

Vertical profiling of atmospheric air pollutants in rural India: A case study on particulate matter (PM10/PM2.5/PM1), carbon dioxide, and formaldehyde

Original

Vertical profiling of atmospheric air pollutants in rural India: A case study on particulate matter (PM10/PM2.5/PM1), carbon dioxide, and formaldehyde / Gautam, S.; Sammuel, C.; Bhardwaj, A.; Shams Esfandabadi, Z.; Santosh, M.; Gautam, A. S.; Joshi, A.; Justin, A.; John Wessley, G. J.; James, E. J.. - In: MEASUREMENT. - ISSN 0263-2241. - ELETTRONICO. - 185:November 2021, 110061(2021), pp. 1-15. [10.1016/j.measurement.2021.110061]

Availability:

This version is available at: 11583/2968855 since: 2022-08-01T14:59:20Z

Publisher:

Elsevier B.V.

Published

DOI:10.1016/j.measurement.2021.110061

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

Elsevier postprint/Author's Accepted Manuscript

© 2021. This manuscript version is made available under the CC-BY-NC-ND 4.0 license
<http://creativecommons.org/licenses/by-nc-nd/4.0/>. The final authenticated version is available online at:
<http://dx.doi.org/10.1016/j.measurement.2021.110061>

(Article begins on next page)

1 Vertical profiling of atmospheric air pollutants in rural India: A
2 case study on particulate matter (PM₁₀/PM_{2.5}/PM₁), carbon
3 dioxide, and formaldehyde

4 Sneha Gautam^{1*}, Cyril Sammuel¹, Aniket Bhardwaj¹, Zahra Shams Esfandabadi^{2,3}, M Santosh^{4,5},

5 Alok Sagar Gautam^{6*}, Abhishek Joshi⁶, Aldin Justin¹, G. Jims John Wesley¹, E J James¹

6 ¹Karunya Institute of Technology and Sciences, Coimbatore, 641114, Tamil Nadu, India

7 ²Department of Environment, Land and Infrastructure Engineering (DIATI), Politecnico di

8 Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy

9 ³Energy Center Lab, Politecnico di Torino, Via Paolo Borsellino 38/16, 10138 Torino, Italy

10 ⁴School of Earth Sciences and Resources, China University of Geosciences Beijing, Beijing

11 100083, China

12 ⁵Department of Earth Science, University of Adelaide, Adelaide SA 5005, Australia

13 ⁶Hemvati Nandan Bahuguna Garhwal University, Srinagar, Garhwal, Uttarakhand, 246174, India

14 *Corresponding Author:

15 Dr. Sneha Gautam

16 Email ID: snehagautam@karunya.edu / gautamsneha@gmail.com / phyalok@gmail.com

1 Vertical profiling of atmospheric air pollutants in rural India: A
2 case study on particulate matter ($PM_{10}/PM_{2.5}/PM_1$), carbon
3 dioxide, and formaldehyde

4 **Abstract**

5 Particulate matter is one of the major air pollutants that challenge the environment and human
6 health. In this study, we used an unmanned aerial vehicle associated with smart, low-cost sensors
7 to record the vertical profiles of particulate matters ($PM_{10}/PM_{2.5}/PM_1$), carbon dioxide, and
8 formaldehyde in a rural area of southern India. Our study covered the surface to 60 m above the
9 ground level compiling data over twenty days of measurements in March 2021. A total of thirty
10 flights were performed in the five selected locations. The data show a decrease in air pollutant
11 concentration with increasing height from the surface. However, statistical data analysis through
12 CHAID Decision Trees and 3-D visualization of the relationship between the pollutants and the
13 height, RH, and temperature show that the concentration of pollutants is more strongly influenced
14 by the location and meteorological parameters rather than the height from the surface. We infer
15 that transport through both advection and convection influences the vertical distribution of air
16 pollutants as inferred from meteorological analysis, including back trajectories using the Hybrid
17 Single-Particle Lagrangian Integrated Trajectory (HYSPLIT4) model. The long-range transport of
18 air mass could also contribute to the high concentration values of particulate matters, as found
19 through the five-day air mass backward trajectory analysis. Although the observed data sets are
20 confined to a height of 60 m AGL, the results from this study provide insights into the vertical

21 distribution of air pollutants, complementing ground-based measurement variations with different
22 spacing and timing.

23 **Keywords:** Particulate matter vertical profile; CO₂; Formaldehyde; Unmanned aerial vehicle;
24 Rural India.

25 **1. Introduction**

26 Our planet's environment is affected by various air pollutants in the atmosphere, particularly as a
27 result of anthropogenic activities (e.g., Li et al., 2015; Silva et al., 2021; Gollakota et al., 2021).

28 The particulate matter with different sizes affects climate change and visibility by reducing the
29 light as well as altering the atmospheric radiative budget (Wang et al., 2015; Praveen et al., 2012).

30 Air pollutants have also significantly severely impacted the life and environment (Lei et al. 2016;
31 Bond et al. 2013). Among these, formaldehyde, an organic component, has been shown to cause
32 serious health issues (Vardoulakis et al. 2020).

33 Ground-based measurements of particulate matter have been reported in several previous studies
34 (Ravina et al., 2021; Liu et al., 2019; Retama et al., 2015; Gautam et al. 2016; Patra et al. 2016;
35 Klompmaker et al., 2015). TA variation in chemical composition, size distribution, and mass
36 concentration of air pollutants at different heights in the urban atmosphere has also been reported
37 (Lu et al. 2016; Minguillón et al. 2015; Ferrero et al. 2010). The upward movement, dispersion,
38 diffusion, accumulation, and deposition of the particle are also influenced by planetary boundary
39 layers (Tang et al., 2016; Gautam et al. 2015). Thus, studies on the vertical profile of air pollutants
40 are critical to assess the air pollutant concentration at different heights and their spatial
41 characteristics, especially in the rural atmosphere. Various techniques such as Tethered balloons,
42 remote sensing, meteorological towers, and human-made aircraft were employed to assess the

43 vertical distribution of air pollutants in different geographic regions (Ran et al. 2016; Han et al.
44 2015; Ding et al. 2009; Strawbridge and Snyder 2004). Unmanned Aerial Vehicles (UAVs)
45 provides one of the robust and alternative methods with high-cost efficiency, flexibility, and
46 mobility to assess the vertical behavior of air pollutants (Schuyler and Guzman, 2017; Villa et al.
47 2016).

48 Previous studies which investigated air pollutant concentration / vertical distribution by using
49 UAVs (Bates et al. 2013) reported notable variation in the distribution patterns of particle
50 concentration. Some studies reported contrasting results of higher concentrations with increasing
51 height causing enhanced light absorption (Bates et al. 2013) or decreasing trend of fine particles
52 with increasing height (Zhu et al. 2019). Some researchers (Chilinski et al. 2016; Ran et al. 2016;
53 Ferrero et al. 2011) have observed lower air pollutants concentration above the planetary boundary
54 layer (PBL) compared to ground level under clean conditions. Some of the recent studies (Lu et
55 al. 2019; Ran et al. 2016) correlated these features to local emissions or local fossil fuel combustion
56 sources rather than the long-range transport sources. Peng et al. (2015) highlighted that the vertical
57 profile (300 and 1000 m above the ground level) of air pollutants, especially PM_{2.5}, might be
58 affected significantly by diurnal variation of temperature. However, one of the limitations in most
59 of these studies is the limited number of days/flights and the restricted data on specific pollutants.
60 Comprehensive investigations to understand the relationship between contaminants and
61 atmospheric stability are rare.

62 Analysis of the vertical distribution of such pollutants is necessary to understand the emission
63 sources, residence period, and dispersion of pollutants in the atmosphere. Most contaminants are
64 emitted from the ground sources and are usually limited to the lower atmosphere, within the PBL

65 (Samad et al., 2020), and the heights vary throughout the daytime, subject to atmospheric
66 conditions.

67 Pollutants from different sources get mixed, and their vertical distribution varies diurnally with
68 height. This layer in the lower atmosphere is termed a mixing layer (Baumbach 1996). Studies
69 have shown that the stability of PBL can reduce the mixing of pollutants due to the stable
70 atmosphere governed by wind speed and solar radiation (Zoras et al., 2006). Higher air pollution
71 episodes were reported previously during the temperature inversion in the lower atmosphere over
72 different geographical conditions (Janhall et al., 2006; Baumbach and Vogt, 2003; Silva et al.,
73 2007; Olofson et al., 2009; Guzmán-Torres et al., 2009; Panday and Prinn, 2009). Temperature
74 inversion hinders the convective air movement, and also restricts the dispersion of pollutants and
75 confines the pollutants within the limited air mass (Allaby 2007). This study was undertaken with
76 a view to assess the vertical distribution of pollutants and meteorological parameters and to
77 understand the temperature inversion and its impact on pollution over the study region.

78 Here we investigate the vertical profile distribution of major pollutants (i.e., formaldehyde
79 (HCHO), carbon dioxide (CO₂), and fine particulate matter (PM)) with meteorological conditions
80 to explore the vertical distribution pattern of air pollutants (i.e., PM₁₀, PM_{2.5}, PM₁, CO₂, & HCHO)
81 in a rural area of southern India. In the present study, we measured the vertical profile of air
82 pollutants (PM₁₀, PM_{2.5}, PM₁, CO₂, & HCHO) using UAVs (450 mm 3s quad multi-rotor setup)
83 for 12 days in March 2021 at the Karunya Institute of Technology and Sciences, Karunya Nagar,
84 Coimbatore, India. A total of 30 flights were employed at five different locations of the university
85 area with a height of 15 m, 30 m, 45 m, and 60 m (regulated by the DGCA (Directorate General
86 of Civil Aviation) above ground level between 08:00 am - 12:00 pm local time. The selected study
87 area is located approximately 28 km away from the urban area (Coimbatore city), thus providing

88 an opportunity to investigate the effects of meteorological parameters (i.e., temperature and
89 relative humidity) and regional transport on the local air pollution. Building Decision-trees (DTs)
90 in IBM® SPSS® software, the strength and effect of meteorological parameters and concentration
91 of the pollutants with height were evaluated for each of the five sampling locations. Furthermore,
92 the vertical distribution of air pollutants was visualized using the Fuzzy toolbox in MATLAB® to
93 understand how the atmospheric stability and layers influence pollutants' behavior at a vertical
94 scale. Our study reveals the influence of temperature and relative humidity. We also present and
95 evaluate cases with transportation influence from the main road (~ 1 km),

96 **2. Material and methods**

97 *2.1 Site Description and Experiment Design*

98 Karunya Nagar is in a rural area located within the Tamil Nadu State of southern India (Fig. 1 1),
99 around 30 km from the densely populated Coimbatore city. The study was piloted at the campus
100 of the Karunya University of Technology and Sciences (10.93620N, 76.74410E). By following
101 the regulation of DGCA, 30 successive flights were undertaken inside and outside the campus.
102 The duration of each round trip of flight (0 – 15m – 30m – 45m – 60 m from the ground and back)
103 was 10 minutes. Before each flight, ground-based measurement was conducted for 5 minutes.

104 *2.2 UAVs platform and instruments*

105 In this study, we conducted vertical monitoring by using a UAV (450mm 3s quad multi-rotor
106 setup). The drone moved upward in the direction from the ground to 60 m above ground level at a
107 constant speed of 1 m/s and then descended along the same path at the same rate. The total
108 developed payload was mounted on the drone for conducting air pollutant and meteorological

109 parameters (i.e., temperature and relative humidity) measurements. All sensors were mounted on
110 the UAV to minimize the influence of the downwash effects (Zhou et al., 2018).

111 The sensor (Prana Air – CIA+) is used for pollution measurement. The "Prana Air – CIA+" was
112 mounted on a quad configuration multi-rotor of 450 mm dimension, which runs on a 35 (12.6 V
113 3800 mah) lipo battery producing an appropriate flying time of 15 minutes. The multi-rotor
114 combined with 10 inches propellers and 900 kV high torque BLDC (Brushless DC) motor can lift
115 1.5 kg of payload in Air. The brain of the multi-rotor (ic) flight controller used in the setup is DJI
116 NAZA H LITE, which offers a steady flight to perform the flight plan. The GPS (Global
117 Positioning System) integrated with the flight controller helps in a stable flight, and features like
118 RTL, failsafe, altitude lock and GPS lock make the flight highly functional. Used an additional
119 flight controller (JHEHCU FTBT) to obtain live altitude telemetry using the JHEHCU FTBT flight
120 controller's barometric sensor. The flight controller also has an OSD (On Screen Display Chip)
121 and an additional intractable camera (RUNCAH Micro Swift 2 600 TVL) and AKK VTX (video
122 transmitter) of 5.8GHz band. The VTX transmits the on-flight footage and OSD data to a 5.8 GHz
123 video receiver connected to an android device.

124 Cluster analysis of air mass trajectories is used to find the contribution function of potential sources
125 of pollutants (Argyropoulos et al., 2013). This approach also provides information on the pathways
126 and flow patterns of air mass followed before reaching the observation site (Borbély-Kiss et al.,
127 1999). Trajectory statistics and transport models combined with satellite or ground-based
128 observations provide spectral and temporal distribution of pollutants and improve the forecast of
129 air quality (Mijling et al., 2012). Cluster analysis of five days' air mass back trajectories was
130 performed using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT4) model
131 (Stein et al., 2015). The meteorological data for the trajectory calculation is obtained from

132 NOAA's Global Data Assimilation System (GDAS, $1^\circ \times 1^\circ$). All trajectories were calculated at
133 500 m above ground level (AGL) ending at the observation site (10.94° N, and 76.74° E) for the
134 observation period between 5 Mar 2021 to 17 Mar 2021. A multivariate statistical tool (Cluster
135 analysis) is used to group the calculated trajectories based on its similarity of spatial distribution
136 and number of optimal clusters considered based on the change in the spatial variance of all
137 obtained trajectories (Draxler et al., 2014).

138 *2.3 Uncertainties associated with the sensor and the reference laboratory to calibrate the* 139 *instrument*

140 In order to overcome the uncertainties associated with the collection of data by the sensor, some
141 criteria were considered in this study as follows. First, in order to procure suitable multi-rotor
142 components fitting the criteria of application, a detailed study was performed to choose the
143 components offering the best performance and endurance for the flight plan of vertical profiling.
144 Therefore, the frame dimension was chosen, which was capable of mounting the payload for
145 vertical profiling. Besides, accurate decisions were made regarding (1) the BLDC motor KV rating
146 providing enough torque and thrust to carry the payload, (2) the proper combination of propeller
147 length and pitch offering good thrust to weight ratio and endurance, and (3) the LIPO (lithium
148 polymer) battery rating providing the fly time required for the flight plan of vertical profiling.

149 Second, DJI NAZA M LITE was considered as the flight controller being used for the multi-rotor.
150 Live data telemetry of parameters like altitude, battery status, live flight footage, and multi-rotor's
151 orientation was required in this study to carry out the flight for data gathering. (1) A separate unit
152 of FC was used to perform the telemetry. (2) The FC chosen was JHEMCU F7BT DUAL GYRO,
153 since it had an inbuilt barometer and on-screen display (OSD). The barometer was used to get
154 altitude data with the help of atmospheric pressure difference. (3) The camera and the VTX (video

155 transmitter) were connected to the JHEMCU F7 flight controller and the data was received using
156 a VRX (video receiver), which was connected to a monitor. (4) With the help of camera footage
157 and OSD details on the monitor, the flight was performed.

158 Third, high wind current was one of the major uncertainty associated with the study. At an altitude
159 of 40 m to 60 m the wind current was high resulting in an unsteady flight and rolling down of the
160 multi-rotor. High wind currents lead to multiple crashes resulting in damage of the multi-rotor
161 components like propellers and frame arms, leading to time-consuming delays to complete the
162 study. Therefore, (1) flights were conducted considering the wind speed, certain flight maneuvers
163 were performed to have a steady flight at high wind speeds; and (2) the flight controllers gain
164 settings were tuned to offer high stability in windy situations.

165 Furthermore, the multi-rotor was built and calibrated by the Aerospace engineering department of
166 Karunya Institute Of Technology And Sciences, and the following calibration procedure was
167 considered for it. First, all the components were connected in a proper and correct way. Second,
168 the transmitter was bound with the receiver. For the research, Radiomaster TX16s was bounded
169 with a Flysky FSi6 receiver operating on 2.4 GHz, offering strong connectivity throughout the
170 flight. Third, the ESC (Electronic Speed Controller) was calibrated, in which the maximum and
171 minimum throttle values were given to the ESC, resulting in the spinning of all motors at the same
172 RPM. And finally, the FC DJI NAZA M LITE was calibrated using the DJI NAZA configurator,
173 which is a PC software.

174 **3. Results and discussion**

175 3.1 Data analysis

176 The distribution of the collected data for PM_1 , $PM_{2.5}$, PM_{10} , CO_2 , and HCHO in each of the five
177 sampling locations are presented through Box and Whisker plots in Figure 2. The vertical lines in
178 each plot (whiskers) show the minimum and maximum values, while the dots above the maximum
179 or below the minimum points illustrate the outliers in the dataset. Besides, the boxes represent the
180 lower and upper quartiles, with a line in the middle as the median. The mean for each plot is
181 illustrated by an “X” sign.

182 Based on the plots in Figure 2, the collected data for different pollutants in this study is skewed,
183 since the density of observations on the two sides of the median is not equal. Considering PM_1 ,
184 $PM_{2.5}$, and PM_{10} , the Petrol Pump has the highest level of data density compared with the other
185 locations, but on the other hand, it has the highest number of outliers. The Administration Block
186 comes after the Petrol Pump in terms of both the density of the collected data and the number of
187 outliers. In contrast with the Petrol Pump and the Administration Block, Bethesda’s data has the
188 lowest density in terms of PM_1 , $PM_{2.5}$, and PM_{10} , but it has no outlier. Except in the Petrol Pump,
189 the range of observed values (between the minimum and maximum) in all the locations are the
190 largest for PM_{10} . The second and third ranks go to $PM_{2.5}$ and PM_1 , respectively. Besides, in all the
191 five locations, PM_1 , $PM_{2.5}$, and PM_{10} keep the same sequence if they are sorted based on the
192 minimum, lower quartile, median, mean, upper quartile, or maximum (i.e. $PM_1 < PM_{2.5} < PM_{10}$
193 in terms of minimum, lower quartile, median, mean, upper quartile, and maximum in all the
194 sampling locations). These sequences are clarified in Table 1.

195 As can be seen from the top right part of Figure 2, the collected CO_2 data in the Petrol Pump has
196 a higher density in comparison with the other locations and is more concentrated between 408 and

197 459 *ppm*. Ignoring the two outliers, the range of data for this greenhouse gas in the Petrol Pump
198 is lower in comparison with the other locations, with a minimum of 408 *ppm* and a maximum of
199 533 *ppm*. The collected data for CO₂ in the Flight Hangar is in contrast with the Petrol Pump since
200 its range is larger (between 4.8 *ppm* as the minimum and 655 *ppm* as the maximum), and its
201 density is lower (between 415 *ppm* as the first quartile and 515.5 *ppm* as the third quartile). The
202 density of observations for HCHO, as illustrated in the bottom right of Figure 2, is the highest in
203 the CTC Block (between 0.010 and 0.011 *mg /m³*), followed by the Petrol Pump (between 0.009
204 and 0.011 *mg /m³*). This is while the Administration Block, the Flight Hangar, and Bethesda are
205 equally ranked third, having 0.009 and 0.012 *mg /m³* as their first and third quartiles. All these
206 three locations have a minimum of 0.009 *mg /m³* in terms of HCHO concentration, which is
207 equal to their first quartile. However, since the outliers are ignored, the maximum HCHO
208 concentration in the Administration Block and the Flight Hangar are equal (both 0.016 *mg /m³*),
209 attributing to them the largest range of observed values. Bethesda is ranked second in this regard
210 since its maximum value is 0.014 *mg /m³*.

211 *3.2 Impact of meteorological parameters and height on the concentration of pollutants in the* 212 *sampling locations*

213 Variations in the concentration of the pollutants evaluated in this study in the five locations at
214 different sampling times indicate the influence of various parameters. The RH and temperature
215 were measured in each trial at each of the four specified heights for sampling. Considering the
216 variations observed between the sampling locations (Figure 2), we infer that some of the influential
217 factors that are specific to each sampling location are not captured in our study. Therefore, here

218 we analyze the role of RH, temperature, and height in different sampling locations on the
219 concentration of pollutants.

220 In order to determine the most relevant factors for the concentration of pollutants, CHAID (CHI-
221 square Automatic Interaction Detection) algorithm (Kass, 1980) was applied to build a Decision
222 Tree (DT) for each of the pollutants. The DT is a data mining technique, which is trained on a base
223 dataset and can identify the existing relationships between independent variables and the
224 dependent variable (Hagenauer and Helbich, 2017) regardless of the linearity or non-linearity of
225 the relationships (Gao et al., 2021). The DT is a tree-like model with several layers of node, in
226 which the first node is the root, the terminal nodes are the leaves, and the internal nodes between
227 the root and the leaves correspond to specific attributes. The CHAID algorithm applied to construct
228 the DTs followed the steps of (a) merging, (b) splitting, and (c) stopping to derive statistically
229 significant segments of data presented in non-binary tree-shaped models (Onwuegbuzie and
230 Johnson, 2021). This algorithm uses Pearson's chi-square test to best split the nodes at each step,
231 and its procedure can be summarized as follows.

232 First, the categories of the independent variables are cross-tabulated with the categories of the
233 dependent variable. Second, the pair of independent variable categories that have the least
234 significant difference are identified and merged if the difference is less than a considered threshold.
235 Third, the compound categories of independent variables are analyzed to identify the most
236 statistically significant binary split if the significance exceeds the threshold. In case the split is
237 done, the algorithm returns to the merging stage and repeats the merging and splitting stages. This
238 repetition continues until all the merged categories of independent variables reach optimality.

239 Finally, the significance of all optimally merged variables is calculated (Kass, 1980; Rashidi et al.,
240 2014; Huang and Lin, 2013).

241 To build the DTs in this research, the records containing missing or corrupted values were excluded
242 from the database of the observations, and the remaining 2271 observations for each of the
243 pollutants were used to build five DTs in IBM® SPSS® software, each for one of the measured
244 pollutants. The role of the dependent variable was given to each of the pollutants in the DTs,
245 whereas the other variables were considered as independent variables. To specify the importance
246 level of *RH*, *temperature*, and *height* in the vertical concentration of pollutants in each sampling
247 location, the variable “*location*” was forced to be used for branching at the first level in the DTs.
248 Figures 3 to 6 illustrate the resulting CHAID DTs for PM_1 , $PM_{2.5}$, PM_{10} , CO_2 , and HCHO,
249 respectively. As can be seen in these figures, all the branching processes in these DTs are highly
250 statistically significant (P-value = 0.000). The mean and standard deviation mentioned in each
251 node refers to the “n” observations located in that node.

252 The DT presented in Figure 3 shows that in the sampling locations Administration Block,
253 Bethesda, and CTC Block, *RH* has the most important role in the concentration of PM_1 . In these
254 locations, when $RH \leq 48\%$, $RH > 71\%$, or $50\% < RH < 55\%$, *temperature* plays the second
255 important role and *height* does not have any significant impact. On the contrary, when $55\% <$
256 $RH < 57\%$ in these locations, *height* plays the second important role, and the *temperature* does
257 not have any significant impact. For the ranges of 48%-50%, and 57%-61% for *RH* in the
258 mentioned locations, neither *height* nor *temperature* play a significant role in the variations in the
259 PM_1 concentration. Finally, for these three sampling locations, when $61\% < RH < 71\%$,
260 regardless of *height* and *temperature*, we can separate Bethesda from the two other locations in

261 terms of the mean of the observations located in that node. For the Petrol Pump, similar to the
262 previously mentioned locations, *RH* has the most significant role. However, in this sampling
263 location, neither *height* nor *temperature* proves to be significantly effective in PM_1 concentration.
264 And last but not least, the branch referring to Flight Hangar identifies *temperature* as a significant
265 player in terms of the changes in PM_1 concentration and removes *RH* and *height* from the list of
266 significantly effective factors in this location.

267 Considering *location* as the branching variable in the first level in Figure 4, Petrol Pump grasps a
268 separate node from the other locations, which are in the same node altogether. In the Petrol Pump,
269 *temperature* is the leading factor in terms of the $PM_{2.5}$ concentration, and only if *temperature* is
270 between 84.6 °F and 85.1 °F (or equivalently, $29.22\text{ °C} < \textit{temperature} < 29.5\text{ °C}$), *RH* is
271 considered the next significantly effective factor. In the other four sampling locations, *RH* is
272 identified as the most significantly effective factor in the concentration of $PM_{2.5}$. When $RH \leq$
273 43%, $RH > 71\%$, or $48\% < RH < 55\%$, *temperature* is the next significantly effective factor,
274 while if $55\% < RH < 57\%$, *height* plays the next important role. Finally, when $43\% < RH <$
275 47% or $61\% < RH < 71\%$, the observations are split again based on *location*.

276 When it comes to PM_{10} , the sampling locations are put into three nodes in the first level of
277 branching in the DT, as illustrated in Figure 5. In the Petrol Pump, *temperature* has the most
278 statistically significant impact on the concentration of PM_{10} , followed by *height*, as the next
279 significant factor. Similar to the Petrol Pump, in the Administration Block and Flight Hangar, the
280 main branches are made based on *temperature*. However, in the next level, *RH* is the leading factor
281 for the observations made in the *temperature* between 82.1 °F and 84.2 °F (or equivalently,
282 $27.83\text{ °C} < \textit{temperature} < 29\text{ °C}$), and *location* becomes important for the observations made

283 in the *temperature* between 84.2 °F and 85.1 °F (or equivalently, $29\text{ °C} < \textit{temperature} <$
284 29.5 °C). Finally, the branching for Bethesda and CTC Block is based on *RH*, followed by
285 *temperature* when $RH \leq 48\%$, $RH > 71\%$, or $50\% < RH < 51\%$, and by *location* when
286 $61\% < RH < 71\%$.

287 Figure 6 shows more splits based on the *location* when analyzing the concentration of CO₂.
288 Although *RH* is the main significant effective factor on the concentration of CO₂, for
289 Administration Block, CTC Block, Bethesda, and Petrol Pump, the second effective factor is
290 different for various ranges of *RH*. In the Administration Block and CTC Block, for $RH > 61\%$,
291 *height* is the next effective factor, while for $50\% < RH < 57\%$, *temperature* plays the next
292 significant role. For other ranges of *RH* values, no significant factor is identified. In Bethesda,
293 when $61\% < RH < 71\%$, no other significant factor is identified, while if $RH \leq 61\%$, *height*
294 is identified as the second significantly effective factor and if $RH > 71\%$, *temperature* plays an
295 effective role in determining the concentration of CO₂. In the Petrol Pump, after *RH*, *height* is
296 identified as a significantly effective factor, but only when $48\% < RH < 57\%$. The case is
297 different in Flight Hangar, as *temperature* is the leading factor in splitting the observations, and
298 *RH* is the second significantly effective factor only for the observations referring to the
299 *temperature* between 79.4 and 85.1 °F (or equivalently, between 26.33 °C and 29.5 °C).

300 The CHAID DT in Figure 7 makes a separation between Petrol Pump and the other sampling
301 locations by considering only two nodes in the first level of branching. In Petrol Pump,
302 *temperature* has been identified as a statistically significant variable to split the observations on
303 the concentration of HCHO. However, for all the other sampling locations, *RH* is the main
304 identified significant factor that makes the splits in the next level of branching. In case $43\% <$

305 $RH < 47\%$, $53\% < RH < 57\%$, or $RH > 71\%$, *height* would be the second significantly
306 effective factor in terms of the concentration of HCHO. For the observations with $48\% < RH <$
307 53% and $57\% < RH < 71\%$, the second split of observations would be based on *location*. For
308 other ranges of *RH*, no factor is recognized as to be statistically significant.

309 We show in Figure 2 a general view of the differences between the observations in each location.
310 Figures 3 to 7 illustrate a more in-depth analysis of the role of location along with the
311 meteorological parameters and height on the concentration of pollutants. The analysis presented
312 in this section confirms the findings from the initial statistical analysis, highlighting that in addition
313 to the meteorological parameters and height, different attributes of the sampling locations may
314 affect the concentration of studied pollutants. These attributes may be linked with the width of the
315 sampling location, the height of the nearby buildings, wind direction, or other factors. However,
316 a detailed analysis of the location attributes is out of the scope of this research, and therefore we
317 provide an analysis of the concentration of pollutants with respect to meteorological parameters
318 and height.

319 *3.3 The concentration of pollutants with respect to meteorological parameters and height*

320 In order to better visualize the changes in the concentration of the studied pollutants with respect
321 to the meteorological parameters and height, a fuzzified DT-based 4-D space is developed for each
322 of the pollutants, and then, the 3-D surfaces extracted from these spaces are presented in this
323 section. To do so, two main steps were taken.

324 First, the recorded observations for each of the pollutants were introduced into a DT with the
325 CHAID growing method to build five new decision trees based on the observations related to the

326 pollutants, this time regardless of their sampling location. The overall accuracy of the DTs was
327 confirmed by their risk estimate (within-node variance). The risk estimate for PM_1 , $PM_{2.5}$, PM_{10} ,
328 CO_2 , and HCHO was 60.35, 90.727, 221.557, 1123.556, and 1.469E-6, respectively. Considering
329 the structure of the DTs, relevant if-then rules were extracted for each leaf, such as “*IF [(RH ≤*
330 *43)) and (TEMP > 85.09))] THEN [PM1 Prediction = 30.37]*”. The predicted values for
331 the pollutants in each node of the tree refer to the mean of the observations located in that node.

332 Second, based on the ranges of values determined by the branches of the DTs, relevant membership
333 functions were designed for the pollutants, height, RH, and temperature to build a Fuzzy Inference
334 System (FIS) in MATLAB® for each of the pollutants. All these membership functions were set
335 in the form of Gaussian functions. Furthermore, the rules extracted from each DT were used to
336 build the Mamdani rule-based inference engine for the FISs.

337 The built FISs can be used to estimate the concentration of pollutants with respect to different
338 levels of RH, temperature, and height (Ranjbari et al., 2021). However, since this is not the main
339 purpose of our study, we have only applied them to visualize the relationship between various
340 levels of meteorological parameters and the pollutants through 3-D surfaces.

341 Figures 8 to 10 show the changes in the concentration of the studied pollutants with respect to *RH*
342 and *temperature*, *height* and *temperature*, and *RH* and *height*, respectively. Each variable follows
343 its own scale in these figures, and a color range of dark blue to bright yellow is used to show very
344 low to very high concentrations of studied pollutants based on their own scale of measurement.

345 Figure 8 provides a general view of the concentration of the pollutants, considering *RH* and
346 *temperature*. As can be seen from this figure, the concentration of each of the pollutants has

347 different behavior in terms of the changes in *RH* and *temperature*. However, the surfaces referring
348 to PM_1 , $PM_{2.5}$, and PM_{10} follow the same behavior in some points. For these three pollutants, high
349 levels of *RH* and *temperature* leads to low concentration of the pollutants. Besides, PM_1 and $PM_{2.5}$
350 show rather similar fluctuations in most parts of the surface. Focusing on the fluctuations caused
351 by the changes in the values in X and Y axes, it can be inferred that changes in the *RH* have a
352 stronger effect than *temperature* in changing the concentration of PM_1 , $PM_{2.5}$, PM_{10} , and CO_2 .
353 However, this cannot be concluded for HCHO, since both variables seem to be effective in making
354 the changes in the HCHO concentration.

355 Having an overview of the surfaces presented in Figure 9, it can be seen that compared with
356 *temperature*, *height* has a very weak role in changing the concentration levels of PM_1 , $PM_{2.5}$, PM_{10} ,
357 and CO_2 . Besides, considerable changes due to *temperature* start to occur when the *temperature*
358 exceeds 80 °F, leading to an increased concentration of PM_1 , $PM_{2.5}$, and CO_2 and decreasing PM_{10} .
359 Again, HCHO concentration shows a different behavior compared with the other pollutants and is
360 slightly affected by both of the considered factors.

361 Referring to Figure 10, the stronger impact of *RH* changes compared with the *height* changes on
362 the concentration of PM_1 , $PM_{2.5}$, PM_{10} , and CO_2 is realizable. As can be seen in this figure, the
363 concentration of PM_1 , $PM_{2.5}$, and PM_{10} have almost similar fluctuations after around 55% of *RH*
364 regardless of the height, but with different levels of pollutant concentration. Besides, considerable
365 fluctuations are observed due to changes in the *RH* level, which highlight the significant role of
366 *RH* in pollutant concentrations. These fluctuations were also observed in Figure 8 when comparing
367 the significance of changes made by *RH* and *temperature*. Similar to the previous figures in this
368 section, different behavior is observed in the HCHO surface, indicating more impact received from

369 *height*, in comparison with the other pollutants. These analyses also confirm the strong role of *RH*
370 and the weak role of *height*, in comparison with other factors, regarding the concentration of the
371 studied pollutants.

372 *3.4 Cluster analysis*

373 This section reports the results of cluster analysis to evaluate the contribution of possible sources
374 of aerosols from different regions. Figure 11 shows the clusters of five days air mass back
375 trajectories arriving at the observation site from different regions. Air mass back trajectories were
376 calculated using the HYSPLIT model and it is used for the indication of general airflow followed
377 by an air parcel. Further, these trajectories were merged together representing a group called a
378 cluster. Differences between trajectories within the clusters are minimized and the difference
379 between clusters is maximized.

380 The distributions of four clusters were calculated for the hourly air mass trajectories clusters
381 obtained for each day of the observation period. The highest number of trajectories belongs to
382 cluster 2 (41%) arriving from the Bay of Bengal region. Cluster 1 (39%) and cluster 4 (17%)
383 contribute significantly to the air mass arriving at the observation site during the observation
384 period. All these trajectories carry the effect of air mass originating from the Bay of Bengal with
385 a longer range for cluster 4 from the altitude range up to 2000 m AGL, as indicated in the vertical
386 profile of air mass with distance from the observation site in Figure 11. The other clusters (except
387 cluster 2) achieve altitudes lower than 500 m AGL only for all hours of observation before reaching
388 the observation site. The lowest contribution of air mass is obtained from trajectories
389 corresponding to cluster 3 (3%) originating from the Arabian sea region. Clusters highlight the
390 pathways of air mass and advected moisture from oceanic regions adjacent to the observation site.

391 Vertical columns in the lower section of figure 11 indicate the percentage contribution of each
392 cluster to the individual day of the observation period.

393 The contribution of each cluster to individual days is presented by the corresponding colors of the
394 respective cluster. It is observed that trajectories corresponding to cluster 2 contributed to almost
395 all days and cluster 1 contains trajectories of days except 09-12 March. Air mass corresponding to
396 cluster 3 arrives at the observation site on 06 and 07 March only, with the lowest number of
397 trajectories corresponding to it. Nair et al. (2008) characterized the influence of marine aerosols
398 originating from the Arabian Sea and Bay of Bengal reaching over the Indian subcontinent. It
399 contains the aerosols dominated by SO_4^{2-} , NH_4^+ , and NO_3^- over the oceanic region, and suggests
400 the presence of ammonium sulfate and ammonium nitrate which are responsible for the radiation
401 budget in the atmosphere.

402 **4. Summary and conclusion**

403 This study presents the vertical distribution of air pollutants based on the measurements conducted
404 by UAV at different fixed locations in a rural area of southern India. The investigations were
405 carried out through 30 flights in March 2021 to gather data regarding the concentration of PM_{10} ,
406 $\text{PM}_{2.5}$, PM_1 , CO_2 , and HCHO as well as RH and temperature in four height levels (15, 30, 45, and
407 60 m) in five different locations within the area of Karunya Institute of Technology and Sciences,
408 Karunya Nagar, Coimbatore.

409 The gathered database was used to build a CHAID DT for each of the pollutants, considering
410 different sampling locations for the analysis. The results indicate the weak role of height on the
411 concentration of pollutants in the sampling locations, and instead, highlight the role of temperature
412 and RH in this regard. Besides, to better visualize the relationship between the concentration of

413 each of the studied pollutants and height, RH, and temperature regardless of the specific sampling
414 locations, new CHAID DTs were built for the pollutants, disregarding the sampling locations, and
415 the extracted “if-then” rules were used to build fuzzy surfaces for each pollutant. These surfaces
416 show that in comparison with the other studied pollutants, HCHO is more variant with the changes
417 in height, and the concentration of HCHO changes more than the other pollutants by changing
418 height and the RH level. The findings are then confirmed by the cluster analysis, which showed
419 that meteorological parameters, regional transport, and atmospheric condition may play an
420 essential role in the vertical distribution of air pollutants.

421 The study area of Karunya Nagar is located in the southernmost part of the Indian peninsula and
422 the prevailing air masses exert more influence on the concentration profile of air pollutants with
423 different sources than inland cities. The significant impact of regional transport/ sources was
424 analyzed using cluster analysis (back- trajectory). Cluster analysis of five days' hourly air mass
425 back-trajectories suggests the contribution of possible sources of air mass transported over the
426 observation site. The maximum contribution of air mass is from the Bay of Bengal, which
427 contributes to the loading of pollutant concentration over a different altitude of India's rural area.
428 Furthermore, the relationship between the vertical concentration of pollutants and meteorological
429 parameters was observed by advanced statistical analysis. The outcomes of the study indicate the
430 potential of identifying the vertical distribution of air pollutants by using UAV measurements.
431 Besides, it can be realized from this study that transport, through both advection and convection,
432 influences the vertical distribution of air pollutants as inferred from meteorological analysis,
433 including back trajectories using the Hybrid Single-Particle Lagrangian Integrated Trajectory
434 (HYSPLIT4) model. The long-range transport of air mass could also contribute to the high
435 concentration values of particulate matters, as found through the five-day air mass backward

436 trajectory analysis. Although the observed data sets are confined to a height of 60 m AGL, the
437 results from this study provide insights into the vertical distribution of air pollutants,
438 complementing ground-based measurement variations with different spacing and timing.

439 However, further studies are suggested to clarify the different times (other times of the day),
440 space/locations, and extended altitudes to gain insights into the vertical profile/movement of air
441 pollutants upward.

442

443 **Acknowledgments**

444 We are thankful to Karunya Institute of Technology and Sciences Coimbatore, Tamil Nadu, India
445 for providing us the required funding to complete this study.

446 **References**

447 Allaby, M., 2007. Encyclopedia of Weather and Climate. Rev. Facts on File (Facts on File science
448 library, New York (2007). [Last Assess:13 July, 2021].

449
450 Argyropoulos, G., Grigoratos, T., Voutsinas, M., Samara, C., 2013. Concentrations and source
451 apportionment of PM10 and associated elemental and ionic species in a lignite-burning
452 power generation area of southern Greece. Environ. Sci. Pollut. Rea. 20, 7214 – 7230.

453 Bates, T.S., Quinn, P.K., Johnson, J.E., Corless, A., Brechtel, F.J., Stalin, S.E., Meinig, C.,
454 Burkhart, J.F., 2013. Measurements of atmospheric aerosol vertical distributions above
455 Svalbard, Norway, using unmanned aerial systems (UAS). Atmos. Meas. Tech. 6, 2115 –
456 2120. <https://doi.org/10.5194/amt-6-2115-2013>

- 457 Baumbach, G., Vogt, U., 2003. Influence of inversion layers on the distribution of air pollutants
458 in urban areas. *Water Air Soil Pollut.* 3 (5–6), 65-76.
- 459 Borbély-Kiss, I., Koltay, E., Szabó, G.Y., Bozó, L., Tar, K., 1999. Composition and sources of
460 urban and rural atmospheric aerosol in eastern Hungary. *J. Aero. Sci.* 30, 369 – 391.
- 461 Bond, T.C., Doherty, S.J., Fahey, D.W., Forster, P.M., Berntsen, T., Deangelo, B.J., Flanner, M.G.,
462 Ghan, S., Kärcher, B., Koch, D., Kinne, S., Kondo, Y., Quinn, P.K., Sarofim, M.C.,
463 Schultz, M.G., Schulz, M., Venkataraman, C., Zhang, H., Zhang, S., Bellouin, N.,
464 Guttikunda, S.K., Hopke, P.K., Jacobson, M.Z., Kaiser, J.W., Klimont, Z., Lohmann, U.,
465 Schwarz, J.P., Shindell, D., Storelvmo, T., Warren, S.G., Zender, C.S., 2013. Bounding the
466 role of black carbon in the climate system: A scientific assessment. *J. Geophys. Res.*
467 *Atmos.* 118, 5380 –5552. <https://doi.org/10.1002/jgrd.50171>
- 468 Chilinski, M.T., Markowicz, K.M., Markowicz, J., 2016. Observation of vertical variability of
469 black carbon concentration in lower troposphere on campaigns in Poland. *Atmos. Environ.*
470 137, 155 –170. <https://doi.org/10.1016/j.atmosenv.2016.04.020>
- 471 Ding, A., Wang, T., Xue, L., Gao, J., Stohl, A., Lei, H., Jin, D., Ren, Y., Wang, X., Wei, X., Qi,
472 Y., Liu, J., Zhang, X., 2009. Transport of north China air pollution by midlatitude cyclones:
473 Case study of aircraft measurements in summer 2007. *J. Geophys. Res. Atmos.* 114, 1 –16.
474 <https://doi.org/10.1029/2008JD011023>
- 475 Draxler, R., Stunder, B., Rolph, G., Stein, A., Taylor, A., 2014. HYSPLIT4 user's guide version 4
476 - Last revision: September 2014.

- 477 Essa, K.S.M., Mubarak, F., Elsaid, S.E.M., 2006. Effect of the plume rise and wind speed on
478 extreme value of air pollutant concentration. Meteorol. Atmos. Phys.
479 <https://doi.org/10.1007/s00703-005-0168-1>
- 480 Ferrero, L., Mocnik, G., Ferrini, B.S., Perrone, M.G., Sangiorgi, G., Bolzacchini, E., 2011. Vertical
481 profiles of aerosol absorption coefficient from micro -Aethalometer data and Mie
482 calculation over Milan. Sci. Total Environ. 409, 2824 –2837.
483 <https://doi.org/10.1016/j.scitotenv.2011.04.022>
- 484 Ferrero, L., Perrone, M.G., Petraccone, S., Sangiorgi, G., Ferrini, B.S., Lo Porto, C., Lazzati, Z.,
485 Cocchi, D., Bruno, F., Greco, F., Riccio, A., Bolzacchini, E., 2010. Vertically - resolved
486 particle size distribution within and above the mixing layer over the Milan metropolitan
487 area. Atmos. Chem. Phys. <https://doi.org/10.5194/acp-10-3915-2010>
- 488 Gao, Y., Wang, Z., Li, C.Y., Zheng, T. and Peng, Z.R., 2021. Assessing neighborhood variations
489 in ozone and PM_{2.5} concentrations using decision tree method. Building and
490 Environment, 188, p.107479.
- 491 Gautam, S., Kumar, P., Patra, A.K., 2016. Occupational exposure to particulate matter in three
492 Indian opencast mines. Air Qual. Atmos. Health 9(2), 143-158.
- 493 Gautam, S., Patra, A.K., 2015. Dispersion of particulate matter generated at higher depths in
494 opencast mines Environ.Technol. Inn. 3, 11-27.
- 495 Gollakota, A.R.K., Gautam, S., Santosh, M., Sudan, H.A., Gandhi, R., Jebadurai, V.S., Shu, CM.,
496 2021. Bioaerosols: characterization, pathways, sampling strategies, and challenges to geo-
497 environment and health. Gondwana Research 99, 178-203, doi.org/10.1016/j.gr.2021.07.003.

- 498 Günter Baumbach. Air Quality Control. Formation and Sources, Dispersion, Characteristics and
499 Impact of Air Pollutants? Measuring Methods, Techniques for Reduction of Emissions and
500 Regulations for Air Quality Control. Springer Berlin Heidelberg (Environmental
501 Engineering), Berlin, Heidelberg (1996).
- 502 Guzmán-Torres, D., Eiguren-Fernández, A., Cicero-Fernández, P., Maubert-Franco, M., Retama-
503 Hernández, A., Villegas, R., Rafael, Miguel, A. H., 2009. Effects of meteorology on diurnal
504 and nocturnal levels of priority polycyclic aromatic hydrocarbons and elemental and organic
505 carbon in PM10 at a source and a receptor area in Mexico City. Atmos. Environ. 43 (17), 2693-
506 2699.
- 507 Hagenauer, J. and Helbich, M., 2017. A comparative study of machine learning classifiers for
508 modeling travel mode choice. Expert Systems with Applications, 78, pp.273-282.
- 509 Han, S., Zhang, Y., Wu, J., Zhang, X., Tian, Y., Wang, Y., Ding, J., Yan, W., Bi, X., Shi, G., Cai,
510 Z., Yao, Q., Huang, H., Feng, Y., 2015. Evaluation of regional background particulate
511 matter concentration based on vertical distribution characteristics. Atmos. Chem. Phys. 15,
512 11165 –11177. <https://doi.org/10.5194/acp-15-11165-2015>
- 513 Huang, C. and Lin, Y., 2013. "Applying CHAID algorithm to investigate critical attributes of void
514 formation in QFN assembly", Soldering & Surface Mount Technology, Vol. 25 No. 2, pp.
515 117-127. <https://doi.org/10.1108/09540911311309086>
- 516 Janhall, S., Olofson, K., Andersson,
517 P., Pettersson, J., Hallquist, M., 2006. Evolution of the urban aerosol during winter
518 temperature inversion episodes. Atmos. Environ. 40 (28), 5355-5366.
- 519 Kass, G.V., 1980. An exploratory technique for investigating large quantities of categorical data.
Journal of the Royal Statistical Society: Series C (Applied Statistics), 29(2), pp.119-127.

- 520 Klompmaker, J.O., Montagne, D.R., Meliefste, K., Hoek, G., Brunekreef, B., 2015. Spatial
521 variation of ultrafine particles and black carbon in two cities: Results from a short -term
522 measurement campaign. *Sci. Total Environ.* 508, 266 –275.
523 <https://doi.org/10.1016/j.scitotenv.2014.11.088>
- 524 Lee, M., Brauer, M., Wong, P., Tang, R., Tsui, T.H., Choi, C., Cheng, W., Lai, P.C., Tian, L.,
525 Thach, T.Q., Allen, R., Barratt, B., 2017. Land use regression modelling of air pollution in
526 high density high rise cities: A case study in Hong Kong. *Sci. Total Environ.*
527 <https://doi.org/10.1016/j.scitotenv.2017.03.094>
- 528 Lei, X., Xiu, G., Li, B., Zhang, K., Zhao, M., 2016. Individual exposure of graduate students to
529 PM_{2.5} and black carbon in Shanghai, China. *Environ. Sci. Pollut. Res.* 23, 12120 – 12127.
530 <https://doi.org/10.1007/s11356-016-6422-x>
- 531 Li, Y.J., Lee, B.P., Su, L., Fung, J.C.H., Chan, C.K., 2015. Seasonal characteristics of fine
532 particulate matter (PM) based on high -resolution time -of-flight aerosol mass
533 spectrometric (HR -ToF -AMS) measurements at the HKUST Supersite in Hong
534 Kong. *Atmos. Chem. Phys.* 15, 37 –53. <https://doi.org/10.5194/acp-15-37-2015>
- 535 Liu, B., He, M.M., Wu, C., Li, J., Li, Y., Lau, N.T., Yu, J.Z., Lau, A.K.H., Fung, J.C.H., Hoi, K.I.,
536 Mok, K.M., Chan, C.K., Li, Y.J., 2019. Potential exposure to fine particulate matter
537 (PM_{2.5}) and black carbon on jogging trails in Macau. *Atmos. Environ.* 198, 23 – 33.
538 <https://doi.org/10.1016/j.atmosenv.2018.10.024>
- 539 Lu, Y., Zhu, B., Huang, Y., Shi, S., Wang, H., An, J., Yu, X., 2019. Vertical distributions of black
540 carbon aerosols over rural areas of the Yangtze River Delta in winter. *Sci. Total Environ.*
541 <https://doi.org/10.1016/j.scitotenv.2019.01.170>

- 542 Minguillón, M.C., Brines, M., Pérez, N., Reche, C., Pandolfi, M., Fonseca, A.S., Amato, F.,
543 Alastuey, A., Lyasota, A., Codina, B., Lee, H.K., Eun, H.R., Ahn, K.H., Querol, X., 2015.
544 New particle formation at ground level and in the vertical column over the Barcelona area.
545 Atmos. Res. 164 –165, 118 –130. <https://doi.org/10.1016/j.atmosres.2015.05.003>
- 546 Mijling, B., Van Der, R. J., 2012. Using daily satellite observations to estimate emissions of short-
547 lived air pollutants on a mesoscopic scale. J. Geophys. Res. Atmos. 117, D17302.
- 548 Moreno-Ríos, A.L., Tejeda-Benitez, L. and Bustillo-Lecompte, C., 2021. Sources, characteristics,
549 toxicity, and control of ultrafine particles: An overview. Geoscience Frontiers, p.101147.
- 550 Nair, V.S., Babu, S.S., Moorthy, K.K., 2008. Aerosol characteristics in the marine atmospheric
551 boundary layer over the Bay of Bengal and Arabian Sea during ICARB: Spatial distribution
552 and latitudinal and longitudinal gradients. Journal of Geophysical Research –Atmosphere,
553 10.1029/2008JD009823.
- 554 Olofson, K.F.G., Andersson, U. P., Hallquist, M., Ljungström, E., Tang, L., Chen, D., Pettersson,
555 J.B.C., 2009. Urban aerosol evolution and particle formation during wintertime
556 temperature inversions. Atmos. Environ. 43 (2),340-346.
- 557 Onwuegbuzie, A.J. and Johnson, R.B. eds., 2021. The Routledge Reviewer’s Guide to Mixed
558 Methods Analysis. Routledge.
- 559 Panday, A. K., Prinn. R. G., 2009. Diurnal cycle of air pollution in the kathmandu valley, Nepal:
560 observations. J. Geophys. Res., 114 (D9). 1295.

- 561 Patra, A.K., Gautam, S., Majumdar, S., Kumar, P., 2016. Prediction of particulate matter
562 concentration profile in an opencast copper mine in India using an artificial neural network
563 model. *Air Qual. Atmos. Health* 9 (6), 697–711. (IF = 2.87)
- 564 Peng, Z.R., Wang, D., Wang, Z., Gao, Y., Lu, S., 2015. A study of vertical distribution patterns of
565 PM_{2.5} concentrations based on ambient monitoring with unmanned aerial vehicles: A case
566 in Hangzhou, China. *Atmos. Environ.* 123, 357–369.
567 <https://doi.org/10.1016/j.atmosenv.2015.10.074>
- 568 Philip, S., Eric L., 2007. Vawdrey, Misty Corbett, Mark Erupe. Fine particle concentrations and
569 composition during wintertime inversions in Logan, Utah, USA. *Atmos. Environ.* 41 (26),
570 5410-5422.
- 571 Praveen, P.S., Ahmed, T., Kar, A., Rehman, I.H., Ramanathan, V., 2012. Link between local scale
572 BC emissions in the Indo -Gangetic plains and large scale atmospheric solar absorption.
573 *Atmos. Chem. Phys.* 12, 1173 –1187. <https://doi.org/10.5194/acp -12 -1173 - 2012>
- 574 Ran, L., Deng, Z., Xu, X., Yan, P., Lin, W., Wang, Y., Tian, P., Wang, P., Pan, W., Lu, D., 2016.
575 Vertical profiles of black carbon measured by a micro -aethalometer in summer in the
576 North China Plain. *Atmos. Chem. Phys.* 16, 10441 –10454. <https://doi.org/10.5194/acp -16 -10441 -2016>
- 578 Ranjbari, M., Shams Esfandabadi, Z., Scagnelli, S. D., Siebers, P.-O., & Quatraro, F. (2021).
579 Recovery agenda for sustainable development post COVID-19 at the country level:
580 developing a fuzzy action priority surface. *Environment, Development and Sustainability*,
581 0123456789. <https://doi.org/10.1007/s10668-021-01372-6>

- 582 Rashidi, S., Ranjitkar, P. and Hadas, Y., 2014. Modeling bus dwell time with decision tree-based
583 methods. *Transportation Research Record*, 2418(1), pp.74-83.
- 584 Ravina, M., Shams Esfandabadi, Z., Panepinto, D., Zanetti, M.C., 2021. Traffic-induced
585 atmospheric pollution during the COVID-19 lockdown: Dispersion modeling based on
586 traffic flow monitoring in Turin, Italy. *J. Clean. Prod.*
587 <https://doi.org/10.1016/j.jclepro.2021.128425>
- 588 Retama, A., Baumgardner, D., Raga, G.B., McMeeking, G.R., Walker, J.W., 2015. Seasonal and
589 diurnal trends in black carbon properties and co -pollutants in Mexico City. *Atmos. Chem.*
590 *Phys.* 15, 9693 –9709. <https://doi.org/10.5194/acp -15 -9693 -2015>
- 591 Samad, A., Vogt, U., Panta, A., & Uprety, D., 2020. Vertical distribution of particulate matter,
592 black carbon and ultra-fine particles in Stuttgart, Germany. *Atmos. Pollut. Res.* 11(8),
593 1441–1450.
- 594 Schuyler, T., Guzman, M., 2017. Unmanned Aerial Systems for Monitoring Trace Tropospheric
595 Gases. *Atmosphere (Basel)*. 8, 206. <https://doi.org/10.3390/atmos8100206>
- 596 Silva, L.F., Santosh, M., Schindler, M., Gasparotto, J., Dotto, G.L., Oliveira, M.L. and Hochella
597 Jr, M.F., 2021. Nanoparticles in fossil and mineral fuel sectors and their impact on
598 environment and human health: A review and perspective. *Gondwana Research* 92, 184-
599 201.
- 600 Stein, A.F., Draxler, R.R., Rolph, G.D., Stunder, B.J.B., Cohen, M.D., Ngan, F., 2015. Noaa’s
601 hysplit atmospheric transport and dispersion modeling system. *Bull. Am. Meteorol. Soc.*
602 96, 2059 –2077. <https://doi.org/10.1175/BAMS - D -14 -00110.1>

- 603 Strawbridge, K.B., Snyder, B.J., 2004. Daytime and nighttime aircraft lidar measurements
604 showing evidence of particulate matter transport into the Northeastern valleys of the Lower
605 Fraser Valley, BC. *Atmos. Environ.* 38, 5873 –5886.
606 <https://doi.org/10.1016/j.atmosenv.2003.10.036>
- 607 Tang, G., Zhang, Jinqiang, Zhu, X., Song, T., Munkel, C., Hu, B., Schäfer, K., Liu, Z., Zhang,
608 Junke, Wang, L., Xin, J., Suppan, P., Wang, Y., 2016. Mixing layer height and its
609 implications for air pollution over Beijing, China. *Atmos. Chem. Phys.* 16, 2459 –2475.
610 <https://doi.org/10.5194/acp-16-2459-2016>
- 611 Vardoulakis, S., Giagloglou, E, et al., 2020. Indoor exposure to selected air pollutants in the home
612 environment: A systematic review. *International Journal of Environmental Research and*
613 *Public Health* 17, 8972.
- 614 Villa, T., Salimi, F., Morton, K., Morawska, L., Gonzalez, F., 2016. Development and Validation
615 of a UAV Based System for Air Pollution Measurements. *Sensors* 16, 2202.
616 <https://doi.org/10.3390/s16122202>
- 617 Wang, Y.Q., Zhang, X.Y., Sun, J.Y., Zhang, X.C., Che, H.Z., Li, Y., 2015. Spatial and temporal
618 variations of the concentrations of PM₁₀, PM_{2.5} and PM₁ in China. *Atmos. Chem.*
619 *Phys. Discuss.* 15, 15319 –15354. <https://doi.org/10.5194/acpd-15-15319-2015>
- 620 Zoras, S., Triantafyllou, A.G., Deligiorgi, D., 2006. Atmospheric stability and PM₁₀
621 concentrations at far distance from elevated point sources in complex terrain: worst-case
622 episode study. *J. Environ. Manag.* 80 (4), 295-302.
- 623 Zhou, S., Peng, S., Wang, M., Shen, A., Liu, Z., 2018. The Characteristics and Contributing
624 Factors of Air Pollution in Nanjing: A Case Study Based on an Unmanned Aerial Vehicle

625 Experiment and Multiple Datasets. Atmosphere (Basel). 9, 343.
626 <https://doi.org/10.3390/atmos9090343>.

627 **Figure captions**

628 Figure 1: Location of Karunya Nagar, Karunya Institute of Technology and Sciences in the Tamil
629 Nadu State of southern India (red circle within map of India), with the flight site and the
630 meteorological station.

631 Figure 2. Box and Whisker plots for graphic presentation of the collected data for PM₁, PM_{2.5},
632 PM₁₀, CO₂, and HCHO in each of the five sampling locations

633 Figure 3. The overall structure of the CHAID DT for PM₁. Locations are as follows. A:
634 Administration Block; B: Bethesda; C: CTC Block; F: Flight Hangar; P: Petrol Pump.

635
636 Figure 4. The overall structure of the CHAID DT for PM_{2.5}. Locations are as follows. A:
637 Administration Block; B: Bethesda; C: CTC Block; F: Flight Hangar; P: Petrol Pump.

638 Figure 5. The overall structure of the CHAID DT for PM₁₀. Locations are as follows. A:
639 Administration Block; B: Bethesda; C: CTC Block; F: Flight Hangar; P: Petrol Pump.

640 Figure 6. The overall structure of the CHAID DT for CO₂. Locations are as follows. A:
641 Administration Block; B: Bethesda; C: CTC Block; F: Flight Hangar; P: Petrol Pump.

642 Figure 7. The overall structure of the CHAID DT for HCHO. Locations are as follows.: A:
643 Administration Block; B: Bethesda; C: CTC Block; F: Flight Hangar; P: Petrol Pump.

644 Figure 8. The concentration of pollutants based on *temperature* and *RH*.

645 Figure 9. The concentration of pollutants based on temperature and height.

646 Figure 10. The concentration of pollutants based on *RH* and *height*.

647 Figure 11. Cluster analysis of five days' hourly air mass back-trajectories arriving at 500 m AGL
648 over the observation site.

649 **Table captions**

650 Table 1. The sequence of PM_{10} , $PM_{2.5}$, and PM_1 concentration in the studied locations in terms of
651 the minimum, lower quartile, mean, upper quartile, and maximum

652

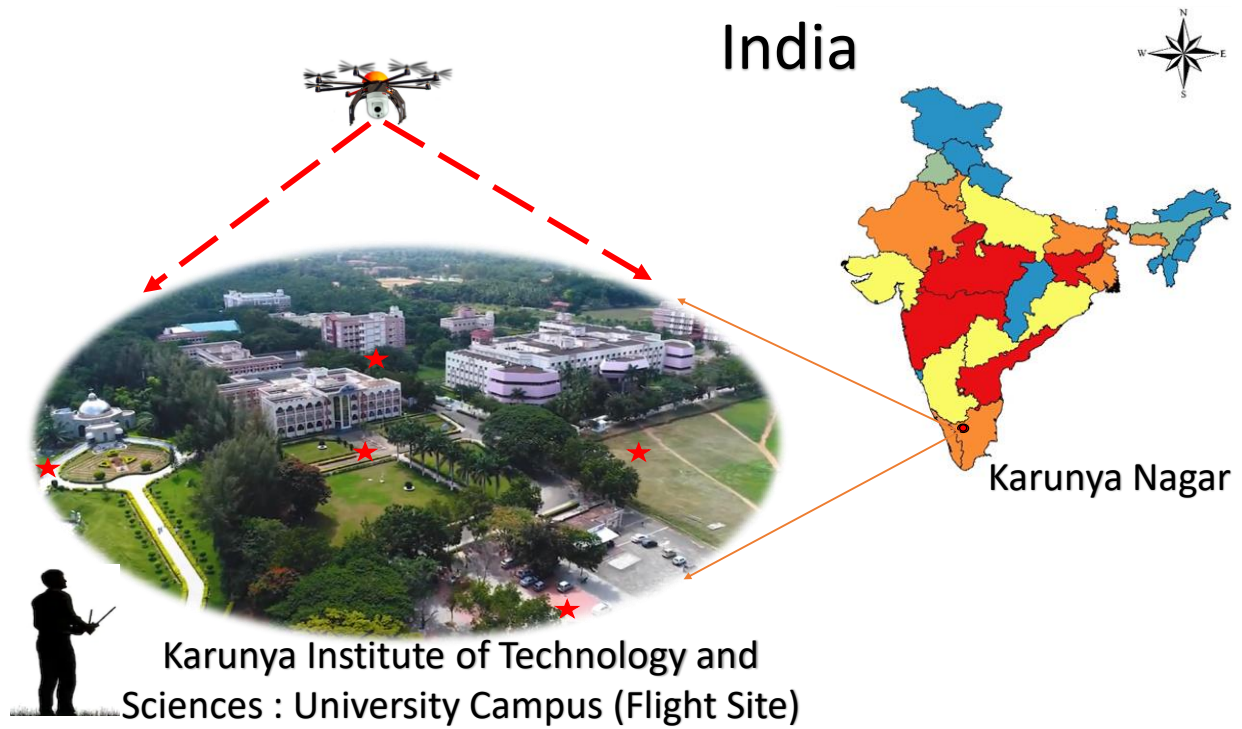


Figure 1: Location of Karunya Nagar, India. Karunya Institute of Technology and Sciences with the flight site and the meteorological station is denoted using a red dot in the picture at the lower-left portion of the figure.

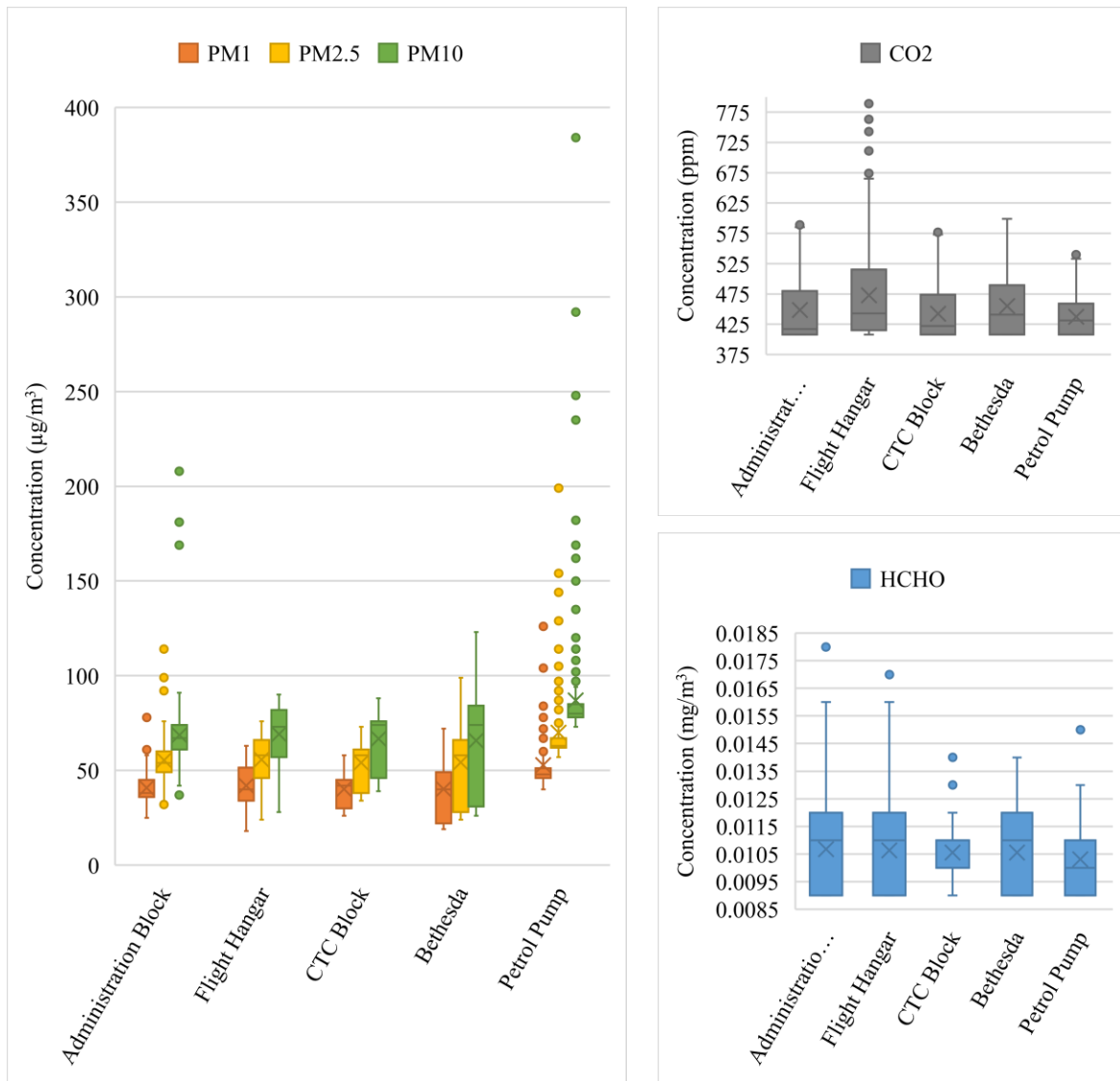


Figure 2. Box and Whisker plots for graphic presentation of the collected data for PM₁, PM_{2.5}, PM₁₀, CO₂, and HCHO in each of the five sampling locations

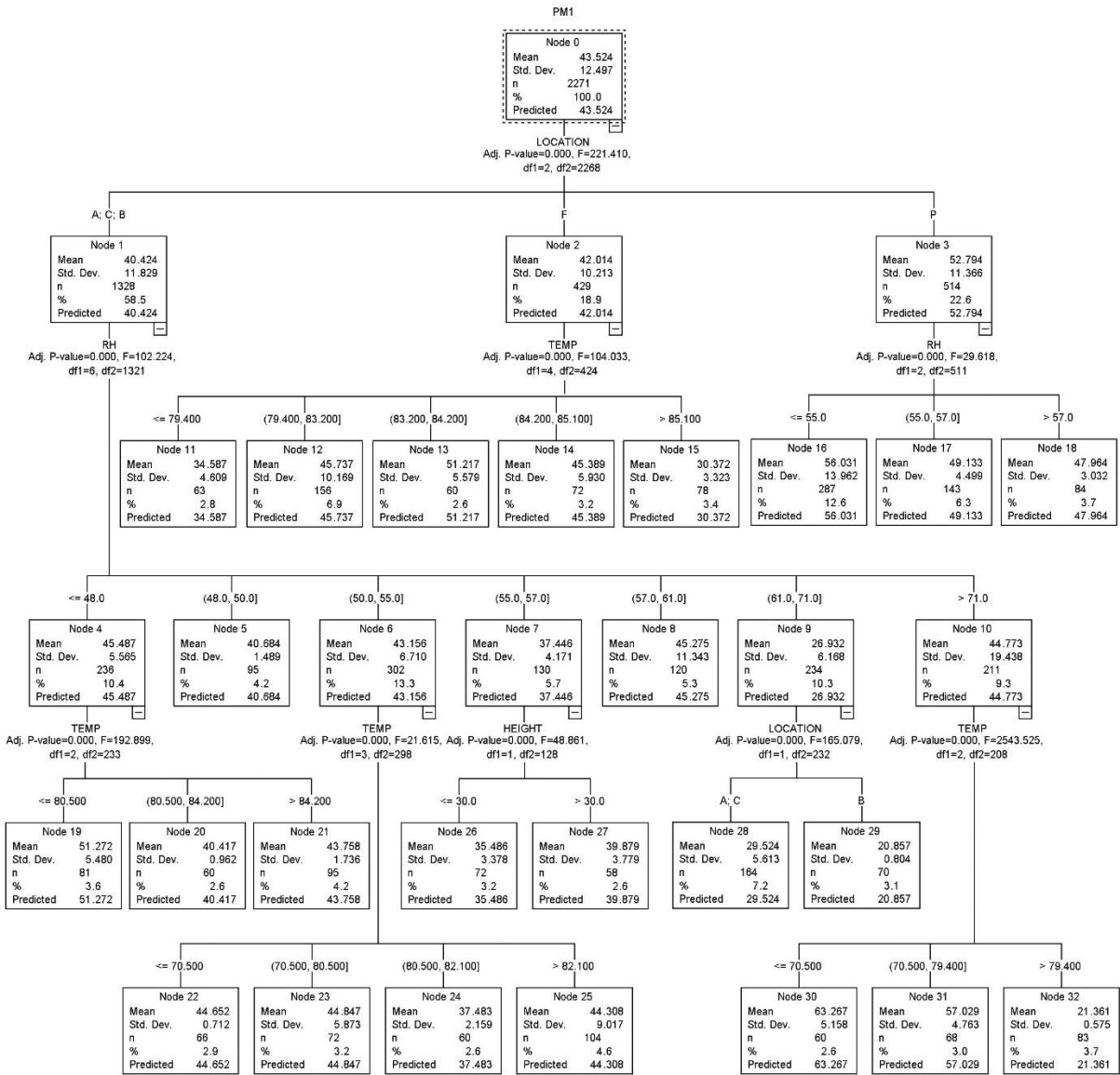


Figure 3. The overall structure of the CHAID DT for PM₁

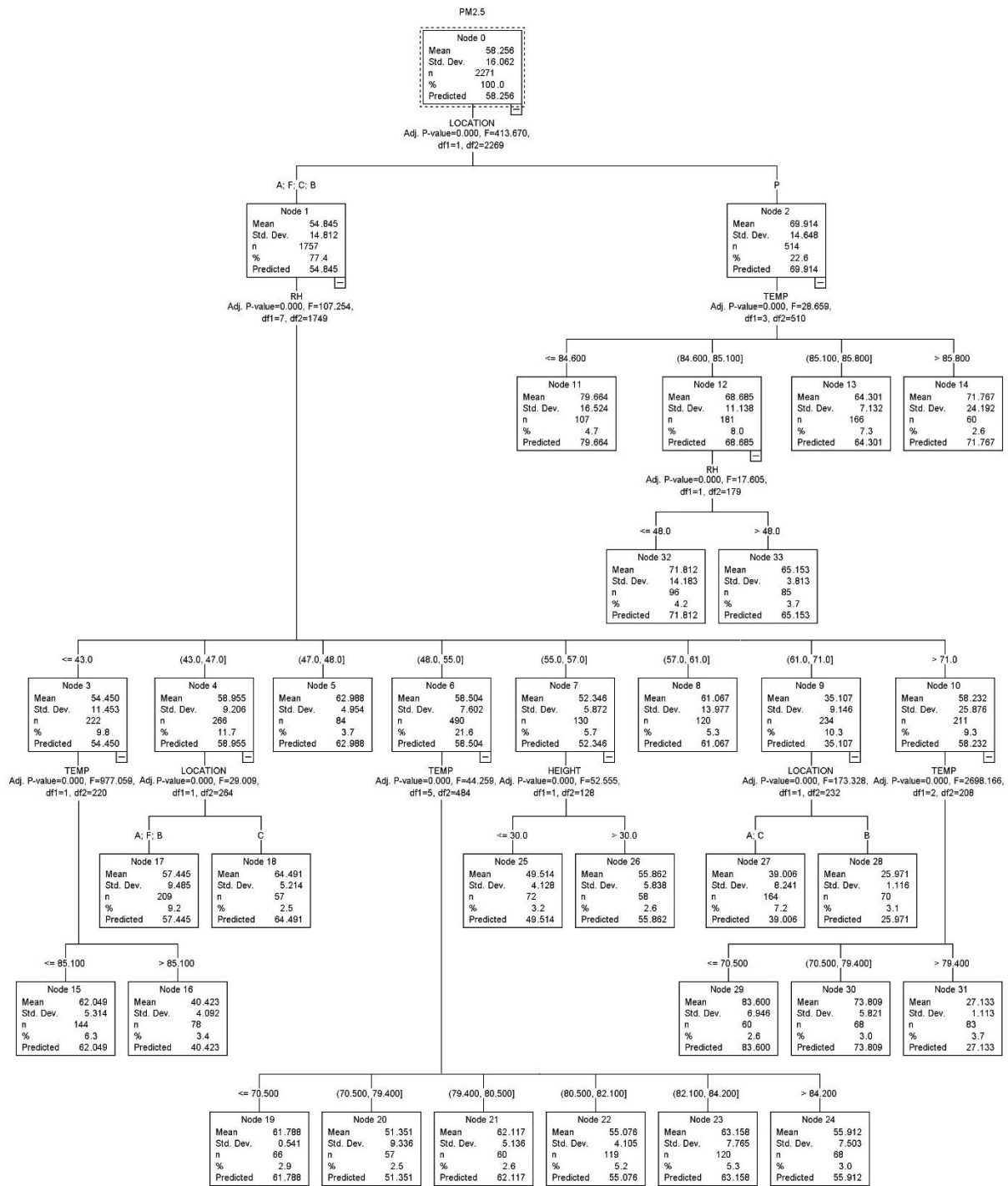


Figure 4. The overall structure of the CHAID DT for PM_{2.5}

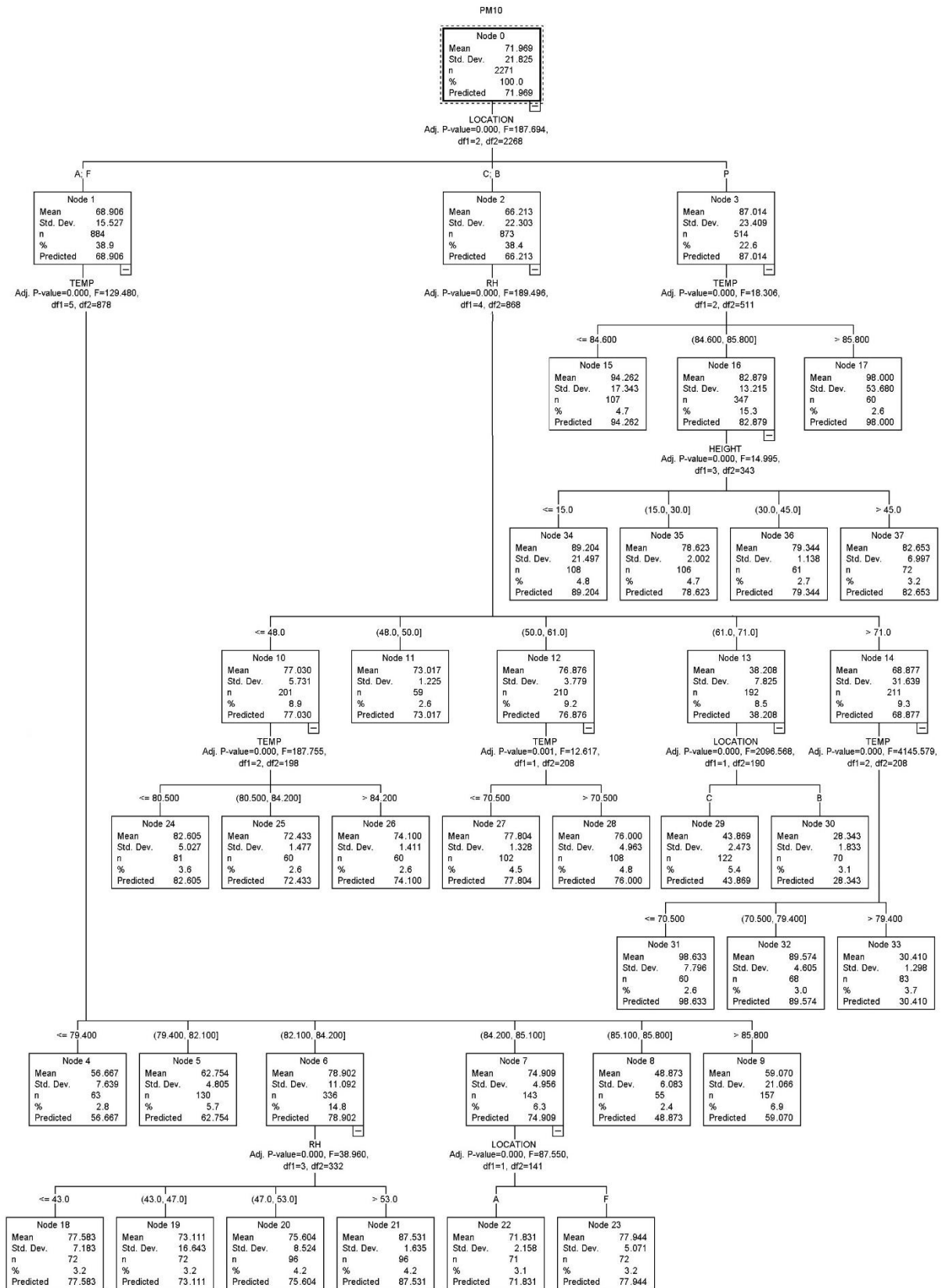


Figure 5. The overall structure of the CHAID DT for PM₁₀

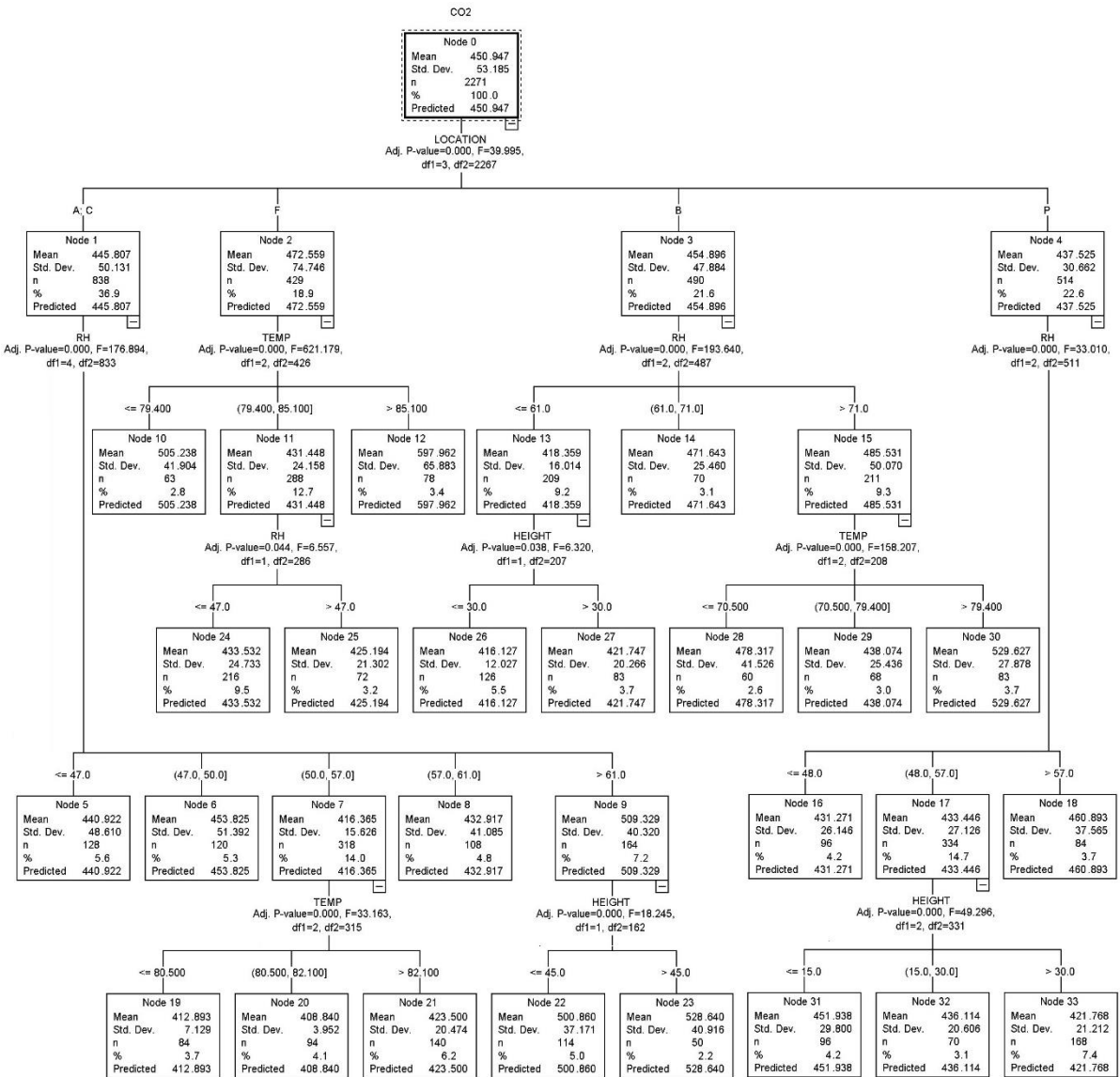


Figure 6. The overall structure of the CHAID DT for CO₂

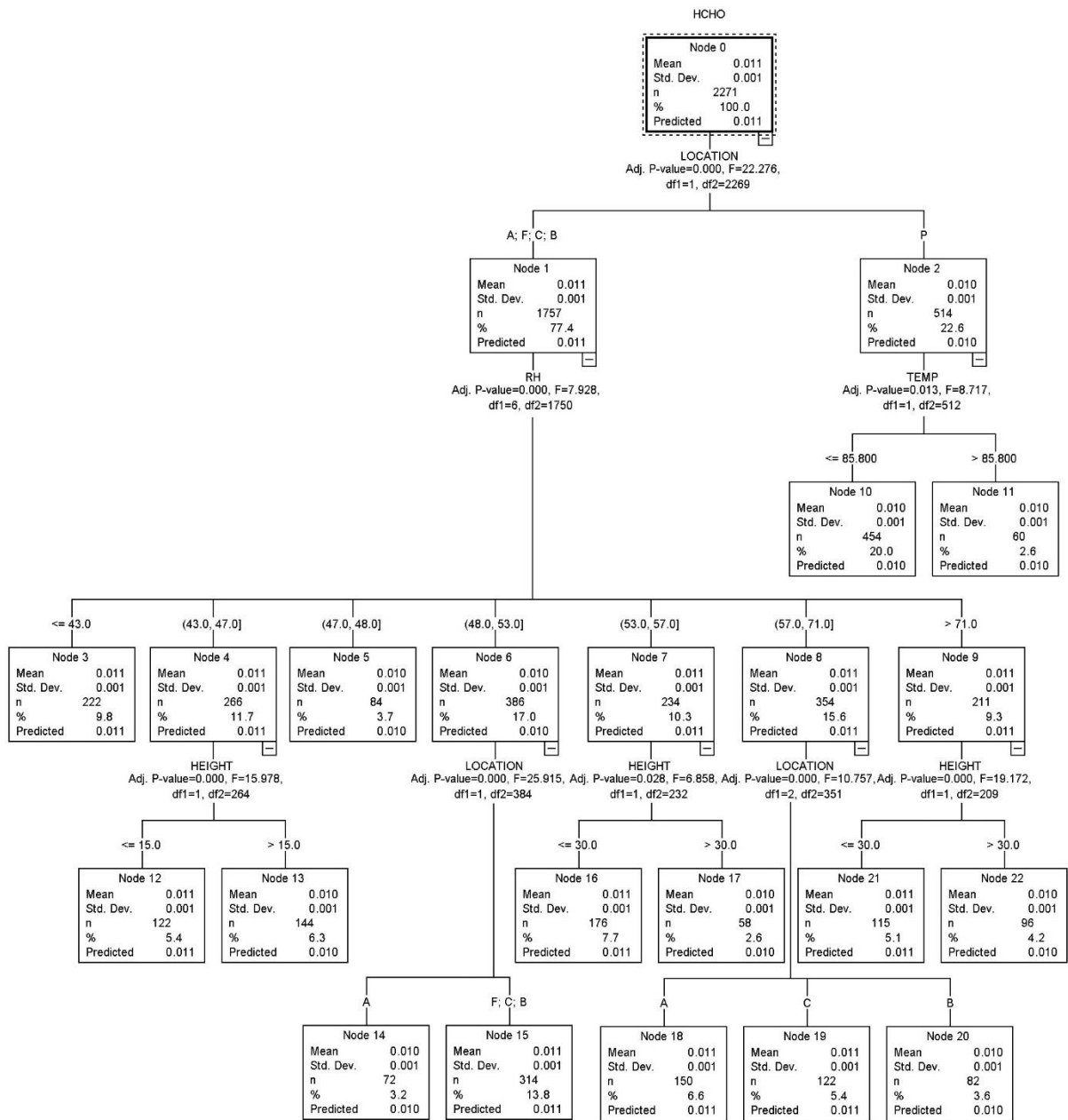


Figure 7. The overall structure of the CHAID DT for HCHO

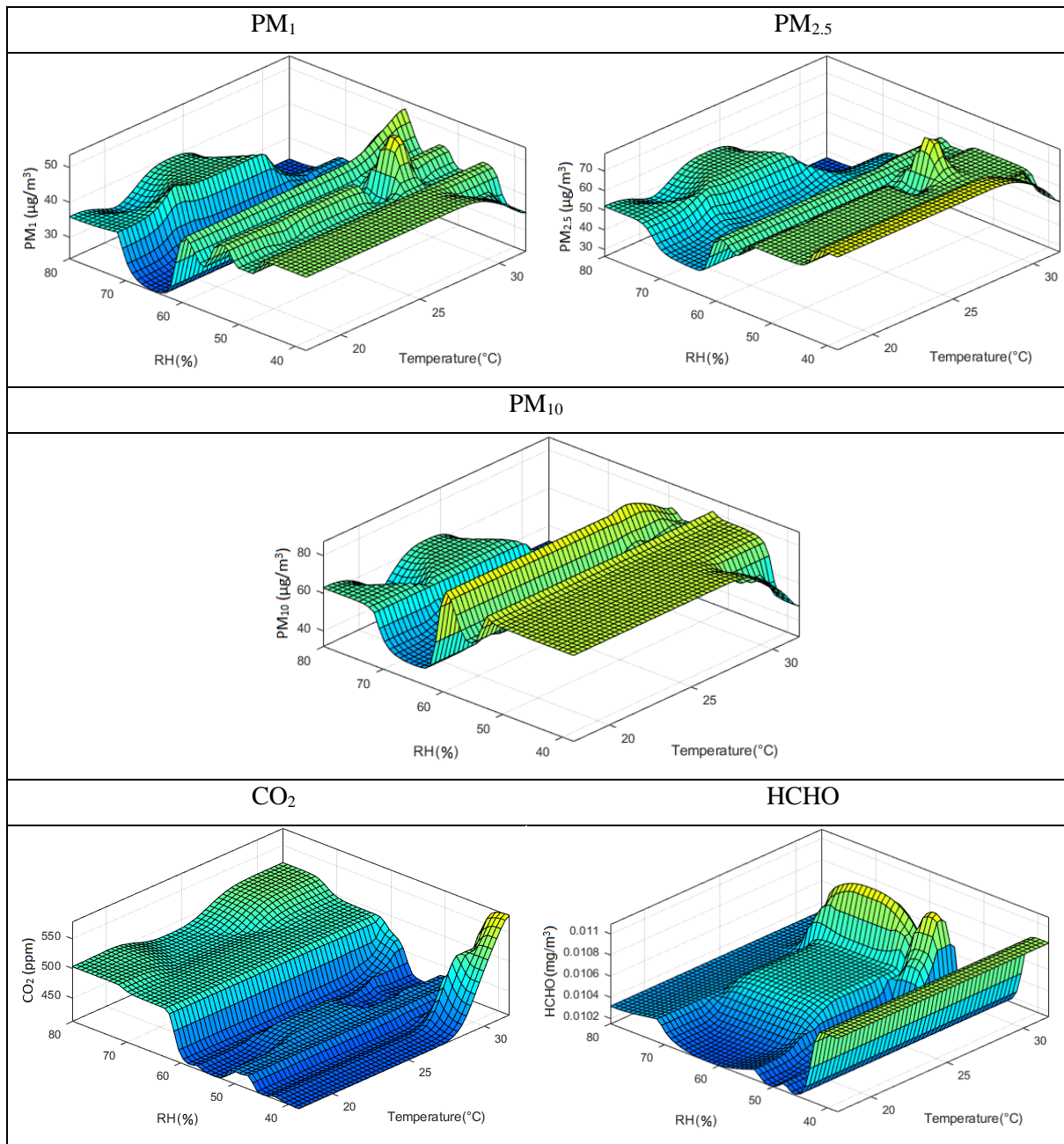


Figure 8. The concentration of pollutants based on *temperature* and *RH*

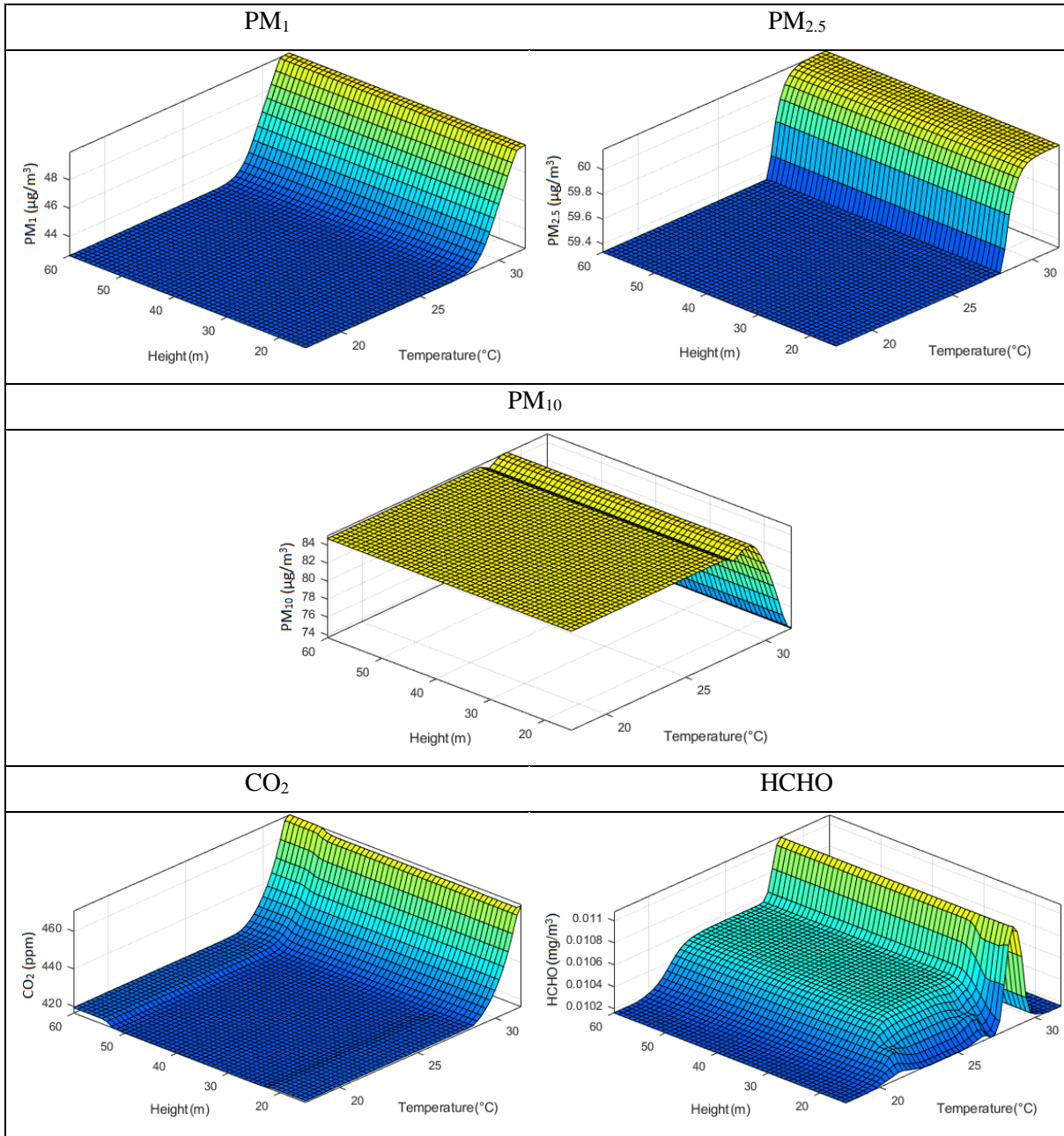


Figure 9. The concentration of pollutants based on temperature and height

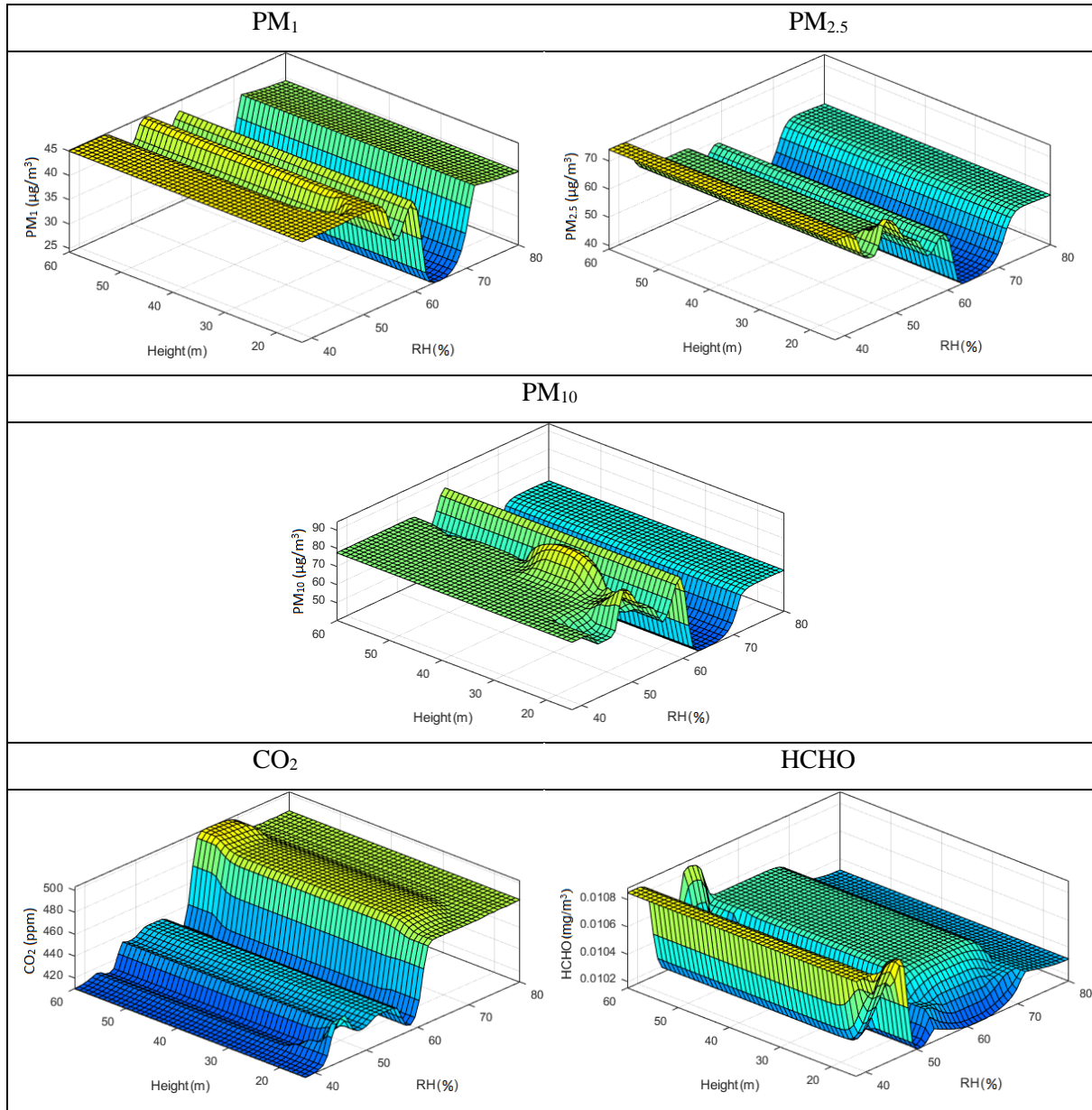


Figure 10. The concentration of pollutants based on *RH* and *height*

Cluster means - Standard
 288 backward trajectories
 GDAS Meteorological Data

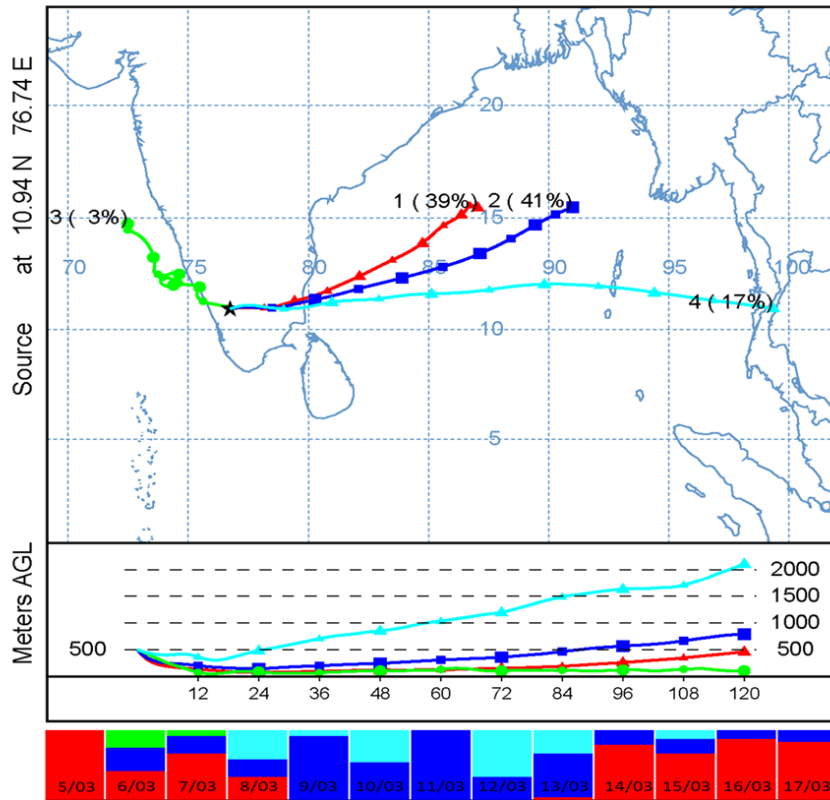


Figure 11. Cluster analysis of five days' hourly air mass back-trajectories arriving at 500 m AGL over the observation site.

Table 1. The sequence of PM_1 , $PM_{2.5}$, and PM_{10} concentration in the studied locations in terms of the minimum, lower quartile, mean, upper quartile, and maximum

Value	Location	Pollutant concentration ($\mu g / m^3$)		
		PM_1	$PM_{2.5}$	PM_{10}
Minimum	Administration Block	25	28	42
	Flight Hangar	18	24	28
	CTC Block	26	34	39
	Bethesda	12	24	26
	Petrol Pump	40	57	73
Lower quartile	Administration Block	36	49	61
	Flight Hangar	34	46	57
	CTC Block	30	38	46
	Bethesda	22	28	31
	Petrol Pump	46	62	78
Median	Administration Block	38	54	67
	Flight Hangar	40	58	73
	CTC Block	42	58	72
	Bethesda	40	58	74
	Petrol Pump	48	63	80
Mean	Administration Block	40.81	55.33	68.68
	Flight Hangar	42.01	55.71	69.14
	CTC Block	40.23	54.11	66.74
	Bethesda	40.21	54.20	65.80
	Petrol Pump	52.79	69.91	87.01
Upper quartile	Administration Block	45	60	74
	Flight Hangar	51.5	66	82
	CTC Block	45	61	76
	Bethesda	49	66	84.25
	Petrol Pump	51.25	67	85

Maximum	Administration Block	58	76	91
	Flight Hangar	63	76	90
	CTC Block	58	73	88
	Bethesda	72	99	123
	Petrol Pump	58	74	94
