

# Quantifying the Uncertainty of a Coupled Plume and Tephra Dispersal Model: PLUME-MOM/HYSPLIT Simulations Applied to Andean Volcanoes

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# Quantifying the uncertainty of a coupled plume and tephra dispersal model: PLUME-MOM/HYSPLIT simulations applied to Andean volcanoes

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17 Keypoints
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- We present an uncertainty quantification for a coupled version of a plume model
   (PLUME-MoM) and a tephra dispersal model (HYSPLIT)
- The model has been tested against field data of 4 eruptions from Andean volcanoes (in Ecuador and Chile) of different magnitudes/styles
- The main conclusion of the uncertainty quantification is that the model is best suited
   for hazard studies of higher magnitude eruptions
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#### 34 Abstract

Numerical modelling of tephra dispersal and deposition is essential for evaluation of volcanic 35 hazards. Many models consider reasonable physical approximations in order to reduce 36 computational times, but this may introduce a certain degree of uncertainty in the simulation 37 outputs. The important step of uncertainty quantification is dealt in this paper with respect to a 38 coupled version of a plume model (PLUME-MoM) and a tephra dispersal model (HYSPLIT). 39 The performances of this model are evaluated through simulations of four past eruptions of 40 different magnitudes and styles from three Andean volcanoes, and the uncertainty is 41 quantified by evaluating the differences between modeled and observed data of plume height 42 (at different time steps above the vent) as well as mass loading and grain size at given 43 44 stratigraphic sections. Different meteorological datasets were also tested and had a sensible influence on the model outputs. Other results highlight that the model tends to underestimate 45 plume heights while overestimating mass loading values, especially for higher magnitude 46 47 eruptions. Moreover, the advective part of HYSPLIT seems to work more efficiently than the diffusive part. Finally, though the coupled PLUME-MoM/HYSPLIT model generally is less 48 efficient in reproducing deposit grain sizes, we propose it may be used for hazard maps 49 production for higher magnitude eruptions (sub-Plinian or Plinian) for what concern mass 50 51 loading.

52

#### 53 Index Terms and Keywords

4314 Mathematical and computer modeling, 3275 Uncertainty quantification, 8428 Explosive
 volcanism, 8488 Volcanic hazards and risks

Tephra fall, tephra dispersal, numerical modelling, uncertainty quantification, Andeanvolcanoes

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# 59 **1. Introduction**60

Volcanic tephra dispersal and deposition represent a threat for many human activities 61 62 since tephra may have a huge impact on aviation and can also damage edifices, infrastructures and vegetation when it accumulates on the ground, even in relatively small quantities. For this 63 reason, numerical models have been developed over the past decades for describing both 64 tephra rise into the eruptive column (plume models - PMs) or its transport by wind advection 65 [tephra transport and dispersal models - TTDM; Folch, 2012]. Since describing in great detail 66 the physics of such phenomena requires complex 3-D multiphase models, it is useful for 67 68 operational purposes (e.g. volcanic ash tracking in real time or hazard maps production) to rely on simplified models, which introduce reasonable physical assumptions. In doing so, 69 though computational times might be reduced, approximations and uncertainties are 70 introduced in the final results of the simulations. Uncertainties need to be therefore quantified 71 72 in order to facilitate decision makers in taking both real-time and long-term informed 73 decisions. With respect to numerical models, uncertainty quantification in literature has been done: i) for PMs, by comparing modelled and observed values of maximum plume height (or 74 75 level of neutral buoyancy) and/or of the mass flow rate (in kg/s), as for instance in Folch et al. [2016] or Costa et al. [2016]; ii) for TTDMs, by comparing modelled and observed ground 76 deposit measurements (mass loadings in  $kg/m^2$ ) and/or ash cloud measurements 77

(concentrations in the atmosphere in kg/m<sup>3</sup>) [e.g., Scollo et al., 2008; Costa et al., 2009;
Bonasia et al., 2010; Folch, 2012].

80 The aim of the present study is therefore twofold. Firstly, we present a coupled version of two different models: i) a renewed version of PLUME-MoM, a simplified 1-D plume 81 model developed by de'Michieli Vitturi et al. [2015], and ii) the HYSPLIT model [Stein et al., 82 2015], a Lagrangian TTDM developed by the National Oceanic and Atmospheric 83 Administration (NOAA) and currently used by several Volcanic Ash Advisory Centers 84 (VAACs) to track and forecast volcanic clouds. Secondly, we provide a quantification of the 85 uncertainty of the coupled version of these two models by testing simulations results with data 86 of four different recent eruptions of three Andean volcanoes (Fig. 1). These eruptions were 87 produced by Cotopaxi [2015 eruption, Bernard et al., 2016a] and Tungurahua [2006 eruption, 88 Eychenne et al., 2012; 2013 eruption, Parra et al., 2016] volcanoes in Ecuador, and Puyehue-89 Cordón Caulle volcanic complex [2011 eruption, Pistolesi et al., 2015] in Chile. With this 90 new coupled model the volcanic particles transport is simulated throughout the whole process 91 that is within the eruptive column and through atmospheric dispersion. Furthermore, the 92 93 uncertainty quantification represents an important aspect regarding hazard maps production.

94 In this article, after describing the eruptions chosen for the uncertainty quantification (section 2.1), we present the PLUME-MoM and HYSPLIT models as well as the coupling of 95 96 these two models (section 2.2.1). Then we present the input parameters used for the simulations (Section 2.2.2) and we describe the strategy adopted for the quantification of the 97 uncertainty of the coupled model (Section 2.3). Results presented in Section 3 serve as a basis 98 99 for the discussion in Section 4 about the uncertainties related to the input parameters and the numerical models and about also the effectiveness of these models when used for producing 100 tephra fallout hazard maps. 101

# 103 **2. Background**

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# 104 **2.1 Eruptions selected**

105 The four eruptions chosen for testing our simulations cover a wide range of eruptive 106 styles (sub-Plinian, violent strombolian, vulcanian, hydrovolcanic to long-lasting ash 107 emission), durations (from few hours up to more than 3 months) and magma compositions 108 (andesitic to rhyolitic/rhyodacitic). The criteria for selecting these eruptions were i) the 109 location of the volcanoes in the same geodynamic context, ii) the existence of both detailed 110 chronologies and meteorological data for the eruptions, and iii) the availability of reasonably 111 well constrained input parameters for the models.

112 *2.1.1 Cotopaxi 2015* 

113 The 2015 eruption of Cotopaxi (C15 – Fig. 1a) started with hydromagmatic explosions 114 on August  $14^{th}$  2015, which produced a 9-10 km-high eruptive column above the crater and 115 moderate ash fallout to the NW of the volcano. Then, it was followed by three and a half 116 months of moderate to low ash emissions with plumes reaching on average 2 km above the 117 crater and directed mostly to the west [*Bernard et al.*, 2016a; *Gaunt et al.*, 2016].

The magmatic character of the eruption increased through time as was shown by microtextural analysis [*Gaunt et al.*, 2016] and ash/gas geochemistry [*Hidalgo et al.*, 2018]. Through frequent sampling missions, the ash emission rate was calculated and correlated with the eruptive tremors, and it decreased during three emission phases following the conduit opening [*Bernard et al.*, 2016a].

123 The fallout deposit was characterized by a very fine-grained ash with mostly blocky 124 fragments and few vesicular scoria [*Gaunt et al.*, 2016]. The hydrothermal components were 125 dominant at the onset of the eruption but rapidly faded and were replaced by juvenile material 126 [*Gaunt et al.*, 2016]. In total, this eruption emitted  $\sim 1.2 \times 10^9$  kg of ash and was characterized 127 as a VEI 1-2 [*Bernard et al.*, 2016a].

128 2.1.2 *Tungurahua* 2013

According to Hidalgo et al. [2015], the eruptive phase XI (T13) at Tungurahua 129 volcano (Fig. 1a) started on July 14th 2013 and lasted 23 days. A vulcanian onset, interpreted 130 131 as the opening of a plugged conduit, was followed by a paroxysm which created a ~14 kmhigh eruptive column [Parra et al., 2016]. The ash cloud created during this eruption was 132 divided into a high cloud (~8-9 km above the crater) moving north and an intermediate cloud 133 (~5 km above the crater) moving west and that produced most of the ash fallout [*Parra et al.*, 134 2016]. The eruption intensity dropped after this paroxysm but ash emission continued with a 135 secondary increase between July 20<sup>th</sup> and 24<sup>th</sup>. Finally the eruption stopped at the beginning 136 137 of August.

138 In total, this eruption emitted  $\sim 6.7 \times 10^8$  kg of fallout deposits ( $\sim 2.9 \times 10^8$  kg for the first 139 day) and  $\sim 5 \times 10^9$  kg of pyroclastic flow deposits (mostly during the first day) [*García Moreno*, 140 2016; *Parra et al.*, 2016].

Parra et al. [2016] performed numerical simulations of the vulcanian onset of this eruption, which occurred on July 14<sup>th</sup> 2013, using the coupled WRF-FALL3D models [*Michalakes et al.*, 2001; *Folch et al.*, 2009]. By comparing the mass loading between the modeled values and the observed ones at four sampling sites, the above-mentioned authors derived a set of Eruptive Source Parameters (ESPs) useful for operational purposes in case of vulcanian eruptions at Tungurahua volcano.

147 2.1.3 Tungurahua 2006

At Tungurahua volcano (Fig. 1a), a paroxysmal eruption (T06) occurred on August 148 16<sup>th</sup> 2006, which was accompanied by regional tephra fallout and many scoria flows and 149 surges that devastated the western half of the edifice [Douillet et al., 2013; Hall et al., 2013]. 150 This eruption was characterized by vigorous lava jetting and fountaining, a vent-derived 151 eruption column reaching 16-18 km above the vent [Steffke et al., 2010; Eychenne et al., 152 153 2012], numerous Pyroclastic Density Currents (PDCs) descending the southern, western and northern flanks of the volcano [Kelfoun et al., 2009; Bernard et al., 2014], and a massive 154 blocky lava flow emplacing on the western flank while the explosive activity waned 155 [Samaniego et al., 2011; Bernard et al., 2016b]. At the climax of the eruptive event, after 3 156 hours of intense PDC formation, the vent-derived ash plume developed into a sub-vertical and 157 sustained column for 50 to 60 minutes [Hall et al., 2013]. The plume spread over the Inter-158 Andean Valley, west of the volcano, and reached the Pacific Ocean, leading to substantial 159 lapilli and ash fallout on the nearby communities and cities (e.g., Riobamba and Ambato) 160 located to the West. The intense PDC activity generated ash-rich, 10 km-high co-PDC plumes 161 that spread over the same areas and deposited fine ash (<90 µm) [Eychenne et al., 2012; 162 Bernard et al., 2016b]. 163

In total, the whole August 2006 eruption produced  $39.3\pm5.1\times10^6$  m<sup>3</sup> of fallout deposit (both vent-derived and co-PDC derived) of which  $24.9\pm3.3\times10^9$  kg were related to the ventderived fall [*Bernard et al.*, 2016b].

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# 168 2.1.4 Puyehue-Cordón Caulle 2011

According to *Collini et al.* [2013], the Puyehue-Cordón Caulle 2011 eruption (PCC11
Fig. 1b) started on June 4<sup>th</sup> at 14:45 LT (18:45 UTC) with the opening of a new vent 7 km

NNW from the main crater of the Puyehue-Cordón Caulle complex ("We Pillán" vent - Fig. 171 1b). The eruptive period, which involved mainly magma of rhyolitic-rhyodacitic composition 172 [Bonadonna et al., 2015a], lasted up to June 2012 [Jav et al., 2014] and comprised both 173 explosive and effusive activity [Tuffen et al., 2013]. The main explosive phase, which 174 dispersed most of the tephra toward E and SE, lasted approximately 17-27 hours [Jay et al., 175 2014; Bonadonna et al., 2015b]. During the first three days of the eruption, the column rose 176 approximately between 9 and 12 km above vent, then between 4 and 9 km during the 177 following week, and less than 6 km after June 14<sup>th</sup> [Bonadonna et al., 2015a; Biondi et al., 178 179 2017].

During the eruption, the mass eruption rate (MER) fluctuated between  $2.8 \times 10^7$  (during 180 the first days) and less than 5x10<sup>5</sup> kg/s after June 7<sup>th</sup> [Bonadonna et al., 2015b]. Pistolesi et 181 al. [2015] subdivided the stratigraphic record in thirteen tephra layers: among them, the first 182 unit (Unit I, layers A-F) represented the tephra deposited between June 4<sup>th</sup>-5<sup>th</sup>. Unit I had a 183 total erupted mass of  $4.5 \pm 1.0 \times 10^{11}$  kg and was sub-Plinian with a VEI of 4 [Bonadonna et al., 184 2015b]. Bonadonna et al. [2015a] calculated the total grain size distribution (TGSD) of Unit I 185 in the range  $-4\phi/11\phi$ , using different datasets and methods. The results indicated a bimodal 186 187 distribution with the two sub-populations (with modes at  $-2\phi$  and  $7\phi$ ) separated by the  $3\phi$ grain size [Bonadonna et al., 2015a]. 188

Collini et al. [2013] performed numerical modellings of this eruption between June 4<sup>th</sup> 189 to June 20<sup>th</sup> using the above-mentioned WRF-FALL3D code. The authors compared both the 190 column mass load (in ton/km<sup>2</sup>) and ground deposit measurements between modeled and 191 observed values. With respect to deposit thickness measurements, they compared deposit 192 thicknesses at 37 locations, resulting in a best-fit line on a computed versus observed graphs. 193 The PCC11 eruption was furthermore modeled by Marti et al. [2017], who simulated the 194 eruption from June 4<sup>th</sup> up to Jun 21<sup>st</sup> using the NMMB-MONARCH-ASH model and 195 compared the same parameters as in Collini et al. [2013]. For the ground measurements, they 196 197 provided comparisons between the simulated and observed isopach maps for both the Unit I 198 and other eruptive units cited in *Pistolesi et al.* [2015], finding a good agreement between modeled and observed data. 199

# 200 **2.2 Numerical modeling**

# 201 2.2.1 Models used and coupling of the codes

For this work, the integral plume model PLUME-MoM has been coupled with HYSPLIT, one of the most extensively used atmospheric transport and dispersion models in the atmospheric sciences community.

Following the approach adopted in *Bursik* [2001], PLUME-MoM solves the equations 205 for the conservation of mass, momentum, energy, and the variation of heat capacity and 206 mixture gas constant. The model accounts for particle loss during the plume rise and for radial 207 208 and crosswind air entrainment parameterized using two entrainment coefficients. In contrast 209 to previous works, in which the pyroclasts are partitioned into a finite number of bins in the Krumbein scale, PLUME-MoM adopts the method of moments to describe a continuous size 210 distribution of one or more group of particles (i.e. juveniles, lithics...). An uncertainty 211 and a sensitivity analysis of the PLUME-MoM model were done by quantification 212 de'Michieli Vitturi et al. [2016] by analyzing the distribution of plume heights obtained when 213 214 varying a series of input parameters (i.e. air radial/wind entrainment, exit velocity, exit temperature, water fraction and wind intensity). The above-mentioned authors showed that 215 plume height distribution was the widest when the parameters varied were the exit velocity, 216 217 exit temperature, water fraction and wind intensity. With respect to the sensitivity, de'Michieli 218 Vitturi et al. [2016] showed that initial water fraction had the strongest influence on plume height determination (i.e. the plume height decreased by a factor of ~1.54 when increasing
water content from 1 to 5 wt%).

221 HYSPLIT belongs to the family of Lagrangian Volcanic ash transport and dispersion models, which have been used operationally since the mid 1990's by the International Civil 222 Aviation Organization (ICAO) to provide ash forecast guidance. The model solves the 223 Lagrangian equations of motion for the horizontal transport of pollutants (i.e. particles), while 224 vertical motion depends on the pollutant terminal fall velocity. The dispersion of a pollutant 225 may be described using three main types of configuration, "3D particle" "puff" or hybrid 226 "particle/puff". Particularly, in the "puff" configuration, pollutants are described by packets of 227 ash particles ("puffs") having a horizontal Gaussian distribution of mass described by a 228 standard deviation  $\sigma$ . The puffs expand with atmospheric turbulence until they exceed the size 229 of the meteorological grid cell (either horizontally or vertically) and then split into several 230 new puffs, each with their respective pollutant mass. In this work, the hybrid "particle/puff" 231 configuration has been used, in which the horizontal packets of particles have a "puff" 232 distribution, while in the vertical they move like 3D particles. This approach allows to use a 233 limited number of puffs to properly capture both the horizontal dispersion and the vertical 234 235 wind shears. Webley et al. [2009] have evaluated the sensitivity of the model with respect to the concentration of ash in the volcanic cloud when two parameters, TGSD and the vertical 236 distribution of ash, were varied. The sensitivity analysis was done with respect to a test case 237 eruption (Crater Peak/Mt. Spurr, Alaska, USA, 1992). They showed that three different 238 TGSDs had little effect on the modeled ash cloud, while a uniform concentration of ash 239 throughout the vertical eruptive column provided results more similar to satellite 240 241 measurements. For this work, some modifications have been implemented in HYSPLIT and are described in Text S1 from the Supporting Information. 242

In the present study we coupled the PLUME-MoM and HYSPLIT models with an ad-243 244 hoc Python script, which computes for each grain size, from the output of the plume model, the mass rates released from the edges of the plume at intervals of fixed height, and the mass 245 flow that reaches the neutral buoyancy level. Then, the script assembles an input file where 246 the source locations for HYSPLIT are defined. In addition, it is employed a utility from the 247 HYSPLIT package to extract the wind profile at the vent, in order to provide this information 248 to the plume model. This coupled model was used for all the studied eruptions, while for 249 some specific cases (i.e. the simulations for the PCC11 eruption) we also implemented a best-250 fitting inverse version of this coupling, which was based on the approach first described by 251 Connor and Connor [2006] and applied, among others, by Bonasia et al. [2010] and Costa et 252 al. [2009]. The parameters for which the inversion was performed and their range of variation 253 254 were identified first. We considered the mass flow rate (in kg/s), the initial water mass fraction (in wt%) and the particle shape factor [Wilson and Huang, 1979; Riley et al., 2003]. 255 We chose these parameters because their uncertainty was higher and/or the models were more 256 sensitive to small variations of them. The procedure was aimed at minimizing the  $T^2$  function 257

$$T^{2} = \sum_{i=1}^{N} w_{i} [ML_{o,i} - ML_{m,i}]^{2}$$

where the sum is extended over N stratigraphic sections used in the inversion,  $w_i$  are weighting factors (in our case all are equal to 1),  $ML_{o,i}$  denotes the observed mass load (in  $kg/m^2$ ) and  $ML_{m,i}$  are the values predicted by the model (in  $kg/m^2$ ). The values of T<sup>2</sup> will be then compared to the standard Chi-2 distribution of *N-p* degrees of freedom, with p=3 the number of free parameters.

- 263
- 264 2.2.2 Modelling features and input parameters

We tested four different types of meteorological data (GDAS, NCEP/NCAR, ERA-Interim, ERA-Interim refined using WRF/ARW; see Text S1 from the Supporting Information for details) with various spatial and temporal resolutions (see Table S1 in Supporting Information), which correspond to the most widely used meteo data for studies similar to ours.

All the HYSPLIT simulations were done using a 0.05° (~5 km) computational grid. 270 After the end of each emission time (i.e. the actual duration of the eruption), a further amount 271 of 12 hours was added to the simulation in order to allow finer particles to settle down. 272 Simulations were performed in a forward way for all the four eruptions. However, a best-273 fitting inverse procedure (see Section 2.2.1) was performed for the PCC11 eruption because 274 the uncertainty in the tephra fallout total mass estimation was the highest among the four 275 chosen eruptions. A total of 600 inversions were performed, corresponding to 200 inversions 276 for each of the three meteo data employed for a given eruption (GDAS, NCEP/NCAR and 277 278 ERA-Interim).

Eruption source parameters (ESPs) were estimated from earlier works for the four 279 eruptions and some of them are reported in Table 1 (the detailed list of parameters for each 280 eruption is available in Table S2 in Supporting information). More specifically: a) the 281 computational grid dimension (i.e. the total span of the computational domain in degrees with 282 283 respect to the vent location) was defined in order to contain all or the vast majority (>95%) of the erupted mass and to reduce as much as possible the computational time; b) the initial 284 water content was assumed as that of typical mean values for andesitic (for C15, T13 and 285 286 T06) or rhyolitic (for PCC11) magmas, following Andújar et al. [2017] and Martel et al. [2018] respectively. For the inverse simulations of PCC11, the initial water content at each 287 iteration was sampled between 6% and 8% [Martel et al., 2018]; c) Particles exit velocities 288 from the vent were assigned two different values [following de'Michieli Vitturi et al., 2015] 289 corresponding to a "weak plume" case (C15 and T13) or to a "strong plume" case (T06 and 290 PCC11); d) The heat capacity of volcanic particles was assumed with a fixed value of 1600 291 J/kgxK following Folch et al. [2016]; e) The particles shape factor was assumed with two 292 different values for andesitic magmas (C15, T13 and T06) and for rhyolitic ones (PCC11) 293 following the results of Riley et al. [2003]. For the inverse simulations of the PCC11 eruption, 294 the particle shape factor values at each iteration were sampled between 0.6 and 0.8 [Riley et 295 *al.*, 2003]; h) the particle density values were assumed to vary linearly between two values ( $\rho_1$ 296 and  $\rho_2$ ) specific of two grain sizes ( $\phi_1$  and  $\phi_2$ ) according to *Bonadonna and Phillips* [2003]. 297 Values of  $\rho_1$ ,  $\rho_2$ ,  $\phi_1$ , and  $\phi_2$  were taken from *Eychenne and Le Pennec* [2012] (C15/T13/T06) 298 and Pistolesi et al. [2015] (PCC11). For each eruption, all the other most relevant features of 299 input parameters are described below. 300

For the Cotopaxi C15 eruption, the simulations covered the whole eruption duration 301 (14/08/2015 - 30/11/2015) for a total of 108 days and 17 hours. Plume heights values were 302 303 obtained from Bernard et al. [2016a]. With respect to the TGSD calculated in Gaunt et al. [2016] we also used several unpublished data (see Table S1 from the Supporting 304 Information). More specifically, a total of 33 samples representative of different times during 305 306 the eruption and from 4 stratigraphic sections were employed. The TGSD was derived from a weighted mean (with respect to different mass loading values) of single grain size 307 measurements. MER values used for the simulations were recalculated from Bernard et al. 308 309 [2016a] to obtain hourly values (see Table S2 from the Supporting Information).

For the Tungurahua T13 eruption, the simulations also covered the whole eruption duration (14/07/2013 – 30/07/2013) for a total of 16 days and 12 hours. We considered observed plume height measurements from two sources: the ones by the Washington VAAC using satellite measurements, and those from observations made by the Tungurahua Volcano Observatory (OVT). Similarly to the C15 eruption, the TGSD was obtained from a weighted mean (with respect to different mass loading values) of single grain size measurements. Hourly values of MER were obtained from unpublished data of the total mass deposited at the Choglontus sampling site at different intervals (Table S2 from the Supporting Information).

For the Tungurahua T06 eruption, the simulations covered 4 hours corresponding to 318 the climatic phases I and II described in Hall et al. [2013]. Plume heights were derived from 319 Steffke et al. [2010]. An average value of the MER was initially derived from the total mass 320 deposited over this period (see Text S1 from the Supporting Information); successively, 321 hourly values of MER were determined after an iterative procedure aimed at obtaining 322 modeled output values of plume heights as close as possible to observed data. This iteration 323 was done separately for each meteo data. The TGSD was recalculated from that of Eychenne 324 et al. [2012] by removing the mass contribution of the co-PDC part (see Text S1 from the 325 326 Supporting Information).

Finally, for the Puyehue-Cordón Caulle PCC11 eruption, the simulations covered the initial part of the eruption corresponding to the emplacement of Unit I [*Pistolesi et al.*, 2015] for a total of 24 hours. Daily average plume heights and MERs from *Bonadonna et al.* [2015b] were employed along with a TGSD calculation from *Bonadonna et al.* [2015a]. For the inverse simulations, the MER was sampled between two values  $(10^{6.75} \text{ and } 10^{6.95} \text{ kg/s})$ , which gave the minimum and maximum total mass values provided by *Bonadonna et al.* [2015b] and reported also in Table S2 (Supporting Information).

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#### **2.3 Uncertainty quantification procedure**

We quantified the uncertainty of the coupled numerical model by comparing modeled and observed values of key parameters of both the PM and the TTDM.

With respect to the PM, we compared the plume height (in meters above vent) observed against the corresponding value at the same time (or at the closest measurement available) given by the model. In this case it is important to remember that plume height in PLUME-MoM is obtained as output value using a fixed MER.

For the TTDM, we compared ground deposit measurements and we adopted a specific 342 approach in order to properly address uncertainty quantification. The results of the 343 simulations were used to compare, at each stratigraphic section, observed and modeled values 344 of mass loading and grain size, the latter one characterized by Md $\phi$  and  $\sigma\phi$  [Folk and Ward, 345 346 1957]. For mass loading we use hereafter the notation "∆ mass loading", which corresponds to the difference between the computed and the observed values of mass loading (in  $kg/m^2$ ). In 347 the corresponding graphs (Figs. 3b, 4b, 5b and 6b)  $\Delta$  mass loading values (for each 348 simulation) and observed mass loadings are reported for each section. A complete list of the 349 stratigraphic sections employed is available in Table S3 from the Supporting information. We 350 considered also the direction of the main elongation axis of the deposit by comparing isomass 351 maps constructed from field data and those given by the model. With respect to mass loading 352 values, additional parameters were also calculated to quantify the uncertainty of the model, 353 which were: 1) the above-mentioned  $T^2$  function (see Section 2.2.1), which was normalized 354 (for each eruption) by dividing it with the mean values of mass loading measured in the field 355 (MML); 2) the percentage of sections for which there was an overestimation and an 356 357 underestimation; 3) the mean overestimation (MO) and the mean underestimation (MU),

$$\begin{cases} MO = \frac{\sum_{i=1}^{N_o} \Delta_i}{N_o} \text{ for } \Delta_i > 0\\ MU = \frac{\sum_{i=1}^{N_u} \Delta_i}{N_u} \text{ for } \Delta_i < 0 \end{cases}$$

where  $N_o$  and  $N_u$  are the number of sections with overestimation and underestimation, respectively; 4) the respective ratios of MO and MU with the mean mass loading values (MML) measured in the field.

With these four parameters the aim was to define, for each eruption and each meteo 361 data, 1) the discrepancy between the observed data and the model  $(T^2/MML - the)$ 362 normalization allows to compare  $T^2$  from different eruptions), 2) whether the model tends 363 mostly to overestimate or underestimate the observed data (% of sections under or 364 365 overestimated), 3) the quantification of, respectively, the absolute model mean 366 underestimation (MU) and mean overestimation (MO) and, 4) how important are MO and MU with respect to the mean values of mass loading measured in the field (MO/MML and 367 MU/MML ratios). Regarding the grain size data, instead, the modeled values of Md $\phi$  or  $\sigma\phi$ 368 were plotted as a function of the observed values at specific stratigraphic sections, and the 369 370 distribution of the data relative to a perfect fit line was discussed.

#### 371 **3. Results**

For all the eruptions, Fig. 2 describes the stratigraphic sections used for uncertainty quantification, Figs. 3-6 provide the results of each comparison, while Tables 2-5 summarize the values calculated for each uncertainty quantification. Complementary data given in the Supporting Information are: the output values (plume heights, mass loadings, Md $\phi$  and  $\sigma\phi$ values, Tables S4-S7) and the simulation outputs in PDF (Figures S1-S16).

377 378

#### 3.1 Cotopaxi 2015

For the C15 eruption, a total of 35 mass loading measurements [from *Bernard et al.*, 2016a] and 4 grain size analyses [unpublished and from *Gaunt et al.*, 2016] were used for comparison with our model (Fig. 2a).

382

For each meteo condition and for the values of MER considered, plume heights 383 comparison (Fig. 3a) shows that PLUME-MoM results are generally lower than those 384 obtained by inverting seismic signal or from satellite/video camera images, though the model 385 data mimic the patterns of observations. The difference between observed and modeled values 386 (Table 2) is ~435-480 m for the seismic signal and video camera images while it is ~1300-387 1400 m for the satellite measurements. We note, however, a few exceptions. For the seismic-388 derived data, exceptions are the days around the 23<sup>rd</sup> of September, where modeled plume 389 heights are systematically higher than the inferred ones. In contrast, Fig. 3a shows that there is 390 a very good correlation between modeled and observed plume heights estimated from video 391 recordings for the first phase of the eruption (August and beginning of September). 392

Ground deposits data show a difference of about  $15^{\circ}-20^{\circ}$  between the directions of modeled and observed main dispersal axes (Figs. 2a and 3b). Notice that the deposits simulated, despite in extremely low quantities (i.e.  $10^{-10}-10^{-11} \text{ kg/m}^2$ ) at more distal locations, are spread all over the computational domain (see Figs. S1 to S3). Mass loading data show that the simulations underestimate field observations at locations in the main dispersal axes (Fig. 3b). Notice that the two sections along the main dispersal axes with the highest underestimations (BNAS and PNC 4 sections, see Table S3 from the Supporting Information) have observed mass loading values of, respectively, 18 and 15 kg/m<sup>2</sup>; for these two sections,

which are very proximal ( $\sim 5$  and  $\sim 7$  km from the vent respectively) the model predicts very 401 low deposition (<1 kg/m<sup>2</sup> for all the simulations). The  $T^2$ /MML values (Table 2) show that the 402 differences between model and observed values are relatively low, and the model generally 403 underestimates the observed values (57% to 77% of the field sections are underestimated). An 404 area of model underestimation might be recognized close to the vent area along the main 405 406 dispersal axes for all the simulations (see Figure S17 from the Supporting Information). The MO and MU values (and also the MO/MML and MU/MML ratios) are similar for the 407 different meteo data, and for all the cases with a higher value of MU and MU/MML (for 408 409 simulations done using the NCEP/NCAR and the ERA-Interim meteo data).

410 The grain size data are scarce but we note that the computed Md $\phi$  values are almost 411 always shifted toward coarser sizes (Fig. 3c) and that the  $\sigma\phi$  values show that the sorting of 412 the computed deposit is much smaller with respect to reality (Fig. 3d). Both computed Md $\phi$ 413 and  $\sigma\phi$  show nearly constant values for a given section but with different meteo data.

# 415 **3.2 Tungurahua 2013**

414

For the T13 eruption, a total of 48 mass loading measurements [unpublished and from *Parra et al.*, 2016] and 29 grain size analyses [unpublished and from *Parra et al.*, 2016] were used for the comparison (Fig. 2b).

The plume heights comparison (Fig. 4a) shows that all the simulations markly underestimate the observations reported from both sources. The mean difference is about -2.1 km to -2.2 km (Table 3). The difference of deposit main dispersal axes is small since the simulations done using GDAS and ERA-Interim data are almost coincident with respect to field data while the NCAR simulation is only 8° shifted toward the SW (Figs. 2b and 4b).

The observed values of mass loading (Fig. 4b and Table S3 from the Supporting 424 Information) are all  $<3 \text{ kg/m}^2$ , similarly with respect to the C15 eruption for the two sections 425 along the main dispersal axes (San Pedro de Sabanag and 12 de Octubre, Table S3 from the 426 Supporting Information). Mass loading differences have a small spread highlighted by low 427  $T^{2}$ /MML values (Table 3). This is also shown by the absolute differences (MO and MU), 428 which are also almost identical despite the model tends to underestimate field data at most 429 sections. For the T13 eruption, the distribution of sections with overestimation and 430 underestimation does not highlight homogeneous areas of model overestimation or 431 underestimation (see Fig. S18 from the Supporting Information). In Table 3 the MO/MML 432 and MU/MML ratios have both values <1, indicating that the difference in mass loading value 433 is less important than the average deposit value of mass loading. In Fig. 4b, the mass loading 434 differences with respect to the observed data are equally positive (overestimation) or negative 435 (underestimation) in proximity of the main dispersal axes, without a clear prevalence. 436

Grain size comparison highlights that, similarly to the C15 eruption, most of the computed grain sizes are shifted toward constant coarser grained values (Md $\phi$ , see Fig. 4c) with a smaller and fairly constant sorting for much of the sections ( $\sigma\phi$ , see Fig. 4d). Notice, however, that some simulation sorting values are along the perfect fit line (mostly NCEP/NCAR simulation) or are even larger than the observed ones (GDAS and the ERA-Interim simulations).

444 **3.3 Tungurahua 2006** 

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For the T06 eruption, a total of 48 mass loading measurements [*Eychenne et al.*, 2012] and 22 grain size analyses [recalculated from *Eychenne et al.*, 2012, see also Text S1 from the Supporting Information] were used for the comparison (Fig. 2c).

Fig. 5a shows that the plume heights simulated are close to observed data, except for 448 the NCEP/NCAR model. The ERA-Interim/WRF model, in particular, provides a low mean 449 overestimation of about 400 m (Table 4). Notice that this simulation was characterized by a 450 fairly low T<sup>2</sup> value, although higher with respect to the parent ERA-Interim simulation (Table 451 4). This difference is due to the iterative procedure described in Section 2.4, which allowed 452 453 finding the hourly values of MERs that minimized the differences in plume heights. Another combination of MERs was instead used for the other three meteorological datasets. 454 Differences in deposit main dispersal axes are the highest of the four studied eruptions and are 455 up to about 40° toward South (see ERA-Interim meteo in Figs. 2c and 5b). 456

With respect to mass loading, the  $T^2/MML$  values (Table 4) highlight a relatively high 457 spread of the data, which is also reflected in the MO and MU values. In this case, it could be 458 considered that most of the sections with underestimation are concentrated in proximity of the 459 460 main dispersal axis highlighted by field data (Fig. 5b). Notice that the NCEP/NCAR provides the highest values of overestimation (MO = 62.57, MO/MML = 7.68). Moreover, the T06 461 eruption is one of the two cases, among the studied ones, where one simulation gives more 462 463 sections with overestimation than sections with underestimation (ERA-Interim/WRF, see Table 4). Considering the spatial distribution of sections with overestimation and 464 underestimation (see Fig. S19 from the Supporting Information), then a homogeneous area of 465 466 model overestimation might be identified in the proximity of the vent area along the main dispersal axes (see Fig. S19 from the Supporting Information). Figure 5b highlights an 467 interesting pattern for all the sections since the difference in mass loading tends to increase 468 469 approaching the main dispersal axis, which is particularly evident for the GDAS and the NCEP/NCAR simulations. 470

The grain size data show a fairly well defined trend of Mdφ values, which are close to
the perfect fit line (Fig. 5c). The model sorting values are instead mostly shifted toward lower
values but define trends mimicking that of the perfect fit line (Fig. 5d).

# 474

# 475 **3.4 Puyehue-Cordón Caulle 2011**

For the PCC11 eruption, a total of 75 mass loading measurements and 24 grain size analyses [*Bonadonna et al.*, 2015a; *Pistolesi et al.*, 2015; unpublished] were used for the comparison (Fig. 2d). For the mass loadings, the thickness data of *Pistolesi et al.* [2015] were multiplied by the bulk deposit density value of 560 kg/m<sup>3</sup> reported in *Bonadonna et al.* [2015a] for Unit I, in order to obtain kg/m<sup>2</sup> values. Daily average plume heights a.s.l. reported in *Bonadonna et al.* [2015b] have been converted into "above vent" values by subtracting the vent elevation reported in *Bonadonna et al.* [2015b] (1470 m a.s.l.).

For this eruption, the simulations generally overestimate the plume heights observed, which are lowered with the inverse procedure (see Table 5, Fig. 6a). The simulated deposit main dispersal axes are all shifted toward the South by 5-10° with respect to the field data (Figs. 2d and 6b).

For the mass loading, most of the  $T^2/MML$  values are the highest among all the 487 simulations, with values up to 22.12 (ERA-Interim) (Table 5). MO and MU values are 488 respectively >100 kg/m<sup>2</sup> and from -18 kg/m<sup>2</sup> up to -54 kg/m<sup>2</sup>. The MO/MML and MU/MML 489 ratios indicate anyway that mean overestimation is 3 to 6 times higher than MML and that 490 491 mean underestimation is 0.3 to 1 times higher than MML. As for the other eruptions, the percentage of sections with overestimation is lower than that with underestimation, except for 492 the simulation done with the GDAS meteo data (Table 5). From Fig. S20 from the Supporting 493 494 Information, the distribution of the sections with overestimation or underestimation highlights 495 a homogeneous area of model overestimation located 30-40 km from vent area along the main dispersal axes. The correlation between high values of mass loading overestimation and the 496

position of the main dispersal axis (Figure 6b) is evident only for the simulation done with the 497 ERA-Interim meteorological data. For the other simulations instead, the sections with the 498 highest differences are uncorrelated with respect to the position of the main dispersal axis 499 given by the model. It is also important to underline that in this case also, sections with 500 highest values of observed mass loadings are not correlated with the deposit main dispersal 501 axis given by field data, a pattern that is confirmed also by the simulations (see Fig. 6b). This 502 latter feature might be correlated with the progressive anticlockwise rotation of the ash cloud, 503 a pattern already discussed by Pistolesi et al. [2015] and Bonadonna et al. [2015b]. To 504 505 confirm this, we have also performed a more detailed analysis using satellite images to track the evolution of the ash cloud during the 04-05/06/2011: details about this method are 506 reported in Text S1 from the Supporting Information. The sequence of images derived (Figure 507 S21 from the Supporting Information) show that at the onset of the eruption the cloud drifted 508 509 southwestwardly  $(130^{\circ})$ , but as time passed, the cloud rapidly moved towards the east, reaching 105°. This compares with the main dispersal axis assessed from the field deposits 510 integrated over the whole Unit I (layers A-F) and yielding a mean direction of 117°. However, 511 512 the maximum mass loading of deposits have been recorded at much higher angles, lying between 130-135° (Figure 6b). This actually correlates with ash emissions occurring at the 513 onset of the eruption, where the ash-rich plume might have produced rapid and en masse 514 515 fallouts along the main ash cloud dispersal axis centered at 130° (Figure S21 from the Supporting Information). This is supported by mass loading values of the deposits, which are 516 very high on the dispersal axis (green dots in Figure S21), ranging from 481.6kg/m<sup>2</sup> close to 517 the vent (section n° 57, Table S3 from the Supporting Information) to 160 kg/m<sup>2</sup> at a greater 518 distance. By contrast, the mass loading of samples located away from the dispersal axis (red 519 dots in Figure S21), shows much lower values of about 5.6 kg/m<sup>2</sup>, although being close to the 520 521 vent. Interestingly, section n° 57 is also the one that tends to have the highest value of underestimations (up to  $-400 \text{ kg/m}^2$ ). 522

Regarding the grain size data, the Md $\phi$  values are spread on both sides of the perfect 523 fit line (Fig. 6c). The NCEP/NCAR simulations (both direct and inverse) tend to give finer 524 grained values with respect to the observed data. The sorting data tend to define two trends of 525 constant values of  $\sigma \phi \sim 0.5$  and  $\sim 2$ , and some model sorting values are higher than the 526 observed ones (Fig. 6d). An important remark for the modeled grain sizes of the PCC11 527 eruption is that none of them show any bimodal distribution in contrast to the observed data. 528 This is particularly evident for the above-mentioned section n° 57, which does not have 529 bimodality and which has an Md $\phi$  shifted toward more coarser-grained values. 530

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#### 533 **4. Discussion**

#### 534 **4.1 Uncertainty in the input parameters**

A significant amount of uncertainty in the simulations may derive from the 535 meteorological data employed. As also shown by other studies [e.g. Devenish et al., 2012; 536 Webster et al., 2012], even small errors in the wind field can lead to large errors in the ash 537 538 concentration, making therefore a point-by-point comparison of modelled with observed data a challenging task. The datasets we considered are among the most widely used in similar 539 numerical modellings [e.g., Weblev et al., 2009; Bonasia et al., 2012; Folch, 2012; Costa et 540 541 al., 2016]: moreover, it has also been used the mesoscale meteorological model WRF/ARW, which has been coupled with other TTDMs in similar works [e.g. FALL3D, Poret et al., 542 2017]. From our results, it is not evident that a particular meteorological dataset provides 543 544 systematically the best results. For instance, the GDAS dataset provides the worst results (in terms of both the T<sup>2</sup> and the MO-MU values) for the lower magnitude C15 and T13 eruptions, 545

while it provides the best results for the T06 and PCC11 eruptions. The NCEP/NCAR dataset 546 shows the opposite as the results are better for the C15 and T13 eruptions with respect to T06 547 and PCC11. The employment of the WRF/ARW model (see also Text S1 from the Supporting 548 Information) did not result in a significant improvement of the results as it gave instead higher 549  $T^{2}$ /MML values with respect to the parent ERA-Interim meteorological file (see Table 4), 550 although for some other models the employment of the WRF/ARW model gave better results 551 [Parra et al., 2016]. Given the high computational times necessary to process original meteo 552 data, the refinement procedure using WRF/ARW was not applied to other longer eruptions. 553 The meteorological data have a considerable effect on the direction of main advection of the 554 volcanic particles, which controls the deposit main dispersal axis direction. This is 555 particularly evident for the T06 eruption, where differences with respect to the observed axis 556 557 are up to 40°. Two main reasons for such differences may be invoked: i) the meteorological data are built in a way such that their parameters remain constant for relatively long periods (3 558 to 6 hours) and for quite large areas  $(0.75^{\circ} \times 0.75^{\circ} \text{ up to } 2.5^{\circ} \times 2.5^{\circ})$ , and within such temporal 559 frames and spatial domains it is not possible to capture the variability of natural phenomena; 560 561 ii) 4-dimensions meteorological files (especially Reanalysis products) might be less accurate over complex terrains (e.g. the Andes), for which the details of the atmospheric flow are less 562 likely captured and there are not a lot of observations available. This could be the case for the 563 564 T06 and T13 eruptions, where the rugged topography of the area surrounding the Tungurahua volcano could have caused secondary atmospheric effects not recorded in the meteorological 565 566 files.

567 A common problem with eruption source parameters is the measurements of plume height. For instance, for the C15 eruption Bernard et al. [2016a] used three different 568 methodologies for plume height estimates (inversion of seismic signals, video cameras 569 570 observations, and satellite measurements), which gave sometimes very different values (see Fig. 3a). For the T06 eruption, Steffke et al. [2010] used two different methods of satellite 571 observations. Therefore, it is not surprising that differences in measurements at the same time 572 can be important. The uncertainty in plume height is also high for the T13 eruption, for which 573 574 two different methods (satellite measurements and visual observations) have been employed, and for the PCC11 eruption as well, for which only daily mean values of plume height have 575 been reported. 576

Mass loading values for the C15, T13 and T06 eruptions have been actually measured 577 for each section (with various methods), but for the PCC11 they have been determined by 578 multiplying the deposit thickness by a mean bulk deposit density value (see Section 3.4). This 579 latter aspect is critical since density of tephra fall deposits may vary considerably owing to 580 drastic density change between different particle sizes [e.g., Bonadonna and Phillips, 2003; 581 Evchenne and Le Pennec, 2012; Pistolesi et al., 2015]. This is particularly important for the 582 PCC11 eruption that has the highest  $T^2/MML$  values (see Table 5), which might also be 583 related to an uncertainty in the observed mass loading data. We also stress that the assumption 584 of a linear variation of particle density with grain size (employed in PLUME-MoM) is a 585 simplification since the density variation may be more complex [i.e sigmoidal rather than 586 linear as for the T06 eruption, Eychenne and Le Pennec, 2012]. Compared to other sources of 587 uncertainty, however, the simplification used in the simulations is expected to have a minor 588 589 effect on the final results.

Finally, it is important to remark that there are also uncertainties in estimations of the initial water mass fraction in magmas. This is due primarily to the use of different methods [e.g., by direct measurements, geological inference, thermodynamic calculation or experimental approaches, see *Clemens*, 1984], among which the direct measurement from melt inclusions in crystals are the most used [see for example *Plank et al.*, 2013]. As a comparison, for this study we relied on estimates made both using direct measurements from melt inclusions and experimental approaches [*Martel et al.*, 2018] or considering only experimental approaches [*Andújar et al.*, 2017]: results gave H<sub>2</sub>O wt. % ranging between 4-6 wt. % and 6-8 wt. .% for andesites and rhyolites respectively. As the water mass fraction has a strong influence on the plume height simulated with PLUME-MoM [see section 2.2.1 and also *de'Michieli Vitturi et al.*, 2016], its careful estimation is therefore of primary importance.

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# 602 **4.2 Uncertainty in the numerical modelling**

When MER values obtained from total deposit measurements are used as input 603 parameters, PLUME-MoM underestimates the plume height measurements for three out of 604 605 four eruptions tested, and there may be two main reasons for that. First, as already discussed in the previous section, the measurements are in some specific cases uncertain. Second, the 606 mass eruption rate, assumed to be equal to the total mass of deposit divided with the eruption 607 duration, may be underestimated in some cases (e.g. the T06 eruption) since deposits of 608 609 pyroclastic density currents are neglected, hence giving lower plume heights. We note, however, that the mean underestimations (and mean overestimations as well) of the model for 610 each eruption are lower with respect to the uncertainty in observed data among different 611 612 methods, and that in some cases (e.g. the T06 eruption) the refinement of the meteorological data using the WRF/ARW model can sensibly reduce the difference in plume height with 613 respect to observed data. 614

615 The PLUME-MoM/HYSPLIT model tends generally to have more points underestimating the mass loading data (see Tables 2 to 5). However, if the absolute mean 616 differences (MO and MU) and their ratios with mean values of mass loading (MO/MML and 617 618 MU/MML) are considered, then model overestimation is systematically higher with respect to underestimation. For example, for the PCC11 eruption and for the simulation done using the 619 ERA-Interim data, MO is almost 10 times higher than MU (Table 5). The high values of MO 620 or MU and of their ratios with MML tend also to be higher for higher magnitude eruptions 621 (e.g. T06 and PCC11): in this regard the inverse procedure reduces considerably the 622 discrepancy between modeled and observed data as indicated for instance by the  $T^2/MML$ 623 value for the PCC11 eruption. 624

The problem of model uncertainty is further illustrated by the difference in mass 625 loading with respect to the orientation of the stratigraphic section (Figs. 3b, 4b, 5b and 6b). 626 There are two opposite situations since the deposit main dispersal axis coincides either with 627 628 the lowest values of  $\Delta$  mass loading (highest underestimation, e.g. C15 eruption, Fig. 3b) or with the highest values of  $\Delta$  mass loading (highest overestimation, T06 eruption, Fig. 7b, and 629 to a lesser extent T13 and PCC11 eruptions). This may be explained considering the advective 630 and diffusive parts of the transport equation used [Folch, 2012]. While the mass seems to be 631 correctly advected in the simulations (although with some deviation with respect to observed 632 data), the equations of HYSPLIT related to turbulent diffusion do not appear to work 633 efficiently, underestimating the horizontal diffusion and concentrating the mass close to the 634 main dispersal axis of advection. A similar issue has been also encountered by Hurst and 635 Davis [2017]. This may explain the above-mentioned mass loading underestimation or 636 overestimation, which are possibly increased by the fact that the HYSPLIT model does not 637 account for complex collective settling mechanisms of volcanic ash caused by aggregation, 638 639 gravitational instabilities, diffusive convection, particle-particle interactions and wake-capture effects [Del Bello et al., 2017; Gouhier et al., 2019]. However, the problem of the effect of 640 diffusion on volcanic plumes dispersal and therefore on particle sedimentation is complex 641 [see for example Devenish et al., 2012]: a more rigorous study is therefore needed for 642 HYSPLIT to investigate the influence of different available diffusion equations on final 643 644 results.

The failure to take into account such mechanisms implies that the simulated finest-645 grained particles are transported much further that in reality. For instance, the C15 eruption 646 has a particularly fine-grained TGSD [due also to its hydrovolcanic nature, Bernard et al., 647 2016a] (see Table S2 from the Supporting Information) so that the mass is transported all over 648 the computational domain (see Figs. S1 to S3 from the Supporting Information). The case of 649 the PCC11 eruption is similar since the TGSD is up to  $12\phi$ , and an estimated amount of ~5% 650 651 of the erupted mass is transported out of the computational domain. While for this eruption the finest fraction of the volcanic clouds circumvented the Southern hemisphere and passed 652 over the South of Australia [Collini et al., 2013], it is possible that part of the fine ash did not 653 654 deposit (see also the issue of grain size analyses in the following paragraph). In this context, the transport of material could have been at its maximum along the main dispersal axes, and 655 therefore the degree of underestimation of mass loading at proximal-medial sites along 656 657 dispersal axes is maximized as well.

Regarding the simulated grain size data, the Md $\phi$  values are systematically coarser-658 grained for the C15 and T13 low magnitude eruptions while they are either coarser-grained or 659 finer-grained for the PCC11 eruption. The shifting toward coarser-grained Md $\phi$  values can be 660 explained by the fact that HYSPLIT neglects the above-mentioned collective settling 661 mechanisms of volcanic ash. For the eruptions where the amount of fine ash is higher (the 662 C15, T13 eruptions and partially the PCC11 one), the fine ash is transported distally, hence 663 causing coarser grain sizes in proximal to medial sections. Moreover, the model is not capable 664 of reproducing the bimodality of grain size distribution observed, as for instance in the PCC11 665 eruption. The  $\sigma\phi$  comparisons show that, instead, for most cases the modeled data tend to 666 have a lower sorting value with respect to the observed ones. These results show that the 667 668 employment of grain size data for model validation is less reliable with respect to mass loading data. 669

Four important issues should be considered to improve the coupled PLUME-670 MoM/HYSPLIT model in the context of tephra fallout hazard assessments and probabilistic 671 hazard maps production. First, the meteorological dataset must be considered carefully since 672 it controls strongly the plume height. Second, the amount of fine ash and the duration of the 673 eruption seem to be more critical than the magnitude of the eruption for mass loading 674 calculations, since the simulations of higher magnitude eruptions of short duration with lower 675 wt% of fine particles (i.e. T06 eruption) are more accurate than simulations of lower 676 magnitude eruptions with longer durations and a higher amount of fines (i.e. the C15 and 677 T13). If the magnitude, the amount of fine particles and the duration of the eruption are high 678 (i.e. the PCC11 eruption), then the model tends to overestimate the natural data. Third, for the 679 above-mentioned reasons, we recommend to employ PLUME-MoM/HYSPLIT in its present 680 configuration for the production of hazard maps related to higher magnitude eruptions (i.e. 681 sub-Plinian or Plinian). This is supported by our simulations of such eruptions (i.e. T06 and 682 PCC11), for which overestimation is much higher (in terms of mean absolute values) with 683 respect to underestimation. This latter point is important in a context of hazard assessment 684 since underestimation may be considered as less acceptable than overestimation. Moreover, it 685 is also important to remind that: a) specifically for our test eruptions, the lower magnitude 686 687 ones tend to have longer durations and are more difficult to model due to the very high variability of both the eruptions parameters and atmospheric conditions, which are less likely 688 to be captured; b) the T06 and PCC11 eruptions are those for which modeled and observed 689 plume heights are more similar. Fourth, the MO/MML and MU/MML ratios may be used to 690 691 account for model uncertainty and to serve as a basis for calculating coefficients that allow the creation of probabilistic maps (from the point of view of mass loading) that quantify the 692 model mean overestimation and underestimation. For this purpose, statistical techniques 693 might be employed to correct the model by estimating its deviance from the observed data. 694

#### 695 **5.** Conclusions

This paper presents the coupling of the PLUME-MoM model with a renewed version 696 of the HYSPLIT tephra dispersal model. These two coupled models have been tested against 697 four eruptions of different magnitudes and styles from three Andean volcanoes. A procedure 698 of uncertainty quantification has been applied by computing the differences between modeled 699 and observed data of plume height, mass loading and grain size (in terms of Md $\phi$  and  $\sigma\phi$ ). 700 Four different meteorological datasets (GDAS, NCAR/NCEP, ERA-Interim, ERA-701 Interim+WRF) have been tested as well. The main conclusions and future perspectives of this 702 uncertainty quantification are: 703

- None of the meteorological datasets tested produced systematically the best results
   for all the eruptions. This implies that if a specific dataset is employed for
   numerical modelling, its uncertainty (as quantified here) should be considered.
- The PLUME-MoM model tends to underestimate measured plume heights, except for the eruption with the highest magnitude tested (i.e. PCC11). Though underestimation might be related to uncertainties in plume height measurements and input data (e.g. mass eruption rate and initial water mass fraction), we note that for most of the cases we investigated the mean underestimations of the model for each eruption were lower with respect to the uncertainty in observed data.
- The PLUME-MoM/HYSPLIT model tends generally to have more points underestimating the mass loading data. If absolute mean differences are considered, however, then overestimation is almost always higher than underestimation. The distribution of sections with overestimation and underestimation does not highlight systematically homogeneous areas of either overestimation or underestimation.
- The advective part of the HYSPLIT model appears to work more efficiently than the diffusive part. Moreover, the failure to take into account any collective settling mechanisms of volcanic ash in HYSPLIT might cause important discrepancies between observed and modeled data of mass loading and, above all, grain size distributions.
  - For the above-mentioned reasons, high amounts of fine particles might reduce the accuracy of the model when simulating mass loading and grain size data.
    - If the PLUME-MoM/HYSPLIT model is meant to be employed for hazard assessment purposes, we recommend considering high magnitude eruptions (i.e. sub-Plinian or Plinian) as target cases, and mass loading as primary parameter.
- Future developments of this project should consider the comparison of simulations outputs with those from other models, in order to identify which model is best suited for a specific eruption type

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743 repository in the Figshare community with the following DOI:
744 https://doi.org/10.6084/m9.figshare.10298036.v1.

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# 996 FIGURE CAPTIONS

Figure 1. Geographical locations of a) Cotopaxi and Tungurahua volcanoes in Ecuador and b)
Puyehue-Cordón Caulle volcanic complex in Chile. Coordinates are in the UTM WGS84 17S
(a) and UTM WGS84 19S (b) systems. Basemap copyright of ESRI®, DigitalGlobe, GeoEye,
Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User
Community.

Figure 2. Stratigraphic sections used for uncertainty quantification (considering only mass loading or both mass loading and grain size) and dispersal axes from field data/simulations with different meteo data for: a) Cotopaxi C15 eruption; b) Tungurahua T13 eruption; c)
Tungurahua T06 eruption; d) Puyehue-Cordón Caulle PCC11 eruption. Digital Elevation Model (30 m- resolution) from Marc Souris, IRD (a-c) and ESRI, USGS, NOAA (d).
Coordinates are in UTM WGS84 17S (a-c) and UTM WGS84 19S (d).

**Figure 3.** Cotopaxi C15 eruption. Comparison of a) column height (observed and computed); b)  $\Delta$  mass loading (left axis) and observed mass loading (right axis) for different sections with respect to their orientation from North; c) Md $\phi$  and d)  $\sigma\phi$  (computed and observed).

**Figure 4.** Tungurahua T13 eruption. a) Column height (observed and computed); b)  $\Delta$  mass loading (left axis) and observed mass loading (right axis) for different sections with respect to their orientation from North; c) Md $\varphi$  and d)  $\sigma\varphi$  (computed and observed).

**Figure 5.** Tungurahua T06 eruption. a) column height (observed and computed); b)  $\Delta$  mass loading (left axis) and observed mass loading (right axis) for different sections with respect to their orientation from North; c) Md $\phi$  and d)  $\sigma\phi$  (computed and observed).

**Figure 6.** Puyehue-Cordón Caulle PCC11 eruption. a) Column height (observed and modeled); b)  $\Delta$  mass loading (left axis) and observed mass loading (right axis) for different sections with respect to their orientation from North; c) Md $\phi$  and d)  $\sigma\phi$  (computed and observed).

#### 1035 TABLES

Eruption name	Computational grid dimension (°)	Initial water content (wt%)	Particles exit velocity (m/s)	Heat capacity (J/kgxK)	Particles Shape Factor	<b>ф</b> 1	$\rho_1$ (kg/m <sup>3</sup> )	φ <sub>2</sub>	$\begin{array}{c} \rho_2 \\ (kg/m^3) \end{array}$
Cotopaxi 2015 (C15)	5x5	5.5%	135	1600	0.75	-1	1487	2	2478
Tungurahua 2013 (T13)	6 x 6	5.5%	135	1600	0.75	-1	1487	2	2478
Tungurahua 2006 (T06)	6 x 6	5.5%	275	1600	0.75	-1	1487	2	2478
Puyehue- Cordón Caulle 2011 (PCC11)	10 x 10	7.0%	275	1600	0.65	-4	500	5	2670

**Table 1.** Main input parameters used for the simulations.

Donomotors	Meteo Data							
Farameters	GDAS NCEP/NCAR		ERA-Interim					
PLUME-MoM								
Mean Difference seismic (m)	-479.02	-443.75	-454.83					
Mean Difference video (m)	-466.24	-434.99	-443.23					
Mean Difference satellite (m)	-1449.64	-1405.96	-1366.64					
HYSPLIT								
T <sup>2</sup> /MML	1.00	0.85	0.93					
% Section Overestimation	42.9%	25.7%	22.9%					

% Section Underestimation	57.1%	74.3%	77.1%
<b>MO</b> (kg/m <sup>2</sup> )	0.47	0.09	0.25
<b>MU</b> (kg/m <sup>2</sup> )	-3.04	-2.66	-2.60
MO/MML	0.21	0.04	0.11
MU/MML	1.37	-1.20	-1.18

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 Table 2. Values calculated for the uncertainty quantification for the C15 eruption.

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Donomistons	Meteo Data								
Parameters	GDAS NCEP/NCAR		ERA-Interim						
PLUME-MoM									
Mean Difference (m)	-2202.05	-2113.75	-2132.03						
HYSPLIT									
T <sup>2</sup> /MML	0.71	1.02	1.49						
% Section Overestimation	29.2%	33.3%	35.4%						
% Section Underestimation	70.8%	66.7%	64.6%						
<b>MO</b> (kg/m <sup>2</sup> )	0.15	0.38	0.40						
<b>MU</b> (kg/m <sup>2</sup> )	-0.47	-0.34	-0.37						
MO/MML	0.28	0.75	0.77						
MU/MML	-0.92	-0.67	-0.73						

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**Table 3.** Values calculated for the uncertainty quantification for the T13 eruption.

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Donomotona	Meteo Data							
Farameters	GDAS	NCEP/NCAR	<b>ERA-Interim</b>	ERA-Interim/WRF				
PLUME-MoM								
Mean Difference (m)	-718.67	-3752.59	-1225.72	404.74				
HYSPLIT								
T <sup>2</sup> /MML	5.41	19.67	1.78	4.59				
% Section Overestimation	39.5%	44.2%	27.9%	55.8%				
% Section Underestimation	60.5%	55.8%	72.1%	44.2%				
$MO (kg/m^2)$	23.96	62.57	15.64	19.73				
<b>MU</b> (kg/m <sup>2</sup> )	-3.32	-2.74	-4.40	-2.88				
MO/MML	2.94	7.68	1.92	2.42				
MU/MML	-0.41	-0.34	-0.54	-0.35				

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**Table 4.** Values calculated for the uncertainty quantification for the T06 eruption.

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	Meteo Data								
Parameters	GDAS	NCEP/NCAR	ERA-	GDAS	NCEP/NCAR	<b>ERA-Interim</b>			
			Interim	(inversion)	(inversion)	(inversion)			
PLUME-MoM									
Mean Difference	296.11	71.79	182.06	195.51	-84.86	33.27			
( <b>m</b> )	270111		102.00	1,0101	0.1100	00127			
HYSPLIT									
T <sup>2</sup> /MML	17.05	9.69	22.12	11.73	8.08	7.08			
% Section	50.7%	30.7%	317%	48.0%	32.0%	38 7%			
Overestimation	50.770	30.770	54.770	40.070	52.070	50.770			
% Section	40 3%	60.3%	65 304	52 0%	68 0%	61 304			
Underestimation	49.3%	09.370	05.5%	52.070	08.0%	01.3%			
MO (kg/m <sup>2</sup> )	165.27	227.60	309.99	133.10	184.06	156.82			
MU (kg/m <sup>2</sup> )	-53.93	-15.57	-31.94	-50.57	-18.72	-36.37			
MO/MML	3.15	4.34	5.91	2.54	3.51	2.99			
MU/MML	-1.03	-0.30	-0.61	-0.96	-0.36	-0.69			

**Table 5.** Values calculated for the uncertainty quantification for the PCC11 eruption.

Figure 1.



Figure 2.



Figure 3.



Figure 4.



Figure 5.



Figure 6.

