

ENV-167

Aerosol sensing

Satoshi Takahama

Laboratory for Atmospheric Processes and their Impacts

27.11.2024

About me

Formation

- BS Civil Engineering
- PhD Chemical Engineering
- Scripps Institution of Oceanography
- EPFL

Research in aerosol science and atmospheric chemistry

After this lecture, you will be able to answer the following questions

- Why do we care about atmospheric aerosols?
- What are some properties of atmospheric aerosols?
- Why do we need to measure chemical constituents?
- What are important light-matter interactions?
- What are the impediments to ubiquitous chemical measurements?

Outline

- Atmospheric composition
- Aerosols
- Aerosol impacts on climate and health
- Light-matter interactions
- Environmental monitoring via infrared

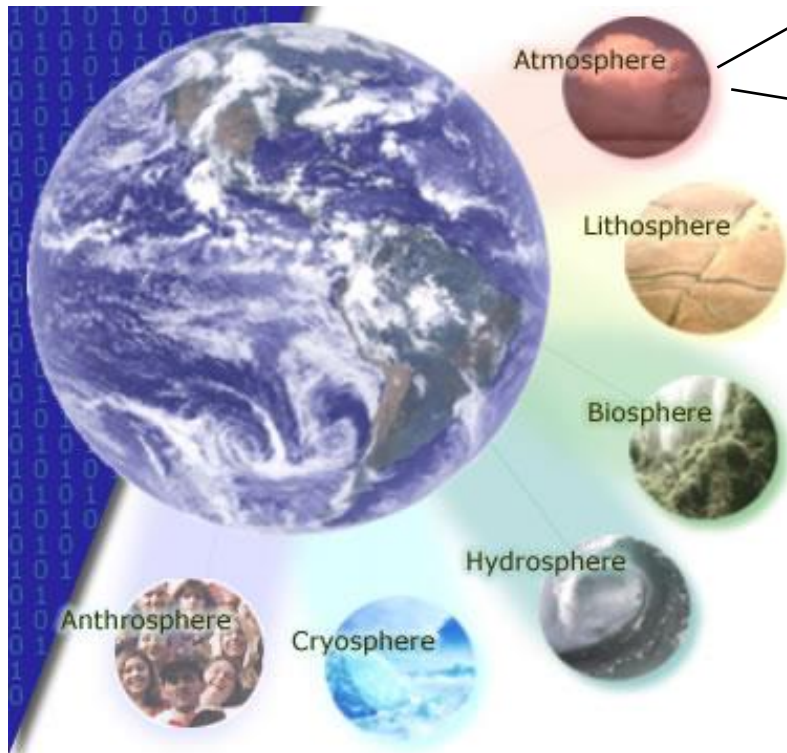
Related lectures:



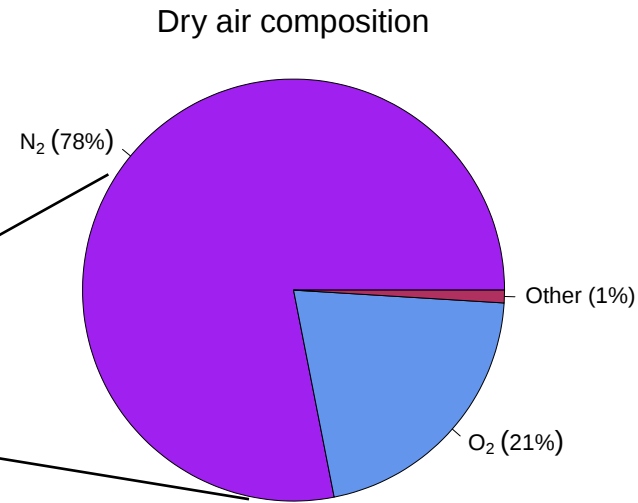
“To reduce pollution, you must first measure it”

“You can’t improve what you don’t measure”

Atmospheric composition



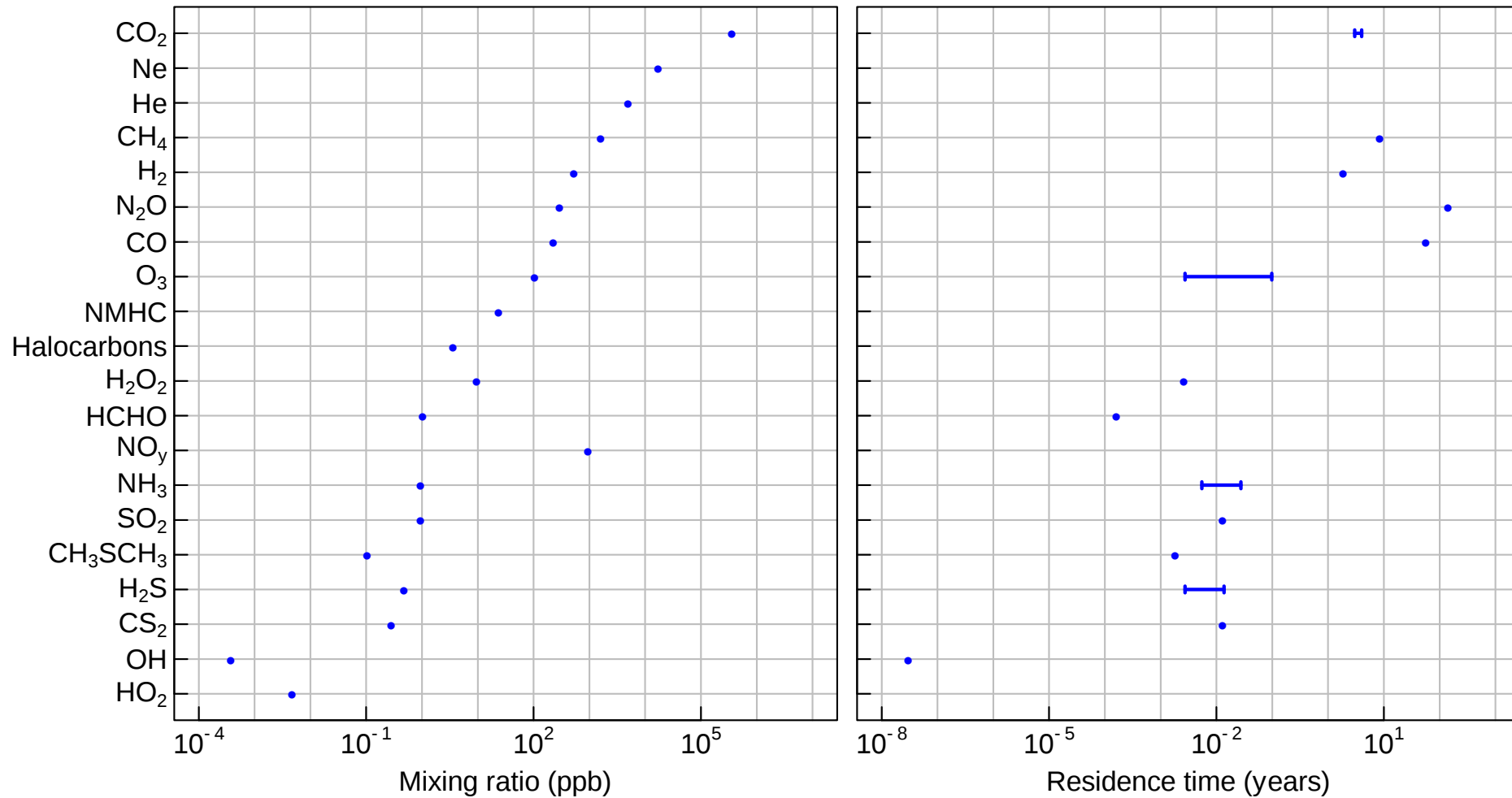
Source: Institute for Computational Earth System Science



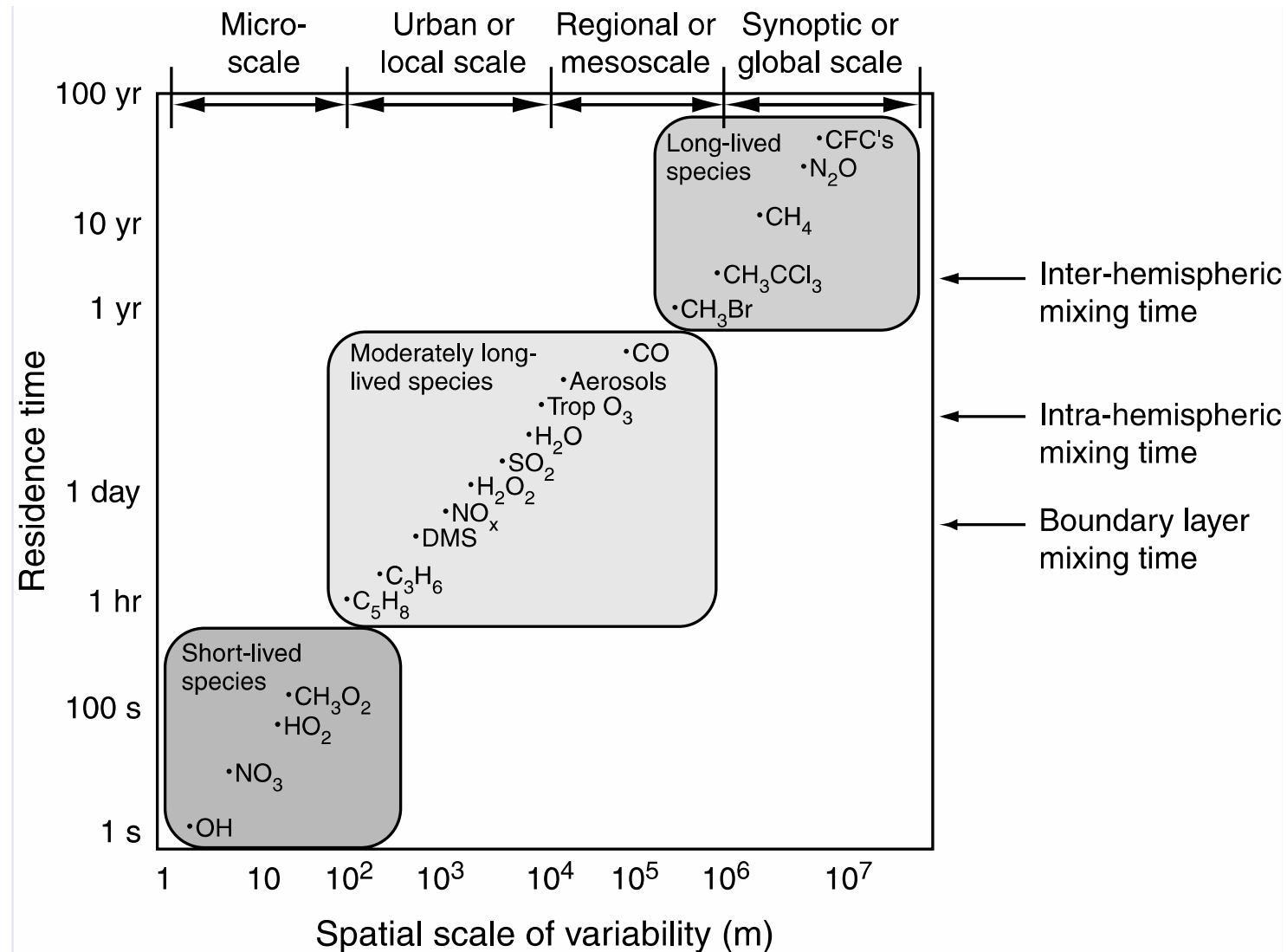
- Interest in trace compounds (in the 1%).
- Contribution of water to mass budget is also on the order of 1%.
- The atmosphere is a highly nonlinear system (magnitude of response is not proportional to its input)
- Elements additionally distributed throughout atmosphere, biosphere, lithosphere, hydrosphere, etc.

Tropospheric species in the gas phase

Data from Wallace and Hobbs, 2006

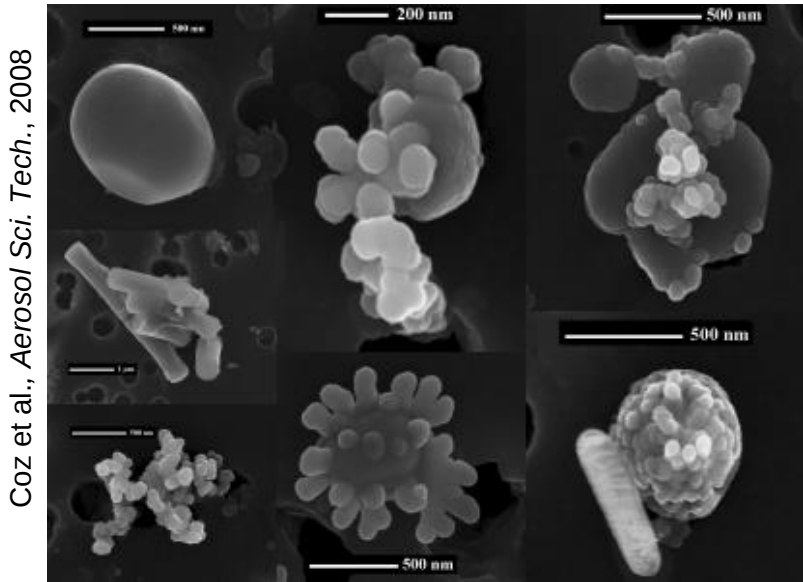


Residence Time and Spatial Scales of Variation of Chemicals in the Atmosphere



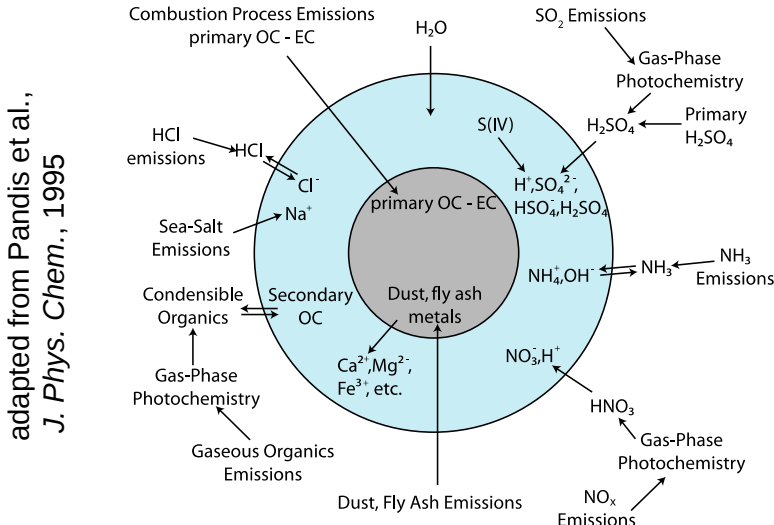
Atmospheric aerosols

Scanning electron microscopy images

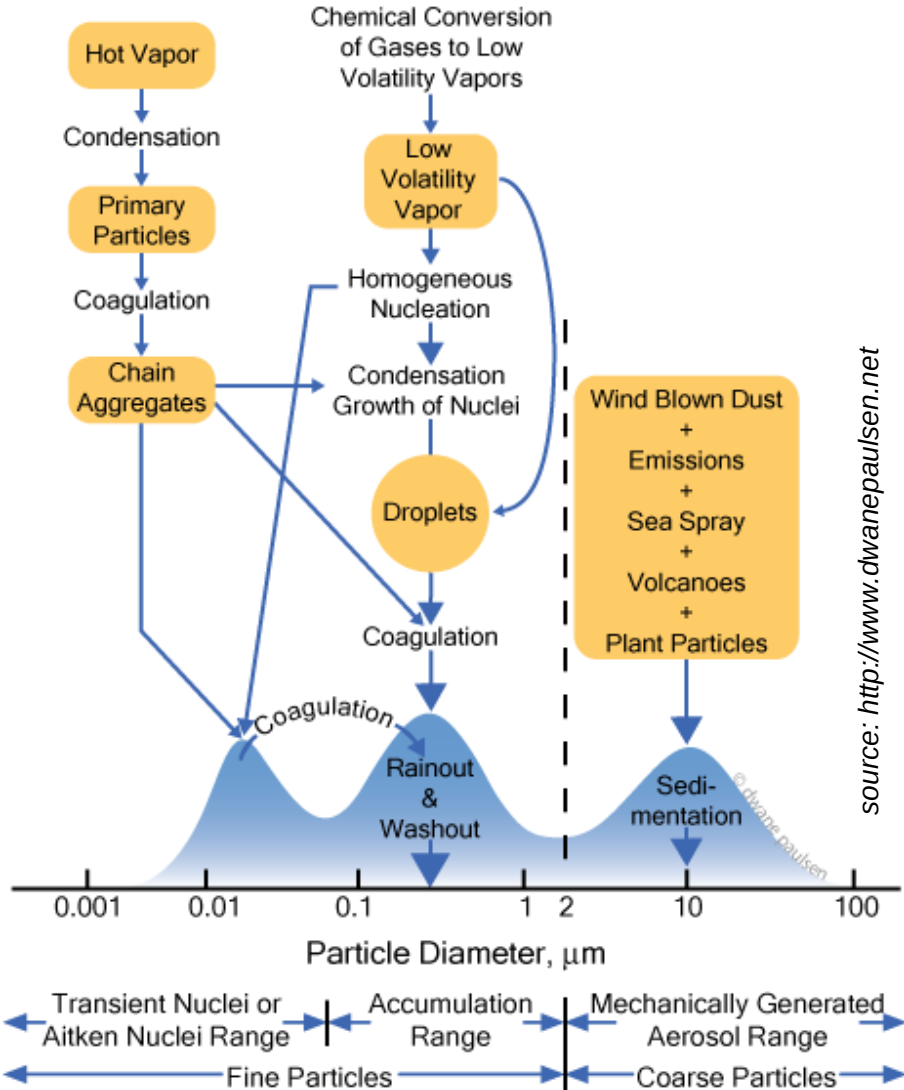


Coz et al., Aerosol Sci. Tech., 2008

- Varies in
- size
 - shape
 - phase
 - composition



adapted from Pandis et al., J. Phys. Chem., 1995



source: <http://www.dwanepaulsen.net>

Aerosol sources

Mixed



Forest fires



Sea spray



Dust

Natural



Volcanic eruptions



Traffic / Transport



Domestic activities



Industry



Agriculture

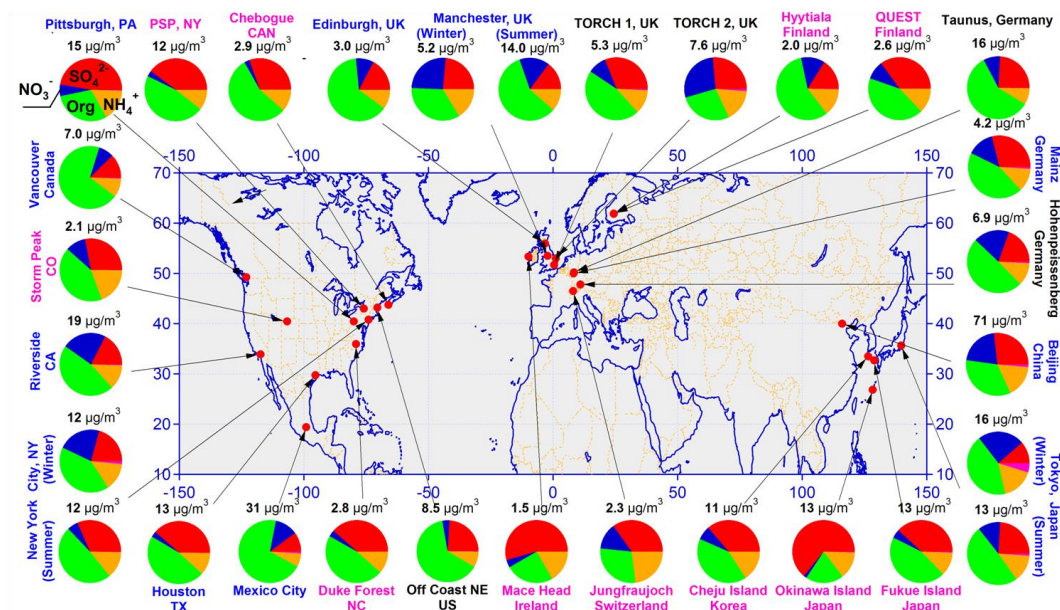
Anthropogenic

Aerosol composition

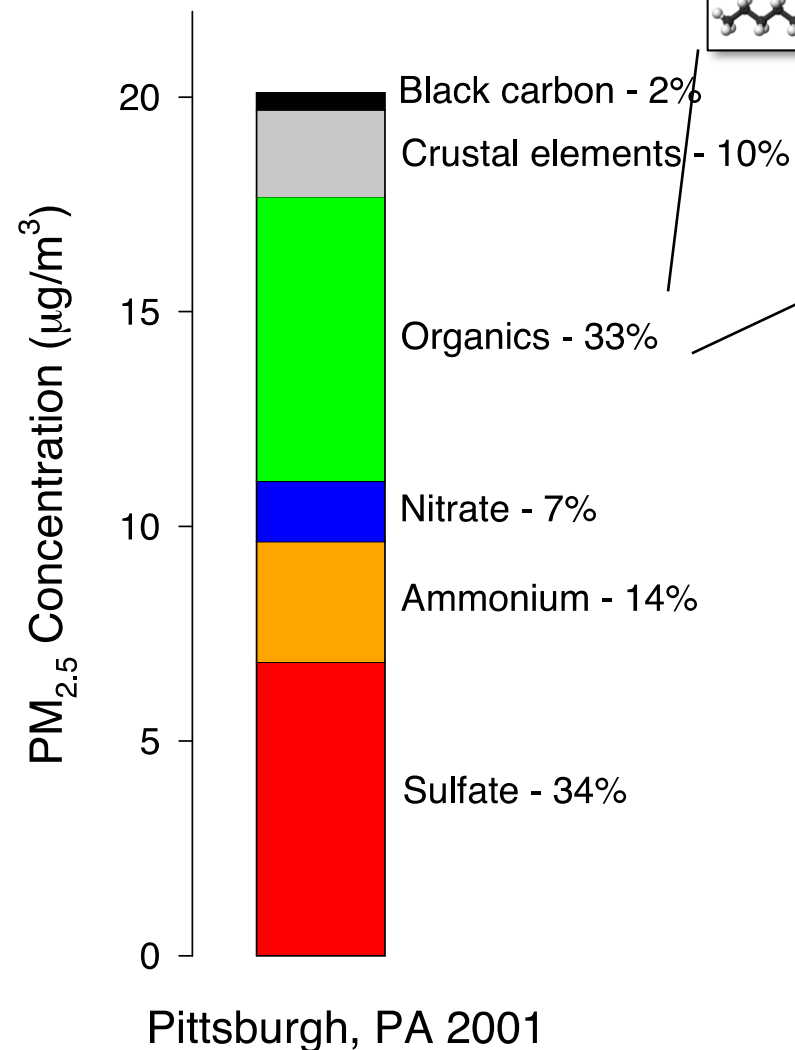
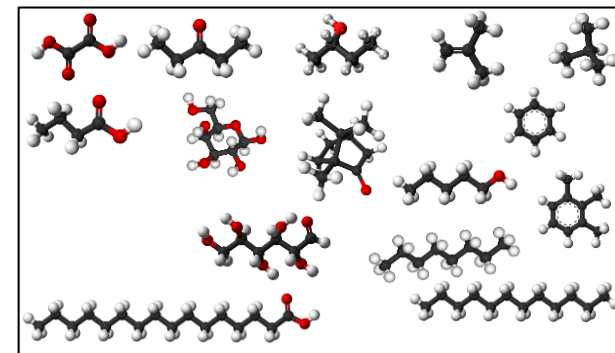
Major components:

- Inorganic salts/ions
- Organic compounds (10,000+)
- Black carbon/soot
- Mineral dust

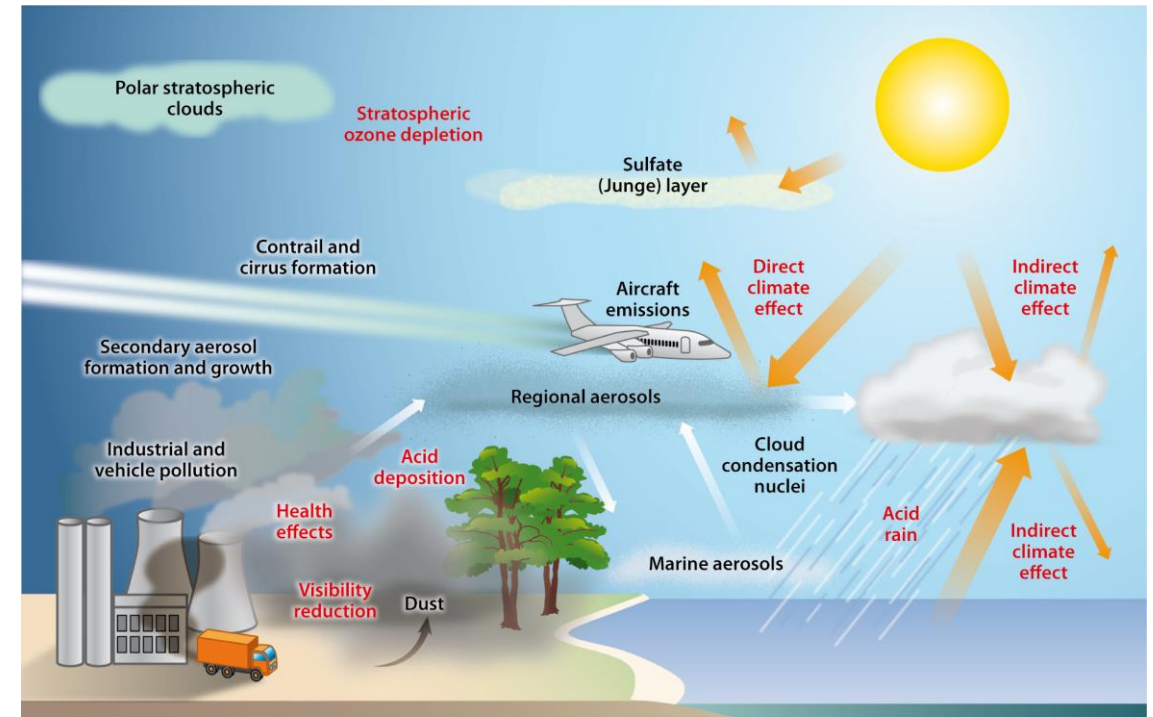
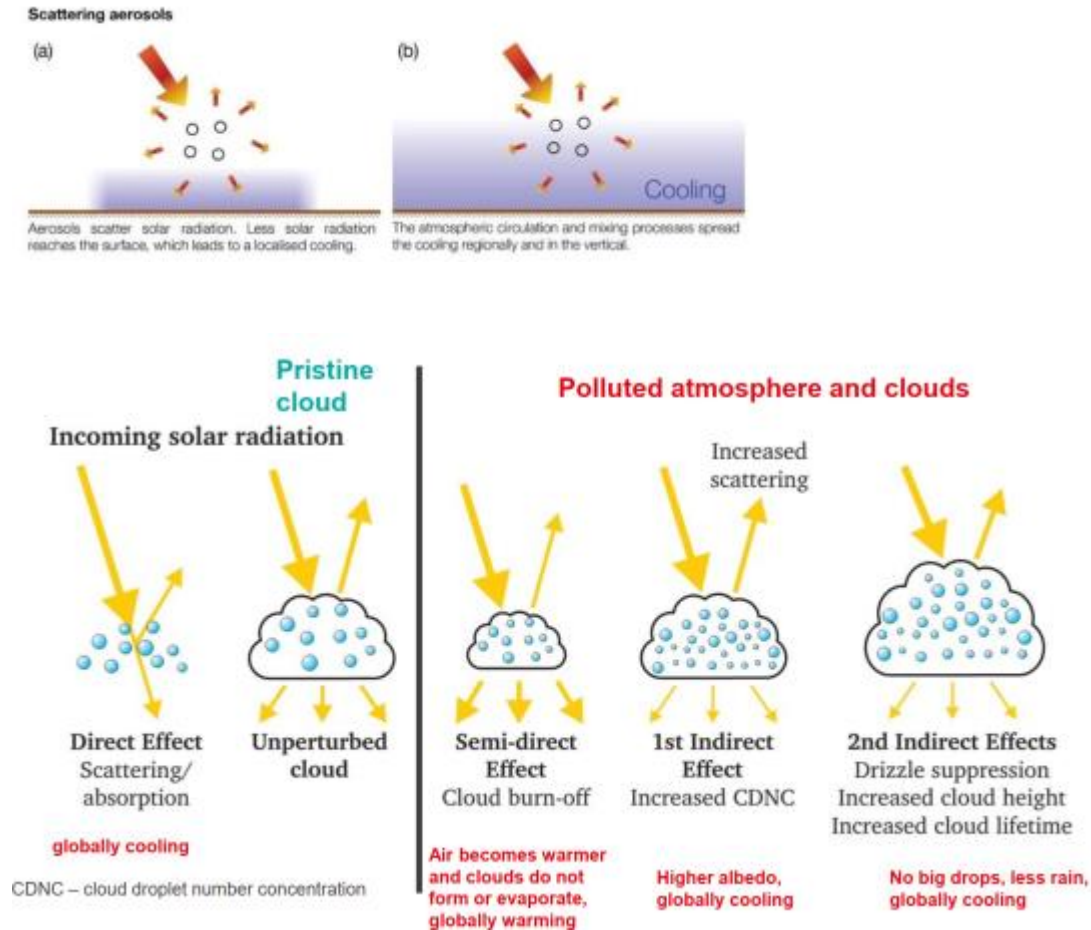
Occurs in different proportions over time and throughout the world



NR-PM₁: Zhang et al., *Geophys. Res. Lett.*, 2007



Aerosols and climate



 Kolb CE, Worsnop DR. 2012.
Annu. Rev. Phys. Chem. 63:471–91

Aerosols and health

The New England Journal of Medicine

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Volume 329

DECEMBER 9, 1993

Number 24

AN ASSOCIATION BETWEEN AIR POLLUTION AND MORTALITY IN SIX U.S. CITIES

DOUGLAS W. DOCKERY, SC.D., C. ARDEN POPE III, PH.D., XIPING XU, M.D., PH.D.,
JOHN D. SPENGLER, PH.D., JAMES H. WARE, PH.D., MARTHA E. FAY, M.P.H.,
BENJAMIN G. FERRIS, JR., M.D., AND FRANK E. SPEIZER, M.D.

Cohort study of 8111 Americans

Medical history and lifestyle examined over 14-16 years

Association found between excess mortality and fine particulate matter pollution

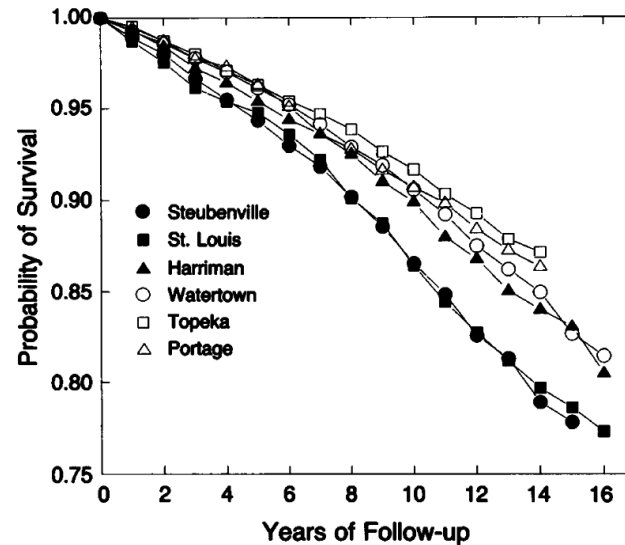


Figure 2. Crude Probability of Survival in the Six Cities, According to Years of Follow-up.

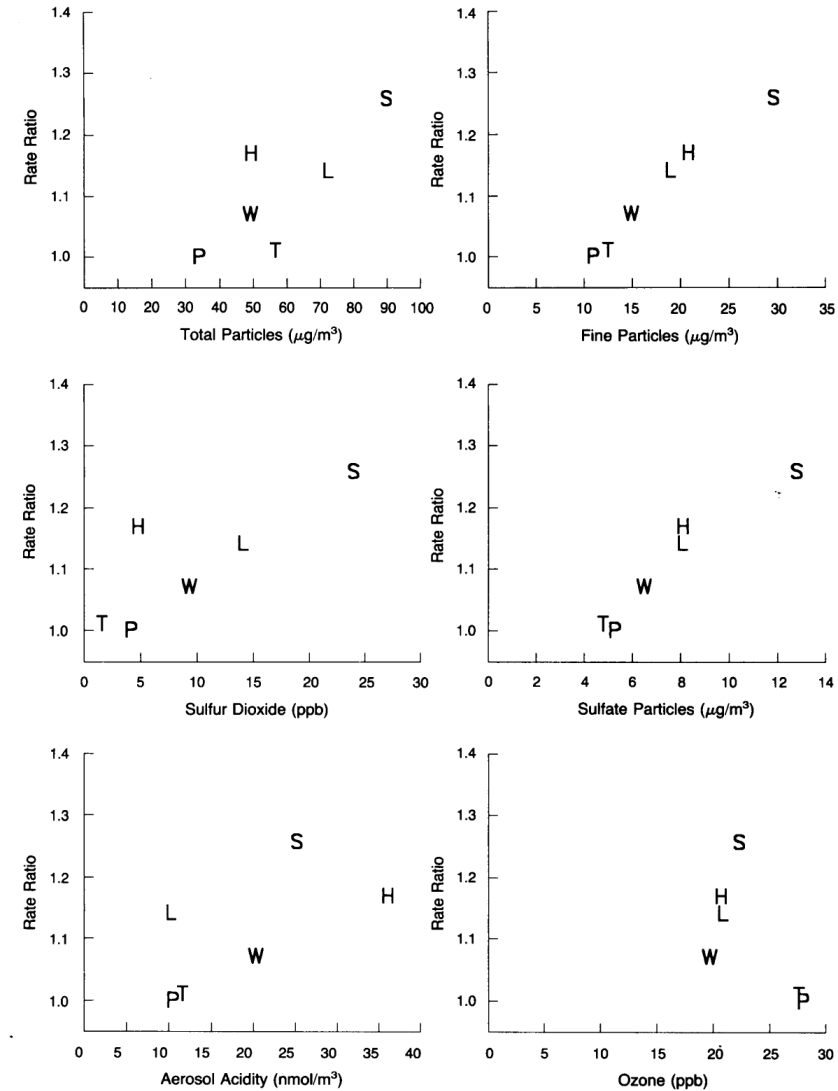


Figure 3. Estimated Adjusted Mortality-Rate Ratios and Pollution Levels in the Six Cities. The letters shown for the measures of air pollution. P denotes Portage, Wisconsin; T Topeka, Kansas; W Watertown, Massachusetts; L St. Louis; H Harriman, Tennessee; and S Steubenville, Ohio.

Survival analysis

Cox proportional hazards model

$$\lambda_A(t) = -\frac{d}{dt} \ln S(t)$$

survival probability

Incidence rate

Baseline incidence rate

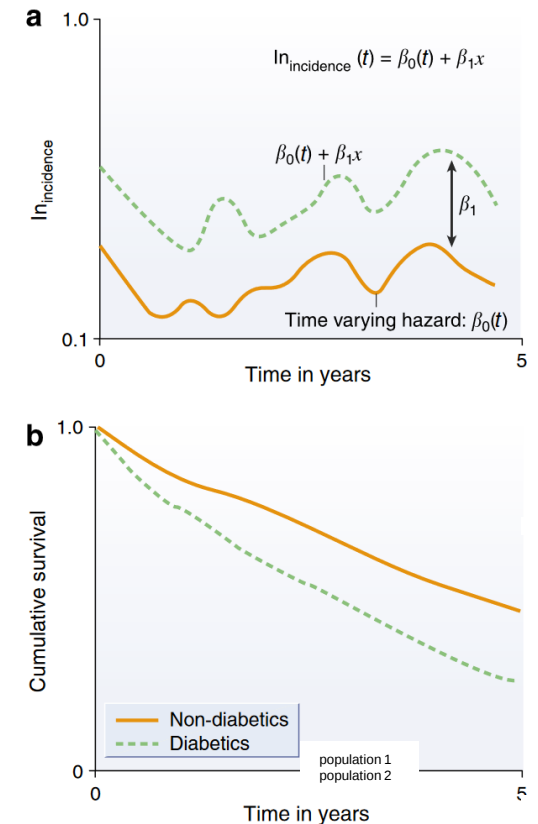
Confounders

Exposure

$$\lambda_A(t) = \lambda_B(t) \times \exp \left(\sum_{i=1}^k \beta_i X_i + \gamma E \right)$$

Log-linear relation to exposure

$$\ln \lambda_A(t) = \beta_0(t) + \sum_{i=1}^k \beta_i X_i + \gamma E$$



adapted from van Dijk et al., 2008

Confounders

- Stratified by age group and sex
- Smoking
- Education level
- BMI
- Exposure to local sources (occupational exposure)

Improvements in estimates (1993 – present)

- Larger cohorts
- Better exposure estimate
 - combine ground-based measurements, satellite remote sensing, and air quality model simulations
 - high resolution
 - capture microenvironments
- More confounding variables
 - environmental variables
 - behavioral, social, and economic variables
 - demographic variables
- Specific chemical constituents

Global urban temporal trends in fine particulate matter (PM_{2.5}) and attributable health burdens: estimates from global datasets

Veronica A Southerland, Michael Brauer, Arash Mohegh, Melanie S Hammer, Aaron van Donkelaar, Randall V Martin, Joshua S Apte, Susan C Anenberg

Lancet Planet Health 2022;
6: e139–46

Published Online

January 5, 2022

[https://doi.org/10.1016/](https://doi.org/10.1016/S2542-5196(21)00350-8)

S2542-5196(21)00350-8

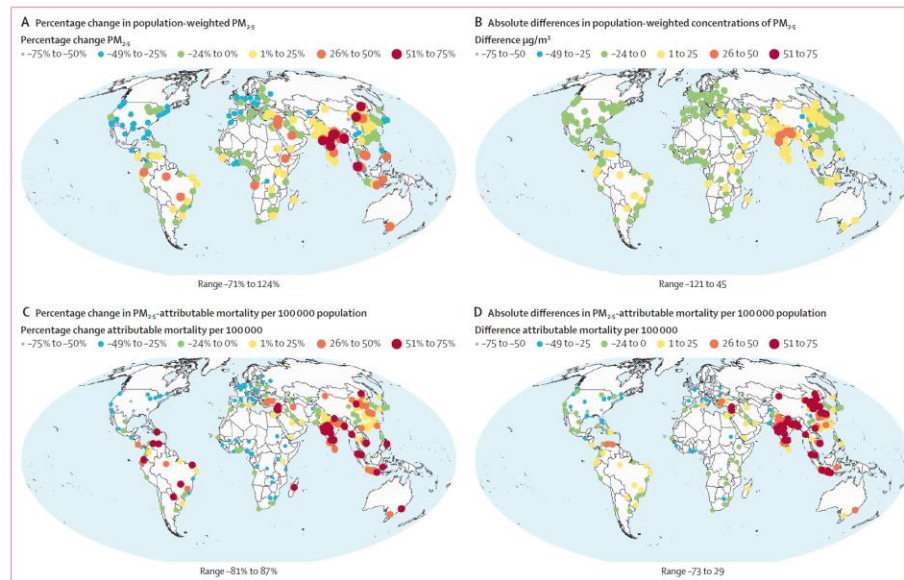


Figure 3: Change in population-weighted PM_{2.5} concentrations and PM_{2.5}-attributable mortality rates between 2000 and 2019 for the top 250 most populated urban areas based on 2019 WorldPop estimates
(A) Percentage change in population-weighted PM_{2.5} concentrations. (B) Absolute differences in population-weighted concentrations of PM_{2.5}. (C) Percentage change in PM_{2.5}-attributable mortality per 100 000 population. (D) Absolute differences in PM_{2.5}-attributable mortality per 100 000 population.

Summary

Background With much of the world's population residing in urban areas, an understanding of air pollution exposures at the city level can inform mitigation approaches. Previous studies of global urban air pollution have not considered trends in air pollutant concentrations nor corresponding attributable mortality burdens. We aimed to estimate trends in fine particulate matter (PM_{2.5}) concentrations and associated mortality for cities globally.

Methods We use high-resolution annual average PM_{2.5} concentrations, epidemiologically derived concentration response functions, and country-level baseline disease rates to estimate population-weighted PM_{2.5} concentrations and attributable cause-specific mortality in 13 160 urban centres between the years 2000 and 2019.

Findings Although regional averages of urban PM_{2.5} concentrations decreased between the years 2000 and 2019, we found considerable heterogeneity in trends of PM_{2.5} concentrations between urban areas. Approximately 86% (2.5 billion inhabitants) of urban inhabitants lived in urban areas that exceeded WHO's 2005 guideline annual average PM_{2.5} (10 µg/m³), resulting in an excess of 1.8 million (95% CI 1.34 million–2.3 million) deaths in 2019. Regional averages of PM_{2.5}-attributable deaths increased in all regions except for Europe and the Americas, driven by changes in population numbers, age structures, and disease rates. In some cities, PM_{2.5}-attributable mortality increased despite decreases in PM_{2.5} concentrations, resulting from shifting age distributions and rates of non-communicable disease.

Interpretation Our study showed that, between the years 2000 and 2019, most of the world's urban population lived in areas with unhealthy levels of PM_{2.5}, leading to substantial contributions to non-communicable disease burdens. Our results highlight that avoiding the large public health burden from urban PM_{2.5} will require strategies that reduce exposure through emissions mitigation, as well as strategies that reduce vulnerability to PM_{2.5} by improving overall public health.

A pollutant is a substance detectable in the environment, at least partially due to human activity, and that may induce adverse effects on the living organisms.

Moriarty 1983

(Breider lecture)



Guideline levels for each pollutant ($\mu\text{g}/\text{m}^3$):		
PM _{2.5}	1 year	10
	24 h (99th percentile)	25
PM ₁₀	1 year	20
	24 h (99th percentile)	50
Ozone, O ₃	8 h, daily maximum	100
Nitrogen dioxide, NO ₂	1 yr	40
	1 h	200
Sulfur dioxide, SO ₂	24 h	20
	10 min	500

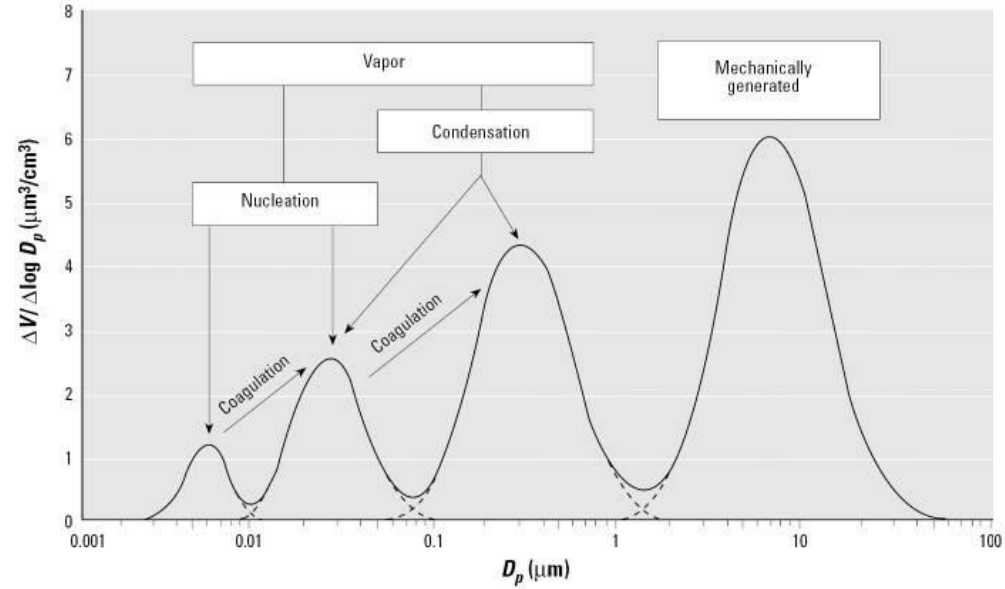
5 (reduced in 2021)

Mechanisms

Nanotoxicology: An Emerging Discipline Evolving from Studies of Ultrafine Particles

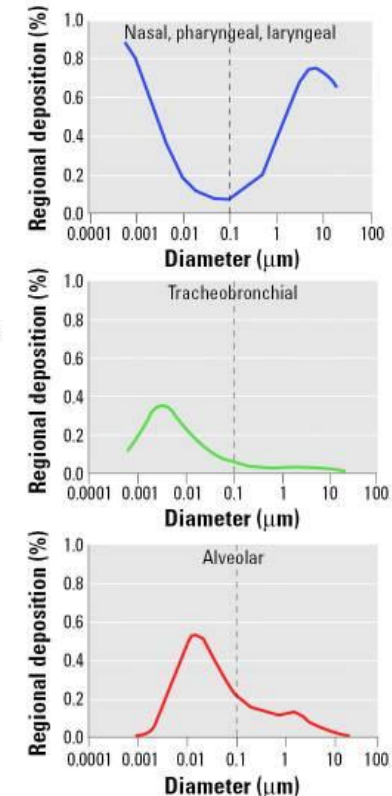
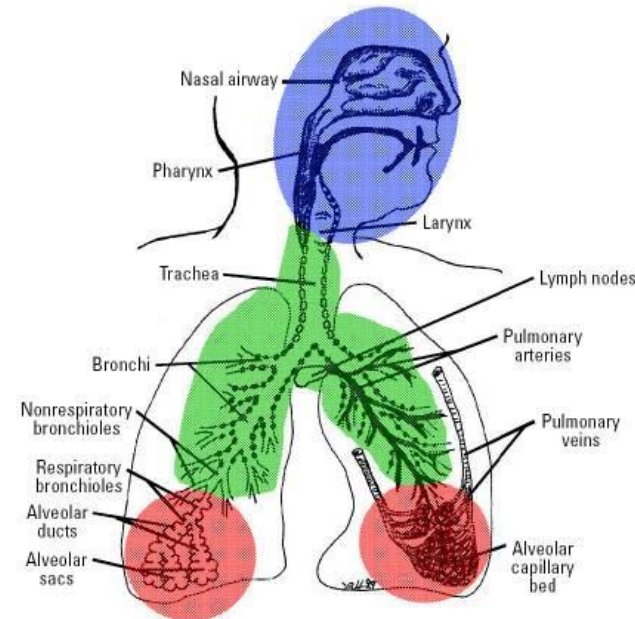
Günter Oberdörster,¹ Eva Oberdörster,² and Jan Oberdörster³

¹Department of Environmental Medicine, University of Rochester, Rochester, New York, USA; ²Department of Biology, Southern Methodist University, Dallas, Texas, USA; ³Toxicology Department, Bayer CropScience, Research Triangle Park, North Carolina, USA



Deposited particles

- mucocilliary clearance
- dissolution and blood stream
- translocation



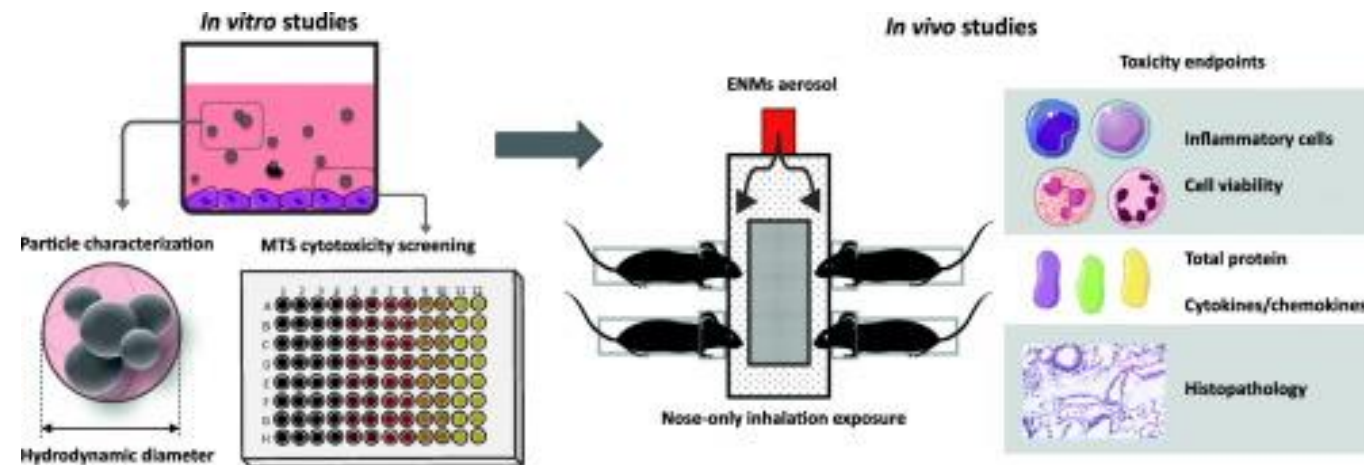
Toxicity studies

in vitro

- acellular / chemical assays
- cellular / biological assays

in vivo

- human subjects
- other animal subjects



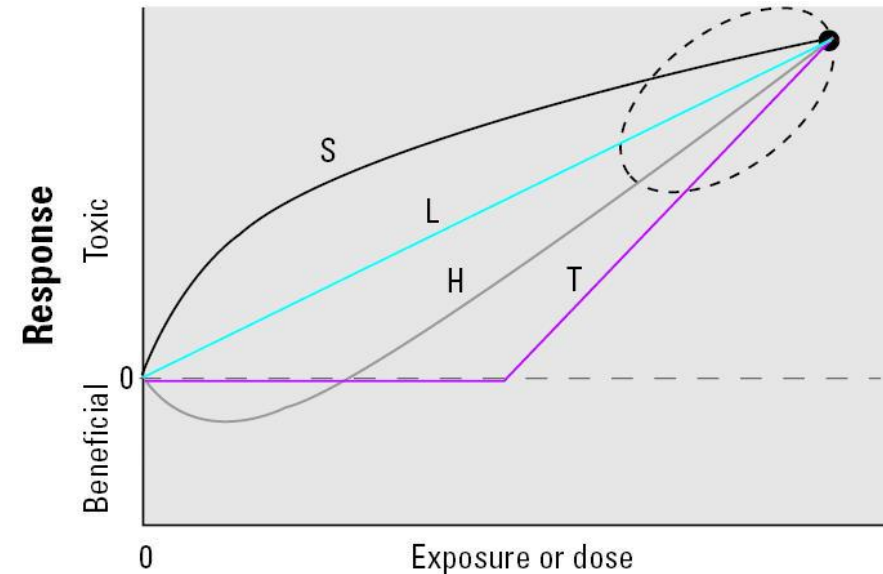
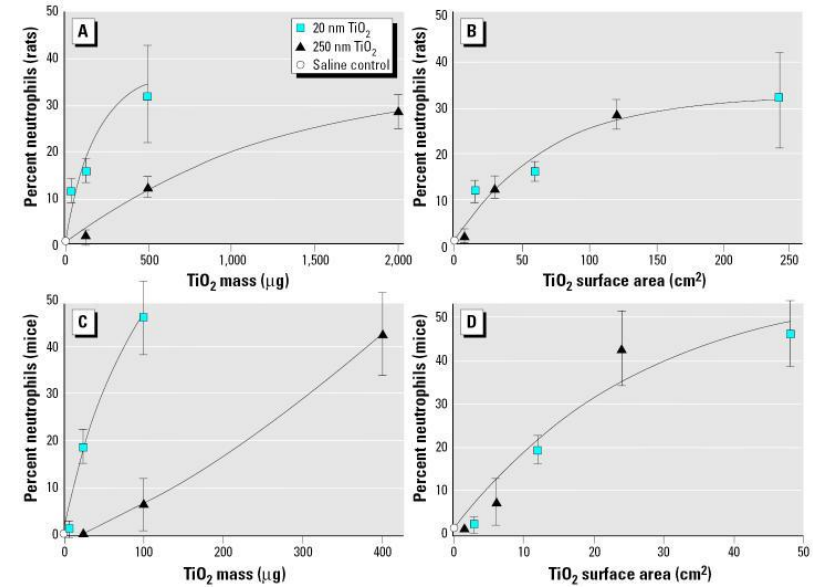
Areecheewakul et al., *Nanoimpact*, 2020

Nanotoxicology: An Emerging Discipline Evolving from Studies of Ultrafine Particles

Günter Oberdörster,¹ Eva Oberdörster,² and Jan Oberdörster³

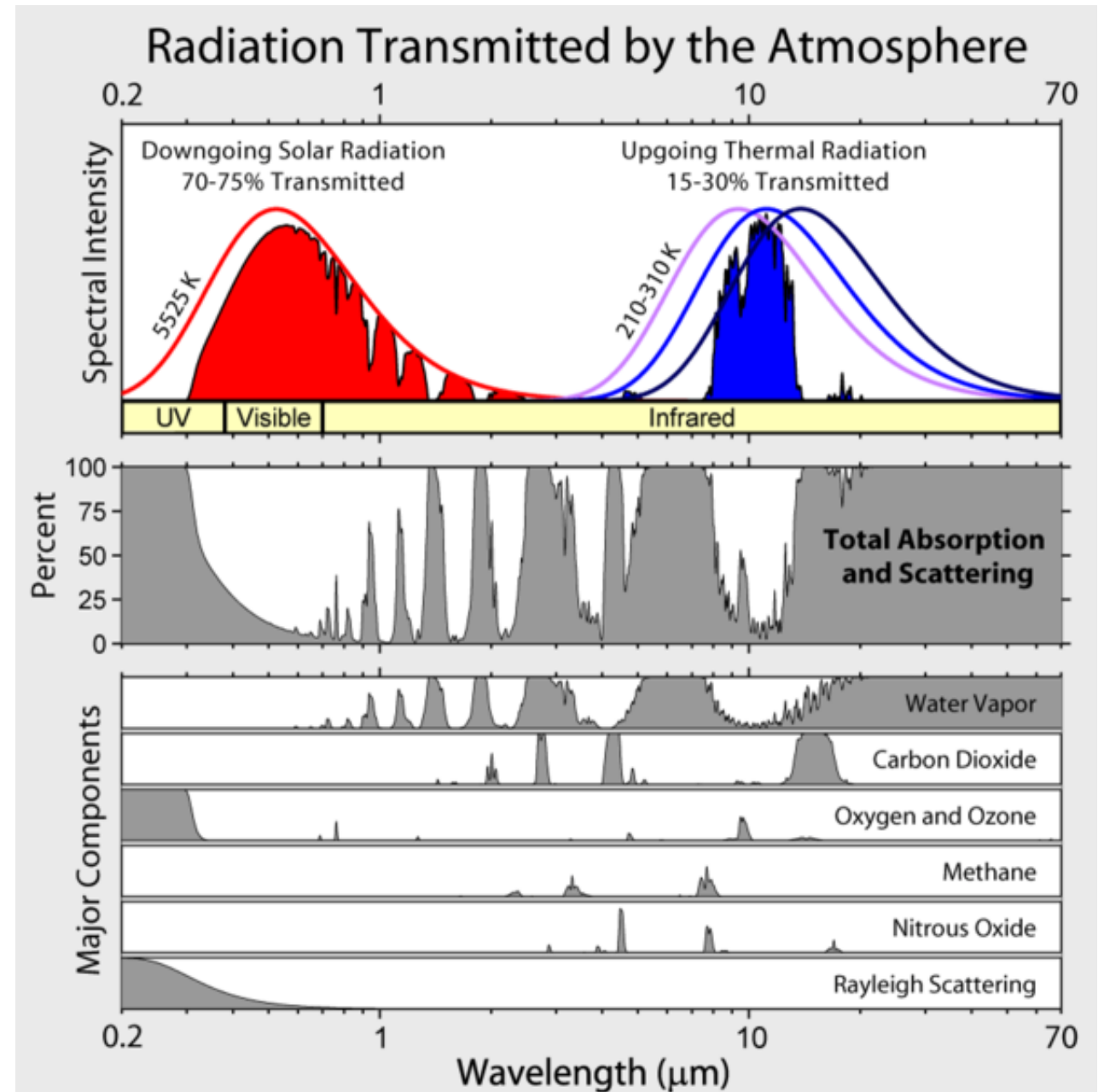
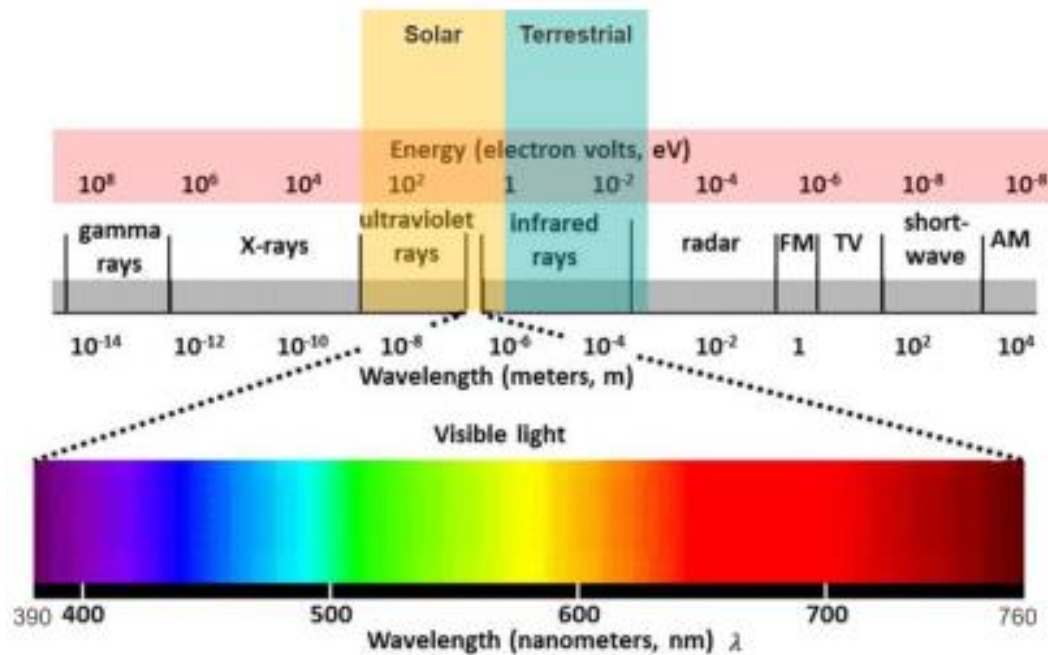
¹Department of Environmental Medicine, University of Rochester, Rochester, New York, USA; ²Department of Biology, Southern Methodist University, Dallas, Texas, USA; ³Toxicology Department, Bayer CropScience, Research Triangle Park, North Carolina, USA

- High dose and exposure concentrations
- Short timescale of experiments
- Interpolation to low concentrations



Measuring chemicals with
infrared (thermal / mid-infrared)
light-matter interactions

Electromagnetic spectrum



Absorption

An oscillating dipole can absorb energy from an oscillating electric field if the field also oscillates at the same frequency.

- ▶ a molecular dipole moment occurs because of unequal sharing of electrons
- ▶ electron densities of molecules are often approximated by point charges on atoms

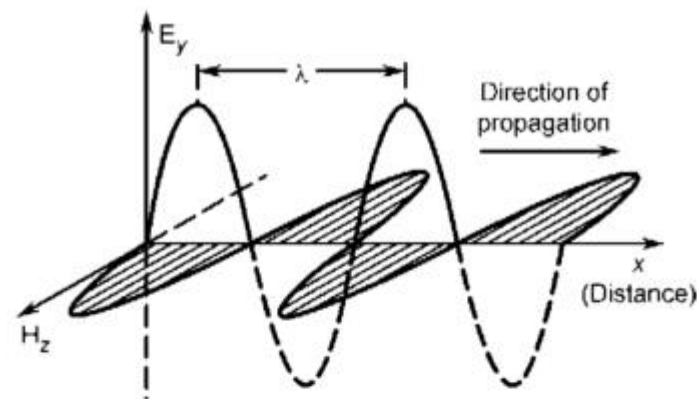
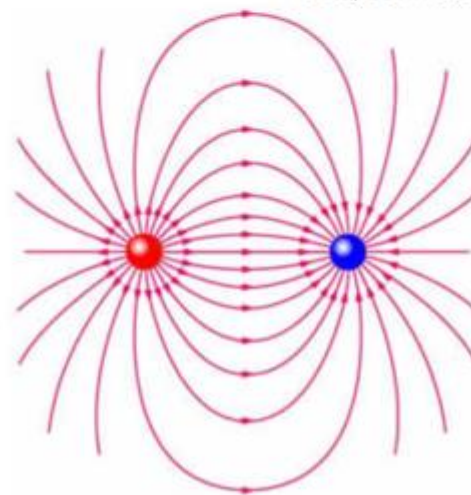
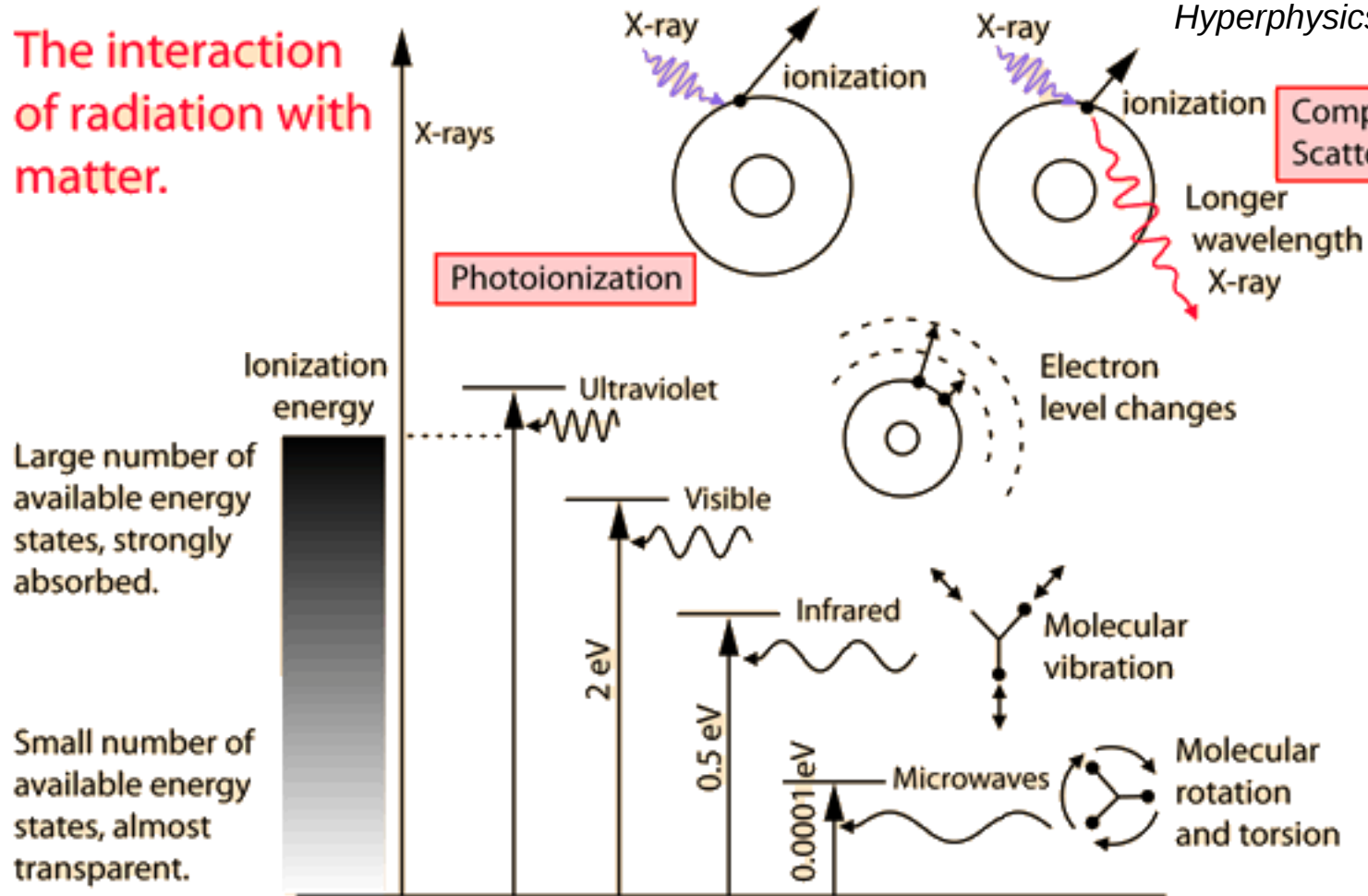


FIGURE 3.10 The instantaneous electric (E_y) and magnetic (H_z) field strength vectors of a plane-polarized light wave as a function of position along the axis of propagation (x) (from Calvert and Pitts, 1966).

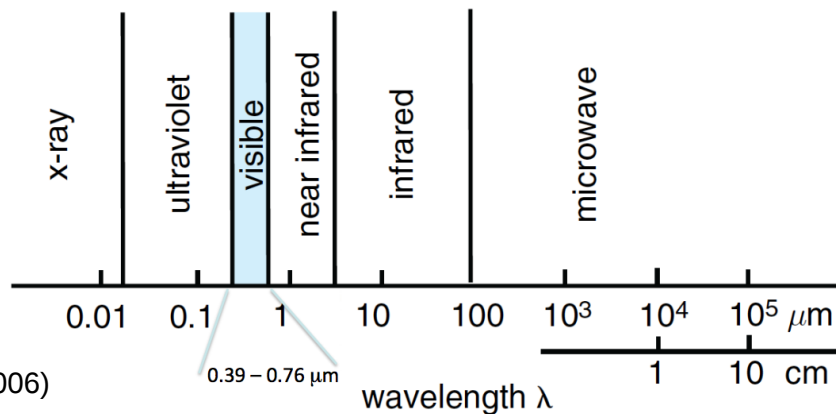
Finlayson-Pitts and Pitts, 1999



The interaction of radiation with matter.



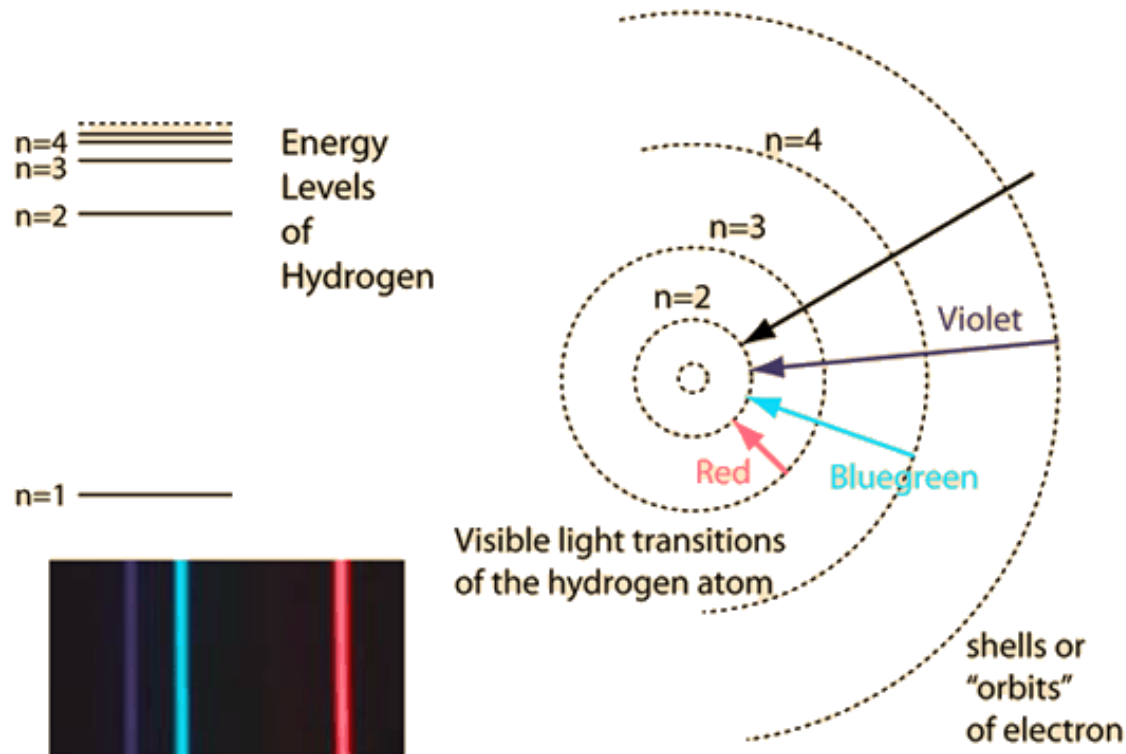
Wavelength (nm)	Description	Transition
~0.0003–0.03	γ-rays	nuclear
~0.03–10	X-rays	core electrons
~30–400	UV	valence electrons
~400–800	Visible	valence electrons
~1000–3 × 10 ⁵	Infrared	molecular vibration
~3 × 10 ⁷ –3 × 10 ¹¹	Microwave	molecular rotation
~3 × 10 ¹¹ –3 × 10 ¹³	Radio	nuclear spin



Relationship between wavelength, energy, and frequency:

$$E = \frac{hc}{\lambda} = hf$$

Conceptual model 1: Bohr's model of the atom



Hyperphysics, Georgia State Univ.

Ultraviolet radiation

- electronic transitions (non-ionizing) induce excited states
- Ionizing at higher energies (*sunburn and skin cancer*)

Visible radiation

- electronic transitions induce excited states

Conceptual model 2: (an)harmonic oscillators

Infrared radiation induces changes in vibrational and rotational motion

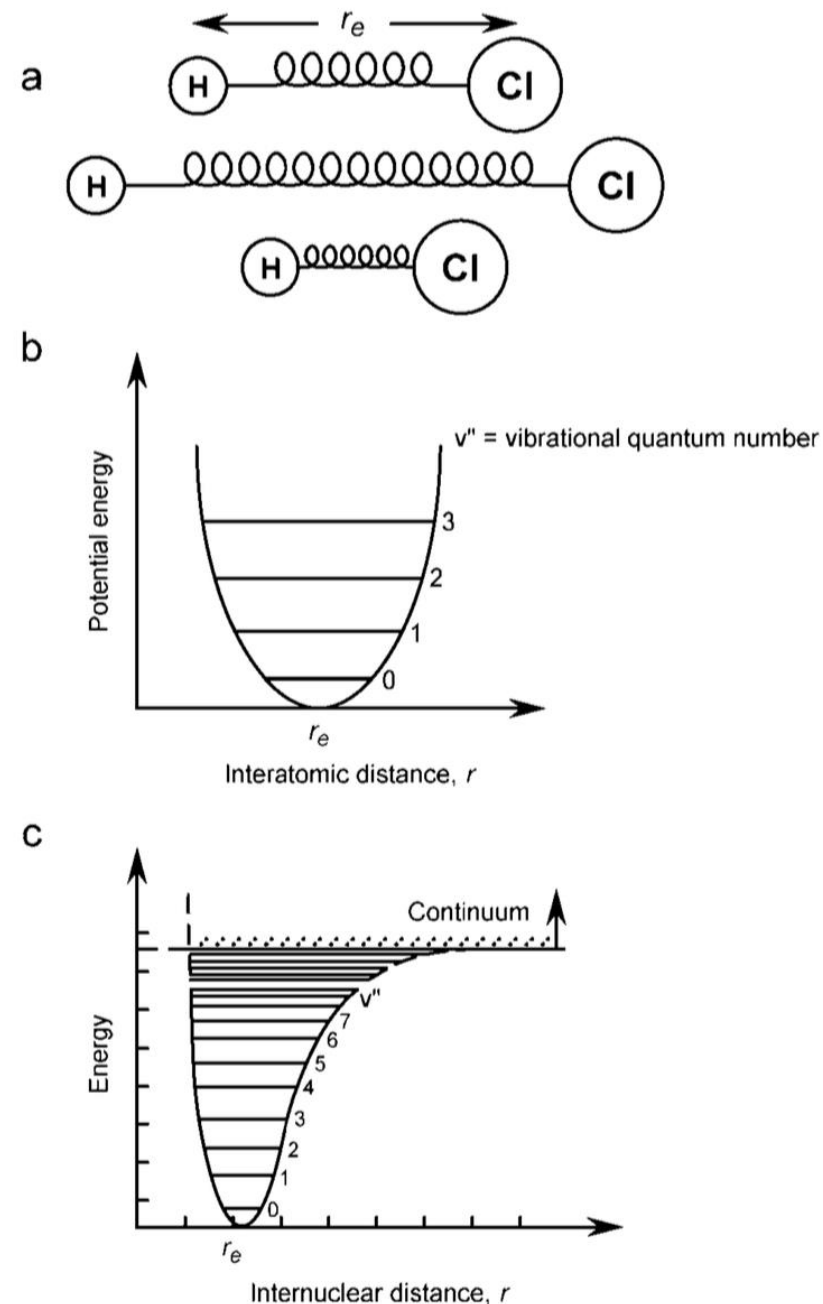
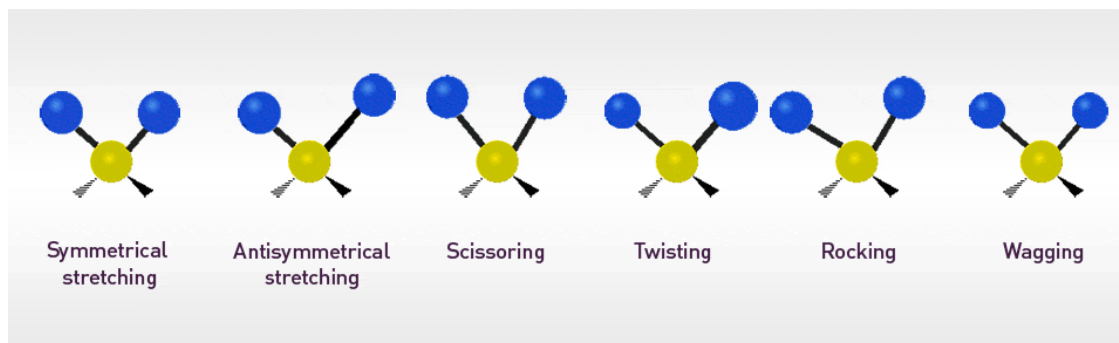


FIGURE 3.2 (a) Vibration of diatomic molecule, HCl, (b) potential energy of an ideal harmonic oscillator, and (c) an anharmonic oscillator described by the Morse function.

Most major constituents of atmospheric aerosols have absorption bands in the mid-infrared

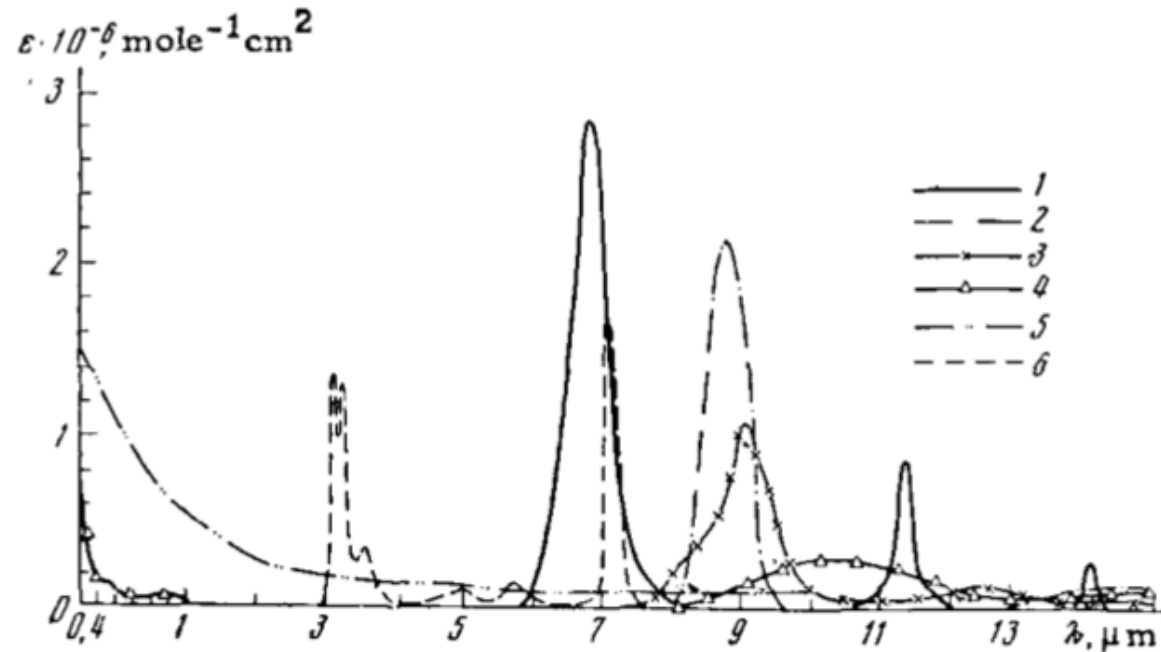
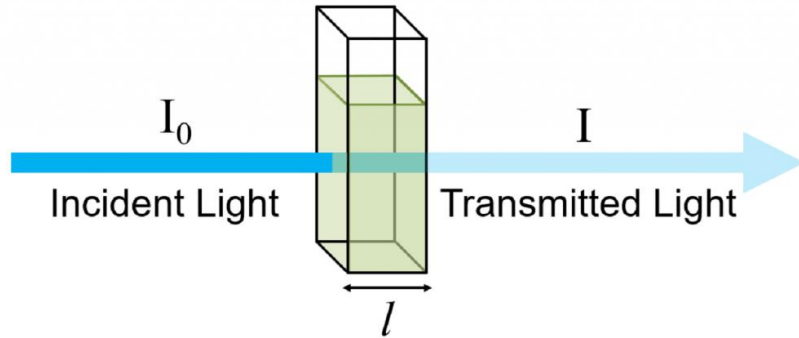


Fig. 5. Molar coefficients of absorption of the most important constituents of the atmospheric aerosol: 1) carbonate class; 2) sulfate class; 3) silicates; 4) amorphous hematite; 5) carbon black; 6) ammonium group.

Radiative transfer models

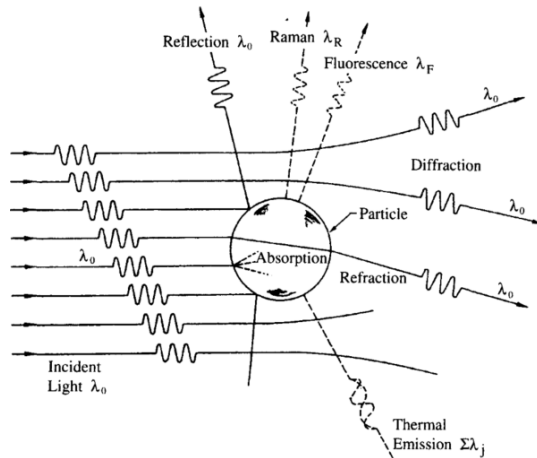


Bouguer-Lambert-Beer law of absorption

$$dI = -N\sigma I d\ell \quad I = I_0 \text{ at } \ell = 0$$

$$T = \frac{I}{I_0} = e^{-N\sigma\ell}$$

$$A = -\log T = N\sigma\ell$$



Particles scatter radiation

$$\sigma \rightarrow \sigma_{\text{ext}} = \sigma_{\text{abs}} + \sigma_{\text{sca}}$$

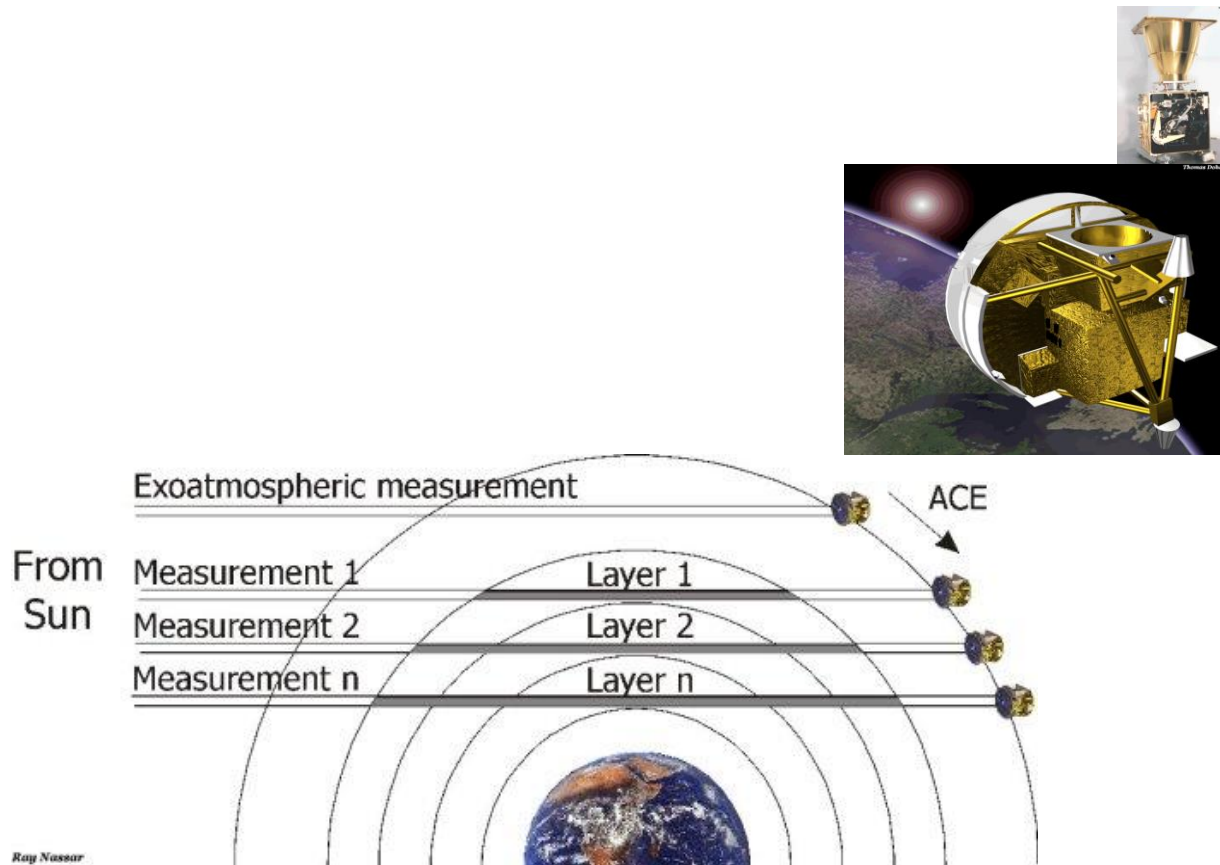
Atmosphere is a mixture of multiple phases

$$A = \ell \left(\sum_{i \in \text{gases}} N_i \sigma_{\text{ext},i} + \sum_{i \in \text{particles}} N_i \sigma_{\text{ext},i} + \sum_{i \in \text{hydrometeors}} N_i \sigma_{\text{ext},i} \right)$$

Applications to environmental monitoring / Earth Observation

ACE-FTS aboard the SCISAT-1

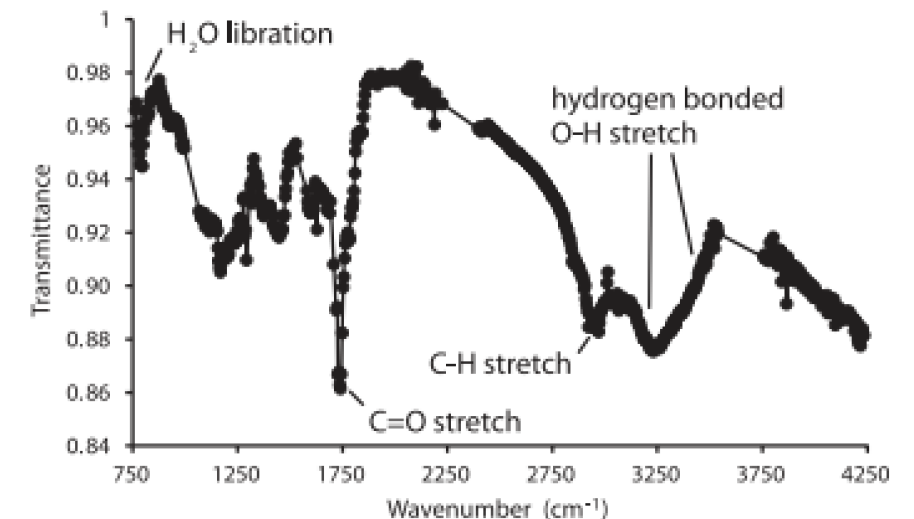
Atmospheric Chemistry Experiment – Fourier Transform Spectrometer



WILDFIRES

Wildfire smoke destroys stratospheric ozone

Peter Bernath^{1,2,3*}, Chris Boone², Jeff Crouse²



Wavenumber $\tilde{\nu} = \frac{1}{\lambda}$

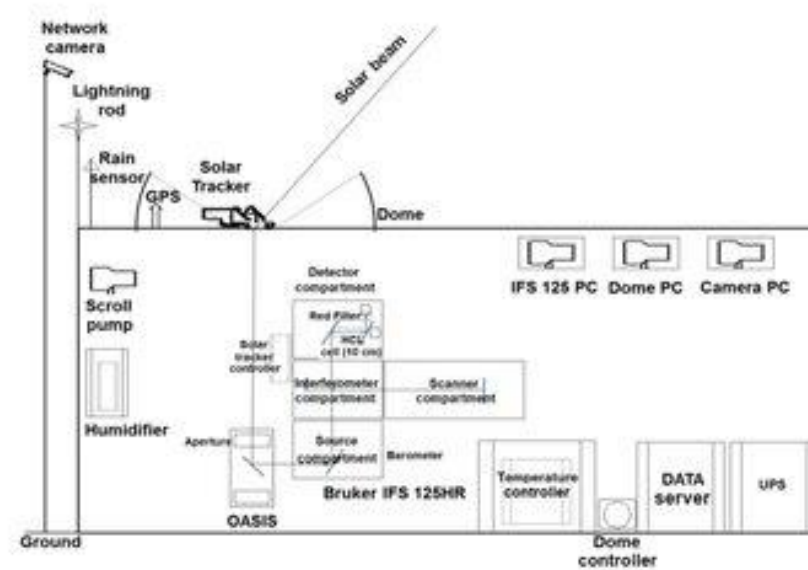
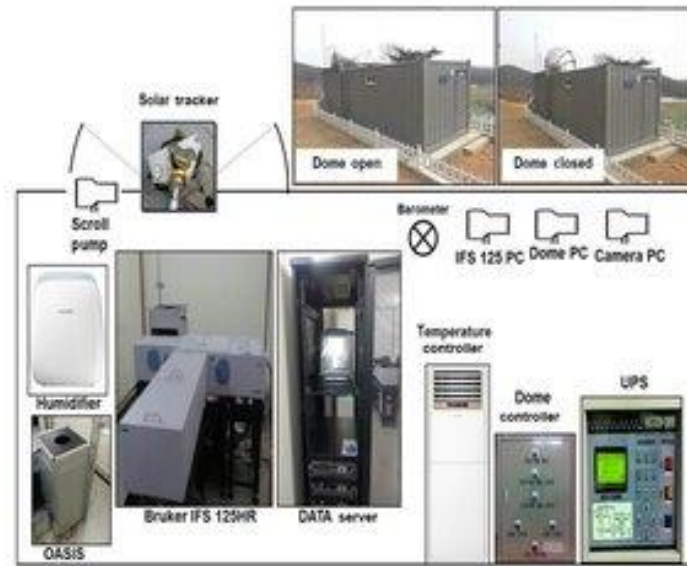
<https://uwaterloo.ca/atmospheric-chemistry-experiment/mission/solar-occultation-orbit>

<https://uwaterloo.ca/atmospheric-chemistry-experiment/instruments/ace-fts>

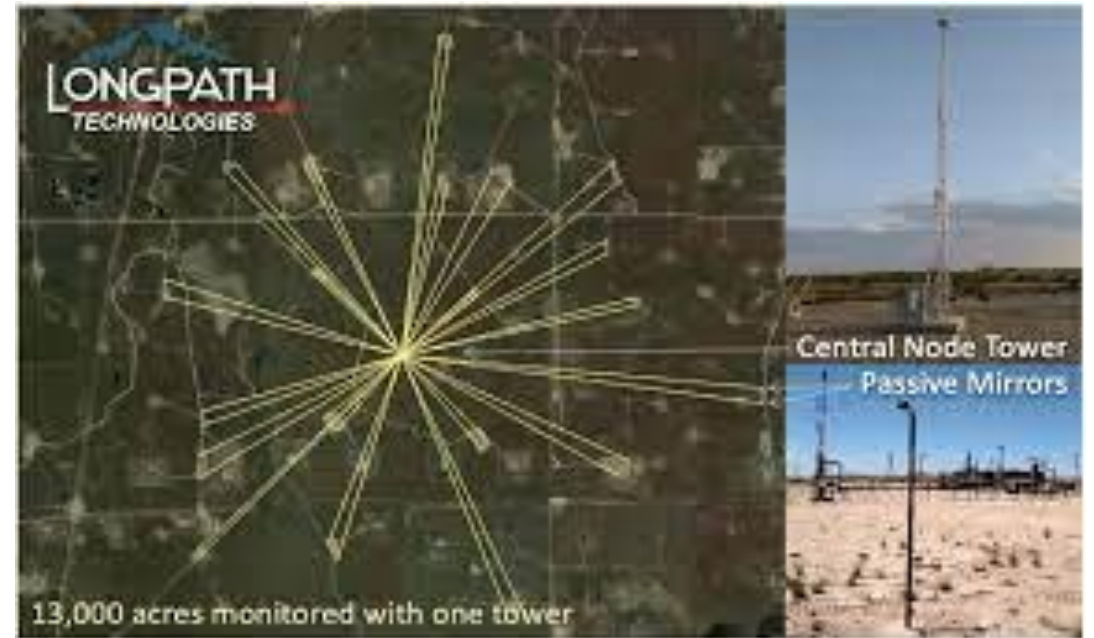
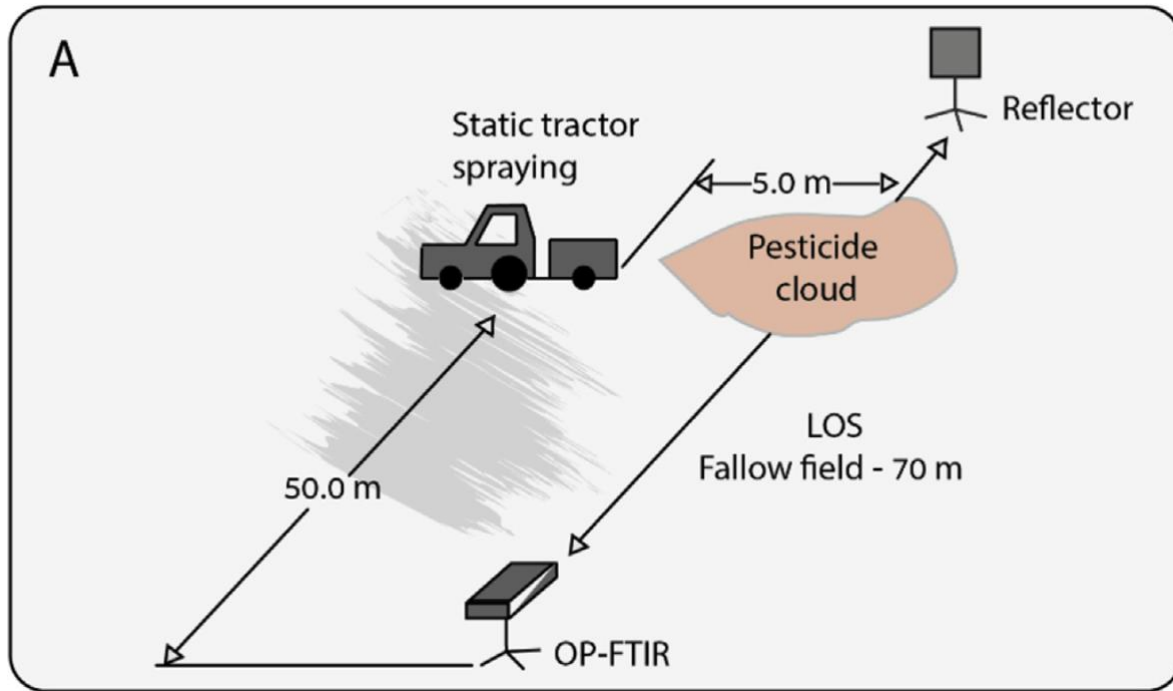
<https://www.nasa.gov/image-article/scientific-satellite-atmospheric-chemistry-experiment-1-scisat-1/>

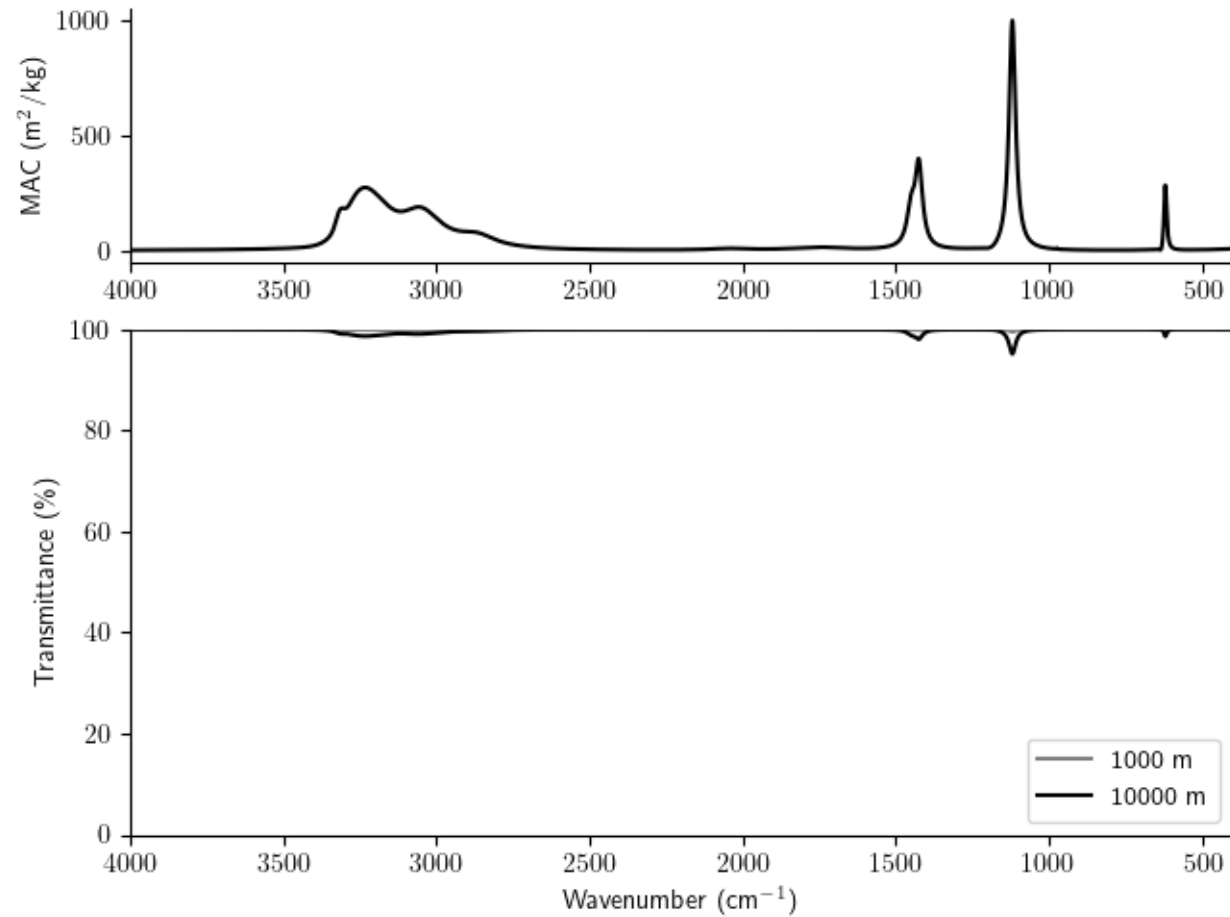
Solar-viewing FTS in the NDACC

Network for the Detection of Atmospheric Composition Change



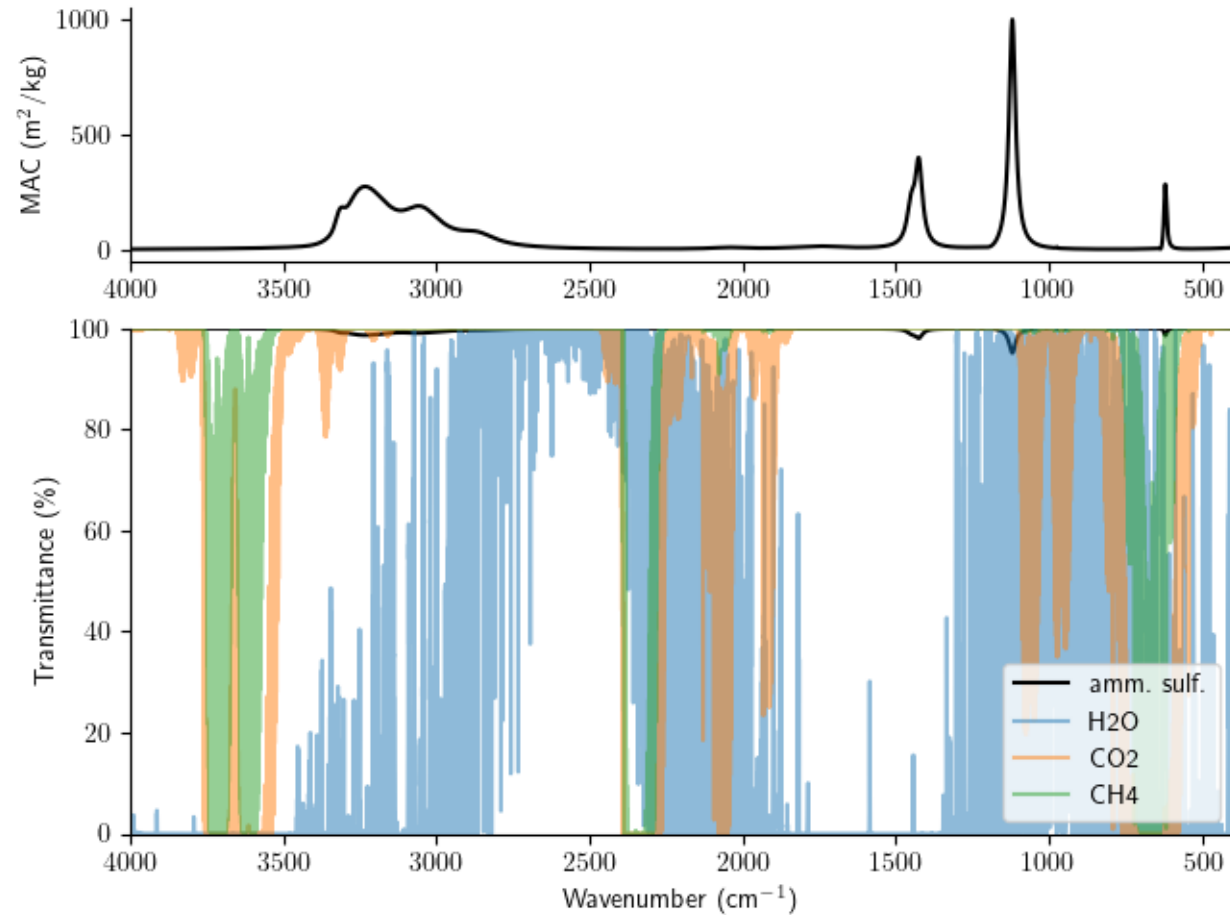
Open-path infrared (“standoff detection”)





virtual experiment

- ammonium sulfate $5 \mu\text{g}/\text{m}^3$
- path lengths 1 and 10 km



virtual experiment

- ammonium sulfate $5 \mu\text{g}/\text{m}^3$
- path length 10 km
- H₂O: 50%RH at 25 deg.C ($11 \text{ g}/\text{m}^3$)
- CO₂: 420 ppm ($0.8 \text{ g}/\text{m}^3$)
- CH₄: 1911 ppb ($1 \text{ mg}/\text{m}^3$)

Advances in open path technologies

- High intensity source
- High spectral resolution (remove gas phase)
- Stable baseline
- Select applications

Proceedings of the Combustion Institute

Mid-infrared dual frequency comb spectroscopy for combustion analysis from 2.8 to 5 μm

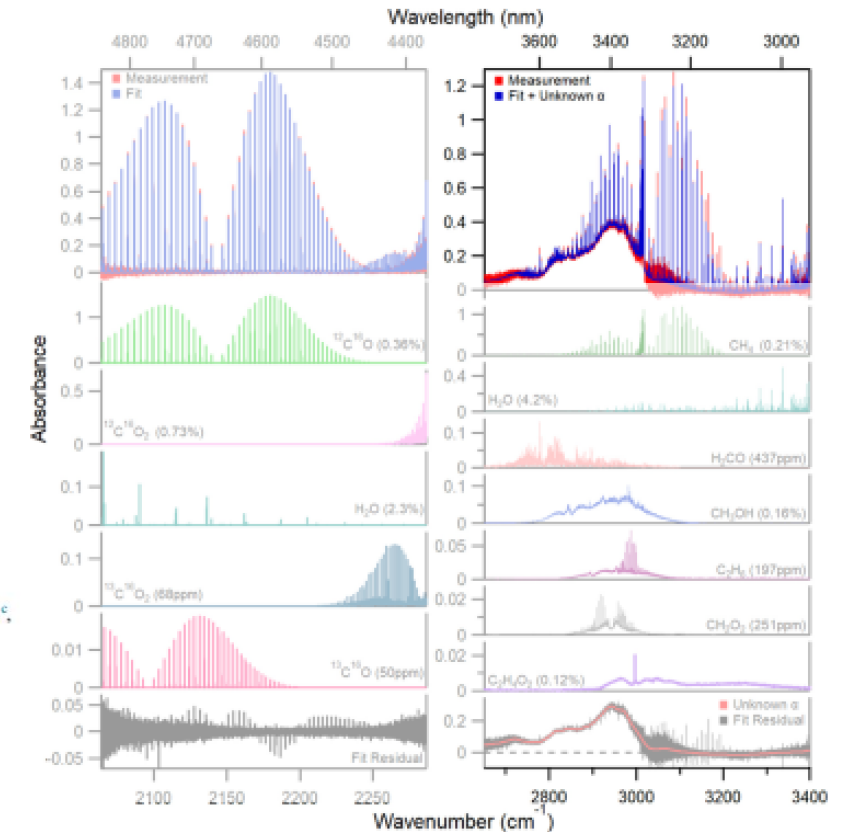
Amanda S. Makowiecki^a, Daniel I. Herman^b, Nazanin Hoghooghi^a,
Elizabeth F. Strong^a, Ryan K. Cole^a, Gabe Ycas^c, Fabrizio R. Giorgetta^c,
Caelan B. Lapointe^a, Jeffrey F. Glusman^a, John W. Daily^a,
Peter E. Hamlington^a, Nathan R. Newbury^c, Ian R. Coddington^c,
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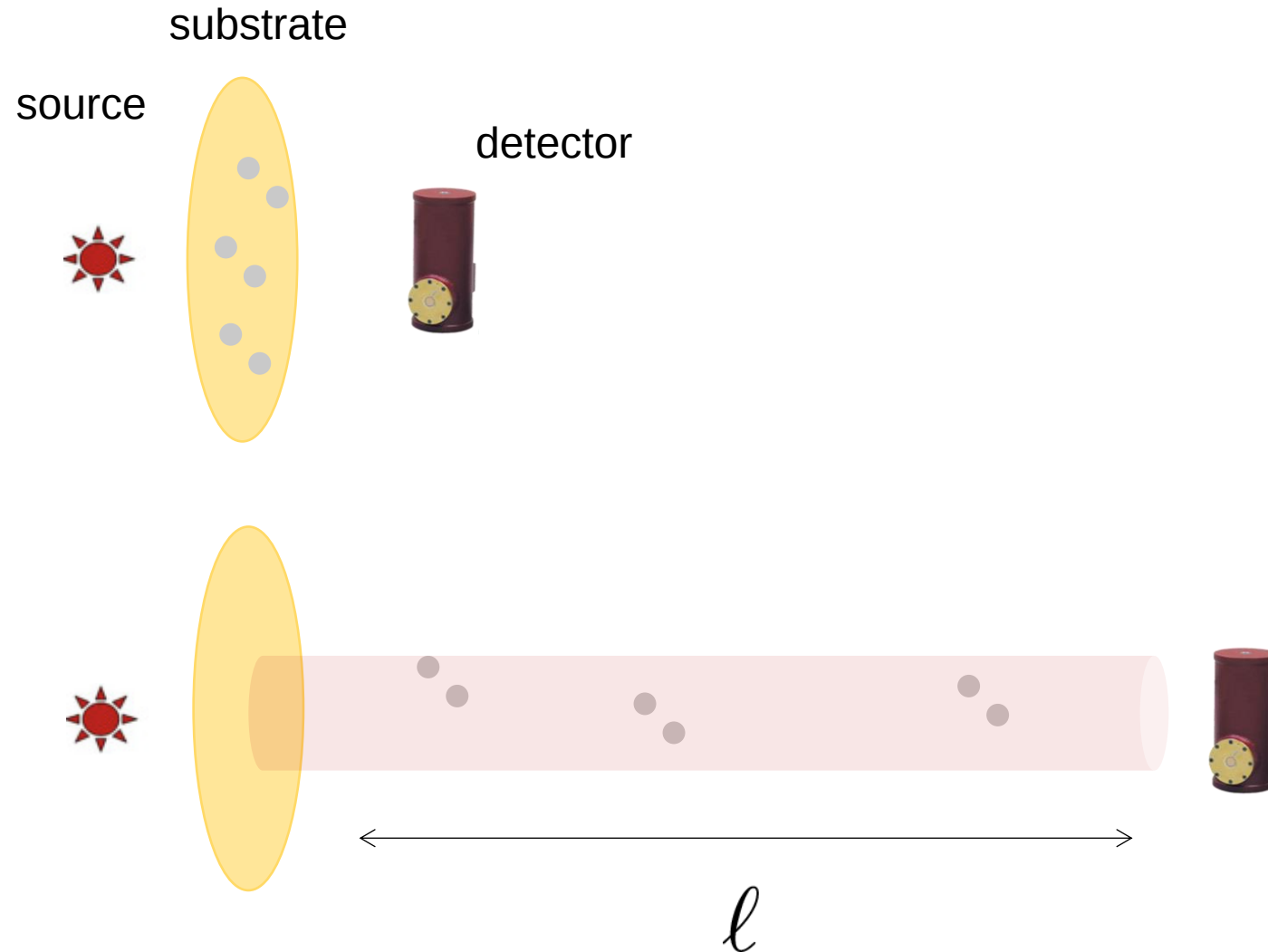
^c National Institute of Standards and Technology, Boulder, CO 80305, USA

Received 7 November 2019; accepted 7 June 2020
Available online 29 September 2020



Mid-infrared in aerosol chemical monitoring

Particle collection for infrared sensing



areal number density

$$A = N^{(\text{area})} \sigma_{\text{ext}}$$

$$N^{(\text{area})} = N \ell$$

$$\ell = v_f t$$

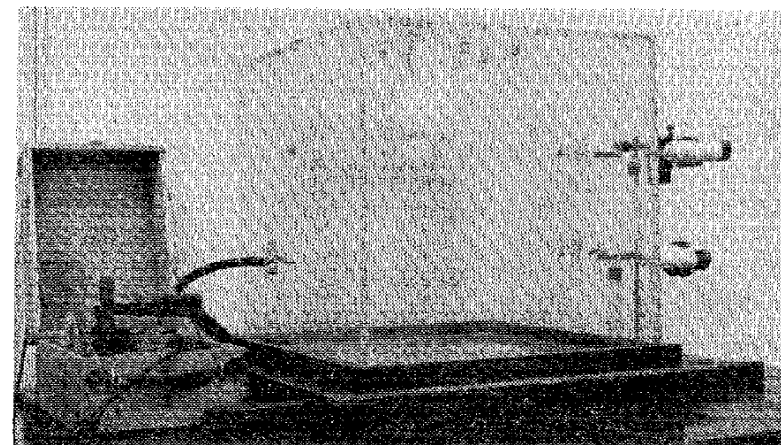
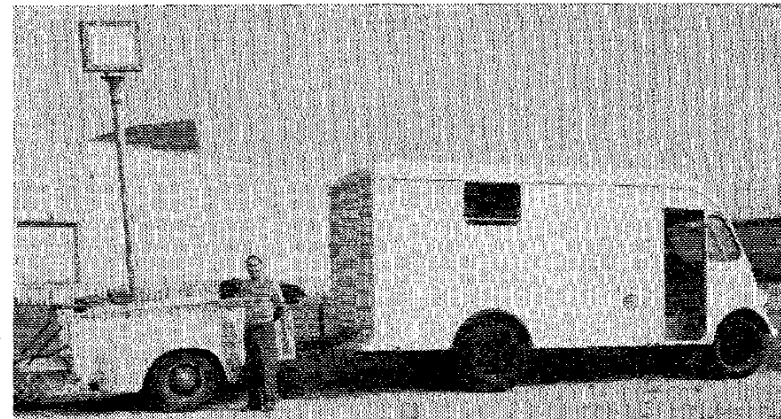
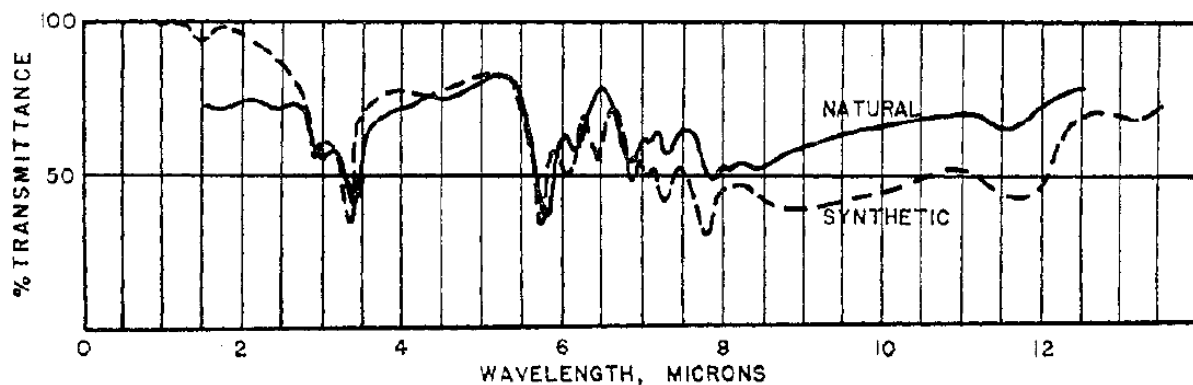
substrate face velocity

Composition of Organic Portion of Atmospheric Aerosols in the Los Angeles Area

PAUL P. MADER, ROBERT D. MACPHEE,
ROBERT T. LOFBERG, AND GORDON P. LARSON
Los Angeles County Air Pollution Control District, Los Angeles, Calif.

June 1952

INDUSTRIAL AND ENGINEERING CHEMISTRY



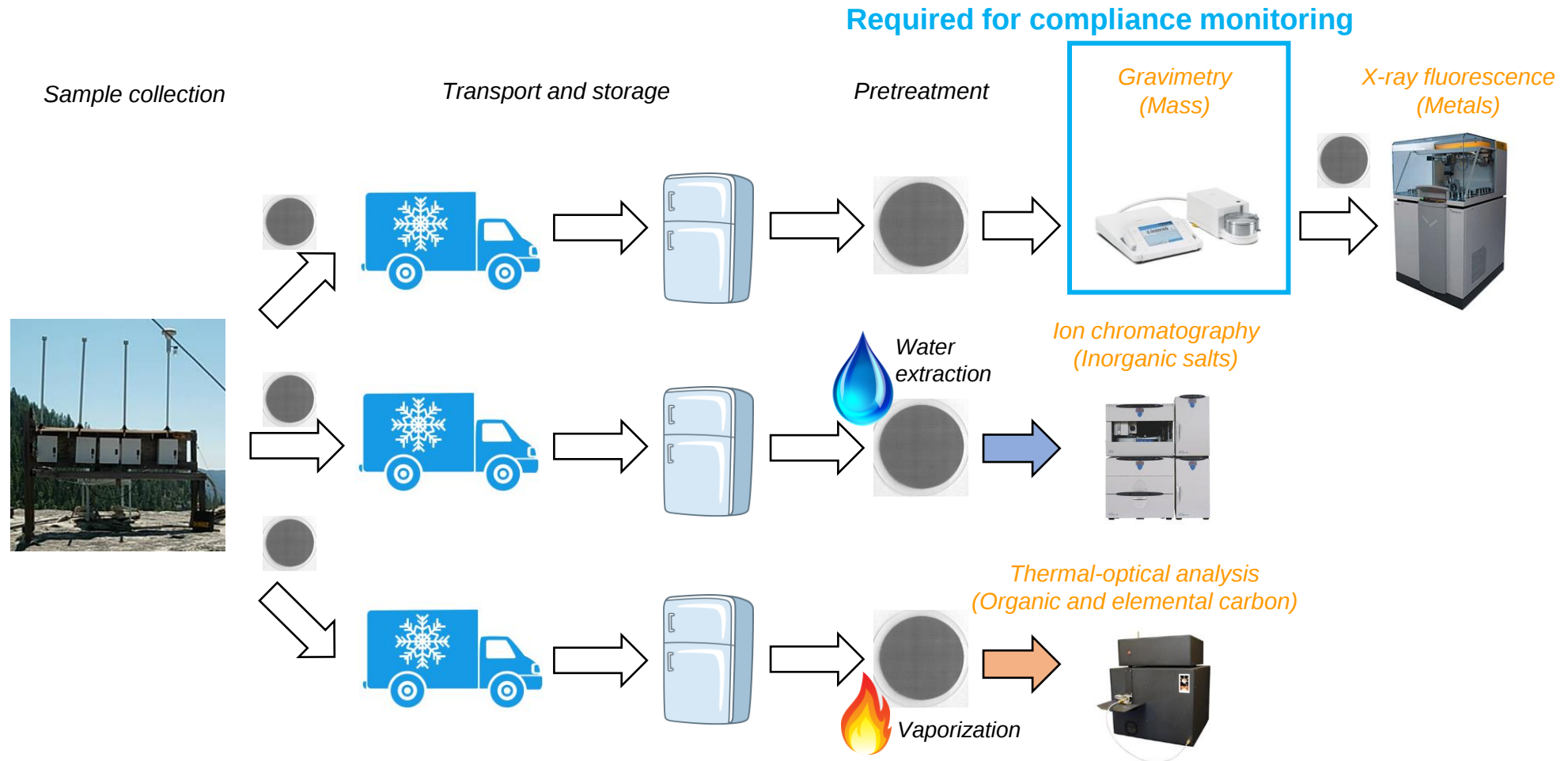
...~45 years later →

Chemical measurement technology tradeoffs

- offline / online
- time resolution
- chemical resolution (number of species)
- quantitative / qualitative
- physical / chemical separation vs algorithmic separation
- scalability – labor and cost

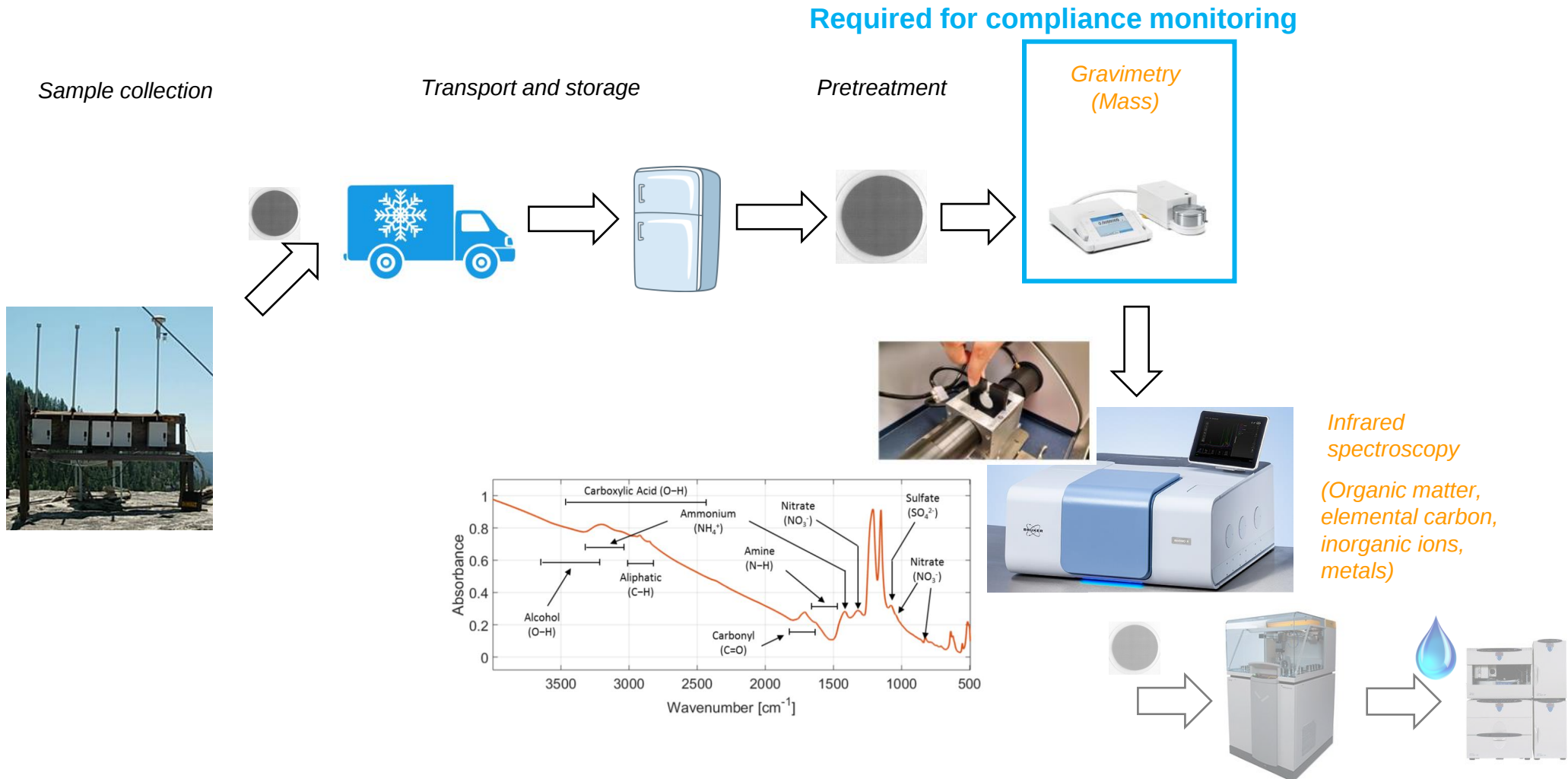
Conventional chemical speciation methods

Laborious and costly



Mid-infrared spectrometry

Single analytical technique for chemical speciation



Challenges for quantitative analysis of atmospheric aerosols with infrared

Environmental infrared spectra is especially complex

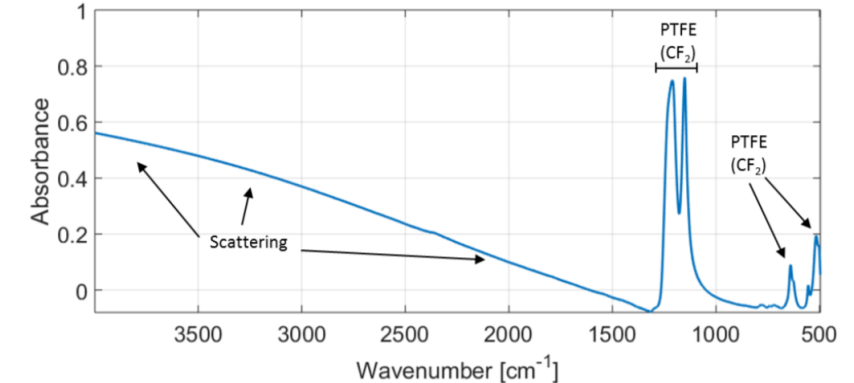
- heterogeneous media leading to scattering and other phenomena
- mixtures leading to overlapped peaks
- interference from substrate

Algorithmic approach

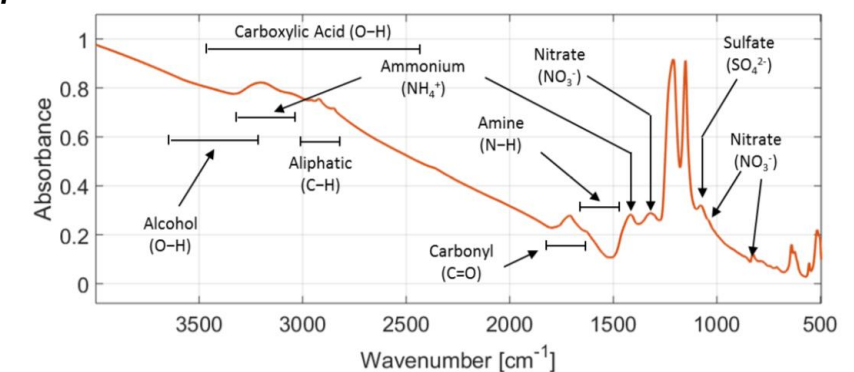
for quantitative analysis of atmospheric aerosols:

- ensure reliability across diverse samples in measurement network
- expert systems (first wave of AI)
- data-drive modeling (machine learning)

blank Teflon filter



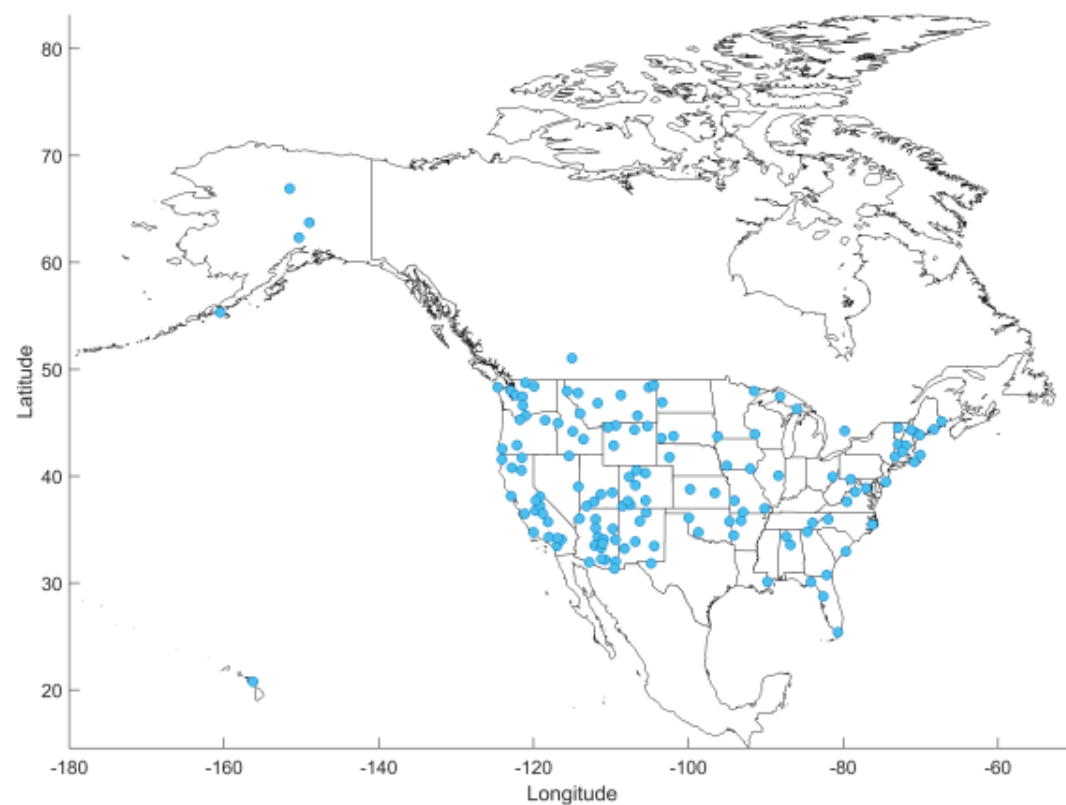
particle-loaded filter



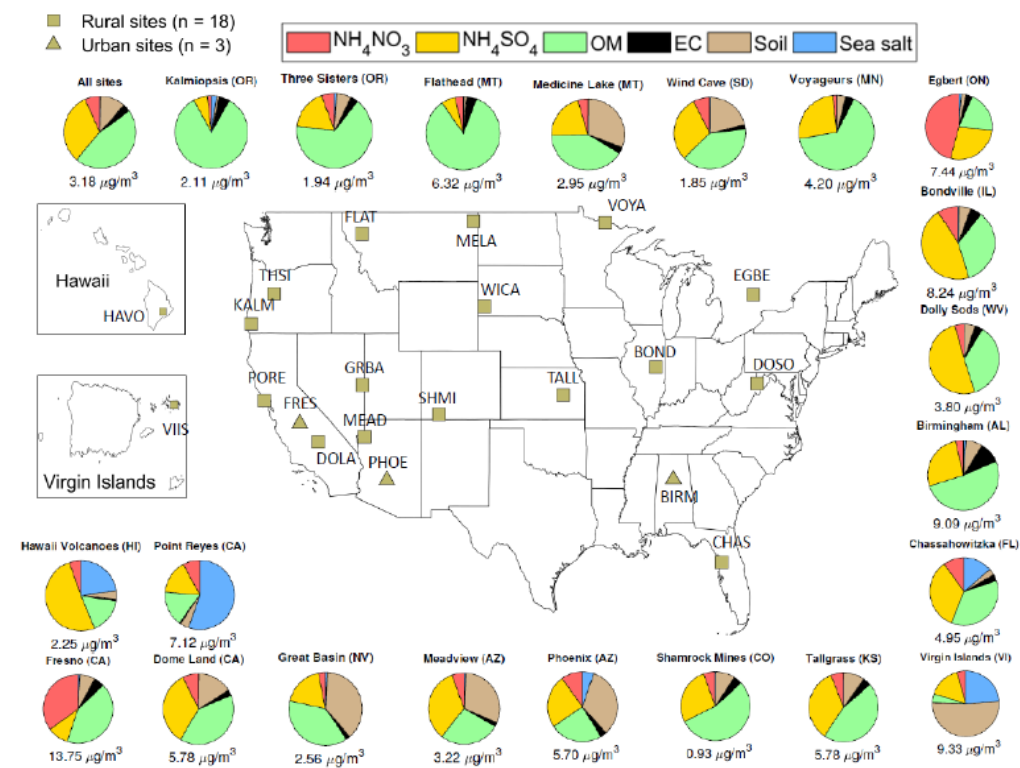
Debus, Takahama et al., *Appl. Spectroscopy*, 2018

Example demonstration in IMRPOVE

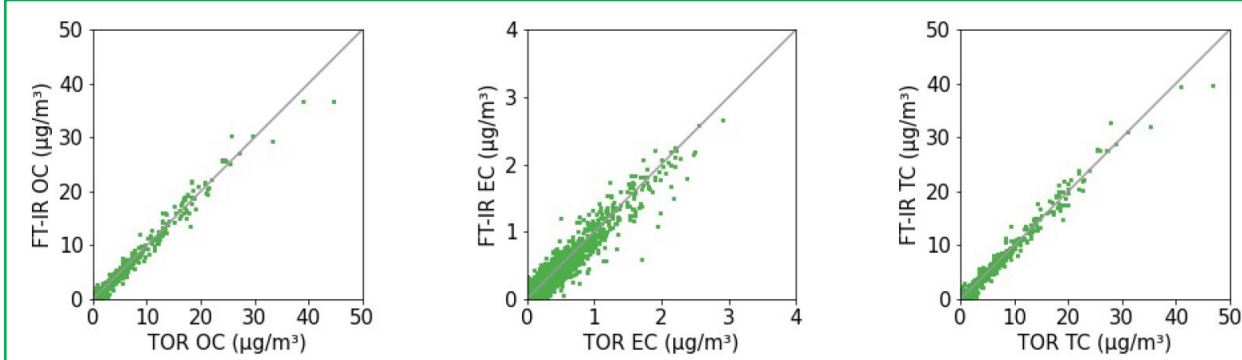
Interagency Monitoring of Protected Visual Environments



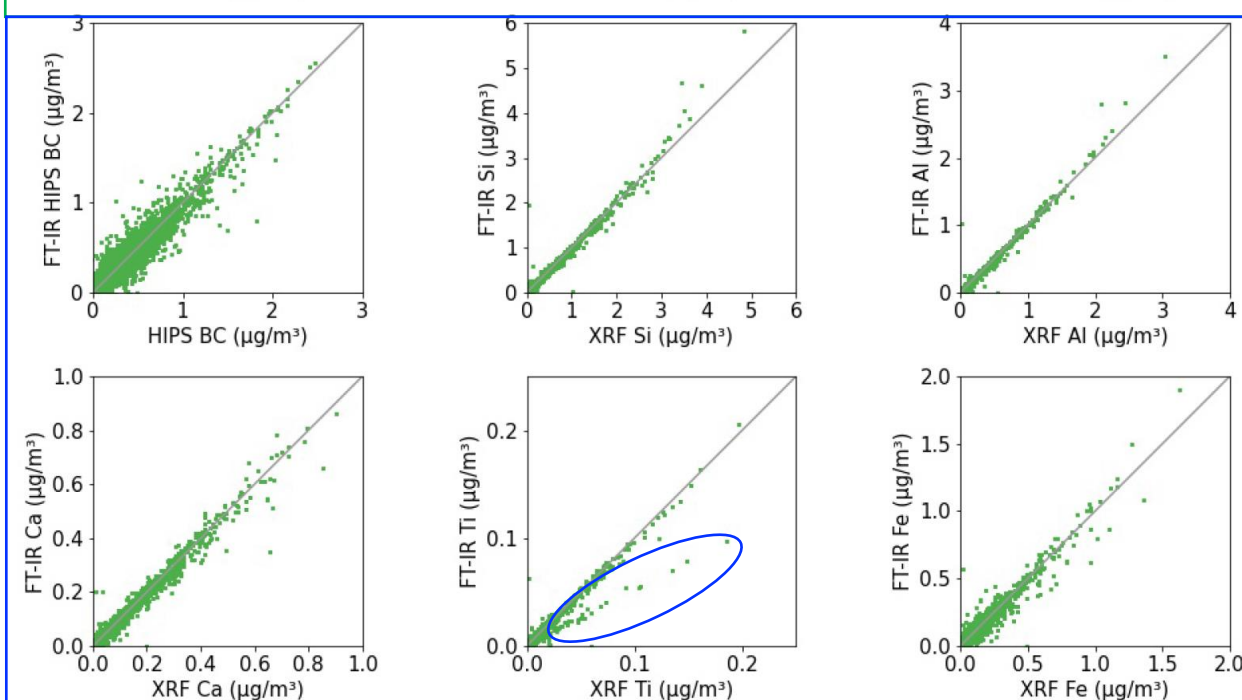
IMPROVE network, 161 sites



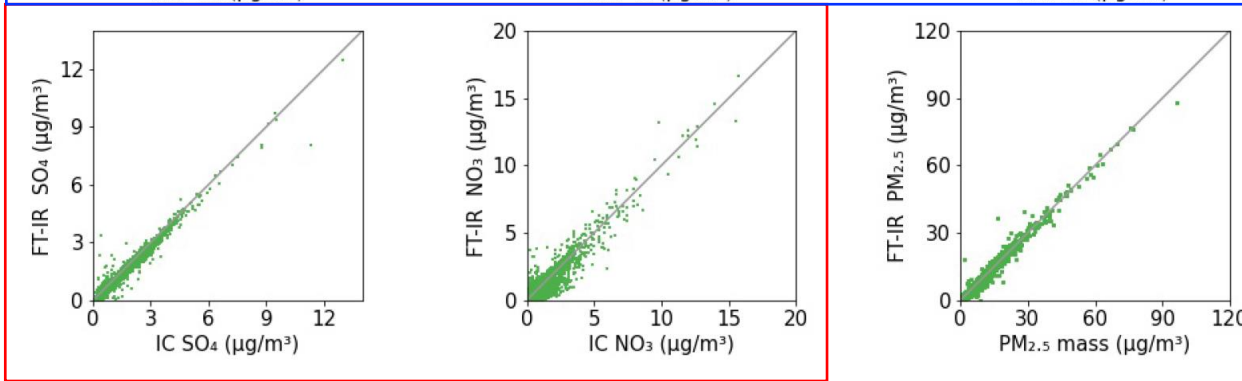
21 sites selected based on abundance of spectral types



carbon



metals



inorganic salts
and PM_{2.5}

Predictions for ~61,500 samples from 2015-2017

Prediction accuracy compared against collocated precision of reference

Error for Ti in Sycamore Canyon (AZ)

Editorials

nature

| Nature | Vol 617 | 18 May 2023

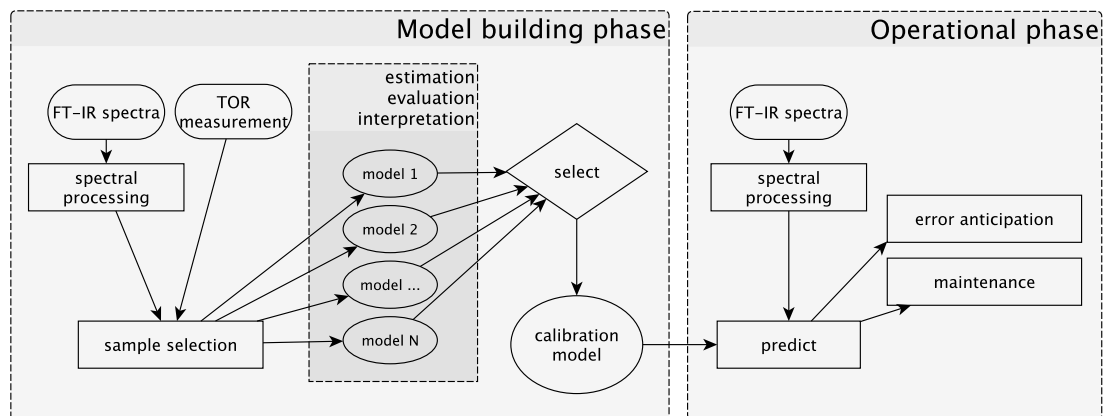
For chemists, the AI revolution has yet to happen

Machine-learning systems in chemistry need accurate and accessible training data. Until they get it, they won't achieve their potential.



The best possible training sets would also include data on negative outcomes.”

Network implementation



Quantification of major species:

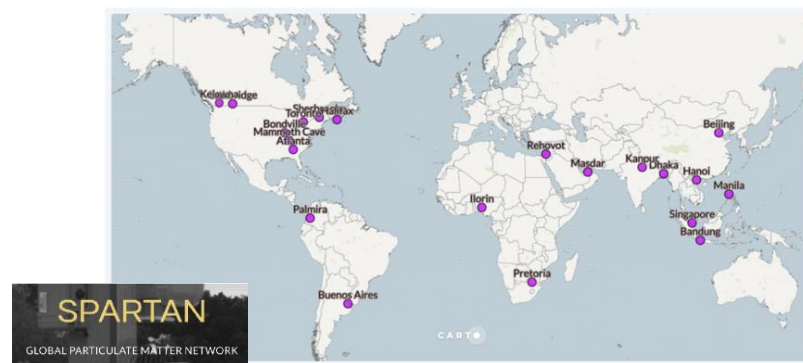
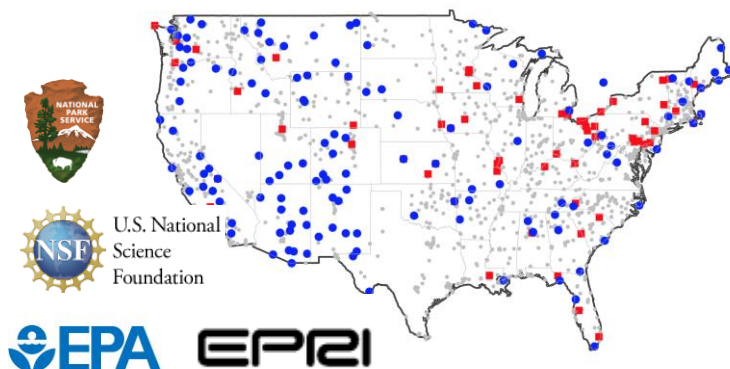
- Organic and elemental carbon
- Organic matter
- Inorganic salts
- Mineral dust

~200,000 samples

over 8 years across 5 separate monitoring networks

EPFL
UC DAVIS
UNIVERSITY OF CALIFORNIA

Takahama et al., *Atmos. Meas. Tech.*, 2019
Debus et al., *Atmos. Meas. Tech.*, 2022



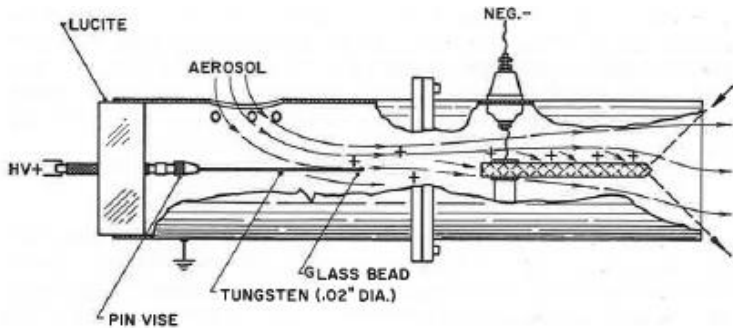
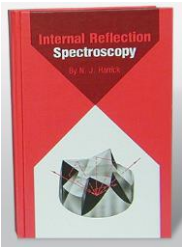
Toward an automated infrared monitor

Methods for particle collection

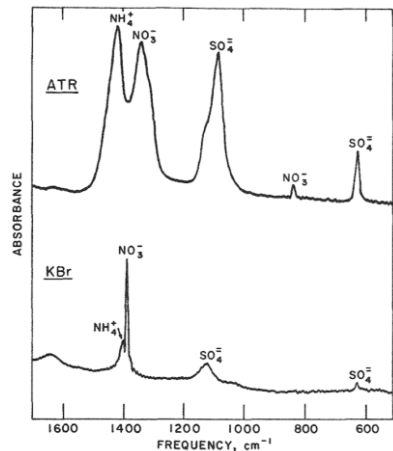
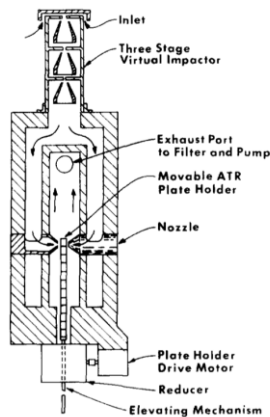
- Passive sedimentation
- Filtration
- Impaction
- Electrostatic deposition
- Thermophoresis

Past designs proposed

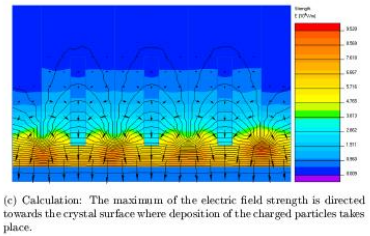
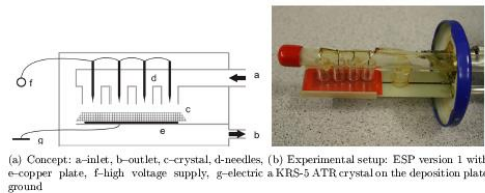
Harrick 1979
(1st printing 1967)



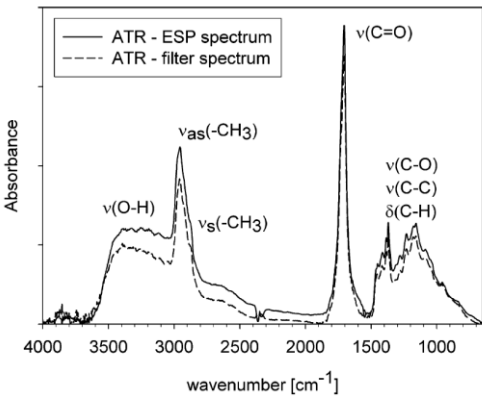
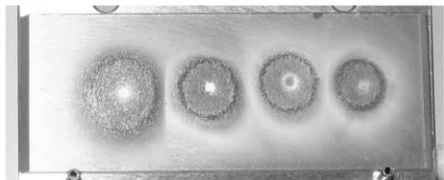
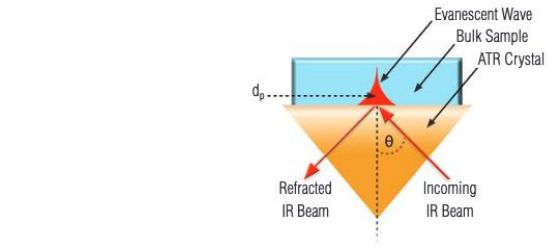
Johnson 1981
Argonne National Lab



Ofner et al. 2008
Tech. Univ. Vienna

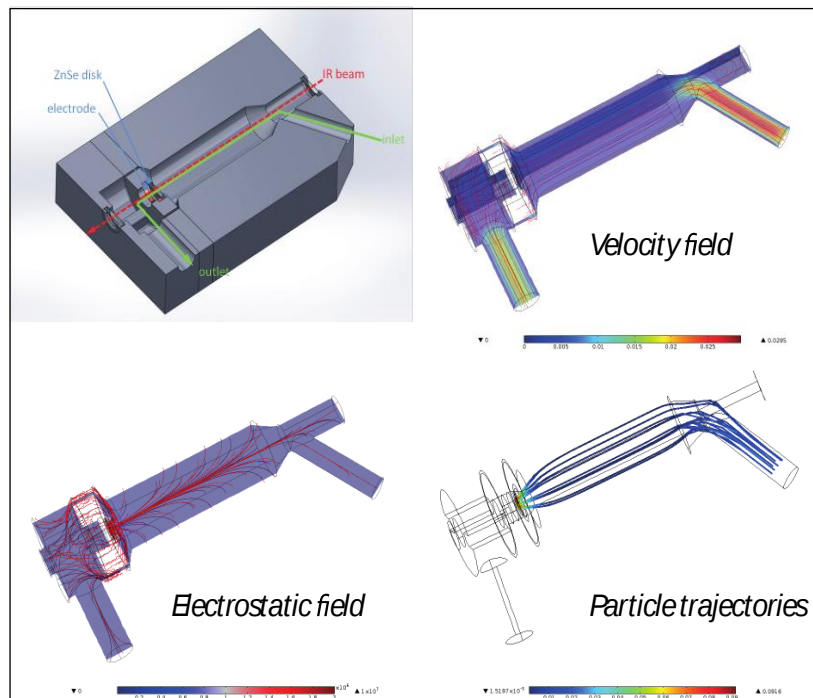


(c) Calculation: The maximum of the electric field strength is directed towards the crystal surface where deposition of the charged particles takes place.



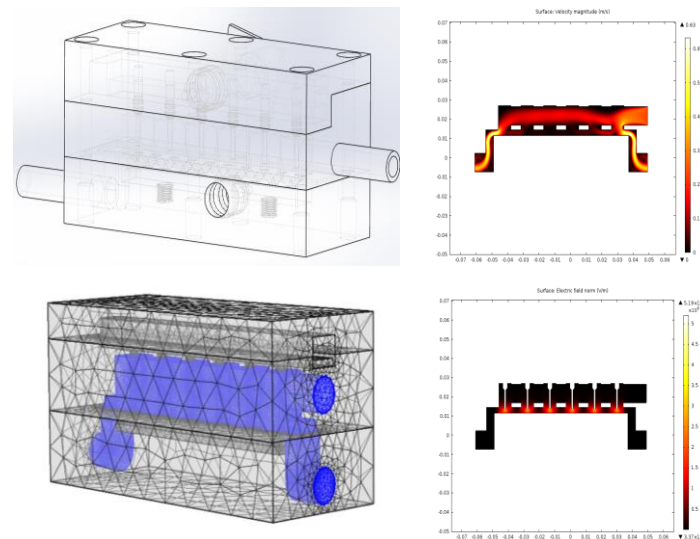
Evolution in design at EPFL

2012-2013

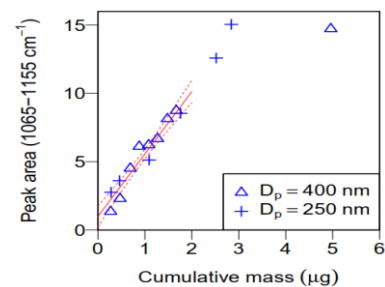


Florian Breider

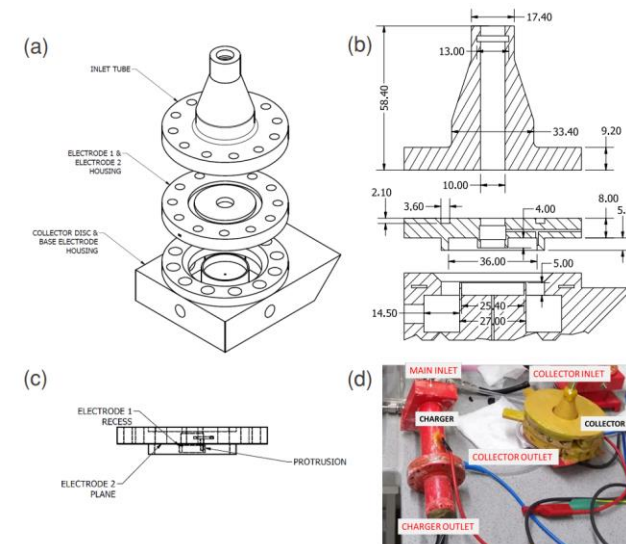
2014-2017



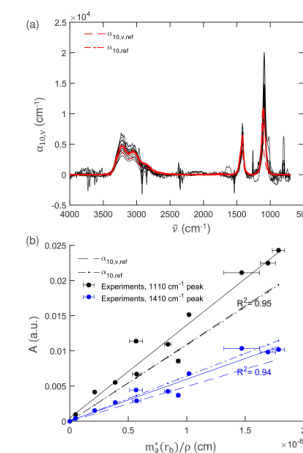
Rob Modini
Christophe Delval



2017-2019



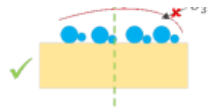
Nikunj Dudani



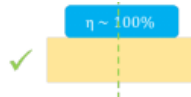
Core innovation in particle collection



Uniform deposition



Minimal chemical modification



High collection efficiency



Low particle size dependence

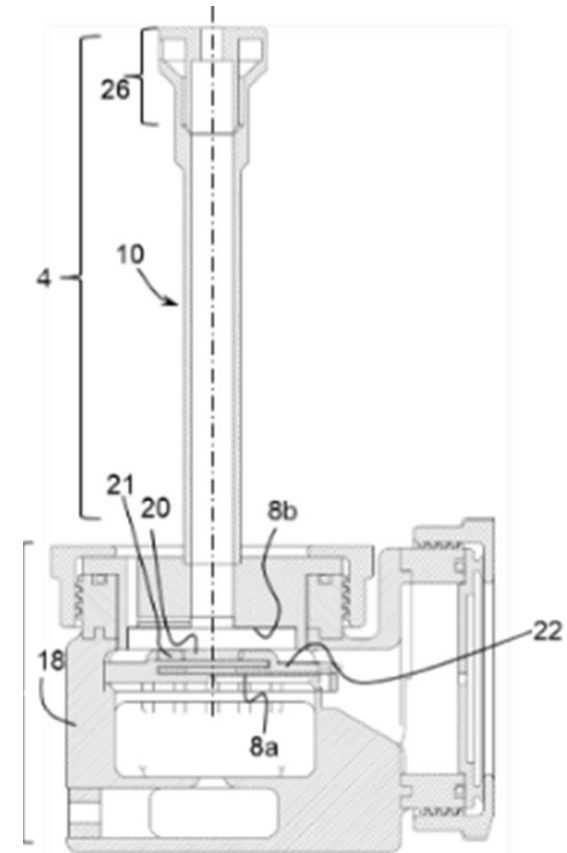


High throughput

$r_f/R_c = \Omega \left(\frac{r_i^*}{r_{lim}^*} \right) \sqrt{r_{geo}^2 + 3\alpha\beta \left(\frac{2 - \Omega^2 r_i^{*2}}{2 - r_{lim}^{*2}} \right)}$ $\Omega = \frac{r_0^*}{r_i^*} = f \left(r_i^*, \frac{H}{R}, \frac{R}{R_c}, \alpha, \beta \right); r_{geo}^* = \left(\frac{r_{lim}^* R}{R_c} \right); \alpha = \frac{Q_a \mu}{e E_0 R_c}; \beta = \frac{D_p}{n C_c R_c}; r_0^* = \frac{r_0}{R}; r_{lim}^* = \frac{r_{i,max}}{R}$ $0 \leq r_i \leq r_{lim}^*; 0 \leq \Omega \leq 1$			
$\Omega^3 - \frac{3}{r_i^{*2}} \left(1 + \frac{v_{elec,r}}{2 v_{in}} \right) \Omega - \left\{ 1 - \frac{3}{r_i^{*2}} \left(1 + \frac{v_{elec,r}}{2 v_{in}} \right) + \frac{3}{r_i^{*3}} \left(\frac{v_{elec,r}}{2 v_{in}} \right) \right\} = 0$ $\text{where } v_{in}/v_{elec} = \frac{1}{E_{corr}} \frac{3\alpha\beta}{r_{lim}^{*2} (2 - r_{lim}^{*2})} \left(\frac{R}{R_c} \right)^{-2}; E_{corr} = f(H/R)$			
Geometric variables	Operating variables	Inlet variables	Performance variables
R_c : Collection disc radius R : Inlet radius H : Electrode separation distance	Q_a : Aerosol flow rate E : Electric field strength V_0 : Voltage difference between $z=0$ and $z=H$	D_p : Particle diameter n : no. of elementary charges on the particle r_{lim}^* : Sheath position r_i^* : Inlet position	$\frac{r_f}{R_c}$: Dimensionless final position of deposition

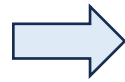
Dudani, PhD thesis, 2021

Dudani and Takahama (US patent)
filed 2020; granted 2024

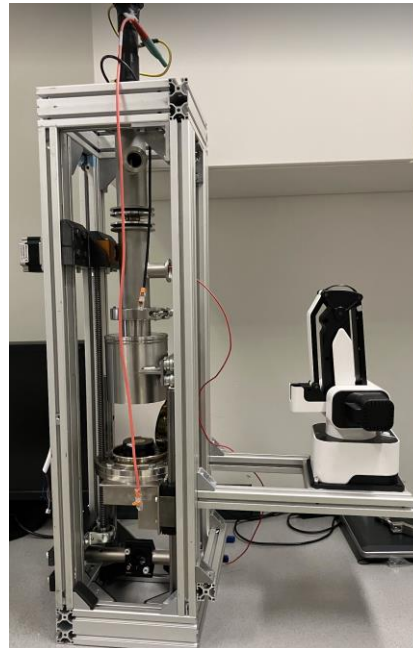


Toward automated measurement

Prototype collector
3-D printed
2019-2021

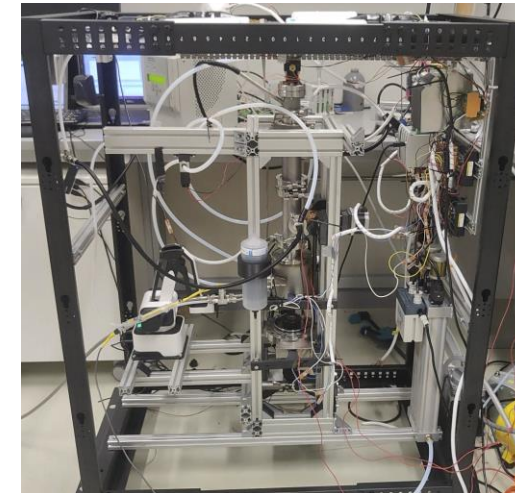


Sample collector
machine fabrication
2023



Fully-integrated
online monitor
2023-2024

Prototype v1



Prototype v2



Aerospec



Nikunj Dudani
CEO, Co-founder



Satoshi Takahama
Scientific advisor,
Co-Founder



Andrea Baccarini
CTO

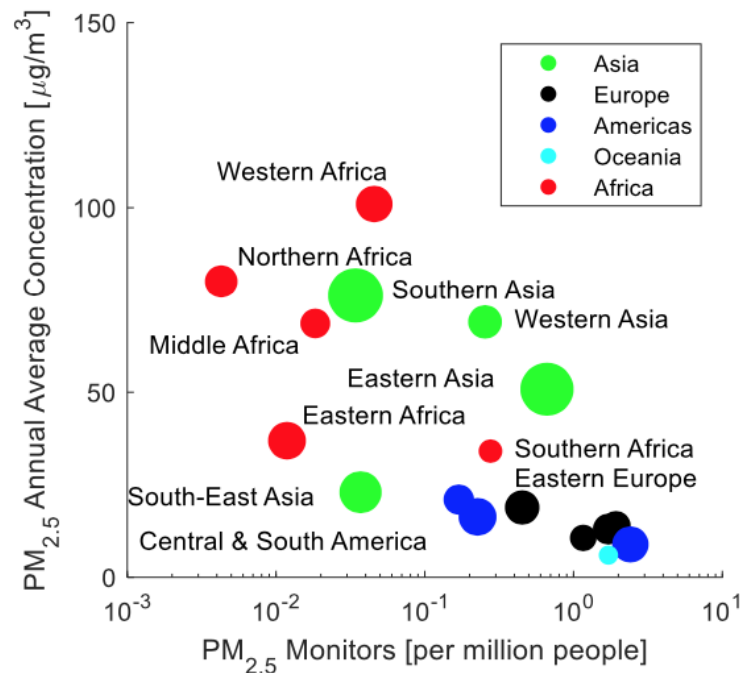


Arthur Blase
Product engineer,
Business development



Kamila Babayeva
Programming guru

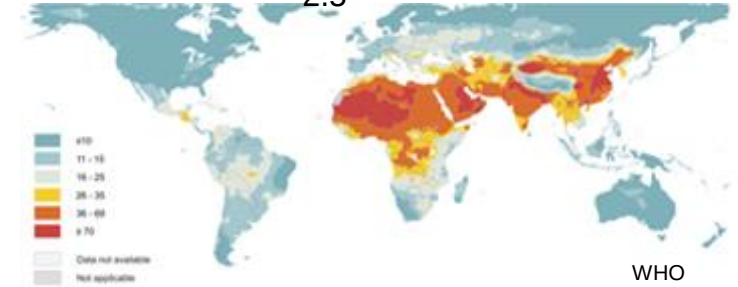
Need for cost-effective monitoring of air pollution



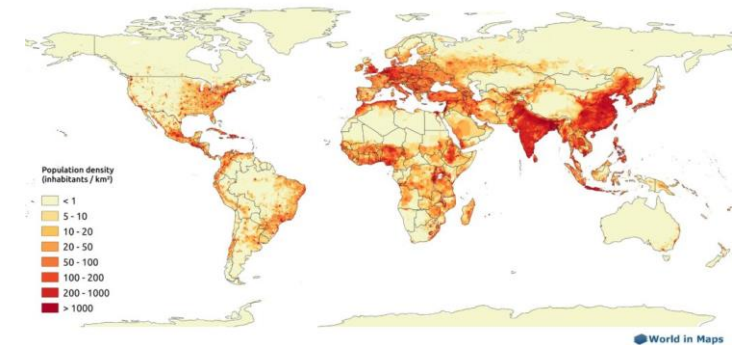
Lack of monitors in high population areas

Malings et al., 2020

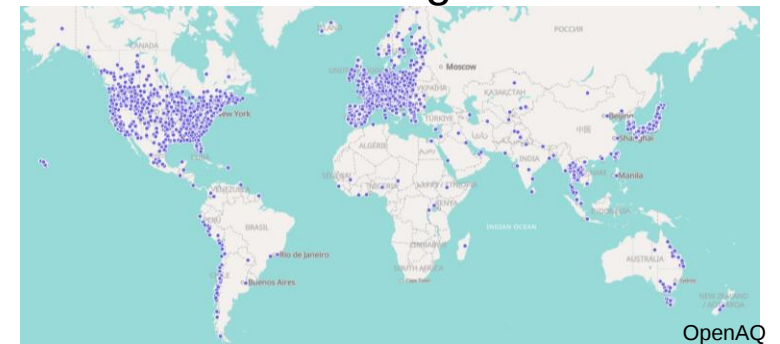
Estimated PM_{2.5} concentrations



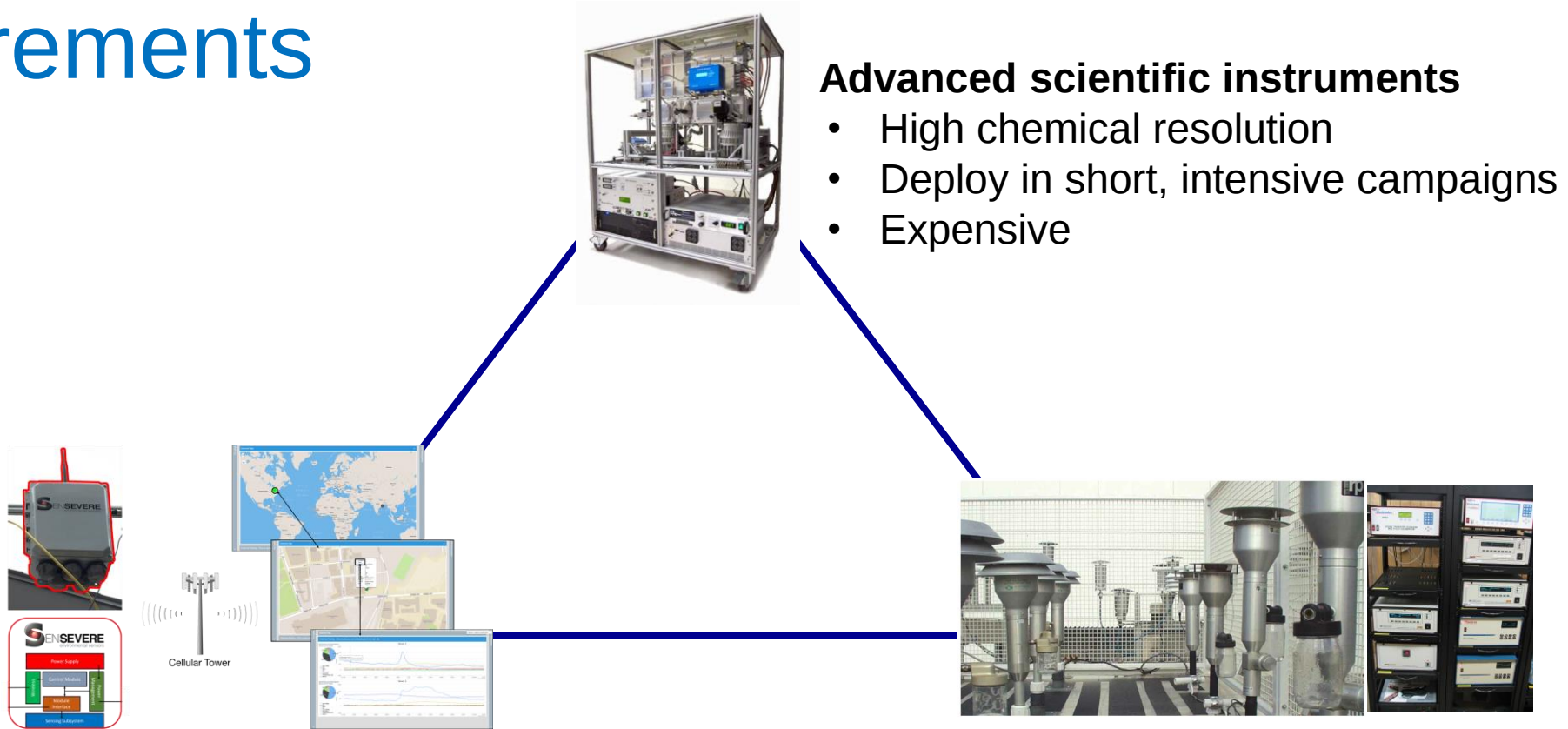
Population density



Available monitoring data



Ground-based aerosol measurements



Complementary monitoring strategies

