Emissions of long-standing and emergent air pollution in Africa obtained with satellite observations and models

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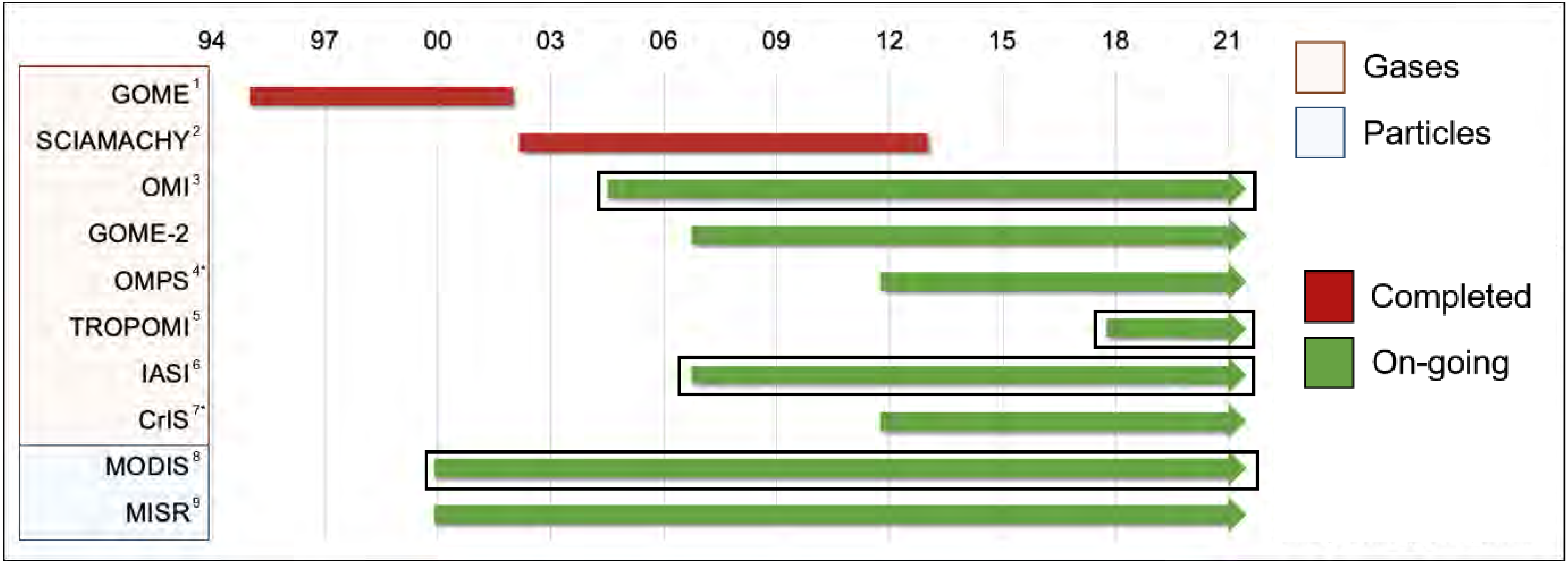
University College London

14 October 2025

Long and consistent record of air pollution from space

(low-Earth orbiting instruments that sample Africa)



Space-based constraints on air pollution:

OMI/TROPOMI: NO_2 (**NO_x**), HCHO (**NMVOCs**)

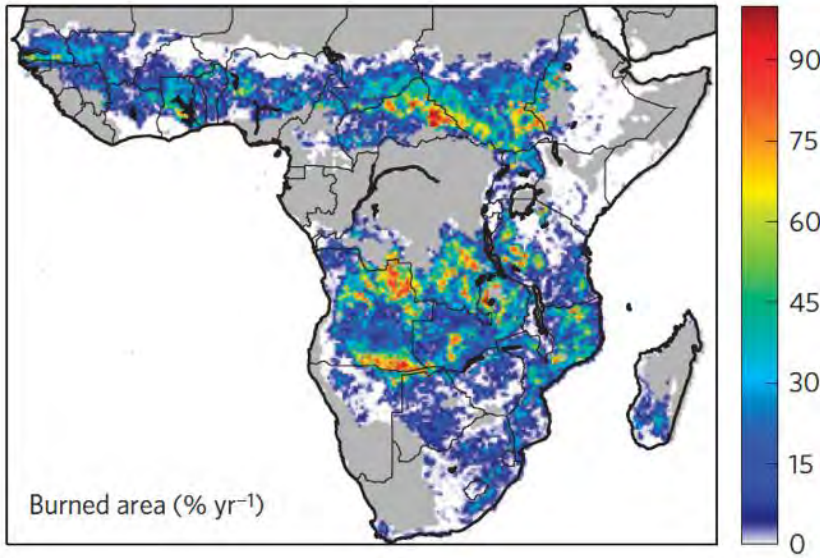
IASI: **NH_3**

MODIS: AOD (**$PM_{2.5}$**)

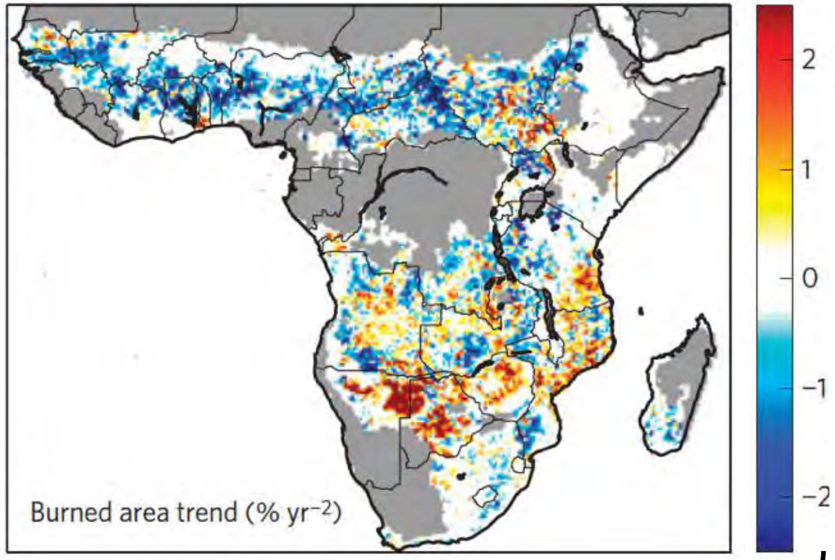
Air Pollution Sources are Evolving

Overall decline in biomass burning activity

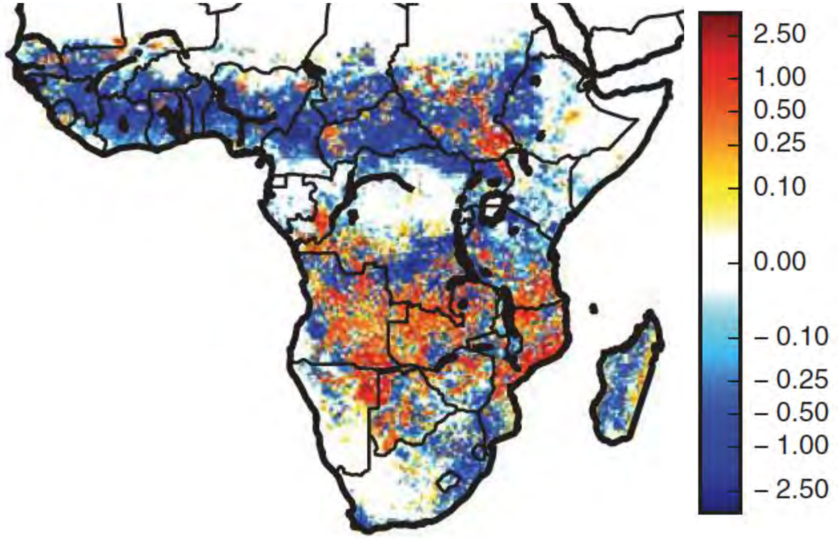
Burned area annual mean (2001-2012)



Burned area annual trend (2001-2012)



Burned area annual trend (1998-2015)



[Andela et al., 2014]

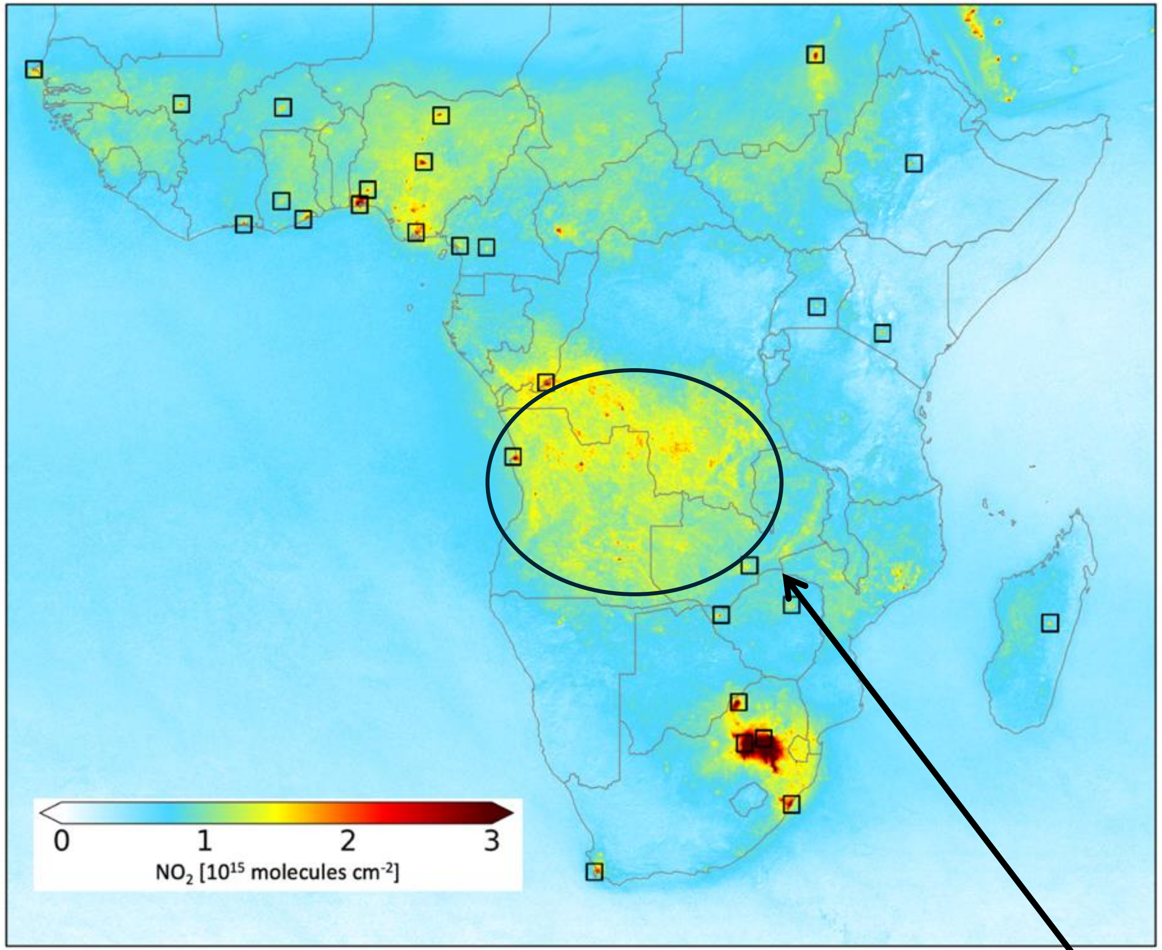
[Andela et al., 2017]

Strong decline north of the Equator due to changes in land cover (transition to agriculture)

Mixed trends south of Equator (attributed to decadal rainfall patterns in 2014 paper)

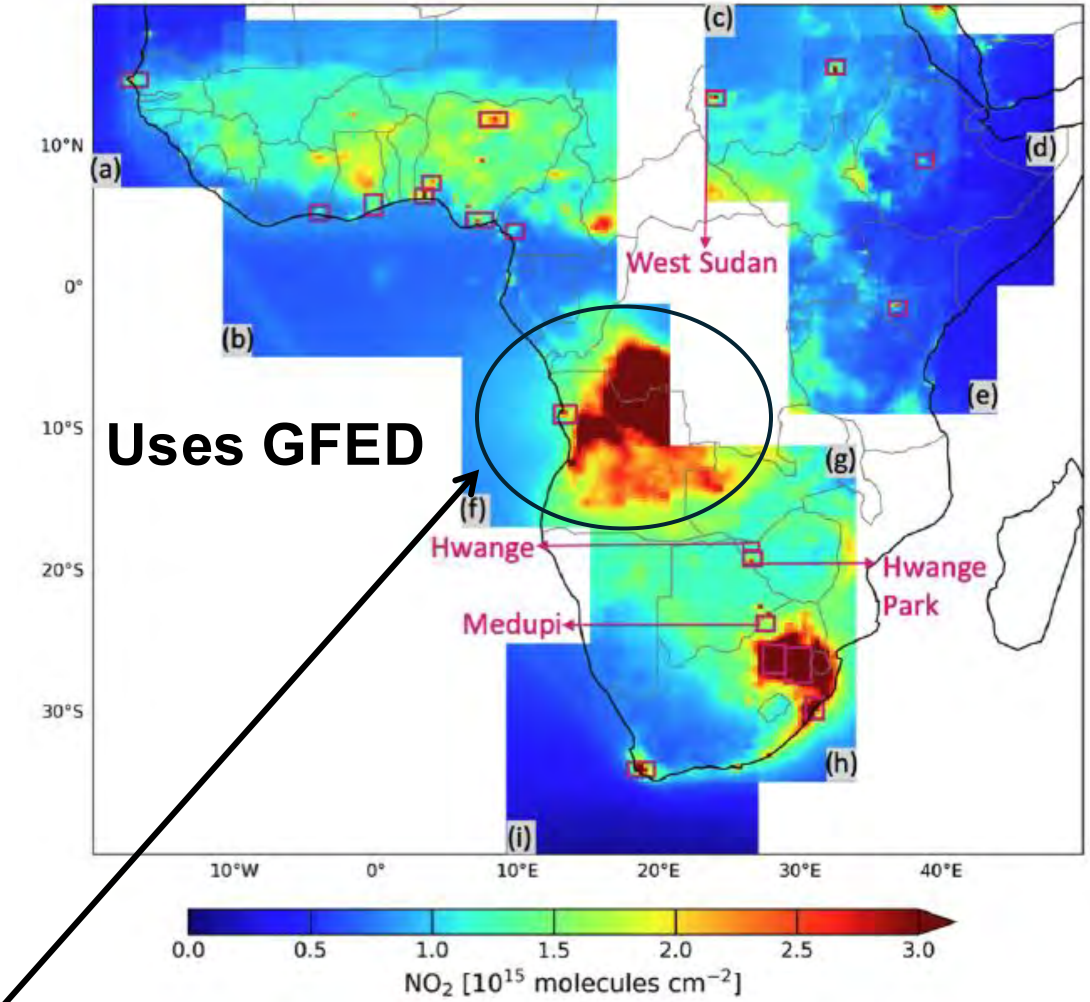
How Well do We Know this “Traditional” Source

TROPOMI annual mean NO_2



[Nana Wei PhD thesis]

Model annual mean NO_2

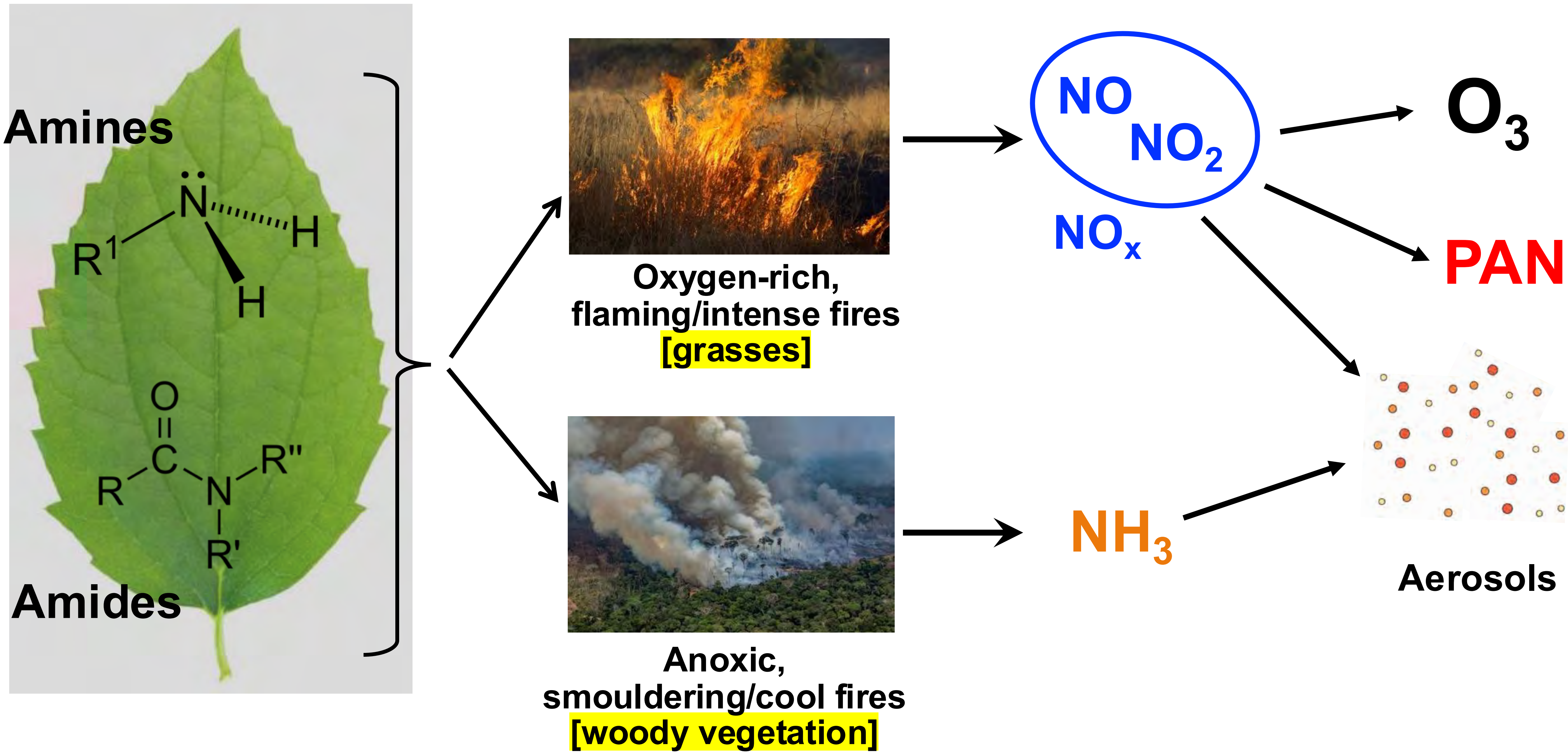


[Nana Wei PhD thesis]

Same scale; different color scheme

Mode overpredicts nitrogen dioxide (NO_2). How well do we know reactive nitrogen emissions?

Open Fire Emissions of Reactive Nitrogen



NO_x and NH_3 affect local air quality, regional climate, and global atmospheric composition

Bottom-Up Biomass Burning Emissions

Emission = DMB x EF

DMB: dry matter burned

EF: emission factor

DMB = Area burned x above-ground biomass x combustion completeness

3 prominent inventories:

GFED: Global Fire Emissions Database

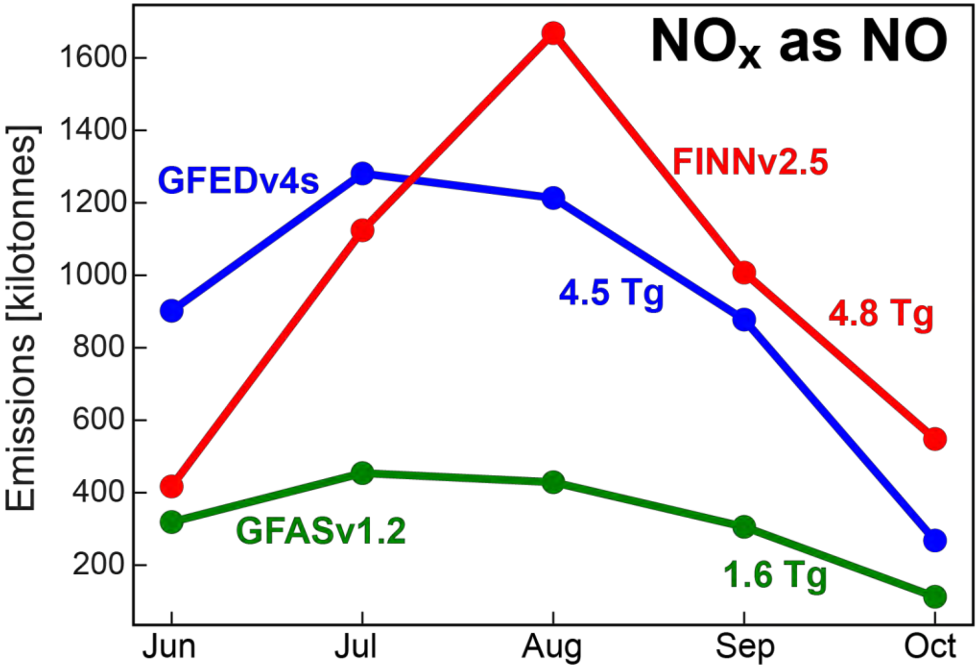
FINN: FIre INventory for NCAR

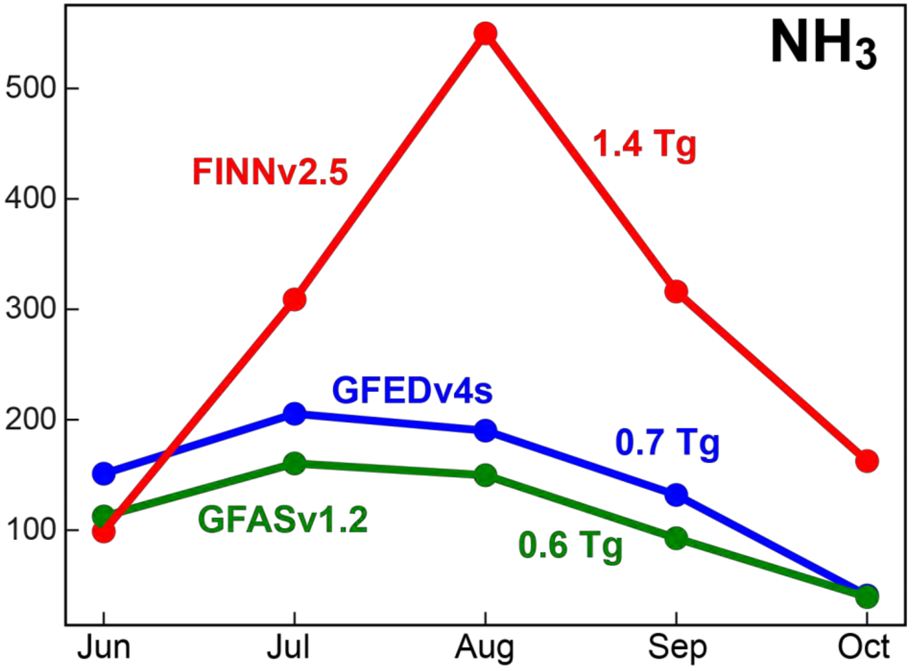
GFAS: Global Fire Assimilation System (CAMS)

DMB determined using distinct satellite data products for each inventory

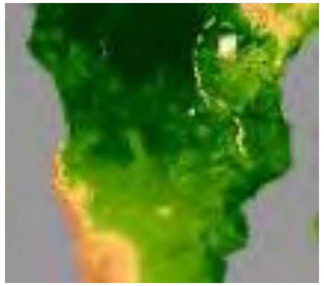
Reactive Nitrogen Emissions in Southern Africa

Monthly bottom-up June-October 2019 emissions





MODIS Landcover



Tropical forest
↓
Woody savanna
↓
Savanna

Mostly savanna fires. Some tropical forest fires.

Apply all 3 inventories to GEOS-Chem to compare to IASI for NH_3 and TROPOMI for NO_2

Very different ozone production efficiencies (OPEs): GFAS more sensitive to NO_x than others.

According to GEOS-Chem, FINN OPE > GFED OPE, as far more VOCs and CO than others:

- **FINN**: 108 Tg CO and 13 Tg C for 21 NMVOCs
- **GFED**: 82 Tg CO and 2 Tg C for 13 NMVOCs

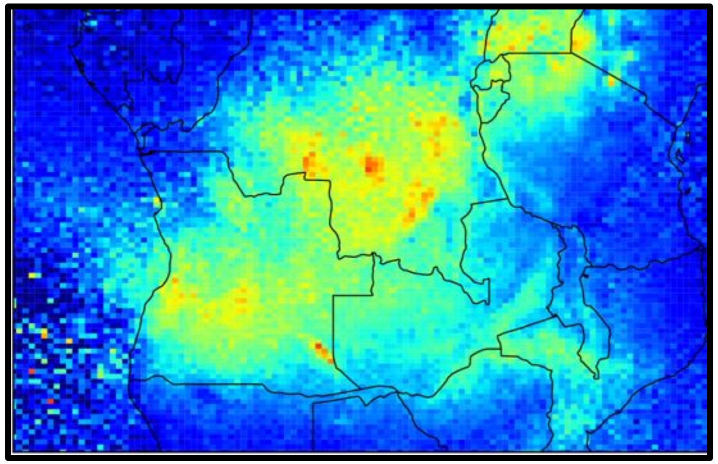
Drive GEOS-Chem with all Three Inventories

Emissions

Driven with 3 difference biomass burning inventories

GEOS-Chem

Model nested over southern Africa



Chemistry, transport, deposition

3D concentrations of NO_2, NH_3 converted to column densities

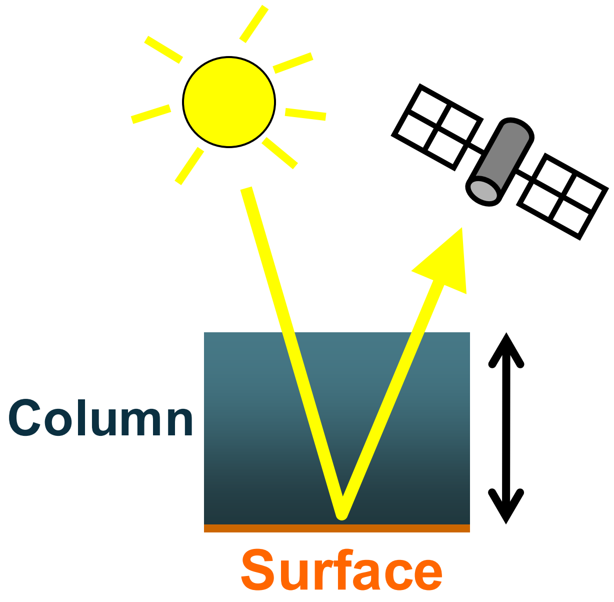
NASA GEOS-FP Meteorology

Simulate model with each inventory turned on to compare the model to IASI and TROPOMI

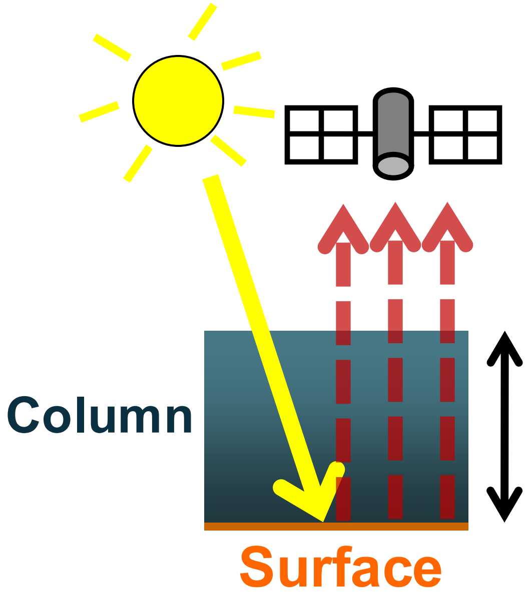
Sample the model at the same overpass time as the instruments

Account for Instrument Vertical Sensitivities

UV-visible instrument (TROPOMI)



Infrared instrument (IASI)



Sensitivity peaks in mid troposphere

Different approach for each instrument:

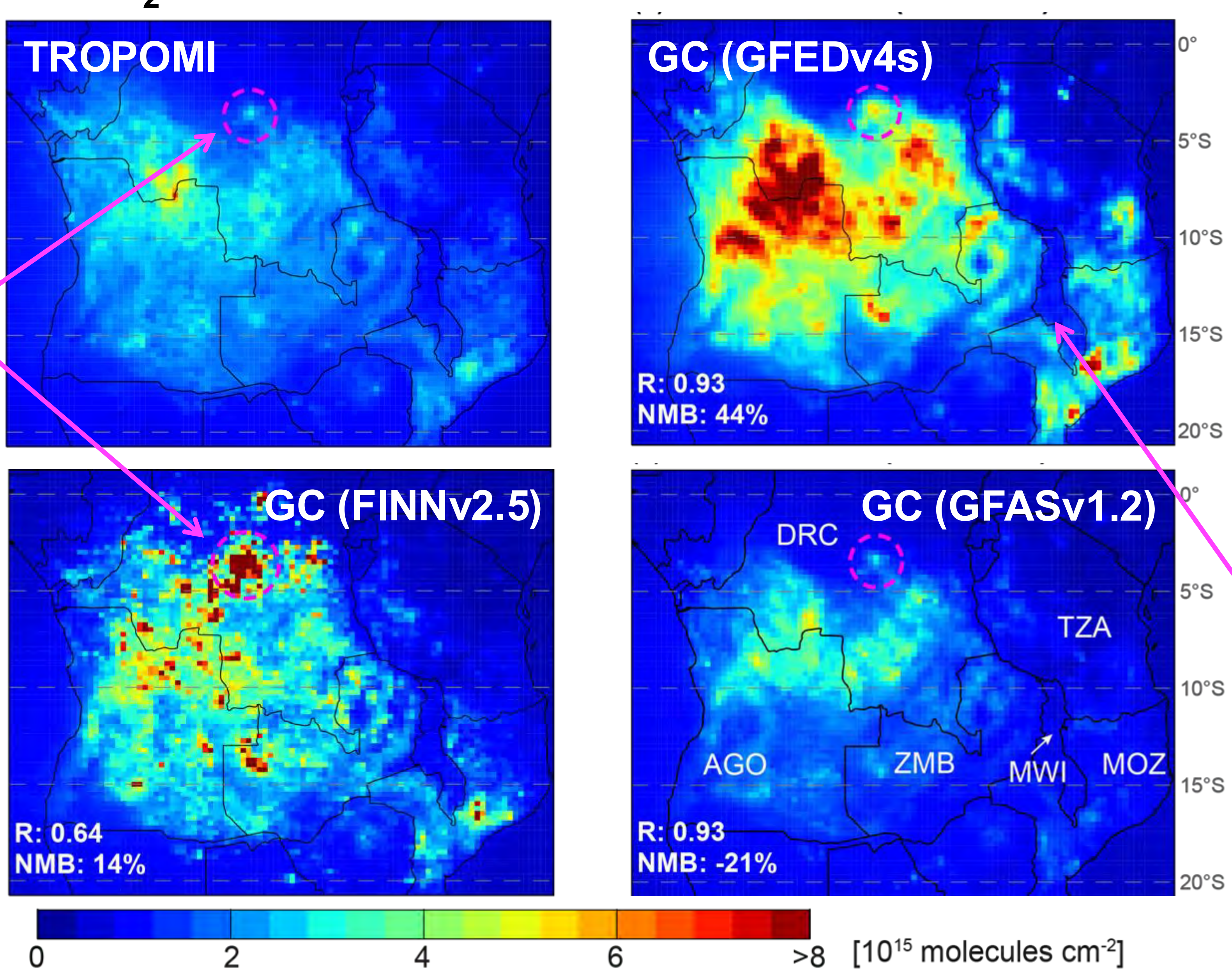
TROPOMI: apply averaging kernels (quantifies vertical sensitivity) to GEOS-Chem

IASI: reprocess (re-retrieve) IASI NH_3 with local GEOS-Chem a priori profiles

Evaluation of Inventories with Satellite Observations

NO_2 vertical column densities for Jun-Oct 2019

GC: GEOS-Chem



Far more NO_x from tropical forests in FINN (fuel load)

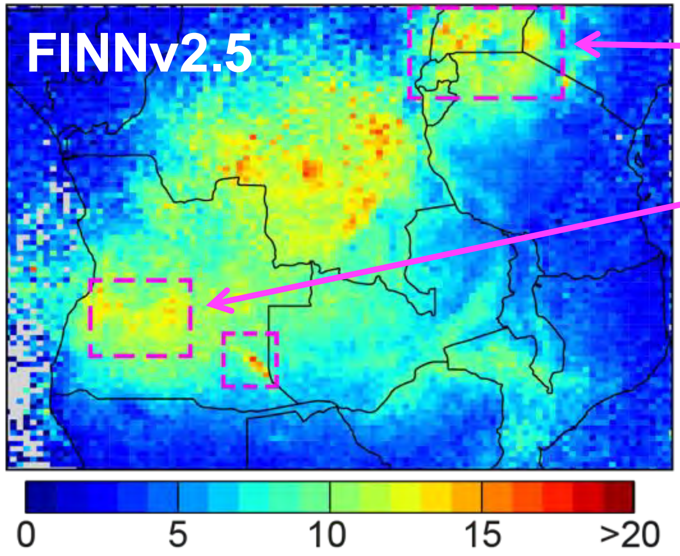
GFED and GFAS NO_2 spatially similar, but >50% difference due to emission factors

Low emissions in Malawi, as spread of fire suppressed by dense population

Evaluation of Inventories with Satellite Observations

NH_3 vertical column densities for Jul-Oct 2019 [10^{15} molecules cm^{-2}]

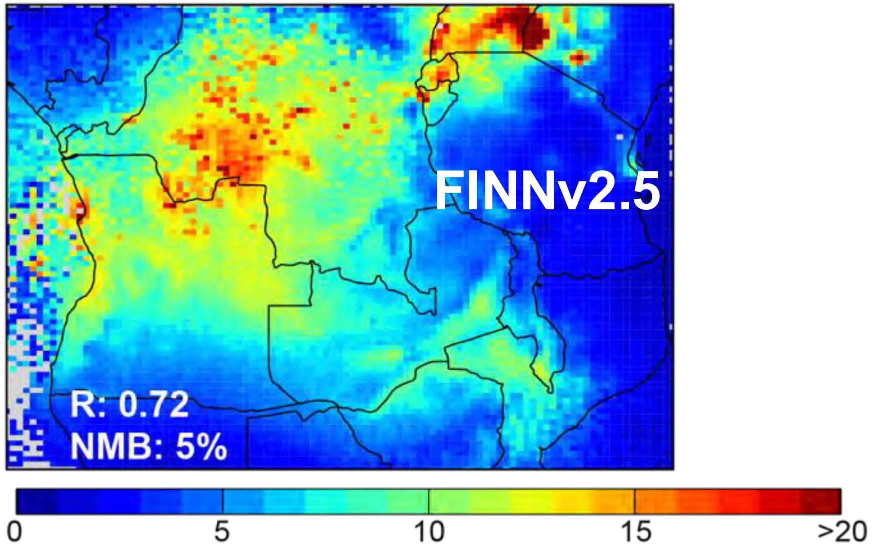
IASI with GEOS-Chem prior:

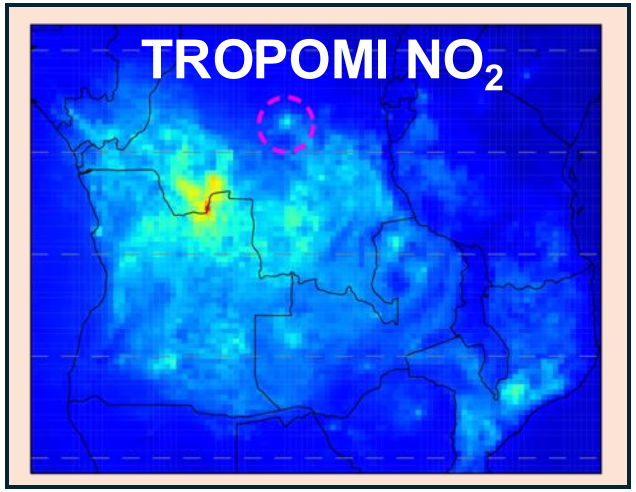


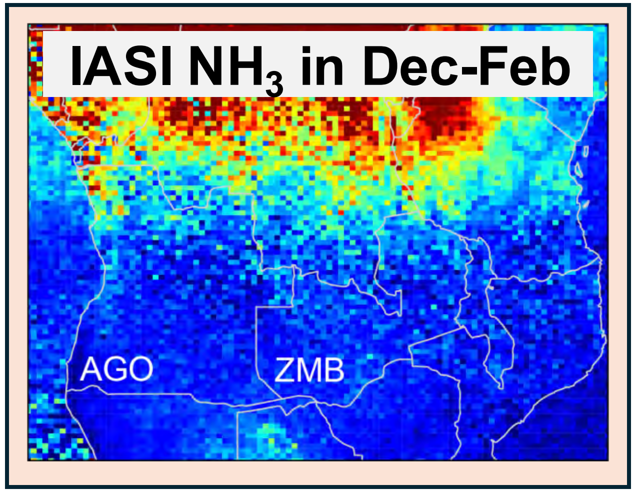
Anthropogenic NH_3 in the Lake Ukerewe Basin

Fire NH_3 in Angola that no inventory reproduces

GEOS-Chem:







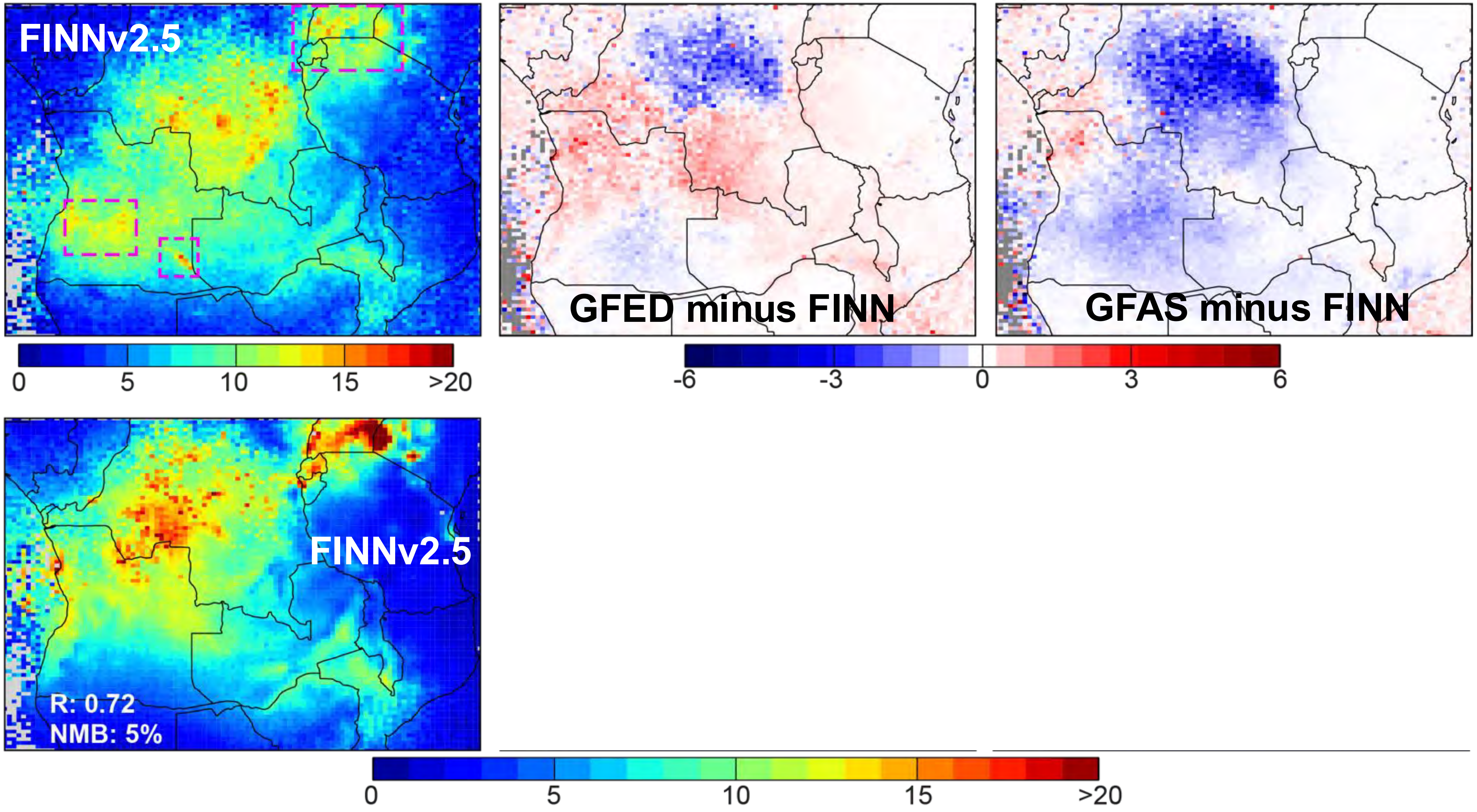
June excluded, as no inventories consistent with IASI observations (R < 0.5)

Evaluation of Inventories with Satellite Observations

NH_3 vertical column densities for Jul-Oct 2019 [10^{15} molecules cm^{-2}]

IASI with GEOS-Chem prior:

GEOS-Chem:

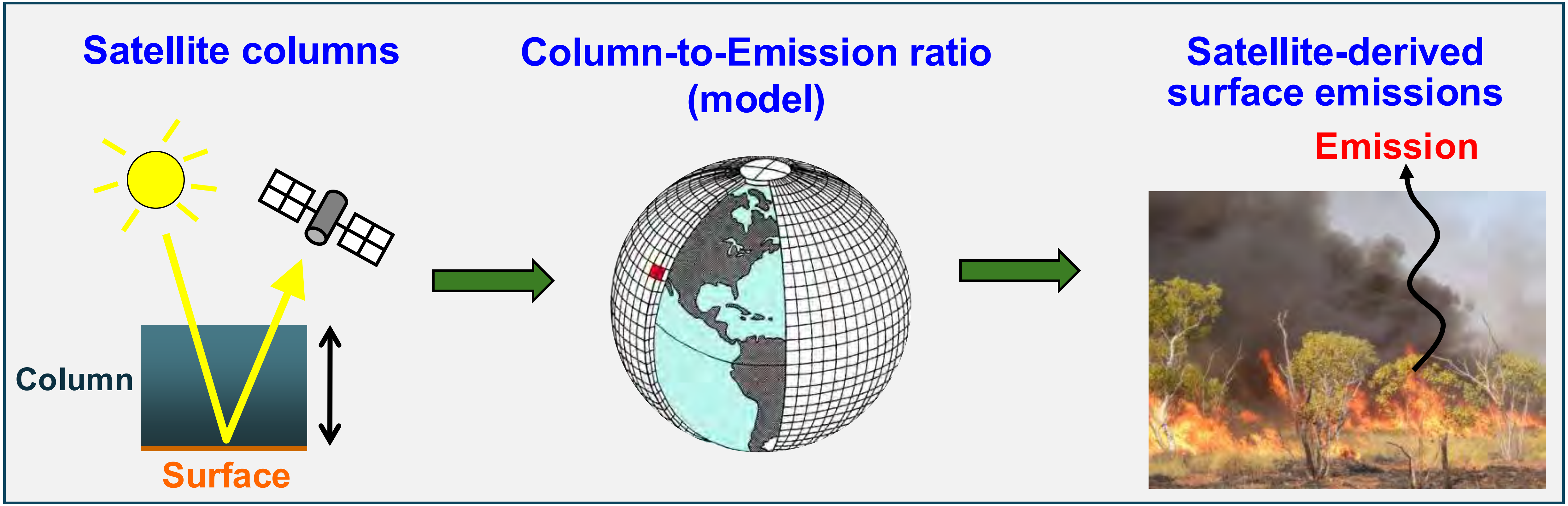


June excluded, as no inventories consistent with IASI observations (R < 0.5)

Top-down emissions estimate

Convert atmospheric **column concentrations** to surface **emissions** using a **model**

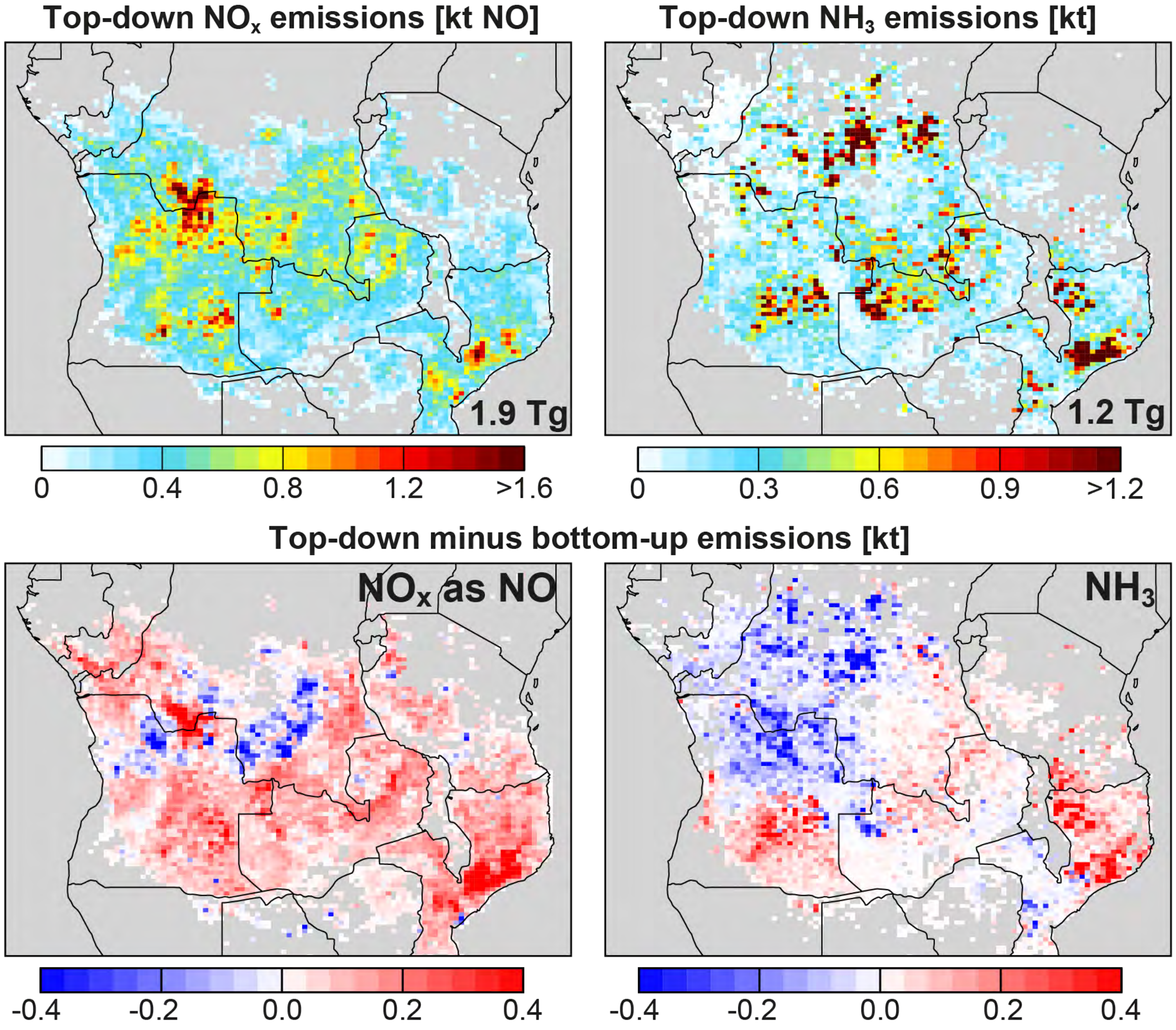
COLUMNS → Conversion Factor → EMISSIONS



Simple mass balance approach, as it's a first order problem (very large errors)

Use best-performing inventory (**GFAS** for NO_x, **FINN** for NH_3) for gridsquares where open fires > 50% total emissions

Top-down Emissions with Best Performing Inventories



Mass-balance approach: convert satellite columns to 24-h monthly emissions using GEOS-Chem

Uses GFAS for NO_x, FINN for NH_3 if biomass burning > 50% total

Distribution normal for NO_x, long-tailed for NH_3

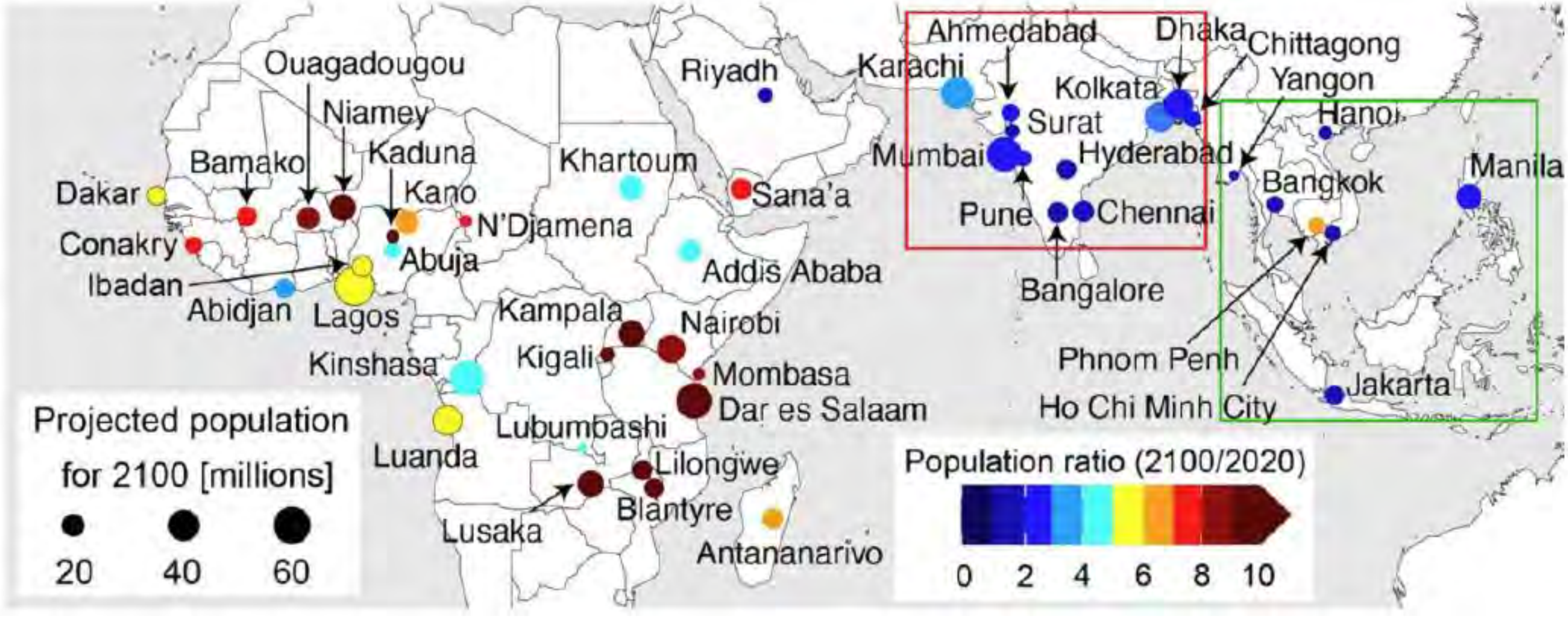
Individual inventories correlate NO_x and NH_3 ($R > 0.8$), but top-down is not ($R < 0.4$)

Emissions peak in similar month to bottom-up: July and August for NO_x and August in NH_3

Observationally constrained OPE of **13 Tg O_3 per Tg NO**

Fastest-growing cities are in the tropics

Air quality trends in the 46 fastest-growing cities in tropical Africa, Asia and the Middle East



[Vohra et al,. 2022]

Regional annual projected population growth rates for 2020-2100 [Hoornweg & Pope, 2017]:

3-31% for Africa, 0.8-3% for **South Asia**, 0.5-7% for **Southeast Asia**

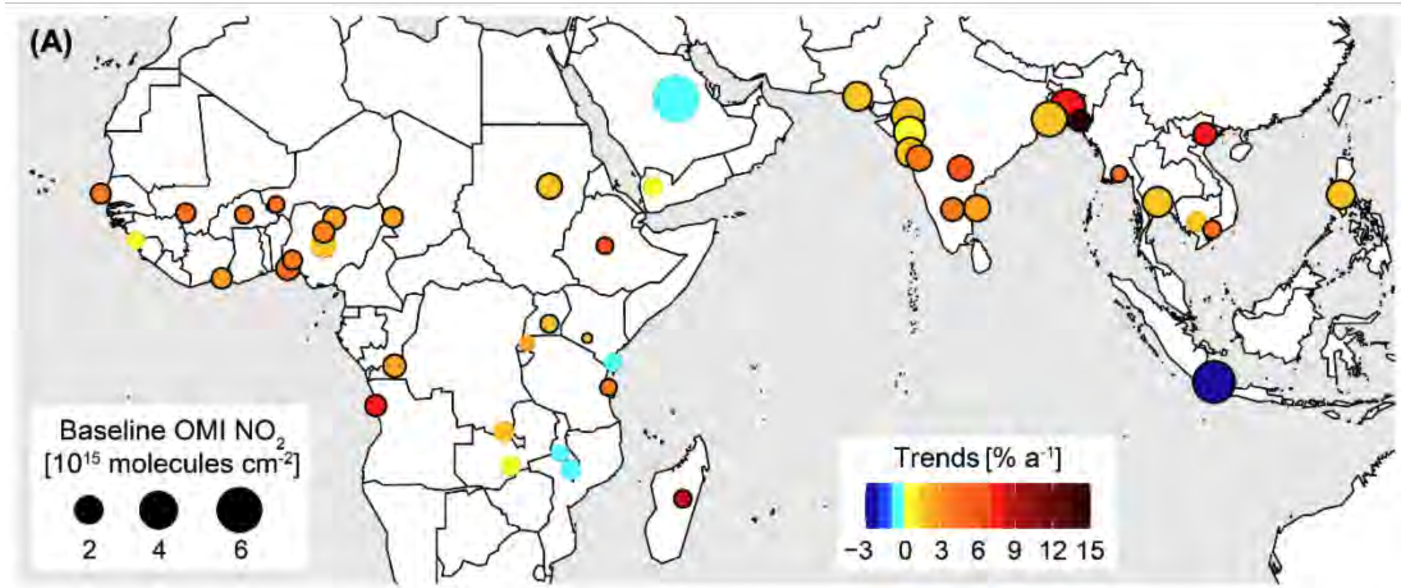
Trends in nitrogen oxides (NO_x) and fine particles ($PM_{2.5}$)

Circle size: starting point

Circle color: trend

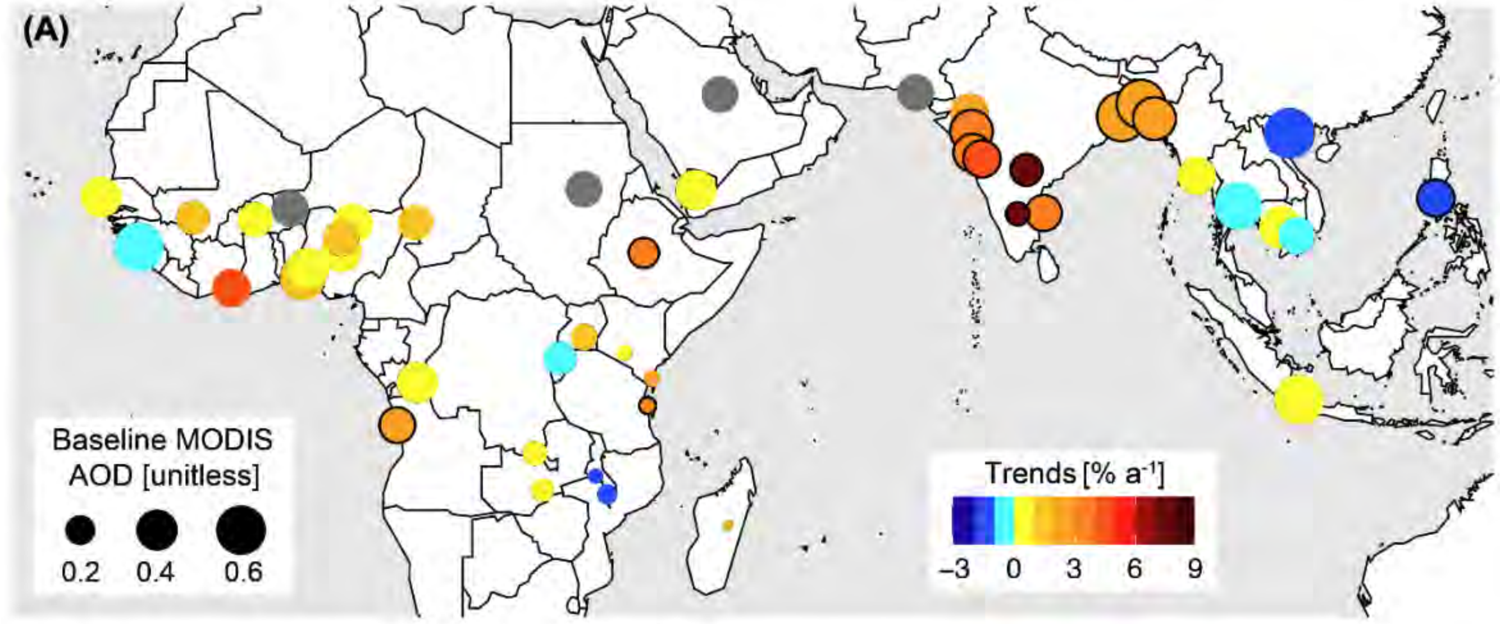
Circle outline: significant

NO_2 trends
(proxy for **NO_x**)
[2005-2018]



NO_x increase:
up to 14% a^{-1}

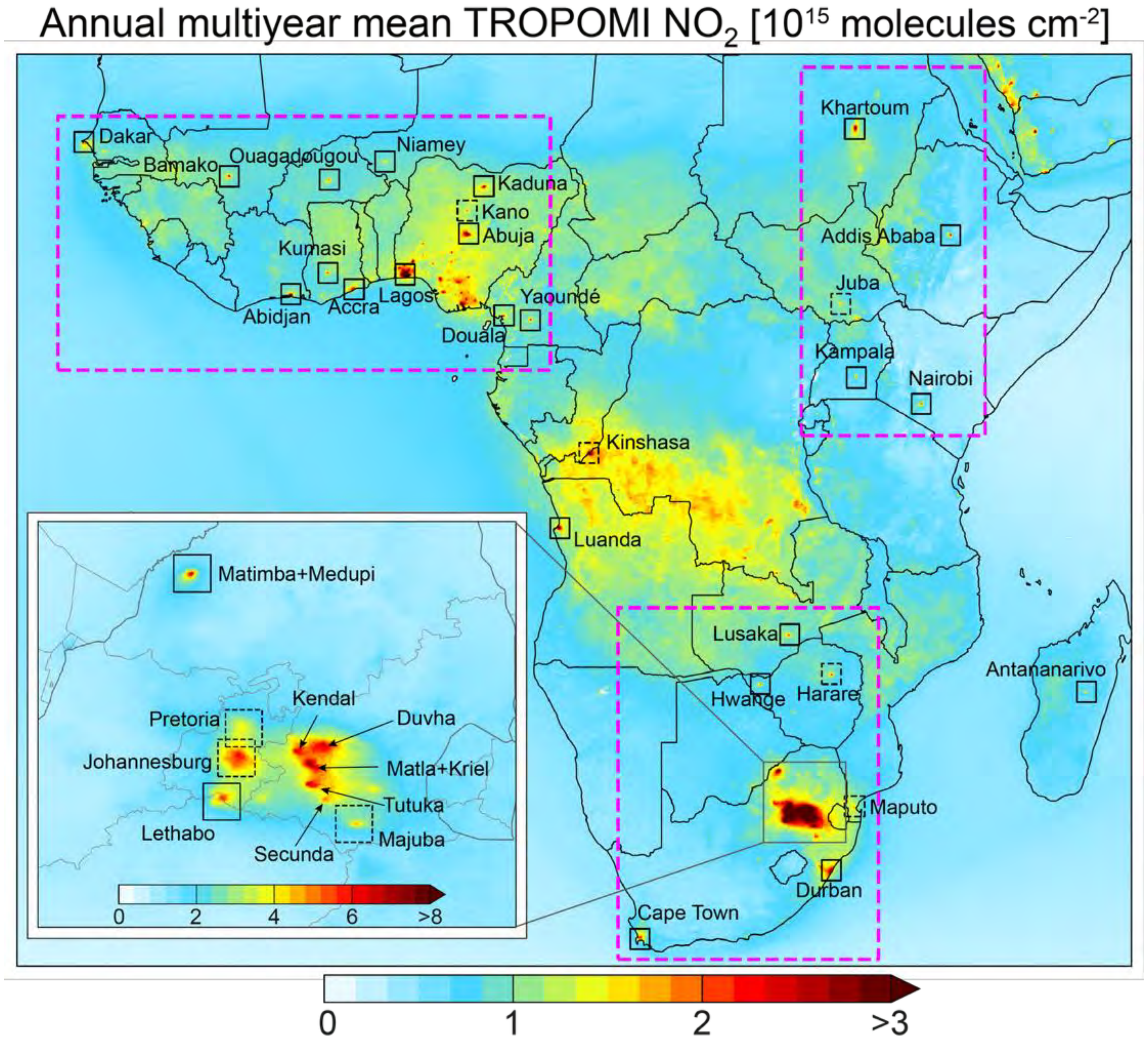
AOD trends
(proxy for **$PM_{2.5}$**)
[2005-2018]



Increases in $PM_{2.5}$ precursors SO_2, NH_3, NO_x

[Vohra et al,. 2022]

Urban and Point Sources Resolved with TROPOMI



Oversample 4 years of TROPOMI data to finer scale (~2 km) than nadir resolution

Identify 32 isolated hotspots: most urban, 4 power plants

Boxes: dashed if attempt to calculate emissions fails; solid if succeeds

Hotspot NO_x Emissions in Sub-Saharan Africa

The largest anthropogenic point source emissions of NO_x are in Sub-Saharan Africa (South Africa)

Rank	Lat [° N]	Long [° E]	Emissions [$kg\,s^{-1}$]	Error [$kg\,s^{-1}$]	Power plants (GPPD)[1]	Cities (WCD)[1]	Comment[2]
1	−26.2875	29.1625	2.76	0.47	Matla; Kriel		
2	−26.5625	29.1625	2.47	0.39			Secunda CTL[3]
3	−23.6875	27.5875	2.47	0.56	Matimba		also Medupi (not listed in GPPD)
4	−26.7375	27.9875	2.03	0.44	Lethabo	Vereeniging	
5	−27.1125	29.7875	2.03	0.31	Majuba		
6	22.3875	82.6875	2.01	0.59	Korba		
7	40.6375	109.7375	1.81	0.57	Baotou	Baotou	
8	21.0125	107.1375	1.80	0.42	Quang Ninh	Ha Long; Cam Pha	
9	−26.0875	28.9875	1.74	0.32	Kendal		
10	−32.4125	151.0125	1.73	0.30	Bayswater; Liddell		

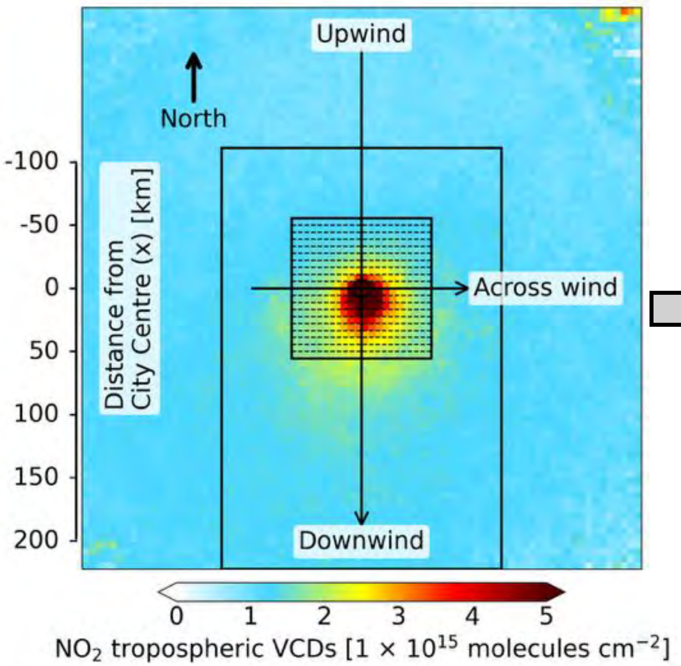
[Beirle et al., 2023]

Unregulated coal-fired power plants (Kriel, Matimba, Lethabo, Majuba, Kendal) and a synthetic fuels plant (Secunda)

Top-down Estimate of Hotspot NO_x Emissions

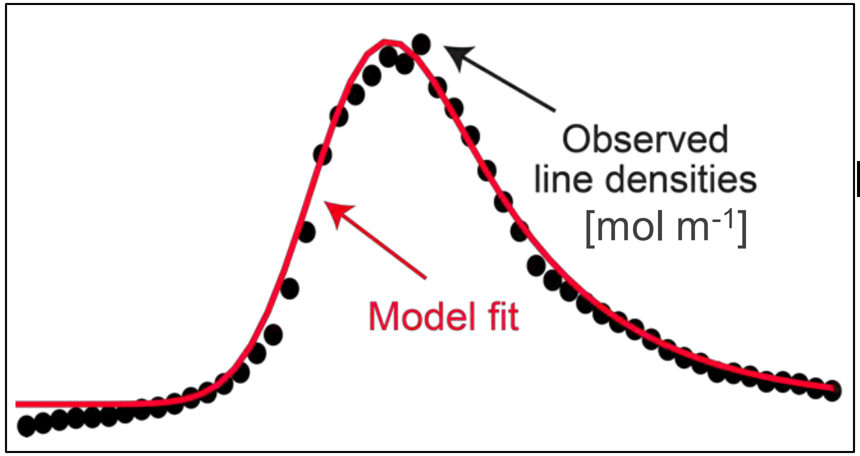
Derive NO_x emissions of isolated hotspots viewed by UV-visible space-based sensors

Wind rotated TROPOMI NO_2 over Lagos



Model fit to line densities to yield best-fit parameters

Across-wind sum of vertical columns



Lagos NO_x emissions and effective lifetime

28 mol NO_x s^{-1}

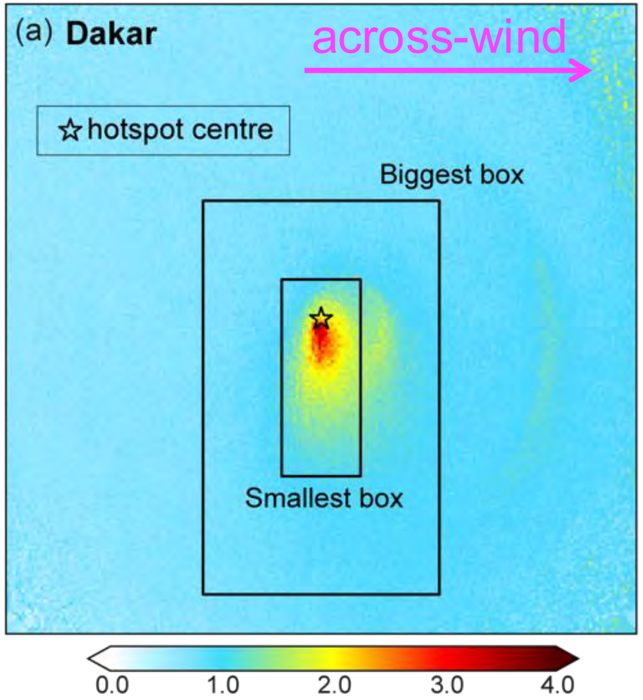
Target hotspots in understudied regions of the world:

Cities in South and Southeast Asia completed [Lu et al., 2025]

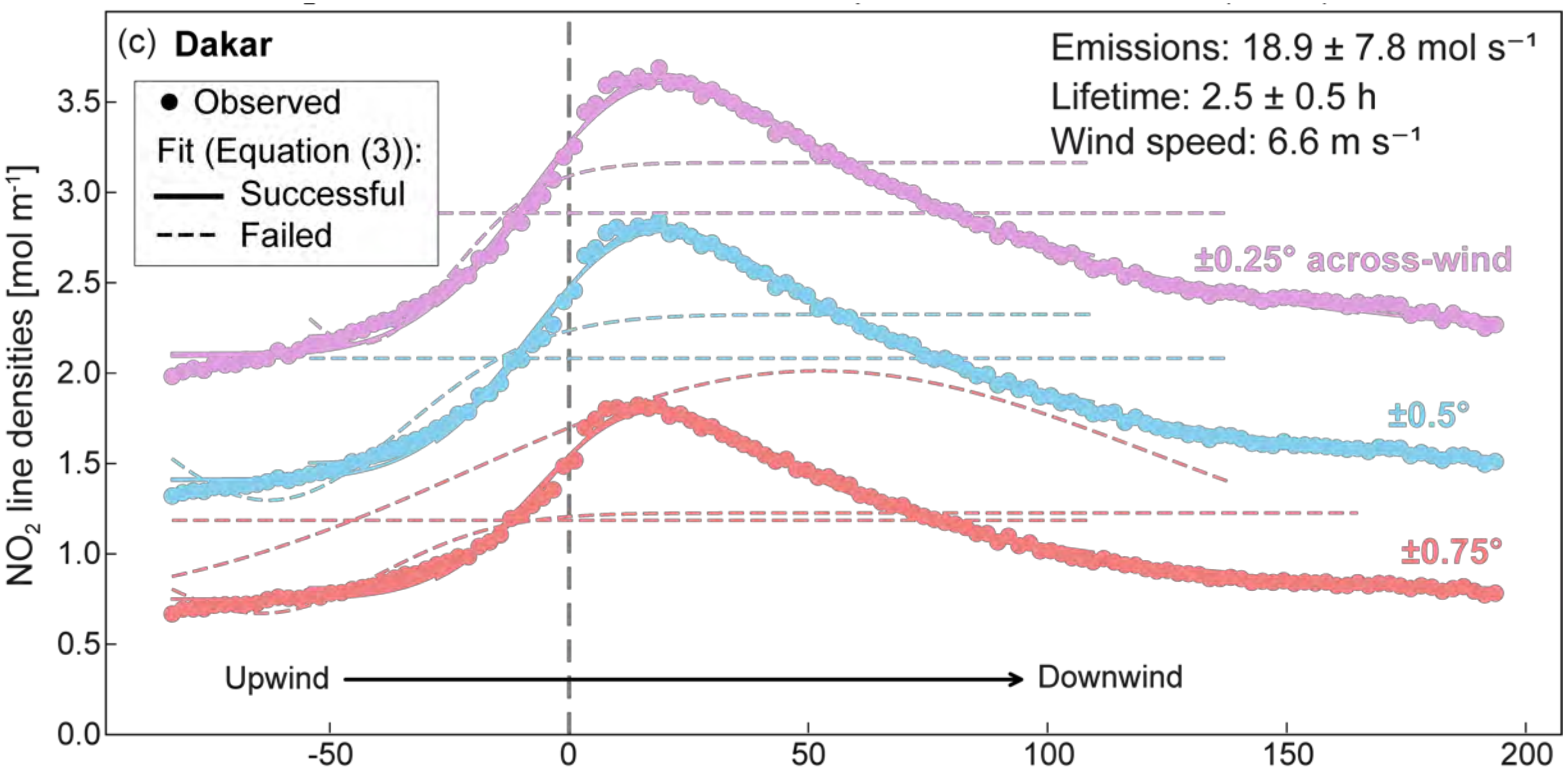
Hotspots in Sub-Saharan Africa in progress [Marais et al., *in prep*]

Hotspot NO_x Emissions Inversion Method

Wind rotate TROPOMI NO_2 about the hotspot centre



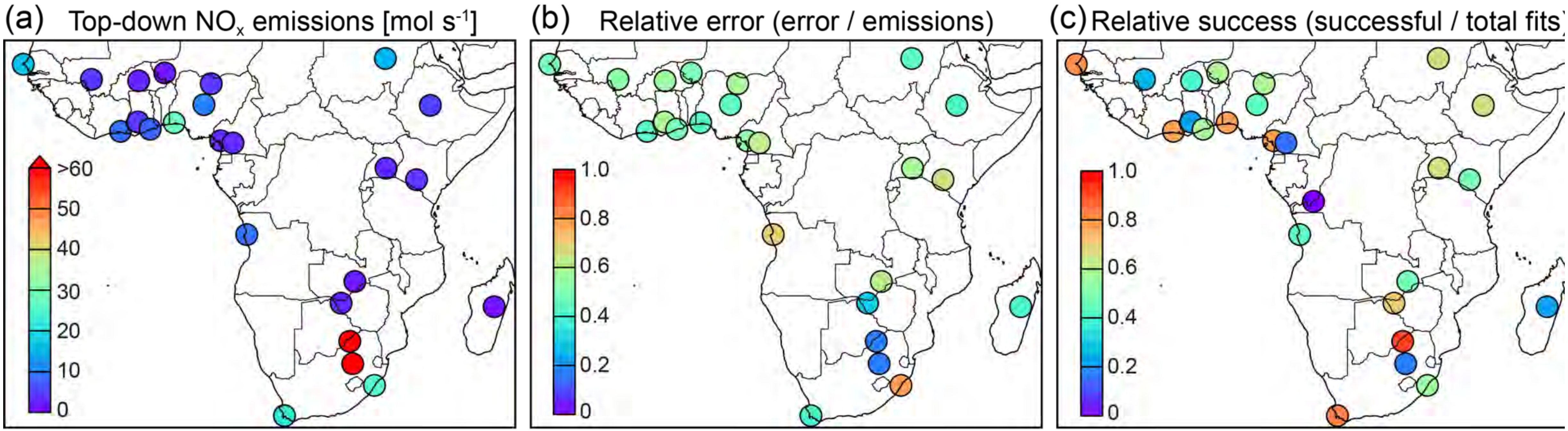
Sum across-wind NO_2 to yield 1D line densities and apply an Exponentially Modified Gaussian (EMG) fit



29 out of 36 successful fits for Dakar (Senegal) yielding the following quantities:

18.9±7.8 mol NO_x emitted s^{-1}, 2.5±0.5 h effective lifetime, 6.6 m s^{-1} wind speed

NO_x Emissions for All Successful Hotspots



Derived emissions for 24 hotspots compared to at most 5 Sub-Saharan hotspots in past studies

Emissions total 207.3 kilotonnes NO

Most hotspots very small (<10 mol s^{-1}) sources of NO_x compared to urban hotspots in Southeast and Southeast Asia (> 60 mol s^{-1} for Delhi and Dhaka [Lu et al., 2025])

Are Power Plant Hotspot NO_x Emissions Accurate?

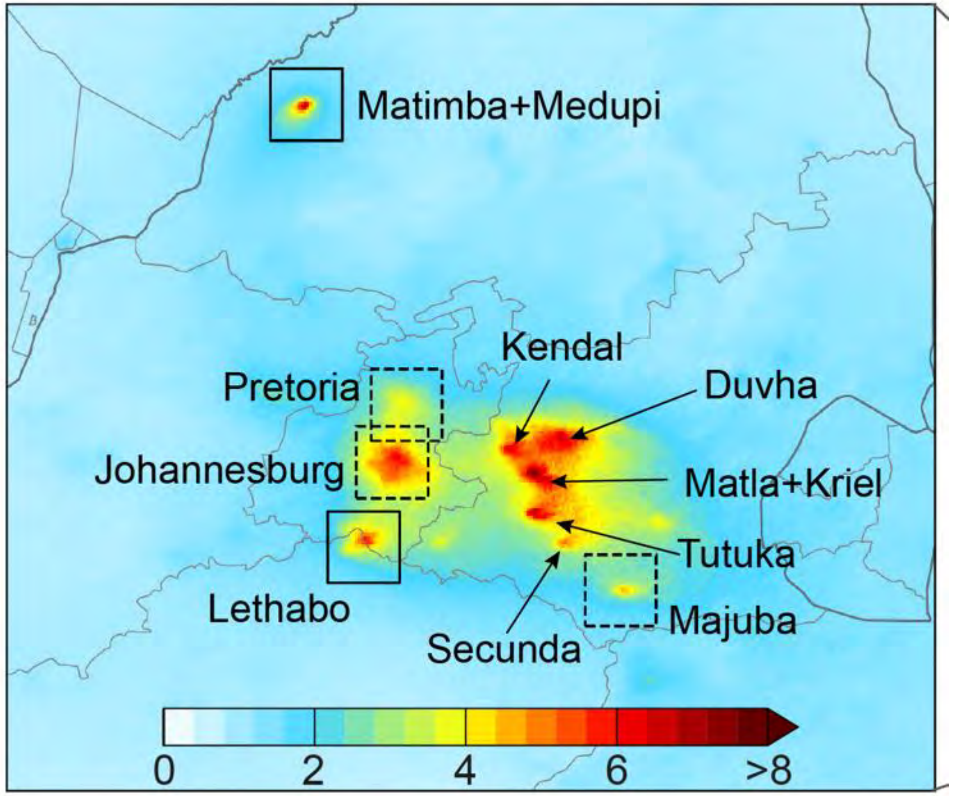
South Africa power plant emissions measured with Continuous Emissions Monitoring Systems (CEMS) (https://www.eskom.co.za/dataportal/emissions/ael/)

Matimba and Medupi:

CEMS: 74.1 mol s^{-1}
Top-down (this work): 69.8 ± 25.7 mol s^{-1}
Top-down (Beirle et al., 2023): 82.3 ± 18.7 mol s^{-1}

Lethabo:

CEMS: 65.2 mol s^{-1}
Top-down (this work): 70.4 ± 23.8 mol s^{-1}
Top-down (Beirle et al., 2023): 67.7 ± 14.7 mol s^{-1}

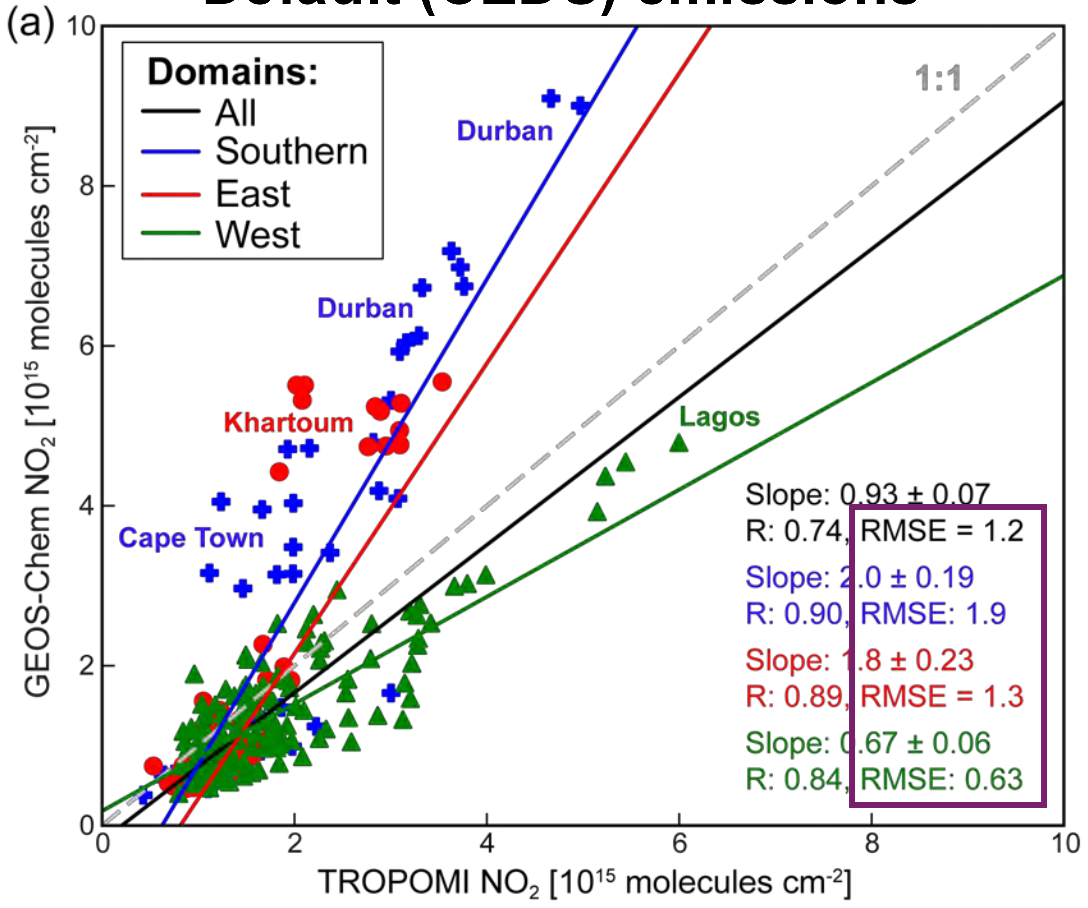


Our values are within 18-20% of CEMS and within 4-15% of an alternate top-down approach

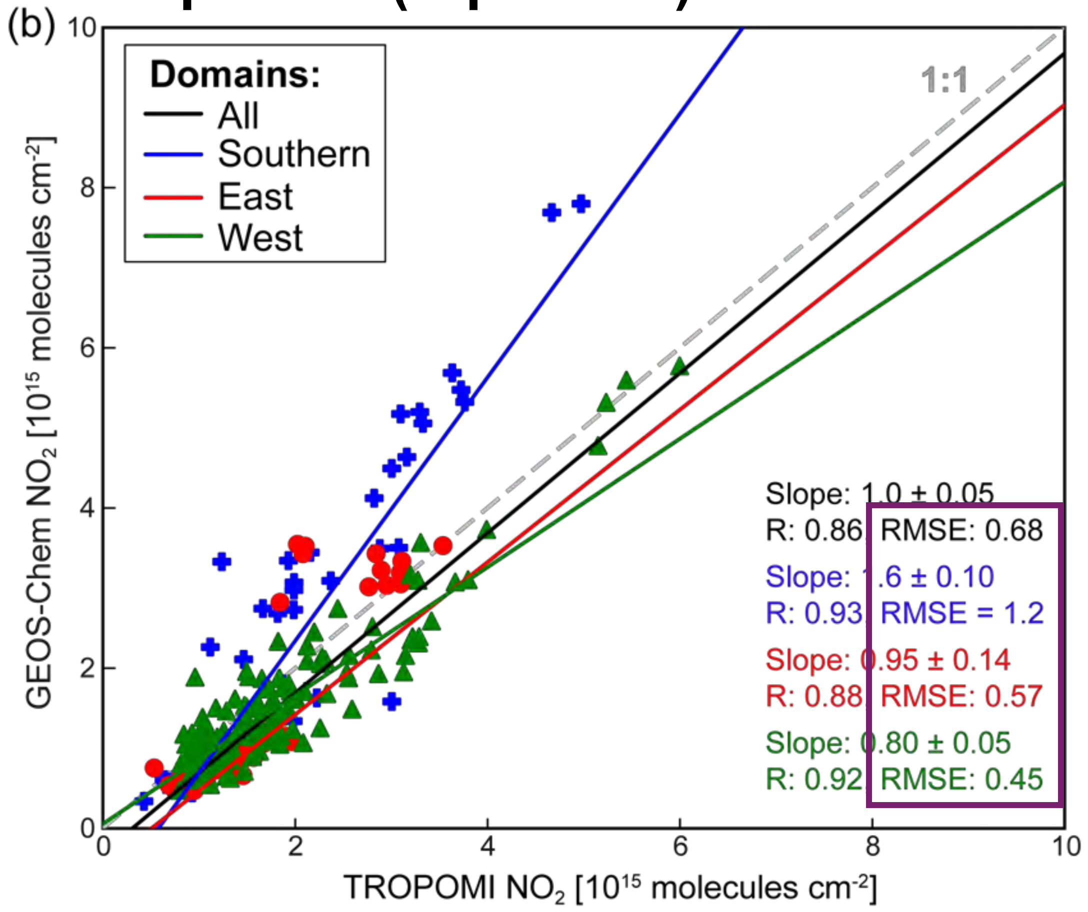
Are Urban Hotspot NO_x Emissions Accurate?

Emissions ⟶ GEOS-Chem ⟶ NO_2 column densities

Default (CEDS) emissions



Updated (top-down) emissions



Urban CEDS emissions total 159 kilotonnes NO, whereas top-down total 135 kilotonnes NO

Concluding Remarks

Satellites offer tremendous potential to quantify air pollutant precursor source strengths in Africa, especially in the absence of ground-based networks.

Able to derive open fire emissions of most reactive nitrogen compounds using a relatively simple mass balance approach and derive annual NO_x emissions for 24 isolated hotspots (21 urban, 3 power plants) by applying a Gaussian-type fit to a wind rotated plume.

Biomass burning inventories collocate NH_3 and NO_x emissions (smouldering and flaming fires), but these are mostly separate in the top-down estimates.

Top-down urban hotspot emissions range from < 2 mol s^{-1} for Antananarivo in Madagascar to 27.7 ± 11.7 mol s^{-1} for the megacity Lagos in Nigeria.

Top-down values improve agreement between modelled and observed tropospheric NO_2 columns, except for Durban and Cape Town. The cause is unclear.

Critical need for ground-based observations to validate satellite observations and top-down estimates.

Where funding permits, I am always seeking opportunities for Africa-based PhD students and postdocs to train under my supervision!