., “Bayesian Estimation of Local Signal and Noise in Multimodel Simulations of Climate Change”, *Journal of Geophysical Research Atmospheres*, Vol.115, pp.1-15, 2010.
- [12] Raftery, A., Gneiting, T., Balabdaoui, F. and Polakowski, M., “Using Bayesian Model Averaging to Calibrate Forecast Ensembles”, *American Meteorological Society*, Vol.133, pp.1155-1174, 2005.
- [13] Giorgi, F., Mearns, L. O., “Calculation of Average, Uncertainty Range, and Reliability of Regional Climate Changes from AOGCM Simulations via the “Reliability Ensemble Averaging” (REA) Method”, *J. American Meteorological Society*, Vol.15, pp.1141-1158, 2002.
- [14] Skamarock, W.C., J. B. Klemp, J. Dudhia, D. O. Gill, D. M. Barker, M. G. Duda, X. Huang, W. Wang, and J. G. Powers, “A description of the advanced research WRF version 3. NCAR Tech”. Note NCAR/TN-475+STR, National Center for Atmospheric Research, Boulder, CO, pp.125, 2008.
- [15] Newhall, C. G. & Self, S., “The Volcanic Explosivity Index (VEI): An Estimate of Explosive Magnitude for Historical Volcanism”, *Journal of Geophysical Research*, Vol. 87(C2), pp.1231–1238, 1982.
- [16] Yoon, J. W., Lee, Y. H., Lee, H. C., Ha, J. C., Lee, H. S. and Chang, D. E., “Wind Prediction with a Short-range Multi-Model Ensemble System”, *Atmosphere*, Vol.17(4), pp.327-337, 2011
- [17] Kim, J. Y., Kim, H. G., Kang Y. H., Yun, C. Y., Kim, J. Y. and Lee, J. S., “A Simple Ensemble Prediction System for Wind Power Forecasting, Evaluation by Typhoon Bolaven Case”, *J. Korean Solar Energy Society*, Vol.36(1), pp.27-37, 2016
- [18] Seo, J. B., Kang, S. R., Kim, M. C., “Predicting the Hazard Area of the Volcanic Ash based on Meteorological Fields and the Impact of Weather Pattern on Diffusional Pathway of Volcanic Ash”, *Journal of the Wind Engineering Institute of Korea*, Vol.20(1), pp.49-55, 2016.
- [19] Kim, M., S, Y., Kang, S. M., “Precision of Weather Pattern Clustering according to Sample Size and Development of Similar Weather Pattern Model”, *Journal of the Wind Engineering Institute of Korea*, Vol.21(2), pp.67~73, 2017.
- [20] BBC News, "UK ash cloud restrictions lifted", May 17, 2010.