The evaluation of mixing methods in HYSPLIT using
measurements from controlled tracer experiments
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Abstract

36 The HYSPLIT dispersion model has different options to estimate the turbulent 37 mixing depending on the availability of stability and turbulent parameters in the 38 meteorological data. Dispersion simulations using different mixing options were 39 conducted to simulate two controlled tracer experiments – the Project Sagebrush phase 1 40 (PSB1) for the sub-kilometer transport and the Cross Appalachian Tracer Experiment 41 (CAPTEX) for the long-range transport. Through the comparisons of velocity variance 42 and the evaluations of tracer concentrations, we evaluated different estimations of the 43 turbulent velocity variance affecting the dispersion results. The mixing options in 44 HYSPLIT are the Belijaars-Holtslag (BH) method, the Kantha-Clayson (KC) method, the 45 turbulent kinetic energy (TKED) option, and the turbulent exchange coefficient (EXCH) 46 option. The KC and EXCH method produced a larger maximum of the vertical velocity 47 variance and at a higher altitude than other mixing options did. The vertical velocity 48 variance profile of the BH scheme had a sharp increase from the surface to the height of 49 the maximum values. The TKED option generated a flat profile with the smallest 50 variation in its value with height. The plumes generated by the BH and TKED method 51 (weaker mixing) had higher concentrations near the surface than those driven by the KC 52 and EXCH option (stronger mixing). The statistical rank for the dispersion result using 53 the TKED option was slightly better than others while the BH mixing generated results 54 with a roughly worse rank. No mixing option always outperformed the other options. 55 HYSPLIT users can select a mixing option according to the scenario and availability of 56 meteorological fields, and use different options to generate dispersion ensembles.

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59 Keywords: HYSPLIT, dispersion, PSB1, CAPTEX, turbulent velocity variance

60 1. Introduction

61 To simulate the movement of pollutants in the atmosphere, a Lagrangian model 62 simulates the emission by releasing many particles at the source location over a period of 63 time. By adding a random component according to the dispersive nature of the 64 atmosphere to the advective motion of each particle, the particles released at the source 65 will be transported and mixed in space and time (Draxler and Hess, 1998). The turbulent 66 component of the process is the product of the computer-generated random number and 67 the standard deviation of the turbulent velocity. HYSPLIT, the dispersion model 68 developed by the National Oceanic and Atmospheric Administration Air Resource 69 Laboratory, uses regional and global products from various numerical weather models – 70 the Weather Research and Forecasting (WRF; Powers et al. 2017) model, the Global 71 Forecast System (GFS; Kanamitsu, 1989) model, the Modern-Era Retrospective analysis 72 for Research and Applications (MERRA; Rienecker et al. 2011), the European Center for 73 Medium-Range Weather Forecasts (ECMWF; Dee et al. 2011), etc. Depending on the 74 availability of stability and turbulent parameters in the meteorological data used to drive 75 the dispersion simulation, users can choose different options in HYSPLIT to estimate the 76 turbulent velocity variances (Stein et al. 2015). The estimation can be based on the 77 stability function diagnosed from other meteorological variables such as friction velocity 78 and mixing height. If the meteorological model does not provide them, temperature and 79 wind soundings are used to diagnose the boundary layer stability parameters. Other 80 methods include using the total turbulent kinetic energy (TKE) or mixing diffusivity to 81 calculate the standard deviation of turbulent velocity (Draxler and Hess, 1997).

82	The main goal of this study is to understand the mixing characteristics generated
83	by different estimations of the turbulent velocity variance affecting the dispersion results.
84	Toward this aim, we conducted meteorological simulations with the Advanced Research
85	core of WRF for the Project Sagebrush phase 1 (PSB1; Finn et al. 2016). The WRF
86	output includes variables required for computing stability parameters, as well as total
87	turbulent kinetic energy and turbulent exchange coefficient so that we can compare and
88	evaluate all mixing options in HYSPLIT with observations taken during the tracer
89	experiment. PSB1 consisted of five tracer releases in the afternoons of October 2013 and
90	aimed for the sub-kilometer scale transport with near neutral or unstable stability
91	conditions. Flux measurements, including turbulent velocity variance, are available along
92	with tracer concentration observations, which provides a platform for the direct
93	evaluation of the turbulent variables and the evaluation of dispersion results
94	corresponding to different mixing options. Prior to this study Ngan et al. (2018) assessed
95	the performance of the WRF-HYSPLIT modeling system for the dispersion scenario
96	represented by PSB1, featuring daytime convective conditions at fine spatial (a few
97	hundred meters) and temporal (10-min averaging) scales. The turbulent mixing is an
98	essential component affecting HYSPLIT's performance but not yet investigated in the
99	previous study. Thus, in the current work, we focus on evaluating the turbulent mixing
100	methods available in HYSPLIT and their impacts on dispersion results as compared
101	against PSB1 which offers a unique set of observations for the comparison of both
102	velocity variance and tracer concentration. In addition, we conducted HYSPLIT
103	simulations driven by the WRF data using different mixing options for the Cross
104	Appalachian Tracer Experiment (CATEX; Ferber et al. 1986). Unlike the Sagebrush

experiment focusing on a fine spatial and temporal scale, CAPTEX consisting of six 3-h releases aimed to simulate the long-range transport and diffusion of pollutants. The evaluations of dispersion results with measured concentrations provide the insight to assess the performance of different mixing methods.

109 The rest of the paper is organized as follows. Section 2 reviews the different 110 options in HYSPLIT to compute the velocity variance. Section 3 describes the model 111 configurations for the meteorological and dispersion models. In Section 4, we evaluated 112 the velocity variance computed in HYSPLIT with measurements taken during the 113 Sagebrush experiments. The dispersion simulations for the controlled tracer experiment – 114 PSB1 and CAPTEX were compared with measured concentration in Sections 5 and 6, 115 respectively. Finally, Section 7 presents the conclusions and future research directions.

116 **2. Overview of mixing options in HYSPLIT**

117 To compute the transport and mixing of particles, HYSPLIT treats the advection 118 and dispersion processes separately. The advection calculation uses the three-dimensional 119 velocity field while the dispersion calculation requires the standard deviations of the turbulent velocity { $\sigma_i = [\sigma_w, \sigma_u, \sigma_v]$ } to add a random component to the advective motion. 120 121 There are different methods to estimate the standard deviation of turbulent velocity based 122 on the availability of stability and turbulent parameters in the meteorological data. The 123 full list of equations for all parameters associated with each method is in Draxler and 124 Hess (1998). An abstract of the four mixing options available in HYSPLIT is described below. 125

126 a. Beljaars-Holtslag (BH) method

Following Beljaars and Holtslag (1991) for a stable surface layer, and Betchov and Yaglom (1971) and Kadar and Perepelkin (1989) for an unstable surface layer, the model computes the normalized profiles for heat and momentum, and then the vertical mixing coefficient according to the profiles and other stability parameters such as friction velocity, convective velocity scale, and Obukhov length. To obtain the vertical velocity variance, the model divides the diagnosed mixing coefficient by a Lagrangian time scale. This option is labeled hereafter as "BH".

134 b. Kantha-Clayson (KC) method

Following Kantha and Clayson (2000), the model defines the turbulent velocity variances as a function of friction velocity, convective velocity scale, and boundary layer depth. HYSPLIT uses it as the default when the momentum and heat flux variables are available in the meteorological data. This method (named hereafter "KC") does not need the intermediate step of computing the mixing coefficient and the use of turbulent time scales.

141 c. Using the turbulent kinetic energy (TKED)

142 If the meteorological data provide the turbulent kinetic energy, the model 143 partitions the values to the vertical and horizontal components using the anisotropy ratio. 144 According to experimental data, about one-third of TKE are assigned to the vertical velocity variance while twice as much of the values are partitioned to the horizontal 145 146 components. HYSPLIT uses this as default anisotropy. However, users can let the model 147 compute the anisotropy factors according to the Kantha-Clayson equations instead of 148 using a partitioning factor constant in space and time. This option is labeled hereafter as 149 "TKED".

150 *d. Using the turbulent exchange coefficient (EXCH)*

151 This method computes the velocity variance by dividing the turbulent exchange 152 coefficient by the vertical Lagrangian time scale, which is set to 100 s following Draxler 153 and Hess (1998). This option is labeled hereafter as "EXCH" and is newly added to 154 HYSPLIT with using the WRF meteorology. The turbulent exchange coefficient is 155 computed within the user-selected planetary boundary layer (PBL) parameterization in 156 WRF. The two classes of PBL approaches are 1.5-order TKE based schemes and first-157 order diagnostic K-profile schemes. The former diagnoses the exchange coefficient as a 158 function of the mixing length, stability function, and prognostic TKE while the latter 159 computes it from variables such as velocity scale, PBL height, and Prandtl number (Shin 160 and Dudhia, 2016).

161 **3. Experimental Data and Model Configurations**

162 The Project Sagebrush phase 1 tracer fields experiment took place at the Idaho 163 National Laboratory (43.59 N and 112.94 W) during October 2013 to understand sub-164 kilometer dispersion by performing continuous 2.5-h inert tracer (SF₆) releases over flat 165 terrain (Finn et al. 2016). Tracer releases were conducted on five afternoons (intensive 166 observation periods, or IOPs) under either neutral or unstable stability conditions. The 167 measurement network consisted of five concentric arcs located from 200 – 3200 m away 168 from the release location. Tracer samples were obtained starting 30 minutes after the 169 release in 10-min intervals. Comprehensive meteorological measurements, including 170 turbulent velocity variance data, were available during the experimental period.

171 The WRF Version 3.7 was used to generate meteorological data for the controlled 172 tracer experiments. The domain configuration and physic options followed Ngan et al. 173 (2018) for PSB1. In this study, we selected the Mellor-Yamada-Nakanishi-Niino (MYNN) 174 2.5 level TKE scheme (Nakanishi and Niino, 2006) for the planetary boundary layer 175 (PBL) parameterization and the corresponding MYNN surface layer scheme which works 176 together with the Noah land surface model (Chen and Dudhia, 2001) as lower boundary 177 conditions to provide the surface forcing for the vertical transport (Shin et al. 2012). The evaluations in Ngan et al. (2018) showed that the meteorological data for IOP4 and IOP5 178 179 featuring unstable conditions with moderate winds were simulated well by WRF. 180 However, the model performance was degraded due to the underestimation of strong 181 winds in IOP3 with neutral conditions and the inaccurate prediction of wind direction in 182 IOP2 featuring unstable conditions with light winds. This study did not include IOP1 due 183 to the sampling network not observing the plume (Finn et al. 2015). HYSPLIT 184 simulations were configured following Ngan et al. (2018); 250,000 Lagrangian particles 185 were released and lasted two-and-a-half hours. The tracer concentration was calculated 186 by summing particles in the volume of 100 x 100 m and from the surface to 25 m above 187 ground. Time averaging was set to 10 minutes. HYSPLIT was driven by WRF model 188 output with a horizontal resolution of 0.333-km (the most inner WRF domain) and a 189 temporal resolution of 5 minutes. A sensitivity test on the meteorological grid and its 190 impact on the dispersion results for tracer releases in PSB1 was presented in Ngan et al. 191 (2018). The analysis shows that under the meteorological conditions represented by PSB1, 192 the HYSPLIT results for IOP 2, 4, and 5 were not sensitive to the grid resolution of the

WRF data. The mixing options described in Section 2 were used to simulate four IOPsconducted in PSB1.

195	CAPTEX took place in the northeastern United State and southeastern Canada
196	from mid-September through the end of October 1983. An inert perfluorocarbon tracer
197	were released to simulate the transport and dispersion of pollutants at scales of hundred to
198	a thousand kilometers (Ferber et al. 1986). Six 3-h releases were conducted at Dayton,
199	Ohio during the afternoon (releases 1-4) and at Sudbury, Ontario, Canada during the
200	nighttime (releases 5 and 7). The measurement network included 85 ground-level stations
201	distributed 300 – 800 km from the source, providing 3- and 6-h average tracer
202	concentrations for three-day periods after the tracer release. WRF data with a horizontal
203	resolution of 9 km was the meteorological input to drive HYSPLIT. The WRF simulation
204	was initialized by the WRF archived dataset and nested in the coarse resolution domain
205	introduced in Ngan and Stein (2017). The simulation used the MYNN 2.5 level TKE-
206	based PBL scheme and its corresponding surface layer scheme, while other physics
207	options followed Ngan and Stein (2017). The hourly meteorological files were used to
208	drive HYSPLIT simulations running with the four mixing options. A concentration grid
209	with ~25-km horizontal resolution was set for the simulations with one vertical layer
210	from $0 - 100$ m above ground. Detailed information of each release is described in Ngan
211	and Stein (2017).

212 4. Comparisons of the velocity variances

Figure 1 is the layout of the sampling arcs for the tracer concentration and the meteorological observation taken during PSB1. The velocity variance (or the standard 215 deviation of velocity) was measured at six locations and different heights (Table 1) with 216 two sodars at the ASC and ART stations, and 3-d sonic anemometers at the other velocity 217 variance sites (Finn et al. 2016). The measurement of TKE by the ASC site tended to 218 match well to the measurement of TKE by the five other sites using the 3-d sonic 219 anemometer while the TKE measurement at the ART site was an order of magnitude 220 higher than the others. Note that the vertical turbulence measurements at these two sodar 221 sites are roughly similar in magnitude much of the time. The difference between two 222 sodars for the observed TKE arises from the measurements along the u and v beams 223 (Finn et al. 2015). Thus, we excluded the ART sodar results that are probably not reliable 224 for the model comparison. This section discusses the velocity variance estimated by 225 different mixing options in HYSPLIT and shows the evaluations with observations taken 226 during PSB1.

a. Comparisons of the vertical velocity variances

228 The vertical velocity variance determines how the particles released at the source 229 location are dispersed in space and time. Figure 2 (a - d) is the profile of the vertical 230 velocity variance from HYSPLIT using four different mixing options during 12-15MST on October 5th, 2013 (IOP2). Both BH and KC methods diagnose the vertical 231 232 velocity variance based upon state variables and variables relevant to the PBL stability. 233 Depending on the stability regimes and the altitudes (within the surface layer, in the PBL, 234 or in the free atmosphere), the model has a different set of equations to diagnose the 235 mixing of particles (Draxler and Hess, 1998). Other than the maximum at the middle of 236 PBL, the profile of BH and KC mixing options had a secondary maximum transitioning 237 from the top of the PBL to the free atmosphere (Figure 2 a and b). The vertical velocity

238	variance profile from the KC option had a small peak within the surface layer while the
239	one from the BH option went to almost zero values near the surface. As shown in Figure
240	2 c and d, the vertical velocity variance profiles from TKED and EXCH options looked
241	quite different. These two methods depend on the profile of TKE and exchange
242	coefficient provided by WRF, respectively. The definition of TKE is the summation of
243	velocity variances (horizontal and vertical) divided by two that represents the strength of
244	turbulence in the flow. It is computed in WRF's PBL schemes (the MYNN schemes in
245	this study) using the prognostic TKE equation. The turbulent exchange coefficient is a
246	scalar to relate the turbulent flux to the gradient of the associated mean variable. The
247	MYNN PBL scheme diagnoses the exchange coefficient according to the prognostic TKE,
248	a mixing length, and a stability function (Nakanishi and Niino, 2006).
249	There are studies, such as Munoz-Esparza et al. (2018), Ferrero et al. (2018), and
250	Hari Prasad et al. (2017), showing the problem of the TKE estimation produced by
251	various WRF's TKE-based PBL schemes. Ferrero et al. (2018) evaluated several PBL
252	parameterizations available in WRF with experimental data conducted in Turin, Italy.
253	The results showed the underestimation of the model TKE in comparison with the
254	measurements (anemometer at 25 m height) in a summer month and less underestimation
255	of TKE in a winter month. We compared the predicted TKE from WRF with observed
256	TKE taken at 30 m height of the GRI tower during PSB1. In addition to the MYNN run,
257	other simulations were conducted with different TKE-based PBL schemes, including the
258	Bougeault and Lacarrere scheme (BouLac; Bougeault and Lacarrere, 1989), the Quasi-
259	Normal Scale Elimination scheme (QNSE; Pergaud et al. 2009), the UW boundary layer
260	scheme (UW; Bretherton and Park 2009), the Mellor-Yamada-Janjic (MYJ; Janjic, 1994),

261 and the Grenier-Bretherton-McCaa (GBM; Grenier and Bretherton 2001). The 262 comparison showed all modeled TKE values were underestimated (Figure 3). Among 263 various PBL schemes, the BouLac underpredicted the least and MYNN was the second 264 least underprediction of TKE. The run using MYJ and QNSE schemes underpredicted the 265 most. The length scales and TKE prediction cause the differences in turbulent exchange 266 coefficient computed by various PBL schemes. Among the six schemes, the GMB and 267 UW schemes produced larger exchange coefficient while the QNSE and BouLac had 268 smaller values during PSB1 (not shown). Thus, these meteorological uncertainties may 269 have impact on the dispersion result when we use TKED and EXCH mixing options to 270 estimate the turbulent velocity variance.

271 The observational tower at the ASC station provides vertical profiles of velocity variance from 30 - 150 m. Observed vertical velocity variance at ASC ranges from 0.2 - 150 m. 272 0.9 m²s⁻² with the maximum at about 100 m height (Figure 2e). Note that the stability 273 274 condition on the day of IOP2 was unstable with low wind speeds. The KC and EXCH option generated a maximum vertical velocity variance of about 1.5 m²s⁻² at an altitude of 275 about 500 m. The TKED profile had the smallest maximum values (about $0.5 \text{ m}^{2}\text{s}^{-2}$) 276 277 among all and a smooth decrease with height from a maximum value to a minimum value 278 in the free atmosphere. In the BH case, the vertical velocity variance profile at about 100 279 m height was similar to the observations but the maximum value was slightly 280 underestimated. Figure 4 is the vertical velocity variance profiles for IOP5 (12 - 15 MST)on October 18th, 2013), which was a weakly unstable condition with moderate wind 281 282 speeds. The modeled vertical velocity variance had less variation throughout the 283 afternoon than the observed values. In comparison with other options, the EXCH profile

284 showed larger temporal variability. Note that the sodar measurements for the turbulent 285 velocity variance available in PSB1 were limited to 30 - 150 m height. The study of Berg 286 et al. (2017) using year-long vertical variance data from Doppler Lidar data for the 287 convective boundary layer showed that the maximum of the composite vertical velocity variance was about $1.2 \text{ m}^2\text{s}^{-2}$ at about 200 - 700 m height. Thus, the velocity variance 288 289 measurements from PSB1 were insufficient to evaluate the simulated maximum vertical 290 velocity variance, which might occur at the altitude above the sodar could reach. 291 The comparison of vertical velocity variance at and below 30 m was done using 292 measurements of 3-d sonic anemometers at the FLX station (3.2 m; Figure 5) and the 293 GRI station (30 m; Figure 6). The magnitude of the observed vertical velocity variance in 294 the afternoons of four IOPs was about $0.2 \text{ m}^2\text{s}^{-2}$ near the surface (3.2 m height). IOP 3 was an exception that its value went up to $0.6 \text{ m}^2\text{s}^{-2}$. As discussed in Finn et al. (2015), 295 296 tracer releases in PSB1 were conducted on days with unstable (or weakly unstable) 297 stability conditions but IOP3 experienced a neutral condition with strong wind speeds. 298 The meteorological evaluation presented in Ngan et al. (2018) showed that WRF failed to 299 generate the rapid increase of high wind speeds observed during IOP3 causing negative 300 bias for the friction velocity. Thus, we expected the KC option would underestimate the 301 turbulent mixing because the velocity variances were diagnosed as a function of friction 302 velocity. In general, the KC and TKED mixing methods overestimated the vertical 303 velocity variance (except IOP3) while the EXCH mixing slightly underestimated it. At 30 m height (GRI station), the observed vertical velocity variance was about $0.4 - 0.6 \text{ m}^2\text{s}^{-2}$. 304 305 The KC, TKED, and EXCH options generated the values comparable to the 306 measurements while the vertical velocity variance from KC was larger than those from

other mixing options. The vertical velocity variance generated by the BH method was
underestimated the most in the comparison with measurements at both 3.2 m and 30 m.

309 b. Estimation of the horizontal velocity variances

310 The mixing methods determine the way the meteorological data are processed to 311 compute vertical and horizontal turbulence. In this study, the horizontal velocity variance 312 was obtained in proportion to the vertical component. Figure 7 is the time series of horizontal velocity variance at the FLX station. The magnitude was about $1.2 - 1.8 \text{ m}^2\text{s}^{-2}$ 313 314 in the afternoon during the period of tracer release. For the BH mixing scheme, the 315 diagnosed turbulence is portioned equally between the vertical and horizontal component 316 resulting in a larger negative bias in the horizontal velocity variance. For the KC and 317 TKED mixing options, the calculation has more turbulence going into the horizontal 318 component than the BH method does (Stein et al. 2015). The horizontal velocity variance 319 in KC and TKED mixing were comparable to the measured values with a small 320 underestimation. The underestimations of horizontal velocity variances were more 321 significant in IOP3 than other episodes because of the under-prediction of the wind fields 322 and vertical mixing.

Using velocity variance measurements taken at different locations and heights in the area of the sampling array, we computed the ratio of the horizontal and vertical components (Table 1). The right-most column of the table includes the data only in the afternoon of four IOP days. The ratio was in the range of 4.5 - 5.8 for data measured near the surface at 3.2 m or 4 m height. It became smaller, ranging about 1.5 - 2.6, when using data observed at higher levels (30 m or 45 m). The sodar measurement at the ASC station showed the ratio of horizontal and vertical velocity variance got to about a one to one 330 ratio at 130 m. For the EXCH mixing option, we selected the maximum (5.8733) and 331 minimum value (1.5430) of the ratios at near surface and 45 m height, respectively. They 332 were applied to compute the horizontal velocity variance. Two cases, labeled as "EXCH" 333 and "EXCHm" using the maximum and minimum ratios, respectively, were included in 334 Figure 7. With a larger scaling factor, EXCH had a larger horizontal velocity variance 335 than EXCHm which used a smaller scaling factor. However, both cases underestimated 336 horizontal velocity variance in comparison with the measurements at 3.2 m height. For 337 the comparison with data at 30 m height, the underestimation decreased.

338

5. Dispersion results for PSB1

339 We conducted HYSPLIT simulations performed with different turbulent mixing 340 parameterizations and driven by WRF meteorological model output for the four IOPs 341 from PSB1. The mixing options described in the previous section were labeled as BH, 342 KC, TKED and EXCH. For the mixing option using WRF's turbulent exchange 343 coefficient, we conducted two simulations "EXCH" and "EXCHm" by applying the 344 maximum and minimum ratio of the horizontal and vertical component of measured 345 velocity variance. The statistical evaluation followed Draxler (2006) which introduced a 346 cumulative score (so called the Rank, ranging from 0 to 4) including four normalized 347 components – the correlation coefficient (R), fractional bias (FB), figure-of-merit in 348 space (FMS), and Kolmogorov-Smirnov parameter (KSP).

349
$$Rank = R^{2} + 1 - \left|\frac{FB}{2}\right| + \frac{FMS}{100} + \left(1 - \frac{KSP}{100}\right)$$

Figure 8 shows the statistical rank of five dispersion simulations for each IOP inPSB1. The model performed differently with varying mixing options for different

352 episodes, but no one mixing option always produced a better result. In general, the range 353 of statistical scores of simulations using different mixing options for IOP4 and IOP5 was 354 smaller than those for the other two IOPs, possibly due to WRF more accurately 355 simulating the wind patterns during IOP4 and IOP5 than IOP2 and IOP3. Other than the 356 dispersion process in which the estimation of turbulent velocity variance is an essential 357 component, the advection process driven by the mean winds determines the movement of 358 the tracer plume. In the IOP4 and IOP5 scenarios, the tracer plume was transported by 359 northwesterly flows steadily from the source toward the outer arcs of the sampling array 360 and without much variation throughout the release duration. In general, the rank for 361 EXCH was better than EXCHm for all four episodes because the larger horizontal 362 velocity variance in the EXCH simulation generated a wider plume. However, the 363 dispersion result was not very sensitive to the horizontal velocity variance since the wind 364 shear was the dominant factor for the spreading of the plume in the horizontal direction. 365 IOP2 had the lowest rank among all four episodes due to the inaccurate prediction 366 of varying wind directions associated with the light winds. The modeled plume was 367 narrower and further downwind, going northeastward to the outer arcs of the sampling 368 array, than the observed plume (Figure 9). In this case, the strong mixing produced by 369 the KC and EXCH method was able to disperse particles more, which resulted in less 370 overestimation (smaller FB in the rank bar-chart) of the tracer concentration compared to 371 other cases. We notice the underprediction of TKE in the comparison of the observed 372 values at the ASC station (not shown) that caused the weak mixing in the TKED method. 373 A sensitivity test was conducted using two times of TKE values from WRF to drive a 374 dispersion simulation with the TKED mixing option. This result had better statistical

scores (Rank=1.67) compared to the result shown in Figure 9 (Rank=1.47) because the
stronger mixing was able to improve the overprediction of the surface concentration and
the coverage of the plume.

378 For IOP3, even though the rank had better statistical scores than IOP2, the 379 simulated plume went out of the sampling array at the beginning of the release. The 380 weaker mixing generated by the BH and TKED method resulted in higher concentrations 381 near the source location (better FB in the rank bar-chart) than EXCH did. However, the 382 BH plume was narrow due to the significant underestimation of the horizontal velocity 383 variance that resulted in getting the worst rank. For the scenario of IOP3, the strong 384 mixing in the EXCH simulation caused more underprediction of surface concentration 385 (worse FB) than other cases. Compared to the TKED plume (Figure 10d), the EXCH plume had a lower concentration and was slightly wider. The surface wind measurements 386 387 indicated strong southwesterly winds during the tracer release while WRF generated light 388 wind speeds and varying wind directions until southwesterly winds picked up during the 389 second hour of the release (Ngan et al. 2018). The underestimation of the turbulence near 390 the surface in the KC mixing option (referring to Figure 5 and Figure 6) due to the 391 negative bias in the wind speed and friction velocity might cause less mixing than others. 392 As shown in the difference plot (Figure 10c), the KC case had more particles 393 accumulating near the source location (in the area within the 200-m arc) while the TKED 394 run moved particles farther away.

395 6. Dispersion results for CAPTEX

396	HYSPLIT simulations driven by WRF with 9-km grid spacing were conducted
397	using the four mixing options for the six releases during CAPTEX. Figure 11 shows the
398	time series of vertical velocity variance profiles for 24 hours after the beginning of an
399	afternoon tracer release at Dayton, Ohio (CAPTEX 1). The KC and EXCH mixing had
400	the maximum vertical velocity variance at the 10th model layer (~900 m) during the
401	afternoon hours (17 – 21 UTC). The maximum values were smaller and occurred at the
402	lower layers in the other two mixing methods. The profile of the vertical velocity
403	variance generated by the TKED method was flat with values ranging from about $1.0 -$
404	1.4 m^2s^{-2} from the surface to the middle of the PBL where the maximum was observed.
405	However, the profile in the EXCH mixing option had large gradients near the surface (the
406	lowest 3 model layers, $0 - 70$ m) and at the top of PBL ($13^{th} - 15^{th}$ model layer, $1.5 - 2.0$
407	km). During the nighttime, close to zero vertical velocity variance values were produced
408	by the EXCH mixing. This is due to a constant Lagrangian time scale that was used for
409	the daytime unstable condition. Unlike PSB1 episodes that all occurred in the afternoon
410	with well-mixed conditions, for scenarios like CAPTEX experiencing different stability
411	conditions throughout the day, a time-varying Lagrangain time scale will be more
412	appropriate for estimating the turbulent velocity variance. Figure 12 is an example of
413	CAPTEX 7, which was a nighttime release at Sudbury, Ontario, Canada. Similar patterns
414	for the vertical velocity variance profile were observed in other releases of CAPTEX.
415	The BH and KC simulations had similar horizontal and vertical distribution
416	patterns of particles for CAPTEX 1 and resulted in comparable statistical ranks (Figure
417	13). There were more particles moved to upper levels and less particles stayed in the
418	lowest 500 m in the TKED simulation. In general, particles were mixed to higher

419 altitudes in the TKED option since its vertical velocity variance profile extended to 420 higher levels than others. In the EXCH case, particles near the surface (the lowest 500 m) 421 moved slower than the particles above. That may be due to the almost zero vertical 422 mixing during the nighttime, resulting in particles remaining over Lake Erie and Lake 423 Ontario and positive bias of tracer concentration in those area. For CAPTEX 7, the 48-424 hour averaged concentration patterns generated by the KC and TEKD mixing were 425 similar as shown in Figure 14. The tracer plume in EXCH was narrow at the beginning of 426 the episode and then became wider in the downwind area that resulted in worse statistical 427 scores than other simulations. The constant turbulent time scale used in the EXCH option 428 for computing vertical velocity variances might cause too little mixing at night and 429 overestimation during daytime. Overall, the statistical rank for all six CAPTEX episodes 430 (Table 2) shows that the TKED mixing had good performance while the BH options 431 produced the worst results. For individual episodes, except CAPTEX 2 in which all four 432 mixing options performed similarly, there was no one scheme that always outperforms 433 the other options. It is appropriate to keep various options for users to choose depending 434 on different scenarios or to create dispersion ensembles.

435

7. Summary and discussion

The turbulent velocity variance is an essential variable in HYSPLIT to determine the mixing of particles. There are different options available in the model to estimate the turbulent velocity variance according to the stability and turbulent variables provided by the meteorological data. In this study, we conducted HYSPLIT simulations driven by WRF meteorology and using different mixing methods for two control tracer experiments – PSB1 and CAPTEX that aimed for the sub-kilometer and long-range transport,

respectively. Through the comparisons of turbulent velocity variance (only for PSB1) and
the evaluation of tracer concentrations with measurements, we assessed the performance
of different mixing options affecting the dispersion results.

445 The KC and EXCH mixing options produced a larger maximum of the vertical 446 velocity variance than other mixing options did. Simulated maximum vertical velocity 447 variance occurred at an altitude of about 500 m, which is above the tower measurement 448 available in the PSB1. The vertical velocity variance profile obtained from the BH 449 method had a sharp increase from the surface to the height of the maximum values (about 450 200 m). The TKED case had a flat vertical velocity variance profile with the smallest 451 variation in its value with height and maximum compared to other cases. The comparison 452 with measurements near the surface (height at 3.2 m and 30 m) taken during the PSB1 453 showed that the BH scheme underestimated vertical velocity variance while the KC 454 option slightly overestimated it. The dispersion results for IOP4 and IOP5 (weak unstable 455 conditions with moderate winds) were less sensitive to the mixing option than the runs 456 for IOP2 (unstable with light winds) and IOP3 (neutral with strong winds). The plumes 457 generated by the BH and TKED method (less disperse due to the weaker vertical velocity 458 variance) had higher concentrations near the surface than those driven by the KC and 459 EXCH option (stronger mixing). The larger horizontal velocity variance in the EXCH 460 generated a slightly wider plume than the one in the EXCHm simulation. HYSPLIT 461 simulations using different mixing options were conducted for six CAPTEX episodes. 462 The statistical rank for the TKED run was slightly better than others while the BH mixing 463 generated results with the worst rank. For scenarios like CAPTEX experiencing different

stability conditions throughout the day, a time-varying Lagrangain time scale may bemore appropriate for estimating the turbulent velocity variance.

466 The model performed differently with the four mixing options in varying 467 scenarios. No one mixing option always outperformed the other options. HYSPLIT users 468 can select a mixing option according to their scenario and availability of meteorological 469 fields, as well as use different mixing options to generate dispersion ensembles. The KC 470 and BH methods re-compute various stability parameters with assumptions for different 471 stability conditions to obtain the turbulent velocity variance for the dispersion process. 472 Errors due to the process of re-diagnosing variables may be carried to the dispersion 473 simulation. However, the advantage of these two methods is that unlike the other options, 474 no extra variable is required. If only basic meteorological parameters such as wind, 475 temperature, and pressure are available, HYSPLIT has an alternative option to estimate 476 the boundary layer stability parameters for computing the turbulent velocity variance 477 (Stein et al. 2015).

478 The TKED and EXCH options depend on the mixing variables (TKE and 479 exchange coefficient, respectively) provided by WRF. If the meteorological data provide 480 well-simulated TKE fields, HYSPLIT can obtain the velocity variance by partitioning the 481 horizontal and vertical components. Thus, the main concern for HYSPLIT is to set a 482 reasonable anisotropy ratio. Note that there is no TKE output if a first-order K-profile 483 PBL scheme is used for running the meteorological simulation. The underestimation of 484 TKE values by WRF in the unstable condition shown in the comparison with 485 measurements from PSB1 needs further investigation. For the EXCH option, the 486 turbulent exchange coefficient is needed, but it is not commonly available in

487 meteorological model output or reanalysis products that can be used to drive HYSPLIT. 488 Different PBL schemes have their ways of computing the exchange coefficient, and the 489 results are rarely evaluated. It is recommended to use a time-varying Lagrangian time 490 scale to estimate the velocity variance with the turbulent exchange coefficient. The 491 uncertainty of TKE and exchange coefficient prediction may influence the dispersion 492 simulation when the velocity variance is computed by the TKED or EXCH mixing option. 493 For future works, we are interested in an evaluation of modeled vertical velocity variance 494 with long-term observations that may further give us insight how each mixing option 495 performs for stable nighttime conditions and unstable daytime conditions. Such 496 measurements may be found in the DCNet research network (Hicks et al. 2013) and 497 Doppler Lidar data (Berg et al. 2017). The DCNet data are measurements at six suburban 498 areas in the eastern United States while Lidar measurements can provide data covering 499 the entire PBL. With continuous measurements, the velocity variance evaluation is not 500 limited to certain days or stability scenarios. Furthermore, Project Sagebrush Phase 2 501 (PSB2; Finn et al. 2018), which was conducted in 2016, consisted of four IOPs during 502 very unstable conditions and four IOPs during very stable conditions. Similar to the setup 503 of PSB1, velocity variance observations are available along with tracer concentration 504 measurements that can be used to evaluate HYSPLIT's turbulent mixing options and their 505 impact on dispersion results.

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510 **References**

- 511 Beljaars, A.C.M., and A.A.M. Holtslag, 1991: Flux parameterizations over land surfaces
 512 for atmospheric models. *J. Appl. Meteorol.*, **30**, 327-341.
- 513 Berg L. K., R. K. Newsom, and D. D. Turner, 2017: Year-long vertical velocity statistics
- 514 derived from Doppler Lider data fro the continental convective boundary layer. J.
- 515 *Appl. Meteorol. Clim.*, **56**, 2441-2454.
- 516 Betchov, R., and A.M. Yaglom, 1971: Commetns on the theory of similarity as applied to
- 517 turbulence in an unstably stratified fluid. *Atmos. Oceanic Phys.*, **7**, 829-832.
- 518 Bougeault, P., and P. Lacarrere, 1989. Parameterization of orography-induced turbulence
- 519 in a mesobeta-scale model. *Mon. Weather Rev.*, **117**, 1872–1890.
- 520 Bretherton, C. S., and S. Park, 2009: A New moist turbulence parameterization in the
- 521 Community Atmosphere Model. J. Climate, 22, 3422–3448,
- 522 doi:10.1175/2008JCLI2556.1.
- 523 Kantha, L.H. and C.A. Clayson, 2000: Small Scale Processes in Geophysical Fluid
- 524 Flows, Vol. 67, International Geophysics Series, Academic Press, San Diego, CA,
- 525 883 pp.
- 526 Kadar, B.A., and V.G. Perepelkin, 1989: Effect of the unstable stratification on wind and
- 527 temperature profiles in the surface layer. *Atmos. Oceanic Phys.*, **25**, 583-588.
- 528 Chen, F., and J. Dudhia, 2001: Coupling and advanced land surface-hydrology model
- 529 with the Penn State–NCAR MM5 modeling system. Part I: Model implementation
- 530 and sensitivity. *Mon. Wea.Rev.*, **129**, 569–585.

- 531 Dee, D. P. and Co-authors, 2011: The ERA-Interim reanalysis: configuration and
- 532 performance of the data assimilation system. *Quarterly Journal of the Royal*
- 533 *Meteorol. Soc.*, **137**, 553-597.
- 534 Draxler, R. R., 2006: The use of global and mesoscale meteorological model data to
- 535 predict the transport and dispersion of tracer plumes over Washington, D.C. *Wea*.
- 536 *Forecasting*, **21**, 383–394.
- 537 Draxler, R. R. and G. D. Hess, 1997: Description of the HYSPLIT_4 modeling system.
- 538 NOAA Tech. Memo. ERL ARL-224, NOAA/Air Resources Laboratory, Silver
- 539 Spring, MD, 24 pp. [Available online at
- 540 <u>http://www.arl.noaa.gov/documents/reports/arl-224.pdf.</u>]
- 541 Draxler, R. R. and G. D. Hess, 1998: An overview of the HYSPLIT_4 modeling system
 542 for trajectories, dispersion, and deposition. *Aust. Meteor. Mag.*, 47, 295–308.
- 543 Ferber, G. J., J. L. Heffter, R. R. Draxler, R. J. Lagomarsino, F. L. Thomas, and R. N.
- 544 Dietz, 1986: Cross-Appalachian Tracer Experiment (CAPTEX-83) final report.
- 545 NOAA Tech. Memo. ERL ARL-142, 60 pp. [Available online at
- 546 <u>http://www.arl.noaa.gov/documents/reports/arl-142.pdf</u>]
- 547 Ferrero, E., S. Alessandrini, and F. Vandenberghe, 2018: Assessment of Planetary-
- 548 Boundary-Layer schemes in the Weather Research and Forecasting model within and
- by above an urban canopy layer. *Bound.-Layer Meteor.*, **168**, 289–319.
- 550 Finn, D., K. L. Clawson, R. M. Eckman, H. Liu, E. S. Russell, Z. Gao, and S. Brooks,
- 551 2016: Project Sagebrush: Revisiting the value of the horizontal plume spread
- 552 parameter σy. J. Appl. Meteorol. Clim., 55(6), 1305-1322. doi: 10.1175/JAMC-D-
- 553 15-0283.1

- 554 Finn, D. and Coauthor, 2015: Project Sagebrush Phase 1. NOAA Tech Memo OAR
- 555 ARL-268, 362 pp. [Available online at

556 https://www.arl.noaa.gov/documents/reports/ARL-TM-268.pdf]

- 557 Finn, D., R. G. Carter, R. M. Eckman, J. D. Rich, Z. Gao, and H. Liu, 2018: Plume
- 558 Dispersion in Low-Wind-Speed conditions during Project Sagebrush Phase 2, with
- 559 emphasis on concentration variability. *Bound.-Layer Meteor.*, **169**, 67–91.
- 560 Grenier, H., Bretherton, C.S., 2001. A moist PBL parameterization for large-scale models
- and its application to subtropical cloud-topped marine boundary layers. *Mon.*
- 562 *Weather Rev.*, **129**, 357–377.
- 563 Hari Prasad, K. B. R. R., C. V. Srinivas, T. Narayana Rao, C. V. Naidu, R. Baskaran,
- 564 2017: Performance of WRF in simulating terrain included flows and atmospheric
- 565 boundary layer characteristics over the tropical station Gadanki. *Atmospheric*
- 566 *Research*, **185**, 101-117.
- 567 Hicks, B. B., E. Novakovskaia, R. J. Dobosy, W. R. Pendergrass, and W. J. Callahan,
- 568 2013: Temporal and spatial aspects of velocity variance in the urban surface
- 569 roughness layer. J. Appl. Meteor. Climatol., **52**, 668-681.
- 570 Janjic, Z.I., 1994: The step-mountain eta coordinate model: further developments of the
- 571 convection, viscous sublayer, and turbulence closure schemes. *Mon. Weather Rev.*,
- **122**, 927–945.
- 573 Kanamitsu, M., 1989: Description of the NMC global data assimilation and forecast
- 574 system. *Weather Forecast*, **4**, 334–342.

575	Munoz-Esparza, D., R. D. Sharman, and J. K. Lundquist, 2018: Turbulence Dissipation
576	Rate in the Atmospheric Boundary Layer: Observations and WRF Mesoscale
577	Modeling during the XPIA Field Campaign. Mon. Weather Rev., 146, 351-370.
578	Nakanishi, M. and H. Niino, 2006: An Improved Mellor–Yamada Level-3 Model: Its
579	Numerical Stability and Application to a Regional Prediction of Advection Fog.
580	BoundLayer Meteor., 119, 397-407.
581	Ngan, F. and A. Stein, 2017: A Long-Term WRF Meteorological Archive for Dispersion
582	Simulations: Application to Controlled Tracer Experiments, J. Appl. Meteor.
583	Climatol., 56, 2203-2220, https://doi.org/10.1175/JAMC-D-16-0345.1
584	Ngan, F., A. Stein, D. Finn, and R. Eckman, 2018: Dispersion Simulations using
585	HYSPLIT for the Sagebrush Tracer Experiment. Atm. Environ., 186, 18-31.
586	Pergaud, J., Masson, V., Malardel, and S., Couvreux, F., 2009. A parameterization of dry
587	thermals and shallow cumuli for mesoscale numerical weather prediction. Bound
588	<i>Layer Meteor.</i> , 132 , 83–106.
589	Powers, J. G. and Co-authors, 2017: The Weather Research and Forecasting Model:
590	Overview, System Efforts, and Future Directions. Bull. Amer. Meteor. Soc., 98:8,
591	1717-1737.
592	Rienecker, M. M. and Co-authors, 2011: MERRA: NASA's Modern-Era Retrospective
593	Analysis for Research and Applications. Journal of Climate., 24, 3624-3648.
594	Shin, H. H., S. Y. Hong and J. Dudhia, 2012: Impacts of the Lowest Model Level Height
595	on the Performance of Planetary Boundary Layer Parameterizations. Mon. Wea.

Rev., **140**, 665-682.

- 597 Shin, H. H. and J. Dudhia, 2016: Evaluation of PBL Parameterizations in WRF at
- 598 Subkilometer Grid Spacings: Turbulence Statistics in the Dry Convective Boundary
- 599 Layer. Mon. Wea. Rev., 144, 1161-1177.
- 600 Stein, A. F., R. R. Draxler, G. D. Rolph, B. J. B. Stunder, M. D. Cohen and F. Ngan,
- 601 2015: NOAA's HYSPLIT atmospheric transport and dispersion modeling system.
- 602 Bull. Amer. Meteor. Soc., 96, 2059-2077.

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- 650 while color-coded circles are measured concentrations. Rank of each simulation is noted
- 651 in each panel. Unit: $\log(pg/m^{-3})$.
- 652

Table 1 The ratio of u- and w-variance computed by using measurements taken during theSagebrush experiment.

Station name	Measurement Height (m)	All data in October	Data on the day of IOPs	Data during 12-18MST on IOP days
G1	4	3.7041	4.1874	4.5567
G2	30	2.4748	2.6607	2.6127
R1	45	1.8743	1.8830	1.9990
R2	3.2	4.2582	4.5396	4.5487
R3	3.2	4.4776	5.1804	5.3276
R4	3.2	4.6456	5.6300	5.8733
FLX	3.2	3.9803	4.6829	5.3066
ASC	30	-	1.5909	1.8236
	40	-	1.4331	1.5430
	50	-	1.4335	1.4650
	60	-	1.3115	1.3045
	70	-	1.1898	1.2175
	80	-	1.1499	1.1052
	100		1.0902	1.0343
	130	-	1.0646	1.0058
	160	-	1.1152	0.8208

657 Table 2 Rank corresponding to HYSPLIT model results for six CAPTEX tracer releases.

Release	BH	KC	TKED	EXCH
R1	2.49	2.50	2.62	2.38
R2	2.78	2.72	2.73	2.79
R3	1.98	1.95	2.11	2.13
R4	2.14	2.18	2.16	2.49
R5	2.64	2.52	2.65	2.68
R7	2.25	2.36	2.33	2.12
All ^a	2.35	2.49	2.51	2.44

^a All data points from six releases are used.

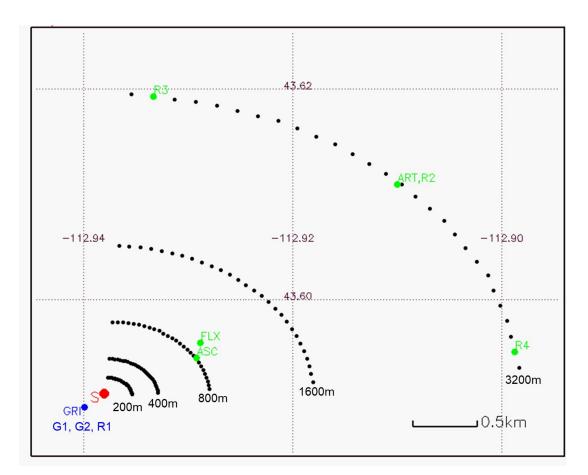
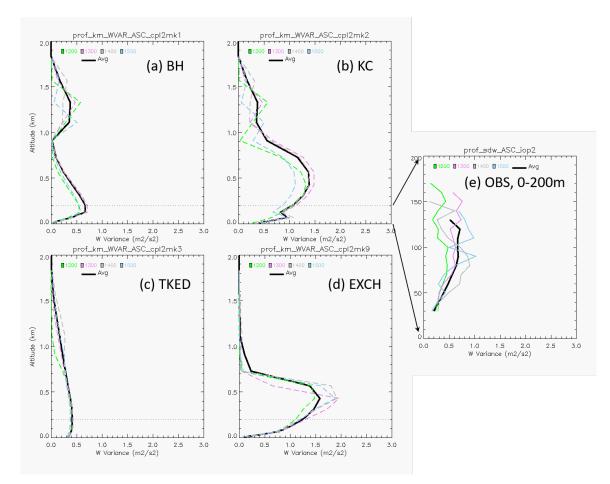


Figure 1 Sampling network for tracer measurements (black dots) for the Sagebrush tracer

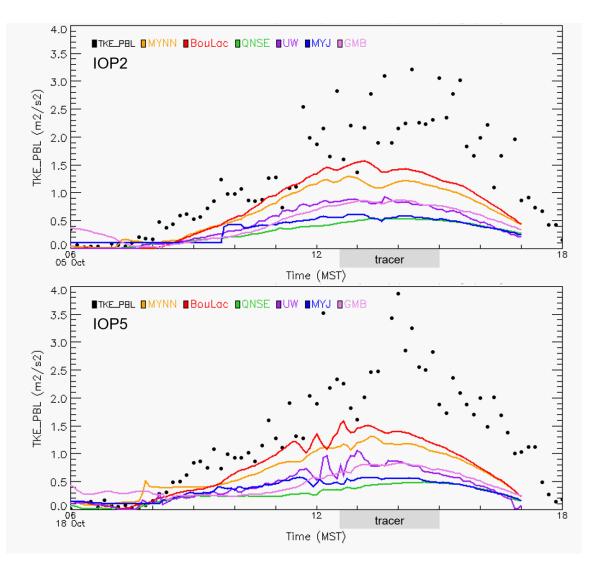
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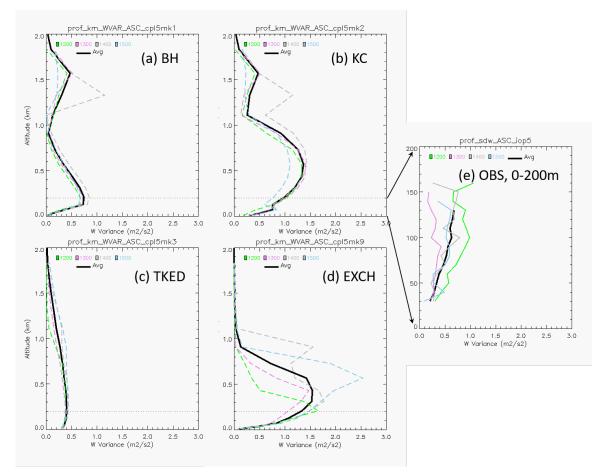
15 MST on October 5th, 2013.



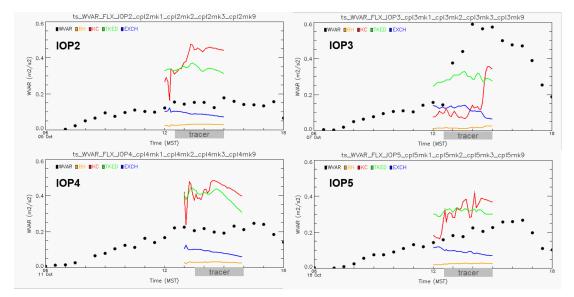


674 Figure 3 The time series of observed and modeled TKE (m²s⁻²) at the GRI tower (30 m height) for

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677 Figure 4 The same as Figure 2 but for IOP 5, 12 – 15 MST on October 18th, 2013.





680 Figure 5 Time series of observed and modeled vertical velocity variance from HYSPLIT. The

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 layer at 10 m.

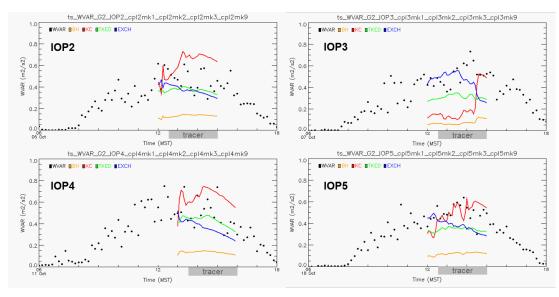




Figure 6 The same as Figure 5, except the measurements were taken at the GRI station at 30 m
 height and the modeled values were at 2nd model layer at 30 m.

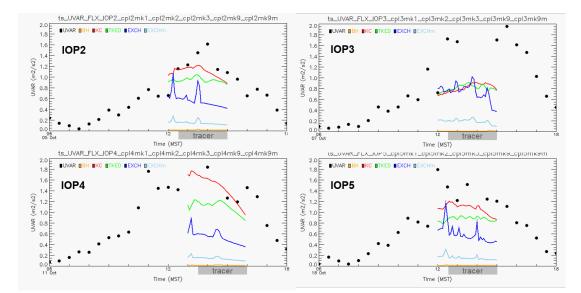
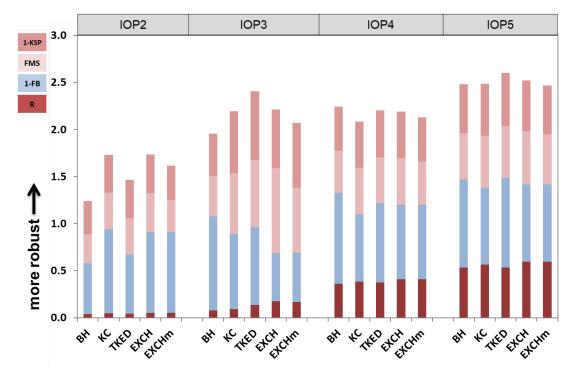




Figure 7 The same as Figure 5, except for the horizontal velocity variance.



692 Figure 8 The statistical Rank of HYSPLIT results using different mixing options.

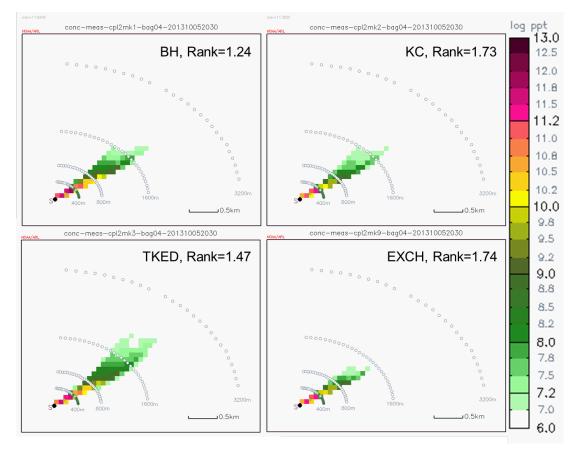




Figure 9 Tracer concentration plots for IOP 2 at 2030 UTC on October 5th, 2013 from HYSPLIT
 simulations using different mixing options. The shaded color is model concentrations while color coded circles are measured concentrations. Rank of each simulation is noted in each panel. Unit: log
 ppt.

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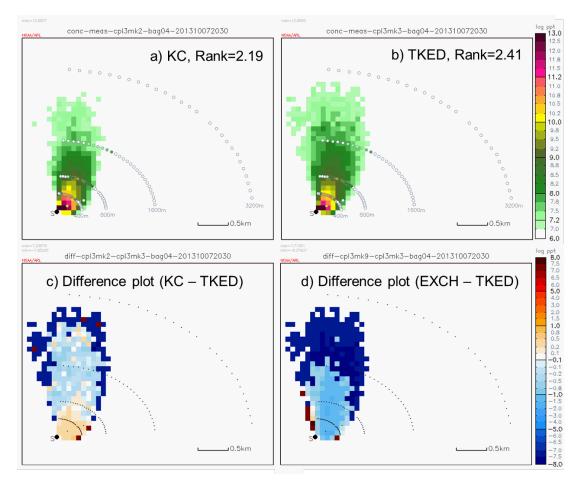
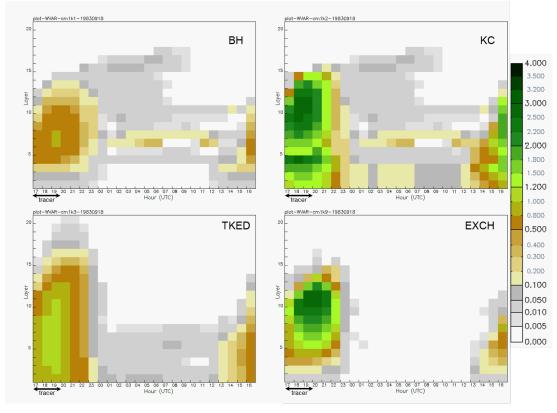


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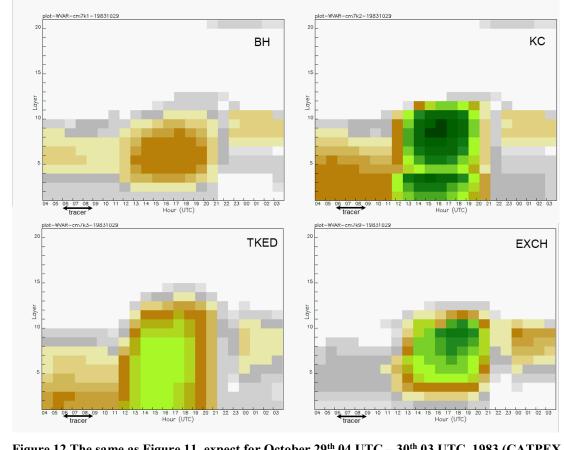


Figure 12 The same as Figure 11, expect for October 29th 04 UTC - 30th 03 UTC, 1983 (CATPEX 7).

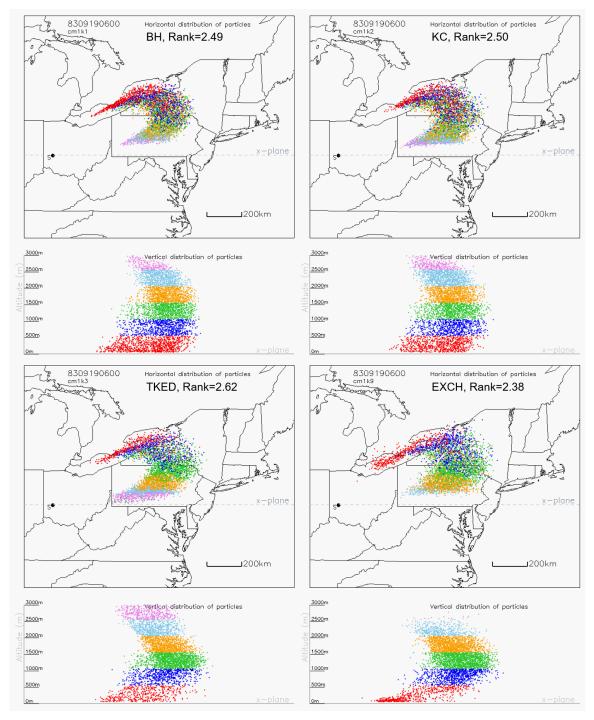


Figure 13 Horizontal and vertical distribution of particles simulated by HYSPLIT using different
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 altitudes. Rank of each simulation is noted in each panel.

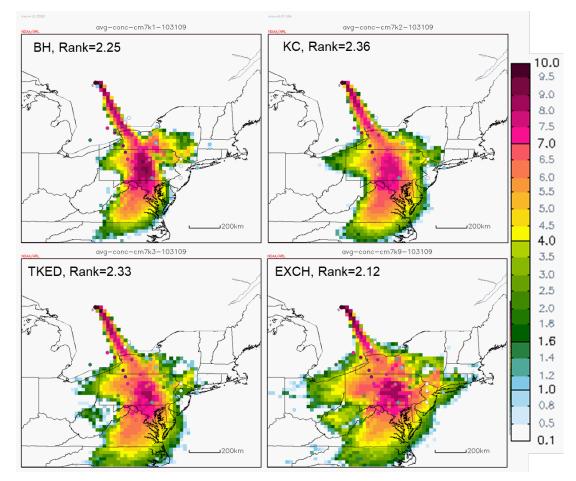




Figure 14 Tracer concentration plots for CAPTEX 7 from HYSPLIT simulations using different
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