Understanding the sources of outdoor air pollution in sub-Saharan Africa: lessons from Ghana
Welcome and overview
Pallavi Pant, HEI, USA

Opening Remarks
Emmanuel Appoh, Ghana EPA, Ghana

Understanding source contributions using source apportionment
Michael Hannigan, UC Boulder, USA
Eloise Marais, University of Leicester, UK

Q&A/ Discussion
Air quality in Ghana and the region is poor
Air quality in Ghana and the region is poor

Average population-weighted PM$_{2.5}$

Ghana: 35 µg/m³
Sub-Saharan Africa: 45 µg/m³

Deaths attributable to ambient PM$_{2.5}$
Ghana: 5,190
Sub-Saharan Africa: 150,800

Household air pollution from solid fuels
Ghana: 9,780
Sub-Saharan Africa: 393,300
And the data are limited

OpenAQ
And the data are limited

Courtesy of Dr. Michael Brauer
How can understanding source contributions help mitigation efforts?

**Identify** what sources contribute the most to poor air quality and health

**Communicate** their health and economic costs to society

**Analyze** which sources are most effective to address first

**Provide** a baseline against which to measure future progress
HEI Communication 19
Contribution of Household Air Pollution to Ambient Air Pollution in Ghana: Using Available Evidence to Prioritize Future Action

Communicating the importance of various sources as contributors to ambient air pollution, especially HAP

Support for sustained development and improvement of emissions inventories at country and regional levels

Support for an expanded air quality monitoring program in the sub-Saharan Africa region

Harmonization of ongoing efforts and better coordination among researchers in the region
What does Ghana’s experience suggest for other low- and middle-income countries?

Existing (and upcoming) global assessments can provide a good starting point.

For local assessments, **systematic development of inventories and monitoring capabilities is key**.

Modelling tools like **LEAP IBC** has been effective starting point for capacity development, to build local emissions inventories and to explore their implications for air quality and health.

Collaboration with international scientists and organizations can leverage and build local capacity; a consistent and coordinated approach is preferable.
Mr. Emmanuel Appoh
Deputy Director
Ghana Environmental Protection Agency
Understanding source contributions using source apportionment methods
Why be a air pollution detective?

To reduce health impacts from a pollutant, you need to know the origin of the pollutant.
Source apportionment is essential to Air Quality Management

- Facilitate engagement with source sectors
- Understand seasonal and spatial distribution of source impacts
- Know what drives episodic events and annual averages
- Assess effectiveness of control programs

Chemical speciation and source apportionment of PM2.5 in Santiago, Chile, 2013
Villalobos, AM, Barraza, F, Jorquera, H, Schauer, JJ, Sci of Tot Env, 2015
Top-Down and Bottom-Up Approaches

- Different resource needs.
- Important spatial and temporal scale differences.
- Each have different strengths and limitations.
- Pollutant problem being investigated is important.

The two approaches can be complimentary.

HEI Communication 19 discusses the two approaches in the context of PM2.5 in Ghana. Read ...
“Contribution of Household Air Pollution to Ambient Air Pollution in Ghana: Using Available Evidence to Prioritize Future Action”

SO₂ – sulphur dioxide; VOCs – volatile organic compounds; NOₓ – nitrogen oxides; NH₃ – ammonia; PM₂.₅ – particulate matter with an aerodynamic diameter equal to or less than 2.5 micrometres (µm)

Primary inorganic and organic PM₂.₅ particles are those released directly to the atmosphere and inhaled by the population; these include dust from roads and black carbon from combustion sources. Secondary inorganic and organic PM₂.₅ particles, on the other hand, are formed in the atmosphere from chemical reactions involving primary gaseous emissions: nitrogen oxides and sulphur dioxide mainly from cities and industrial areas; ammonia mainly from agricultural sources; and volatile organic compounds from solvent use. Because of their small size, both primary and secondary particles can be transported over large distances.

FIGURE 1: SOURCES AND COMPOSITION OF PM₂.₅

United Nations Environment Programme (UNEP), November 2018
Top-Down Detective Work

High Level Overview

Top-Down Source Apportionment Math

Mathematical Framework

- Requires monitoring expertise.
- Looks back in time.

\[ x_{ij} = \sum_{k=1}^{p} g_{ik} f_{jk} + e_{ij} \]

- species \( j \) measured in sample \( i \)
  (ambient measurements)
- mass from source \( k \) in sample \( i \)
  (source contribution)
- mass fraction of species \( j \) from source \( k \)
  (source profile or fingerprint)

- # of sources = \( p \)
- # of species = \( n \)
- # of samples = \( m \)
Mathematical Framework

\[ x_{ij} = \sum_{k=1}^{p} g_{ik} f_{jk} + e_{ij} \]

- \( x_{ij} \): species \( j \) measured in sample \( i \) (ambient measurements)
- \( g_{ik} \): mass from source \( k \) in sample \( i \) (source contribution)
- \( f_{jk} \): mass fraction of species \( j \) from source \( k \) (source profile or fingerprint)
- \( e_{ij} \): residual

**Parameters:**
- \( \# \text{ of sources} = p \)
- \( \# \text{ of species} = n \)
- \( \# \text{ of samples} = m \)
Simple Case

when $p = n$

\[
x_{\text{cholesterol}} = g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}}
\]

\[
x_{\text{silicon}} = g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}}
\]

# of sources $p = 2$

# of species $n = 2$

# of samples $m = 1$
Simple Case

\[ x_{\text{cholesterol}} = g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}} \]

\[ x_{\text{silicon}} = g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}} \]

What are the caveats?

\# of sources  
\[ p = 2 \]

\# of species  
\[ n = 2 \]

\# of samples  
\[ m = 1 \]
Example ...

Simple Case

\[ x_{\text{cholesterol}} = g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}} \]

\[ x_{\text{silicon}} = g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}} \]

What are the caveats?

1. The profiles need to be unique (linearly independent).
2. Need to use all the important sources for the compounds
3. Compounds are not altered from source to receptor

When \( p = n \)

# of sources \( p = 2 \)  # of species \( n = 2 \)  # of samples \( m = 1 \)
Example ...

Simple case with pretend numbers

\[
15 \left( \frac{\text{ng cholesterol}}{\text{m}^3} \right) = g_{\text{meatcooking}} \times 0.01 \left( \frac{\text{ng cholesterol}}{\text{ng meat smoke}} \right) + g_{\text{dust}} \times 0.002 \left( \frac{\text{ng cholesterol}}{\text{ng dust}} \right)
\]

\[
250 \left( \frac{\text{ng silicon}}{\text{m}^3} \right) = g_{\text{meatcooking}} \times 0.00001 \left( \frac{\text{ng silicon}}{\text{ng meat smoke}} \right) + g_{\text{dust}} \times 0.12 \left( \frac{\text{ng silicon}}{\text{ng dust}} \right)
\]

You measure

You measure

(or someone else measured and published)

# of sources
\( p = 2 \)

# of species
\( n = 2 \)

# of samples
\( m = 1 \)
Ambient PM$_{2.5}$ samples

- Gravimetric
- Ion Chromatography
- Thermal Optical Transmission

bulk

ambient chemical speciation database

Source emissions sample

Chemical Mass Balance

Source contributions

(+): Clear link to sources
(-): Need complete set of source samples

Positive Matrix Factorization (PMF)

Factor contributions

(+): No source samples needed
(-): Linking factors to sources adds uncertainty

GC-MS

organic molecular markers

ICPMS

Metals/elements
**Filter Analysis Spectrum**

- **Quartz fiber**
- **Field**
  - **Mass Gravimetric**
  - **Mass on filter data**
  - **Sulfate, Nitrate, … Ion Chromatography**
  - **Ion mass on filter data**
  - **Aluminum, Arsenic, … ICPMS**
  - **Trace metal mass on filter data**

- **Teflon Filter Analysis Spectrum**
  - **EC, OC, OC fractions**
  - **Thermal Optical Transmission**
  - **Organic species masses on filter data**
  - **Carbon mass on filter data**
  - **GC-MS**
  - **Anthracene, Cholesterol, Levoglucosan, …**
System of Equations

One Level of Complexity

\[ x_{\text{cholesterol}} = g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}} \]

\[ x_{\text{silicon}} = g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}} \]

\[ x_{\text{oleicacid}} = g_{\text{meatcooking}} f_{\text{oleicacid,meatcooking}} + g_{\text{dust}} f_{\text{oleicacid,dust}} + e_{\text{oleicacid}} \]

\[ x_{\text{iron}} = g_{\text{meatcooking}} f_{\text{iron,meatcooking}} + g_{\text{dust}} f_{\text{iron,dust}} + e_{\text{iron}} \]

# of sources
\[ p = 2 \]

# of species
\[ n = 4 \]

# of samples
\[ m = 1 \]
System of Equations

One Level of Complexity

\[ \begin{align*}
    x_{\text{cholesterol}} &= g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}} \\
    x_{\text{silicon}} &= g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}} \\
    x_{\text{oleicacid}} &= g_{\text{meatcooking}} f_{\text{oleicacid,meatcooking}} + g_{\text{dust}} f_{\text{oleicacid,dust}} + e_{\text{oleicacid}} \\
    x_{\text{iron}} &= g_{\text{meatcooking}} f_{\text{iron,meatcooking}} + g_{\text{dust}} f_{\text{iron,dust}} + e_{\text{iron}}
\end{align*} \]

If \( X \) and \( F \) are measured, how do we solve for \( G \)?

\# of sources \( p = 2 \)

\# of species \( n = 4 \)

\# of samples \( m = 1 \)
Backing Up
Why do this?

Uncertainty in ambient measurements
Uncertainty in source profiles
Stochastic nature of emissions and transport
Assumptions not perfectly valid
This math is more interesting
To Solve ...

Determine $G$ such that the residual is as small as possible.

$$Q^* = \sum_{j=1}^{4} (e_j)^2$$

$Q^*$ = sum of the squared residual

\[ x_{\text{cholesterol}} = g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}} \]

\[ x_{\text{silicon}} = g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}} \]

\[ x_{\text{oleicacid}} = g_{\text{meatcooking}} f_{\text{oleicacid,meatcooking}} + g_{\text{dust}} f_{\text{oleicacid,dust}} + e_{\text{oleicacid}} \]

\[ x_{\text{iron}} = g_{\text{meatcooking}} f_{\text{iron,meatcooking}} + g_{\text{dust}} f_{\text{iron,dust}} + e_{\text{iron}} \]
Improved solution ...

Determine $G$ such that the uncertainty weighted residual is as small as possible.

$$Q = \sum_{j=1}^{n} \left( \frac{e_j}{s_j} \right)^2$$

$Q =$ sum of the uncertainty weighted squared residual

$$x_{\text{cholesterol}} = g_{\text{meatcooking}} f_{\text{cholesterol,meatcooking}} + g_{\text{dust}} f_{\text{cholesterol,dust}} + e_{\text{cholesterol}}$$

$$x_{\text{silicon}} = g_{\text{meatcooking}} f_{\text{silicon,meatcooking}} + g_{\text{dust}} f_{\text{silicon,dust}} + e_{\text{silicon}}$$

$$x_{\text{oleicacid}} = g_{\text{meatcooking}} f_{\text{oleicacid,meatcooking}} + g_{\text{dust}} f_{\text{oleicacid,dust}} + e_{\text{oleicacid}}$$

$$x_{\text{iron}} = g_{\text{meatcooking}} f_{\text{iron,meatcooking}} + g_{\text{dust}} f_{\text{iron,dust}} + e_{\text{iron}}$$
Let’s Look at Some Ambient Data

Denver, CO, USA in 2003

One year of daily PM2.5 samples

nC29 (ng/m3)
nC30 (ng/m3)
What do you see?

Denver, CO, USA in 2003

nC30 (ng/m3) vs nC29 (ng/m3)
An Edge

Denver, CO, USA in 2003
What do you see?

Denver, CO, USA in 2003

Two Edges
Denver, CO, USA in 2003

Source Profile

Two Edges
Maybe we don’t need source profiles if we have a lot of samples.
Top Down Model Spectrum

\[ x_{ij} = \sum_{k=1}^{p} g_{ik} f_{jk} + e_{ij} \]

knowledge about sources, \( f_{jk} \)

- Multivariate Receptor Model
  - Explanatory Factor Analysis Models
    - \( p \) is unknown
    - \( F \) is unknown
    - \( m > 1 \)
  - Confirmatory Factor Analysis Models
    - \( p \) is hypothesized
    - \( F \) is partially known
    - \( m > 1 \)
  - Regression Models
    - \( p \) is known
    - \( F \) is known
    - \( m = 1 \)

none \rightarrow PMF \rightarrow UNMIX \rightarrow CMB \rightarrow complete

Chemical Mass Balance Model
Chemical Mass Balance (CMB)

- US EPA maintains a CMB tool
  - Current version, CMB8.2
  - Requires uncertainties of both $X$ and $F$

- Advantage:
  - Can be applied to **one sample**

- Disadvantage
  - Requires $F$ (source profiles)

- Most effective application
  - Near-source (well characterized source emissions)

**Major Limitation:**

Need **Representative** Source Fingerprints
Positive Matrix Factorization (PMF)

- US EPA maintains a PMF tool
  - Current version, PMF5.0
  - Requires uncertainties for $X$
- Advantage:
  - Do not need a representative source profiles
- Disadvantage
  - Need a lot of ambient samples
  - Sources must vary temporally to be resolved
  - Matching output ‘factors’ to real-world sources is challenging
- Most effective application
  - Time series in one urban area

**Major Limitation:**
Mapping output Factors to real-world Sources
Hannigan with African Megacites
(US EPA, Ghana EPA, IEc & World Bank)

- Goal is source apportionment of PM2.5 samples collected in Accra by Ghana EPA
- Training of Ghana EPA staff on filter handling, chemical speciation, and source apportionment
- Develop and refine SOPs
- Several trips to Accra and a trip to Boulder by Ghana EPA
- Initial PM2.5 filters from roadsides

My group is developing relevant source profiles that include open burning.
How is it going with the PM2.5 filters?

![Graph showing Carbonaceous PM2.5 vs OC (ug/m^3)]

![Graph showing Motor Oil Markers (smoky vehicles)]

**Equation:**

\[ y = 0.6633x + 0.0155 \]
Quick comparison with US samples ...

Motor Oil Markers (smoky vehicles)

Accra Samples spanning
- Jan 26th – May 27th
- All Roadside

PRAPPE Samples spanning
- Winter-Spring-Summer
- Urban Roadside, Rural Highway, Rural State Park
More organic source tracers ...

Interestingly, these do not look like source profiles from Denver
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Kintampo Health Research Center
Ghana EPA
Mr. Appoh and his team ...
Jerry Asumbere, John Kofi, Johnson Ade
Data streams for quantification of source emissions
Challenges and Opportunities Developing Emission Inventories for Africa

By 2100, 13 of the 20 largest cities will be in Africa

Eloise Marais

(heparisresearchgroup.co.uk/)

HEI Webinar
21 August 2019
By 2100, Africa’s population will rival that in Asia

Population projections, 2015-2100

Africa is the next frontier for development, so understanding pollution sources is imperative
Emission Inventory Development

The approach is standard

(1) Estimate Emissions:

\[ \text{Emissions} = \text{Activity Factors} \times \text{Emission Factors} \]

(2) Map Emissions:

Landscan population distribution

Satellite observations of gas flares

But there are Data Gaps and Uncertainty Challenges
Africa has a ubiquitous mix of inefficient pollution sources

Regional DICE-Africa inventory developed to address deficiencies in global inventories (available for download: http://maraisresearchgroup.co.uk/dice-africa-data.html)
Africa is in a unique position to avoid dependence on fossil fuels

Already substantial investment in fossil fuels for energy and transport

Generating capacity increases by almost 130%, population by 54%

[Marais et al., submitted]
Vehicle emissions from DICE-Africa for 2012 are scaled by population growth to obtain 2030 emissions.

Emissions of SO₂ and NOₓ double from 2012 to 2030 [Marais et al., submitted]
Inventory Application to a Chemical Transport Model

GEOS-Chem

Emissions (natural/human) -> GLOBAL 3D MODEL

Chemistry
Transport
Dry/wet deposition

3D global/regional atmospheric concentrations

Offline assimilated meteorology (NASA GMAO)

http://acmg.seas.harvard.edu/geos_chem.html
Impact on air quality (annual mean PM$_{2.5}$)

Annual mean fine particle (PM$_{2.5}$) obtained from GEOS-Chem at high spatial resolution

We use this to estimate that **48,000 premature deaths** likely from exposure to future fossil fuel PM$_{2.5}$

[Marais et al., submitted]
Impact of Charcoal Production on Air Quality and Climate

Large and dramatic increase in charcoal use, despite an increase in access to electricity

Charcoal Production in Africa

6-9% per year increase in production

Major export in Somalia fueling civil unrest

Includes plastic burning to initiate combustion

[FAOSTAT, 2014]

[Bockarie et al., in prep]
Updated and improved inventory of charcoal emissions

Pollutant emissions from charcoal production, use and transport

Rural production nearby roads, transport on densely packed diesel trucks, use in urban centres

[Bockarie et al., in prep]
Impact of charcoal supply chain on local air quality

Charcoal contribution to surface concentrations of fine particles (PM$_{2.5}$) and ozone

Maps show difference in GEOS-Chem with and without charcoal emissions

Up to 1 $\mu$g m$^{-3}$ contribution to PM$_{2.5}$. Smaller impact on surface ozone. Preliminary results suggest the impact on regional radiative forcing may be large.

[Bockarie et al., in prep]
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A link to the webinar video is available on our website.

You can find country-specific information on [www.stateofglobalair.org](http://www.stateofglobalair.org)

Country profiles for several sub-Saharan African countries are available on our website.

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