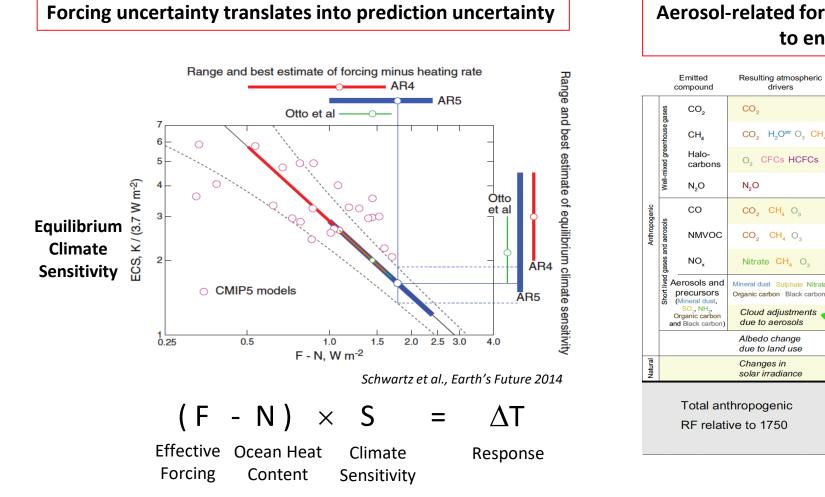
The Three-Way Suborbital Satellites Retrieval Validation Assumption Refinement **Targeted Microphysical**, Frequent, **Regional Context Cloud-Dynamical**, & **Global Coverage Aerosol-Chemical Detail** Aerosol & Cloud Amount & Type Maps Aerosol Plume, Layer, & Cloud Heights **Current State Point-Location Model Validation** Initial Conditions **Time Series** Parameterizations Assimilation Underlying Mechanisms **Aircraft Targeting** Aerosol Source Identification **Aerosol-type Retrieval** Aerosol Aging Assessment Priors/Weights Cloud Regime Identification Retrospective Source Identification **Data Integration** Aging Assessment Space-time Interpolation Aerosol-Cloud Interactions & Aerosol Climate Forcing

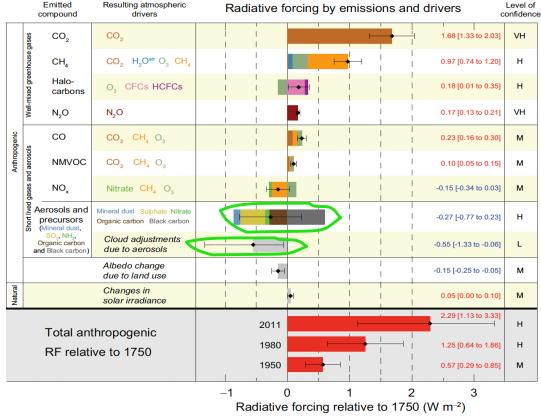
Models

Calculation & Prediction

Climate Forcing – Aerosol Effects Produce the Biggest Prediction Uncertainties → Aerosol-Cloud Interaction and Particle Microphysical Property Assumption Uncertainties Dominate; Trace-gas Distributions also matter



Aerosol-related forcing uncertainties need to be reduced to enable climate predictions



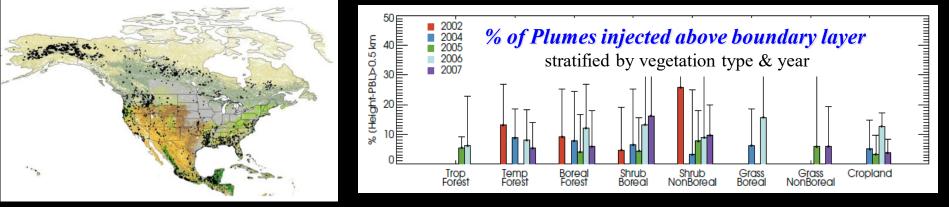


Models

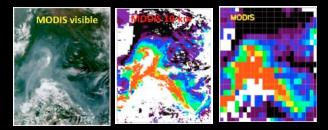
Calculation & Prediction

Wildfire Smoke Injection Heights & Source Strengths

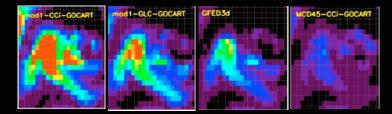
[These are the two key parameters representing aerosol sources in climate models]



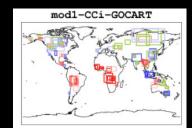
Val Martin et al. ACP 2010; 2012, 2018;m Pan et al., in preparation

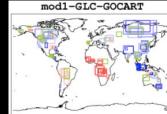


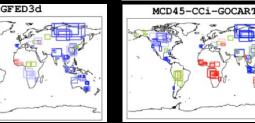
MODIS Smoke Plume Image & Aerosol Amount Snapshots



GoCART Model-Simulated Aerosol Amount Snapshots for Different Assumed Source Strengths





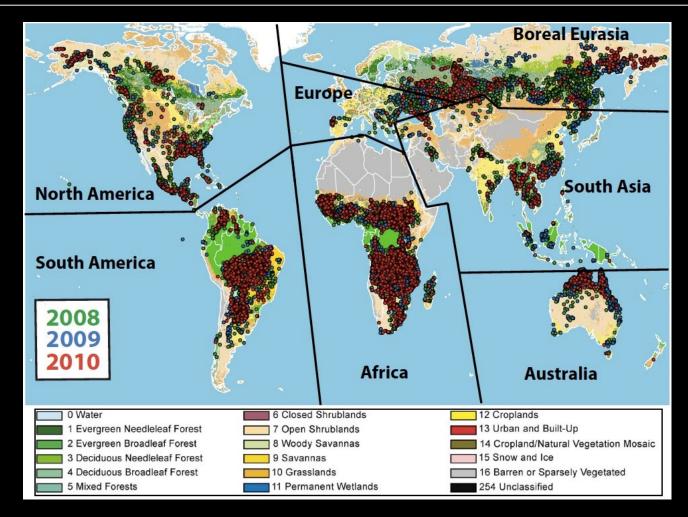


Different Techniques for Assuming Model Source Strength **Overestimate** or **Underestimate** Observation Systematically in Different Regions

These two projects are the subjects of current AeroCom/AeroSat **Experiments**

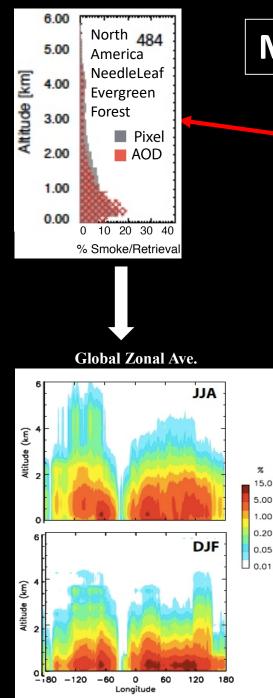
Petrenko, Kahn, et al., JGR 2012; 2017; 2023 in prep.

Global Climatology of Smoke-Plume Injection Heights



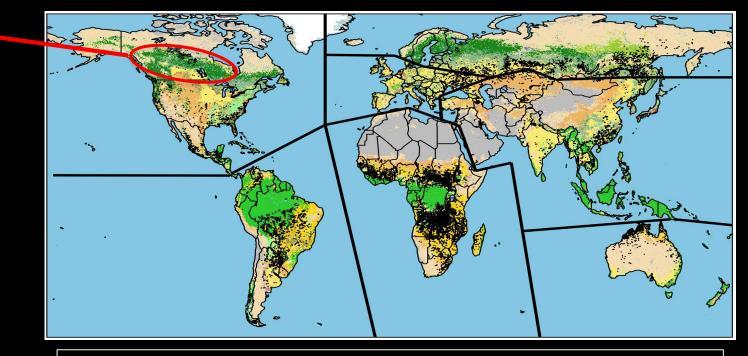
- About 23,000 smoke plumes digitized 2008-2010 (~13,000 for 2008); overpass ~10:30 AM local time
- Each plume is Operator-Processed using MINXv4.0, and Quality Controlled
- Available on-line: https://misr.jpl.nasa.gov/getData/accessData/MisrMinxPlumes2/

Val Martin, Kahn & Tosca; Remt. Sens. 2018



1.00

MISR Wildfire Smoke Injection Height Climatology

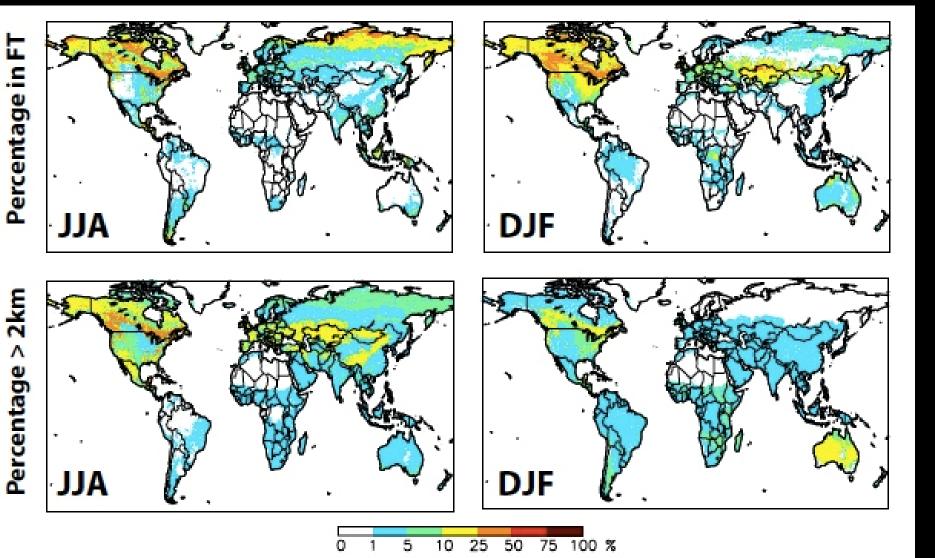


- Individual Heights at 1.1 km Horizontal res., ~250-500 m Vertical res.
- Both *Pixel-weighted* and *AOD-weighted* profiles derived
- Fire emissions are *Stratified by Altitude*, *Region*, *Ecosystem*, & *Season*
- The cases in each stratum are Averaged to produce a statistical summary
- Inter-annual and/or sub-seasonal temporal resolution might be needed in some cases; requires detailed, regional study (e.g., Amazon)

https://misr.jpl.nasa.gov/getData/accessData/MisrMinxPlumes2/

Val Martin, Kahn & Tosca; Remt. Sens. 2018

Global Distribution of Percent Injected Within/Above the PBL Based on MERRA-2 Hourly PBL 10:00-13:00 LT



Accounting for uncertainty FT = PBL + 500 m

[PBL from MERRA-2]

2 km threshold avoids dependence on PBL height estimate

Constraining Source Strength Using Satellite AOD and Forward Modeling

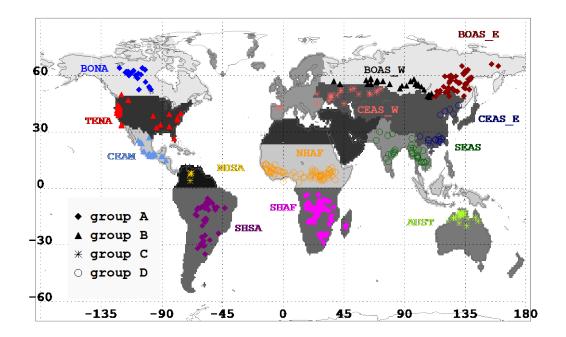
447 satellite **snapshots provide instantaneous constraint** on a source strength

75 60 45 30 15 ₿ 0 -15 -30 -45 -60 -135 -90 -45 45 90 135 180 Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

Fire cases for *Petrenko et al.* **source-strength studies** (1) plumes with at least one linear dimension of **100 km**, to be useful for global modeling studies with fairly coarse resolution of 1° or larger

(2) a coordinated pattern of elevated AOD,

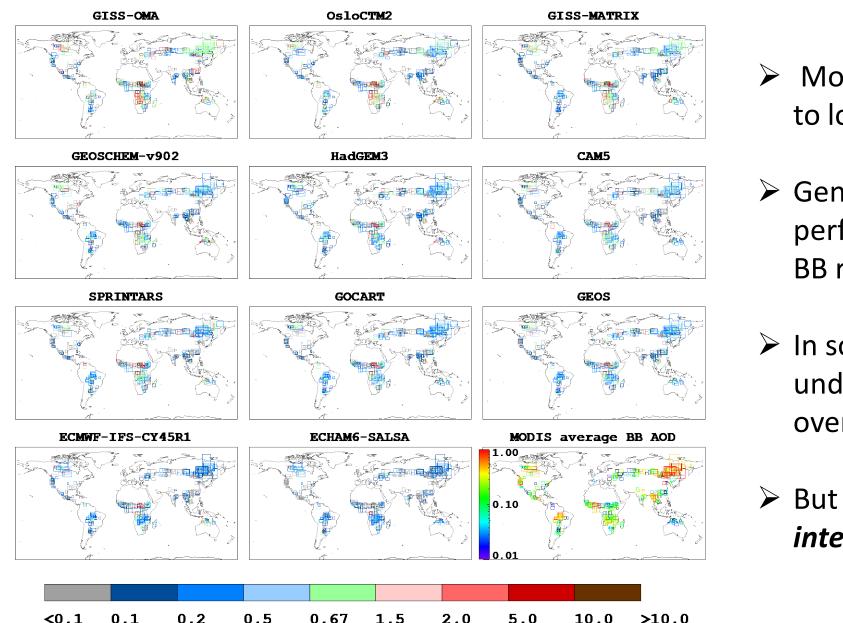
(3) a visible smoke plume in the satellite imagery, and(4) a fire signal in the MODIS thermal anomaliesproduct (MOD14)



GFED-based Biomass Burning regions

The 13 regions with the BB cases in each region. BONA = Boreal North America, TENA = Temperate North America, CEAM = Central America, NHSA = Northern Hemisphere South America, SHSA = Southern Hemisphere South America, NHAF = Northern Hemisphere Africa, SHAF = Southern Hemisphere Africa, BOAS_W = Boreal Asia West, BOAS_E = Boreal Asia East, CEAS_W = Central Asia West, CEAS_E = Central Asia East, SEAS = Southeast Asia, AUST = Australia

Petrenko, Kahn, Chin et al. 2023

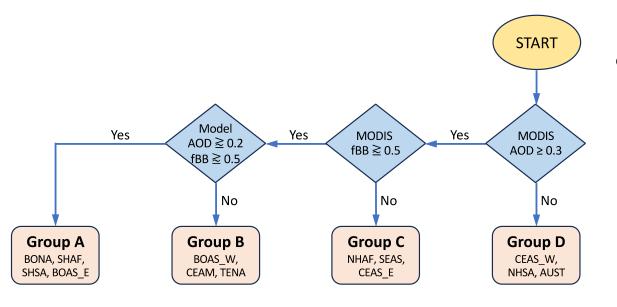


Ratio of model-simulated BB AOD (AOD_BB1 – AOD_BB0) to the BB AOD derived from MODIS for all individual fire cases.

- Models are ranked from highest to lowest overall model BB AOD
- Generally consistent model performance within individual BB regions
- In some regions, models all under- (USA, SEAsia) or overestimate (NCAfrica) BB AOD
- But there are also significant inter-model differences

Petrenko, Kahn, Chin et al. 2023

Grouping BB regions for source-strength estimation



Using satellite observations to constrain BB aerosol simulations work best in regions

- With relatively high total MODIS AOD
- Low/uncomplicated background aerosol (BB aerosol dominates)

BB regions can be divided into **four groups** w.r.t. source-strength estimation method applicability:

➢A: *High AOD, low background*, high BB AOD fraction, high confidence: boreal NH, woodlands of SH

≻B: *Med AOD, low BG*, medium confidence, possibly missing emissions: cultivated lands

➤C: *High AOD, high & complex background*, low confidence: NH Africa, SE Asia, China

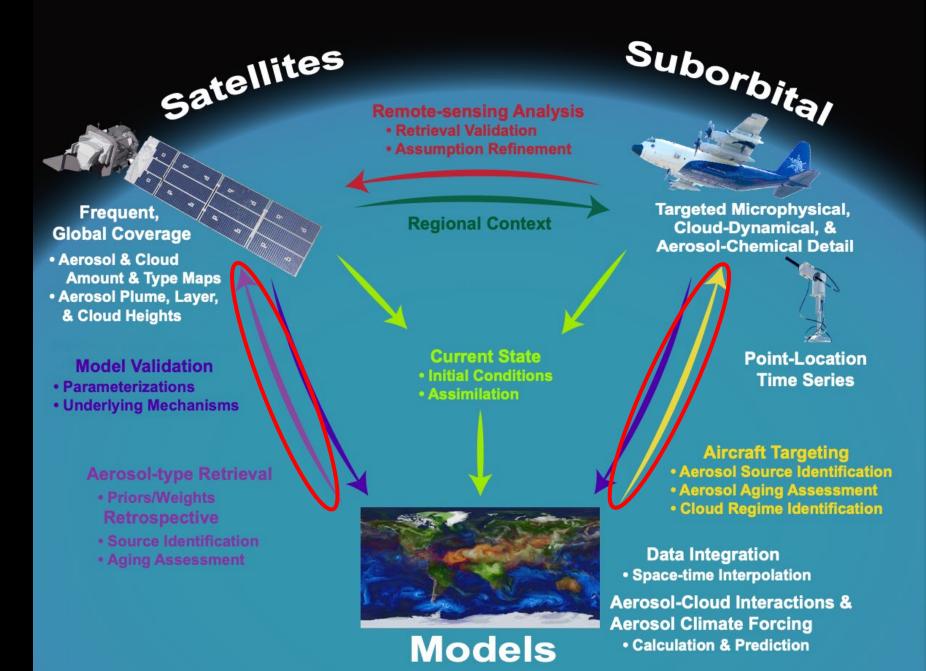
D, Low total AOD, sporadic burning events, low confidence: Europe Australia, LAmerica

Several factors in addition to emissions input affect AOD calculations

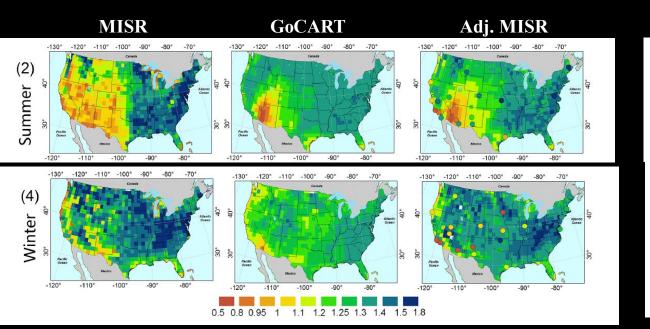
in the model (all of which require their own constraints, and *the required measurements are currently lacking*):

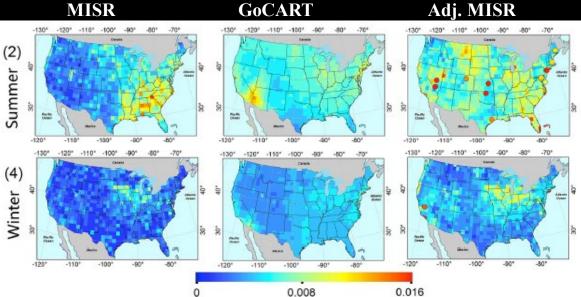
- ≻OA/OC ratio
- >Aerosol removal rates (hence loads)
- >Hygroscopic properties and chemical and physical interactions
- > Optical properties (e.g., mass extinction efficiency)

➤Additional measurements and methodology development needed to separate BB signal in satellite data



MISR ANG, AAOD Results Constrained by GoCART Model





Shenshen Li, R. Kahn, et al. AMT 2015

ANG

$$\text{Diff}_{\text{ANG}} = |\alpha_{\text{MISR}} - \alpha_{\text{GOCART}}| \le \varepsilon_{\text{ANG}}$$

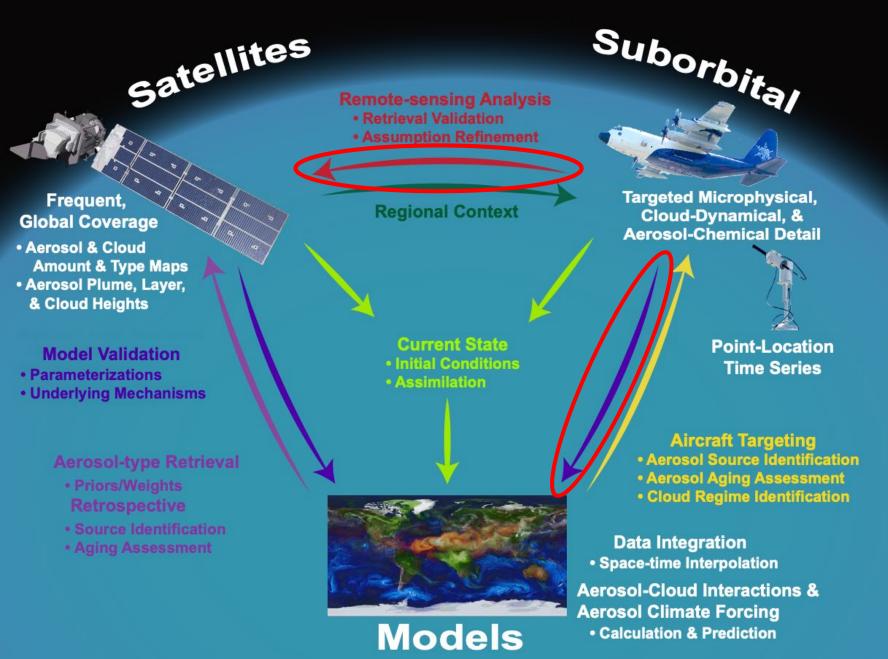
We rank the ε_{ANG} , ε_{AAOD} and select the common or the lowest mixtures

AAOD

$$Diff_{AAOD} = |Fraction_{MISR_AAOD} - Fraction_{GOCART_AAOD}| \le \varepsilon_{AAOD}$$

 $Fraction_{\rm MISR_AAOD}$ is the absorbing fraction of total AOD

Where remote-sensing data are ambiguous, can use a model to weight the options



SAM-CAAM Concept

[Systematic Aircraft Measurements to Characterize Aerosol Air





Primary Goal: [This is currently a **concept-development effort**, not yet a project]

 Characterize <u>statistically</u> particle properties for major aerosol types globally, to provide detail unobtainable from space, adding value to models & satellite aerosol data, offering

improved aerosol property assumptions for:

- -- *Modeling* aerosol direct forcing and aerosol-cloud interactions
- -- Satellite retrieval algorithm climatology options or priors

<u>Plus</u>: More robust *translation between satellite-retrieved aerosol optical properties and* species-specific aerosol mass and size tracked in *aerosol transport, climate, & air quality* Substantially reduce model uncertainty & enhance the value of 23+ years of satellite aerosol models Retrieval products

Suborbital In Situ Required for PDFs of Particle Microphysical Properties



Aerosol intensive properties required for key aerosol science objectives, but *cannot be retrieved adequately* or are *entirely unobtainable from remote sensing*

- Hygroscopicity* – Ambient particle hydration, aerosol-cloud interactions

Mass Extinction Efficiency – Translate between retrieved optical properties from remote sensing & aerosol mass book-kept in models

Spectral Light-Absorption – Aerosol direct & semi-direct forcing, atmospheric stability structure & circulation

CCN Properties* – At least part of the CCN size spectrum is too small to be retrieved by remote-sensing

Acquiring such data is feasible because:

Unlike aerosol amount, *aerosol microphysical properties tend to be repeatable* from year to year, for a given source in a given season

Kahn et al., BAMS 2017

*Under special conditions, hygroscopicity (Dawson et al. 2020) and CCN # (Rosenfeld et al. 2016) can be derived from remote sensing; however: (Stier, ACP 2016)

