Personal air pollution exposure assessment of rural and urban residents in greater Beijing area

Improving personal exposure metrics

20 March 2019, Leeds UK

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Introduction

Global burden of non-communicable disease
Limitations of epidemiological research

AIRLESS project

Novel monitoring methodological framework
1. Performance of the personal air quality monitor
2. Mobile air pollution network
3. Time-activity-location model

Personal exposure measurements
Preliminary health outcomes
Future work
The world is changing …

A shift in the burden of disease in counties with high rates of infectious disease
Health effects of air pollution: Time for reassessment?

1) Issues related to methodological bias – aggregated exposure metrics and health outcomes

2) Lack of monitoring infrastructure in rural settings

3) Concerns about confounding/multi-collinearity

- Similar emission sources (traffic), dispersion processes ⇒ correlation (NO$_2$, PM)

- O$_3$ titration in high pollution areas… ⇒ anti-correlation

Modelled annual averages based on measurements made in 2010

⇒ Cannot distinguish causal links
The AIRLESS project

Personal exposure measurements at high spatial and temporal resolution + detailed medical outcomes ⇒ underlying mechanisms of chronic disease

urban cohort

rural cohort

Air Pollution Exposure and Dose

- Personal air quality monitor
- Personal exposure to individual air pollutants
- Activity-related parameters
- Inhalation rates
- Inhaled air pollution dose

Medical parameters

Clinical monitoring

Health Outcomes
**PAM**: To capture the personal exposure to air pollution of an individual

- **Global Positioning System (GPS)**
- **Battery**
- **Electrochemical sensors**: CO, NO, NO₂, (O₃)
- **Optical Particle Counter (OPC)**
- **Accelerometer**
- **Microphone**
- **SD Card**
- **Temperature and RH**

[dimensions 12.5 cm x 9 cm x 8 cm; weight 400 g; resolution 1 min]

Highly portable sensor platforms

Outdoor co-location of 60 PAMs with the reference instrument on the roof of PKU. Time-series of pollutants measured with the PAM and reference instruments.

Reproducibility between 10 PM sensors
But do they work indoors?

Excellent agreement with commercial portable instruments

Indoor co-location of a PAM (blue) with portable commercial instrumentation (red) in an urban flat in China during the non-heating season. A second PAM was deployed outdoors (grey).

NO$_2$ reference: cavity attenuated phase shift spectroscopy (CAPS), University of York
PM$_{2.5}$ reference: spectrometer (GRIMM 1.108), NERC
Mobile air pollution monitoring networks

3D presentation of CO concentrations measured by the urban sensor network (grey)

- CO / ppm
- PAMs
- extracted background
- Nov 12, Nov 19, Nov 26, Dec 03, Dec 10, Dec 17
- Extracted background
- 0, 5, 10, 15, 20, 25, 30

- No of participants
- 0, 50, 100, 150
- Nov 21, Nov 28, Dec 5, Dec 12, Dec 19

- percentage of time spent indoors / %

Beijing

Pinggu

- home location of participant
- visited locations during participation
Mobile air pollution monitoring networks

- Real-time validation of the PAM performance during daily life across seasons and settings
- Capture the heterogeneity of personal exposure in high spatial and temporal resolution in under-researched rural locations

Pinggu winter

- PM$_{2.5}$ (µg/m$^3$)
- CO (ppb)
- NO (ppb)
- NO$_2$ (ppb)
- O$_3$ (ppb)

Pinggu summer

- PM$_{2.5}$ (µg/m$^3$)
- CO (ppb)
- NO (ppb)
- NO$_2$ (ppb)
- O$_3$ (ppb)

Extracted background

reference

All PAMs
Automated time-activity model

PAM enables:
- Assignment of exposure levels to different activities
- Capture of exposure during commuting
- Activity-weighted exposure

Map of visited places of case participant, coloured by location category (motorised travel, walking, home, indoor other).

Comparison between dose estimations using a generic inhalation rate (white bars) and using activity-dependent inhalation rates (coloured bars).
**Variability of personal exposure to air pollution**

Overall CO exposure of each individual in the Beijing and Pinggu cohort. The area of the pie is proportional to their total exposure over the whole participation time. The colours indicate the contribution from background pollution levels (red), indoor (green) and outdoor (blue) emission sources in the surroundings.

<table>
<thead>
<tr>
<th></th>
<th>Beijing</th>
<th>Pinggu</th>
</tr>
</thead>
<tbody>
<tr>
<td>Background</td>
<td>47%</td>
<td>37%</td>
</tr>
<tr>
<td>Indoor local sources</td>
<td>49%</td>
<td>58%</td>
</tr>
<tr>
<td>Outdoor local sources</td>
<td>5%</td>
<td>4%</td>
</tr>
</tbody>
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**Mean overall CO exposure of all participants**

Indoor exposure is a significant part of total personal exposure.

Novel sensing technologies can revolutionise health studies.
Distinct health outcomes between cohorts

Monocytes (a type of white blood cell used as a biomarker for inflammatory response) ~ personal exposure to PM$_{2.5}$

Urban residents had acute health responses associated with personal exposure to PM$_{2.5}$

graph: Yiqun Han
...which could not be captured when using outdoor measurements as metrics of exposure

Monocytes (a type of white blood cell used as a biomarker for inflammatory response) ~ outdoor PM$_{2.5}$ from fixed monitoring station
Future work

An illustrative example of the proposed methodology to develop a modelling tool to estimate personal exposure to air pollution at high spatial and temporal resolution in large-scale studies.
Summary

Novel sensing technologies can improve personal exposure metrics by increasing coverage in pollutant species, space, time, microenvironments and geographical settings.

Mobile air pollution networks can validate sensor performance in real-time and input for outdoor and indoor models.

Automated time-activity-location classifications can integrate inhalation rates in personal exposure estimates.

Together with detailed medical outcomes to investigate the underlying mechanisms of air pollution impacts on health revolutionising epidemiological evidence.

Future work involves the development of an open-source, extendable and validated methodological framework to estimate air pollution exposure at the individual level across seasons and geographical locations.
Acknowledgements

• **The AIRLESS study team** – Tong Zhu, and Frank Kelly, Yangfeng Wu, Jing Liu, Rod Jones, Majid Ezzati, Paul Elliott, Meiping Zhao, Junfeng Zhang, Queenie Chan, Benjamin Barratt, Gaoqiang Xie, Yiqun Han, Lia Chatzidiakou, Anika Krause, Hanbin Zhang, Li Yan, Yunfei Fan, Yongkai Hu, Wu Chen, Yanwen Wang, Samuel Cai, Wuxiang Xie, Xi Chen, Teng Wang, Aoming Jin, Pengfei Liang, Yingruo Li

• **CAS Cambridge Team** – Rod Jones, Lekan Popoola, Andrea Di Antonio, Ray Freshwater, Anika Krause

• **The AIRPOLL and AIRPRO study team** for reference data

• **All participants** from Pinggu and Peking University
Appendix
Mobile air pollution monitoring networks