A23M-3097: Ultrafine Particle Transport from Arriving Aircraft

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INTRODUCTION

- Ultrafine particles (UFP; <0.1 µm diameter; Fig. 1) are highly variable in space and time and as such can be challenging to model for use in epidemiology studies.
- Recent studies have shown that airports are contributors to local air pollution (Fig. 2).
- Research is needed to understand the impact from individual aircraft and how to incorporate flight activity into UFP exposure models.

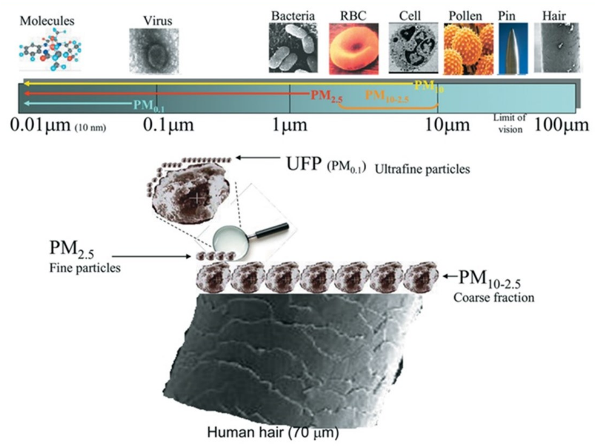

Fig 1 (left). Scale of particle sizes with examples. Ultrafine particles are those particles sized 0.1 µm (0.1 x 10^{-6} m) and smaller. Image adapted from Brooks et al. (2008).[1]

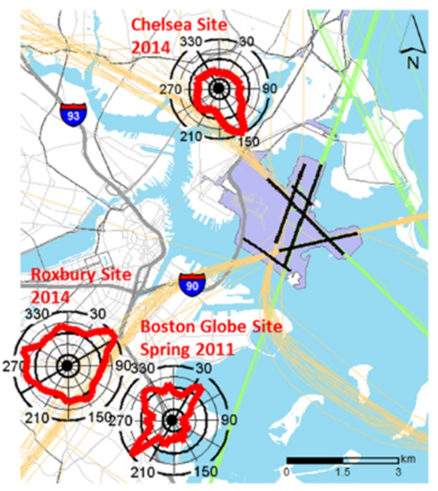

Fig 2 (right). Ultrafine particle concentration by wind direction as measured at stationary sites around Boston Logan International Airport. Winds from the airport correlate with some of the highest observed concentrations. Image adapted from Hudda et al. (2016).[2]

OBJECTIVE

Our aims were to:

1) Conduct ambient monitoring of UFP measured as particle number concentration (PNC; a proxy for UFP) at sites with varying proximity to landing flight paths, and

2) Characterize UFP transport from aircraft exhaust during landings along the 4L/R runway trajectory at Boston Logan International Airport (MA, USA) using machine learning.

METHODOLOGY

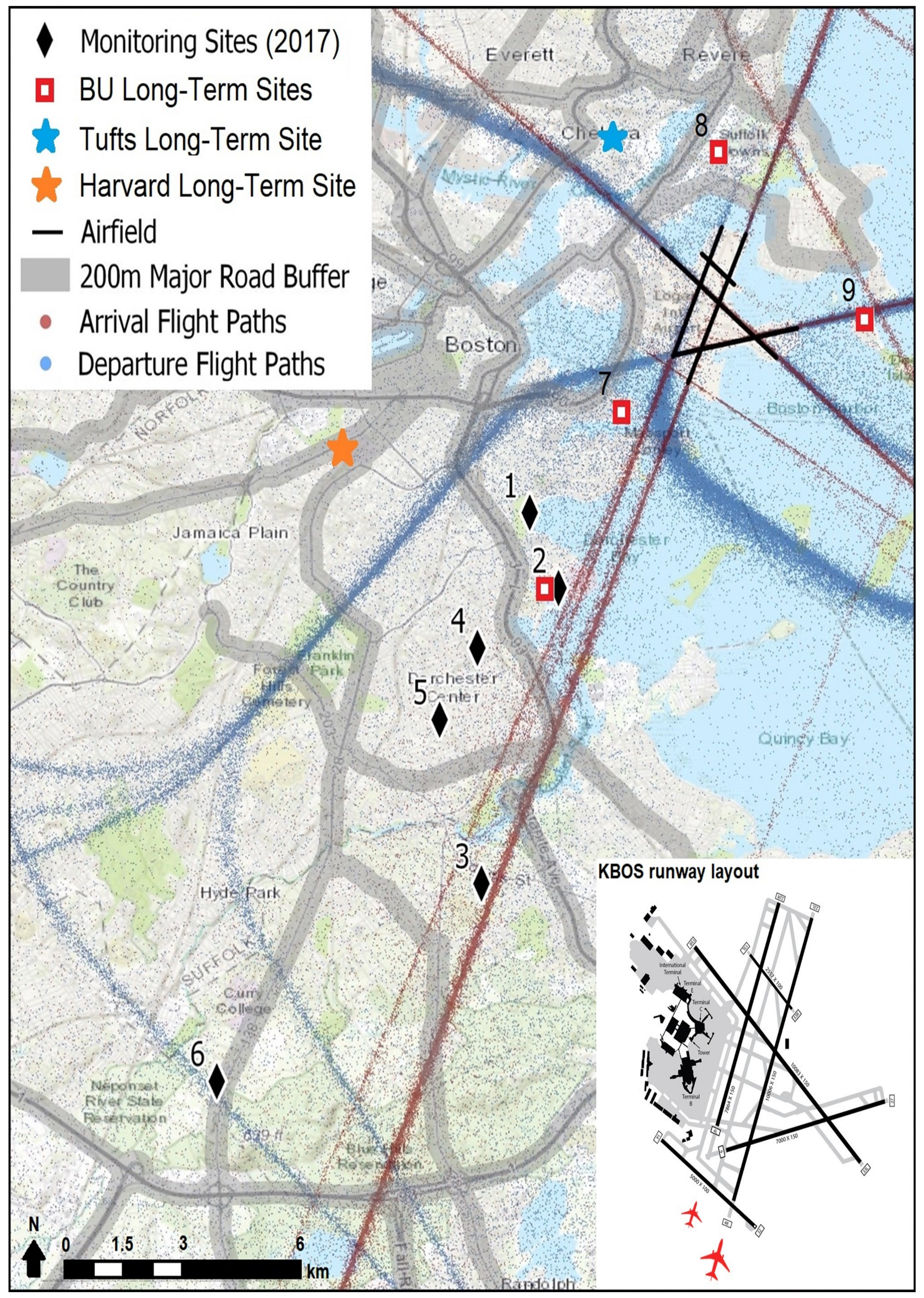

Fig 3. Map of monitoring sites, flight paths, and runway configurations for Boston Logan International Airport (Boston, MA).

- Particle number concentration (PNC) was measured on selected weeks at Sites 1-6 (Fig. 3) from April-September 2017 at 1-second resolution.
- Wind speed and direction and temperature were measured at each site. Regional meteorology was obtained from Logan Airport (KBOS); mixing height was calculated from upper-air data from Chatham, MA.
- Flight activity data were acquired from the U.S. Federal Aviation Administration, which included three-dimensional positions of aircraft at ~5-sec resolution.
- We used machine learning regression to identify key covariates and optimize prediction of PNC at Univ. of MA Boston (Site 2) based on a random forest approach (i.e., decision tree-based algorithm; Fig. 4). Each tree was grown by a bootstrap sample with random subsets of predictors selected at each split. Final models were based on the average results of all trees and were compared to linear models.
- Models were built based on 1-hr ln(PNC) at different scales: 50^{th}, 95^{th}, and 99^{th} percentiles.

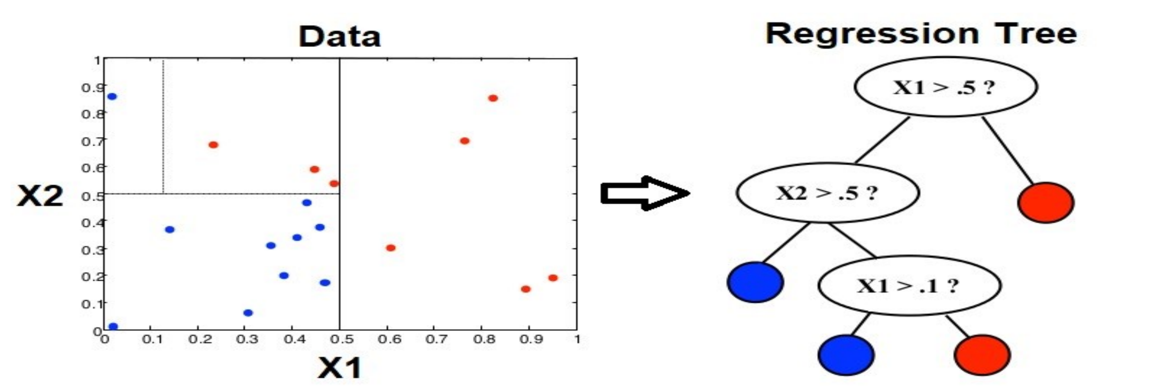

Fig 4. Visual diagram of random forest regression applied to an example data set. The computer splits the data into a specified number of bins (user defined), tests a specified number of dependent variables at random for each tree branch and selects the variable resulting in the least error, and so on.

RESULTS

- All monitoring sites had similar 50^{th} percentile PNC, but peak PNC (>95^{th} percentile) were higher for those sites closest to the airport and with lower elevation of arriving aircraft (Table 1).
- Planes landing along 4L/R resulted in higher PNC than when planes were not landing on 4L/R, under similar wind conditions (Fig 5). Similar results were observed comparing PNC during the 5-min period before and after flights began arriving.
- When flights were landing on 4L/R, the 99^{th} percentile of 1-sec PNC during winds from the east (no traffic) was 88,000 particles/cm^3. Concentrations dropped >50% when flights were landing along other trajectories during these same winds.
- Random forest regression trees explained >55% of 1-hr PNC variance for all models tested, using 10 explanatory variables in each model. As hourly PNC was aggregated using higher percentiles of 1-sec PNC (i.e., 95^{th} and 99^{th} percentile as compared to 50^{th} percentile), models explained more of the PNC variance with no change in variables included. While meteorological variables were still ranked most important, they lost some importance when modeling the tails of the PNC distribution (Fig 6).

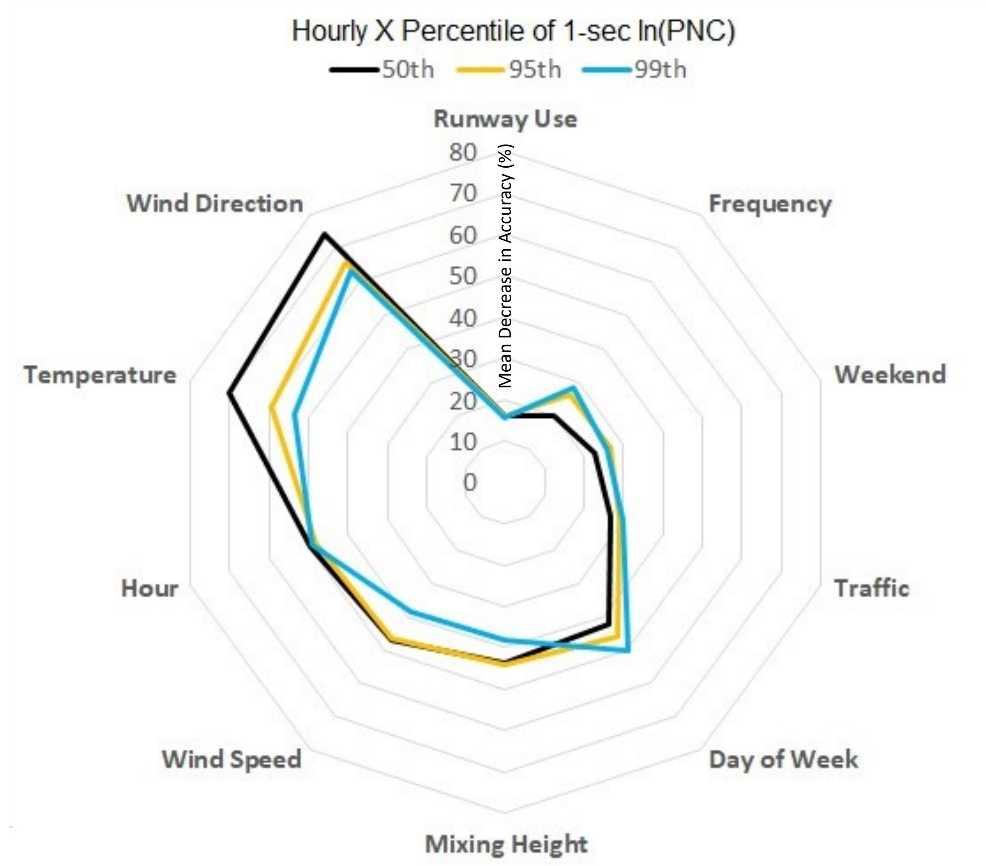

Fig 6. Spider plot showing the importance of each variable in the random forest model based on the mean decrease in model accuracy (as measured by mean square error). As PNC is aggregated to the hour by higher percentiles, meteorological variables lose importance while variables related to schedules or flight activity gain importance. Flight frequency has the largest percent gain in model importance when comparing 95th and 99th percentile models to the 50th percentile.

Table 1. Summary table for Sites 1-7 (corresponding to locations in Fig. 1) highlighting the differences in X-percentiles for 1-second PNC. PCTL = percentile.

	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6
Sample Size (days)	67	71	57	61	57	62
Location	2^{nd} Floor	Ground	2^{nd} Floor	Ground	Ground	Ground
Nearest Runway	4R	4R	4R	4R	4R	4R
Distance to Runway (km)	4.0	4.9	10.8	6.7	8.2	16.6
0.1^{st} PCTL	800	1,100	1,600	2,500	2,000	1,800
1^{st} PCTL	1,000	2,900	2,500	5,100	2,900	2,500
5^{th} PCTL	4,300	5,800	4,300	8,200	5,700	4,300
50^{th} PCTL	14,100	16, 600	11,600	20,600	17,100	12,000
95^{th} PCTL	55,600	63,000	28,000	67,900	47,100	31,400
99^{th} PCTL	116,800	119,200	47,400	103,200	70,700	50,500
99.9^{th} PCTL	180,200	206,600	87,500	150,800	96,500	95,800

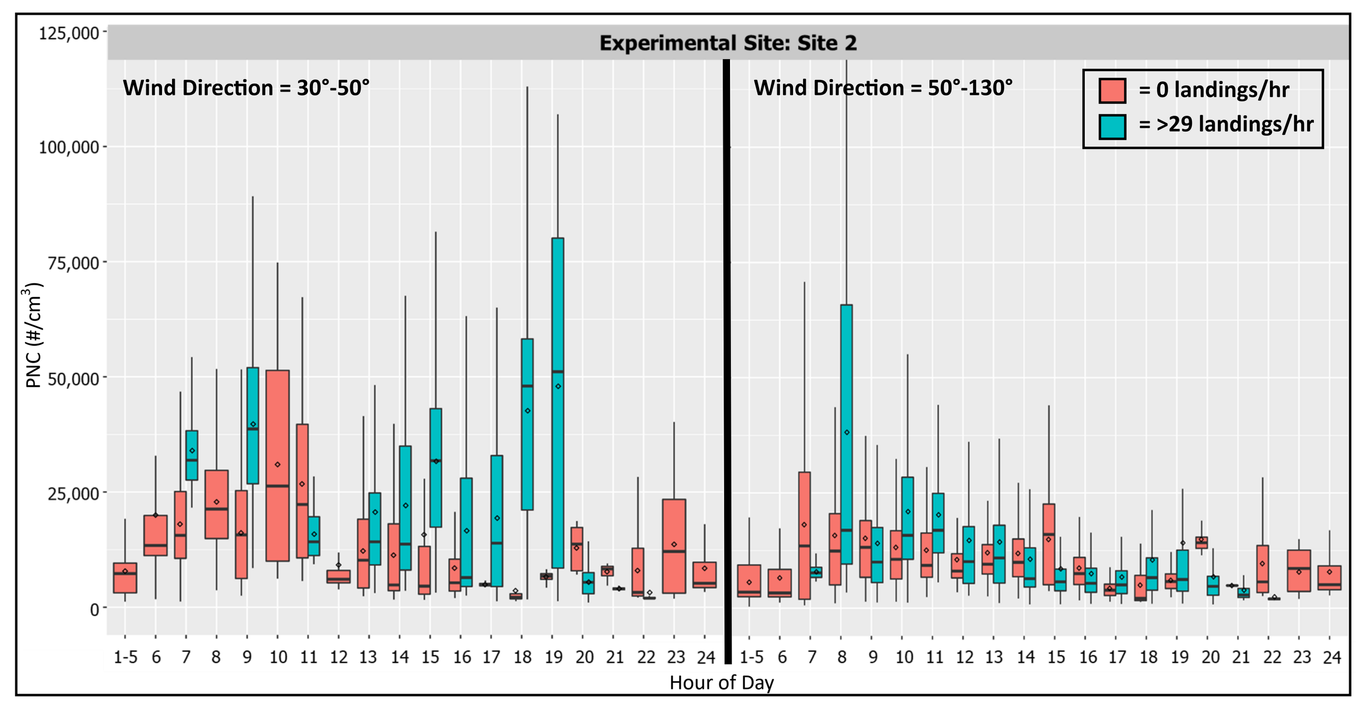

Fig 5. Comparisons between PNC measured at Site 2 during flight activity and no flight activity (i.e., planes landing on either 4L or 4R runways) under different wind conditions.

- Explanatory variables from the RF model showed a similar improvement in R^2 in a linear regression model as PNC were aggregated to the hour using higher percentiles of 1-sec PNC (Table 2).
- Linear models had increasing significance for Frequency term (# planes/hr) as PNC percentiles increased: p=0.98 (50^{th}), p=0.27 (95^{th}), p=0.03 (99^{th}).

Random Forest Model (% Variance Explained)	Linear Model (% Variance Explained)
50^{th} percentile: 56%	50^{th} percentile: 16%
95^{th} percentile: 60%	95^{th} percentile: 26%
99^{th} percentile: 60%	99^{th} percentile: 30%

Table 2. Comparisons between the variance explained by the same 10 variables in a random forest regression model vs. a linear regression model.

CONCLUSION

Our results suggest that aircraft can play a role in explaining peak ambient UFP exposures during landing. Downwind transport of UFP from aircraft exhaust needs further investigation.

Acknowledgments

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References

1.Brooks et al. 2008, *Clinical Science*.

2.Hudda et al., 2016, *Environmental Science and Technology*.

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