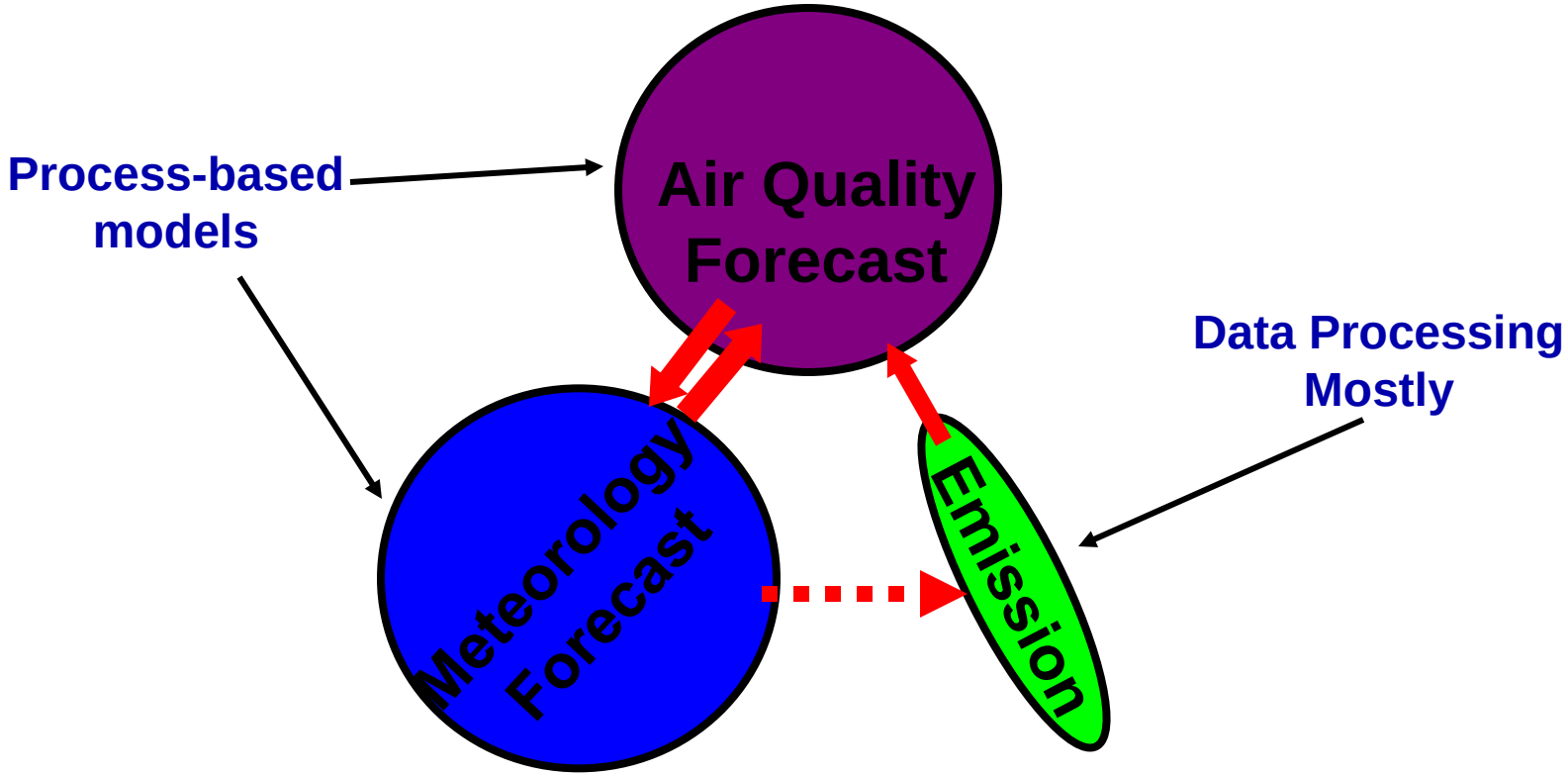
Towards Emission Forecasting

Daniel Tong, Pius Lee, and Rick Saylor

NOAA Air Resources Laboratory

Acknowledgments: NOAA/OAR/ARL *Air Quality & Emission Sciences Team (AQUEST);*
Ivanka Stajner, Richard Artz and Rohit Mathur for inspiring discussions.

AQF: An unbalanced system



Emissions remain one of the largest uncertainties for AQF

Approaches for Emission Data Generation

- **Approaches to prepare emissions**
  - **Emission Inventory based data processing.**
  - **Emission modeling;**

    1. Bottom-up or top-down emission modeling;

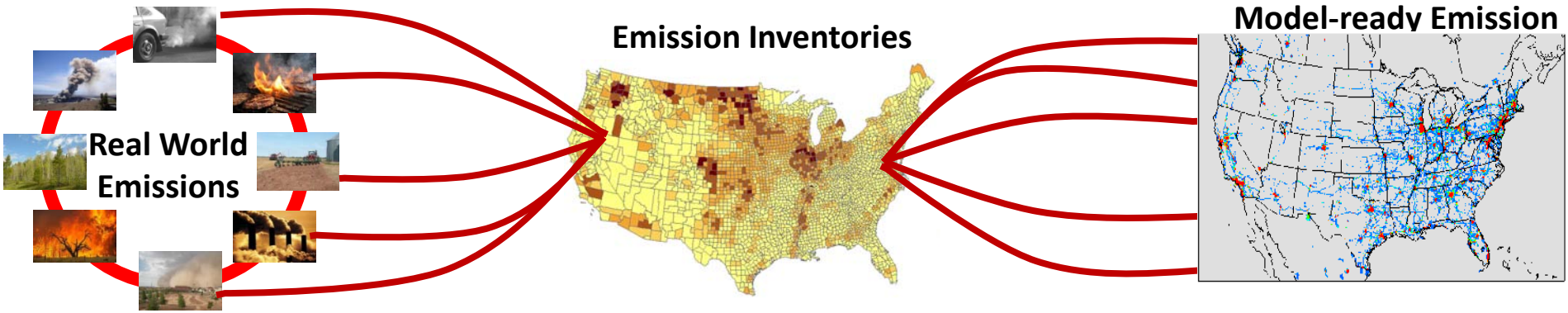
    2. Hybrid approaches (inverse modeling etc.);

- **Application of each approach**
  - **Inventory-based approach predominantly for anthropogenic emissions;**
  - **Bottom-up emission modeling for natural sources (biogenic, dust, fires, seasalt);**
  - **Top-down and inverse modeling used to adjust existing emissions to improve model performance.**

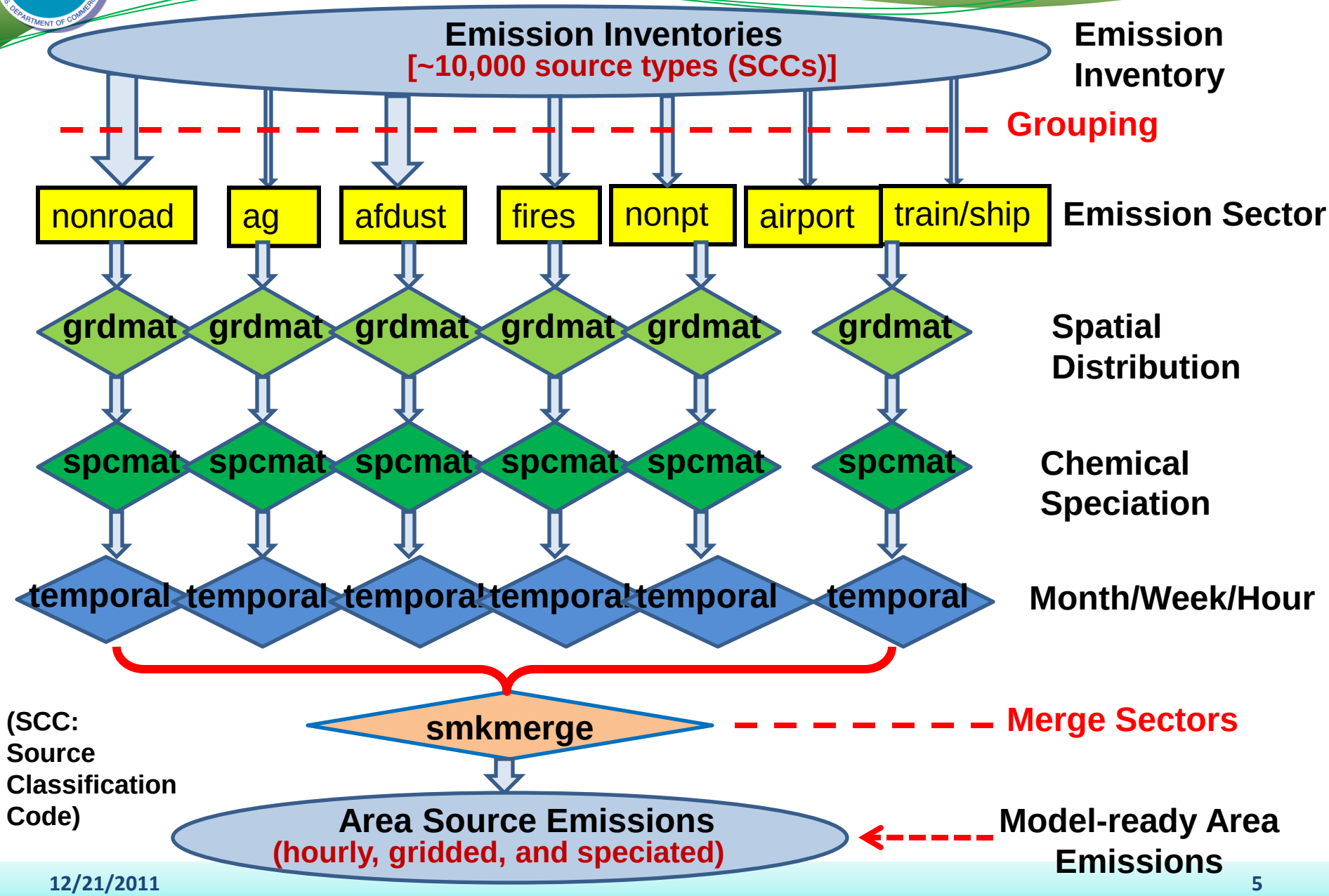
Limitations of Inventory-Based Approach

- **Emission inventories are costly and time-consuming**
  - Emission Inventories always 2 – 10 years old.
  - Frequency of updates driven by regulatory needs, not forecasting needs;
  - Large gap between forecasting need and data availability;

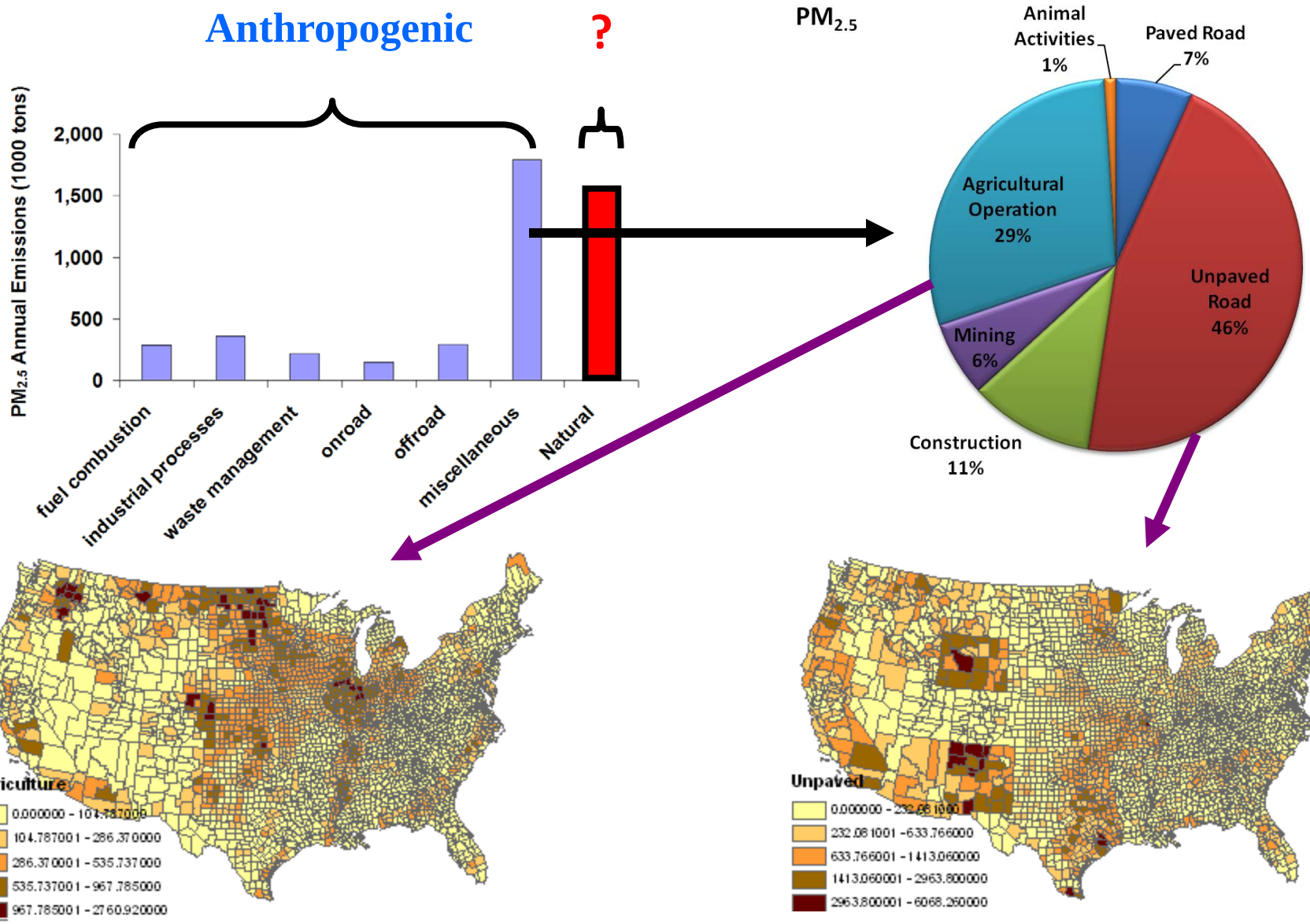
- **Lack of understanding of emission uncertainties**
  - Information lost when compiling emission inventories;
  - Reconstructing such information using SMOKE introduces extra uncertainties;
  - Some emission data not supposed to be used for AQ forecasting.



Inventory-Based Emission Processing: US Area Sources



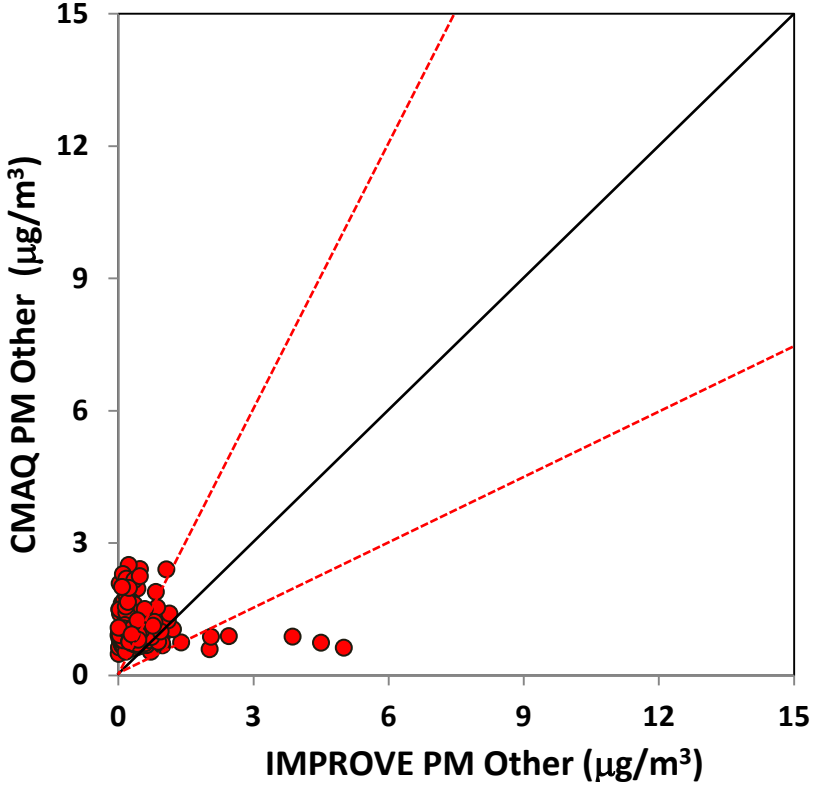
$PM_{2.5}$ Emissions in the United States



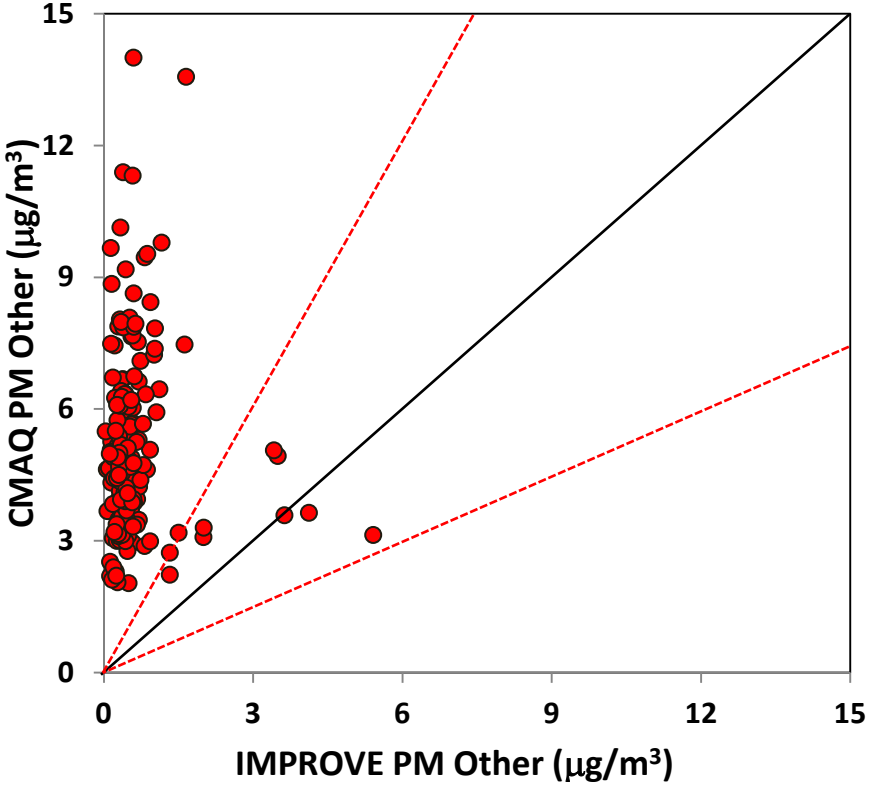
CMAQ vs. IMPROVE Observations (January 2002)

- Two CMAQ runs: with and without anthropogenic dust emissions;
- Dust contribution is calculated from the difference;

Fugitive Dust contribution < 1μg/m³



Fugitive Dust contribution > 2μg/m³

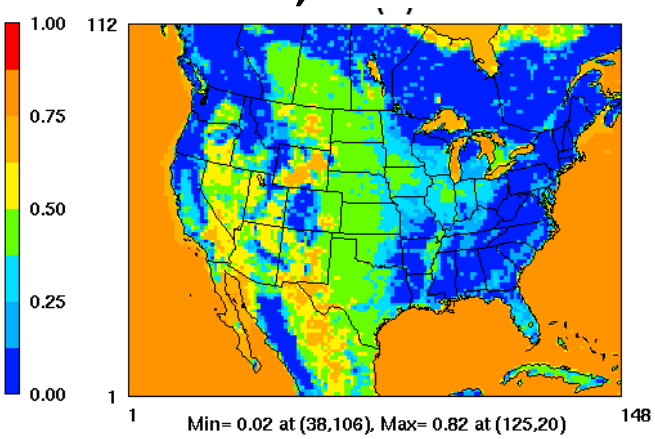


(Source: Tong et al., 2009)

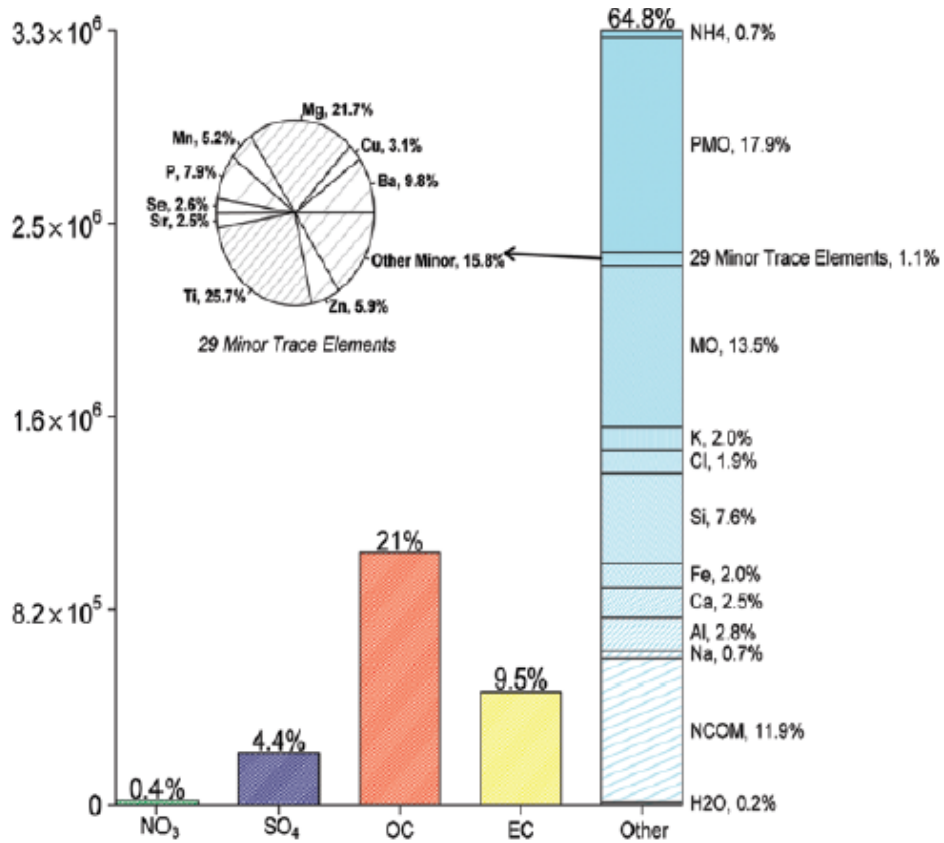
Revising fugitive dust emission

Collaboration with George Pouliot, David Mobley, Heath Simon, Prakash Bhave, Tom Pace, Rohit Mathur, Tom Pierce (US EPA)

- **Further Speciation PM Other;**
- **Temporal allocation – Adopt nonroad mobile source profiles for fugitive dust emission;**
- **Apply transportable fraction to raw emissions;**



(Tong et al., 2010)



(Simon et al., 2010)

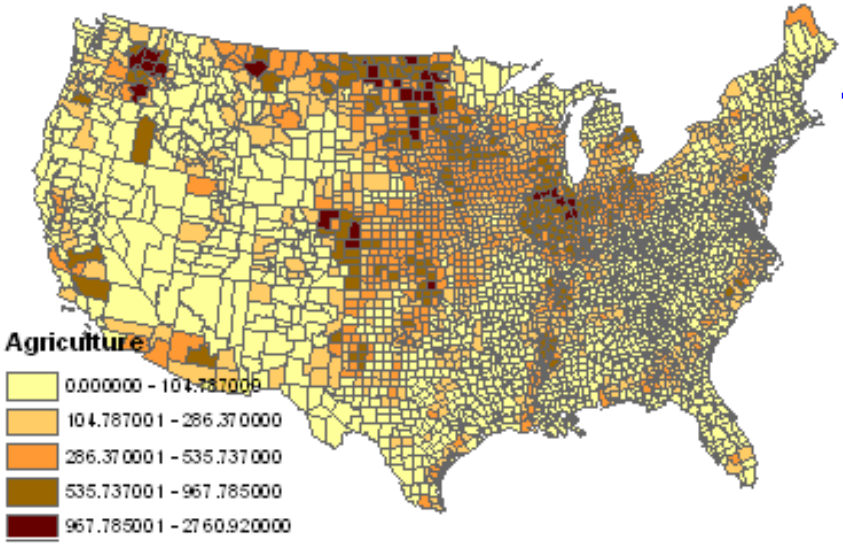
- **Meteorological adjustments by soil moisture and snow/ice cover;**

Agricultural Dust Emission

The AP-42 method for agricultural dust emissions (US EPA, 1983):

$$R = M \times e \times (1 - c)$$

R -- estimated mass emission rate;
M -- source extent;
e -- specific emission factors;
c -- fractional efficiency of control.



Things not considered:

-- Meteorology (soil moisture and ice/snow cover);
-- Seasonal variability;
-- Year-to-year variations;
-- Increased soil conservation practices;

Agricultural Dust Emission (Tennessee as an example)

Tillage Practices by Crop, Tennessee, 2004-2008

Crop	Year	Total Acres Planted	No-Till [1]		Other Conservation Tillage [2]		Conventional Till [3]		Double Cropped [4]	
			Acres	% of Total[5]	Acres	% of Total[5]	Acres	% of Total[5]	Acres	% of Total[5]
Soybeans	2004	1,210,000	800,000	66.1	260,000	21.5	150,000	12.4	300,000	24.8
	2005	1,130,000	750,000	66.4	260,000	23.0	120,000	10.6	170,000	15.0
	2006	1,160,000	880,000	75.9	180,000	15.5	100,000	8.6	210,000	18.1
	2007	1,040,000	820,000	78.8	160,000	15.4	60,000	5.8	310,000	29.8
	2008	1,410,000	1,110,000	78.7	220,000	15.6	80,000	5.7	540,000	38.3
Corn	2004	680,000	450,000	66.2	140,000	20.6	90,000	13.2	25,000	3.7
	2005	650,000	430,000	66.2	140,000	21.5	80,000	12.3	20,000	3.1
	2006	550,000	400,000	72.7	100,000	18.2	50,000	9.1	20,000	3.6
	2007	870,000	600,000	69.0	170,000	19.5	100,000	11.5	25,000	2.9
	2008	700,000	500,000	71.4	130,000	18.6	70,000	10.0	30,000	4.3
Sorghum	2004	20,000	9,000	45.0	7,000	35.0	4,000	20.0	1,500	7.5
	2005	22,000	9,000	40.9	6,000	27.3	7,000	31.8	1,500	6.8
	2006	14,000	7,000	50.0	4,000	28.6	3,000	21.4	1,000	7.1
	2007	22,000	7,000	31.8	8,000	36.4	7,000	31.8	1,000	4.5
	2008	25,000	11,000	44.0	6,000	24.0	8,000	32.0	1,500	6.0

Emission Forecasting Model

An emission forecasting model simulates the detailed processes underlying emissions.

This can be accomplished through combining emission activity and process modeling with the use and integration of near real time data collected from routine ground-level networks and monitors, remote sensing devices, and up-to-date survey and census data (Tong, Lee and Saylor, 2011).

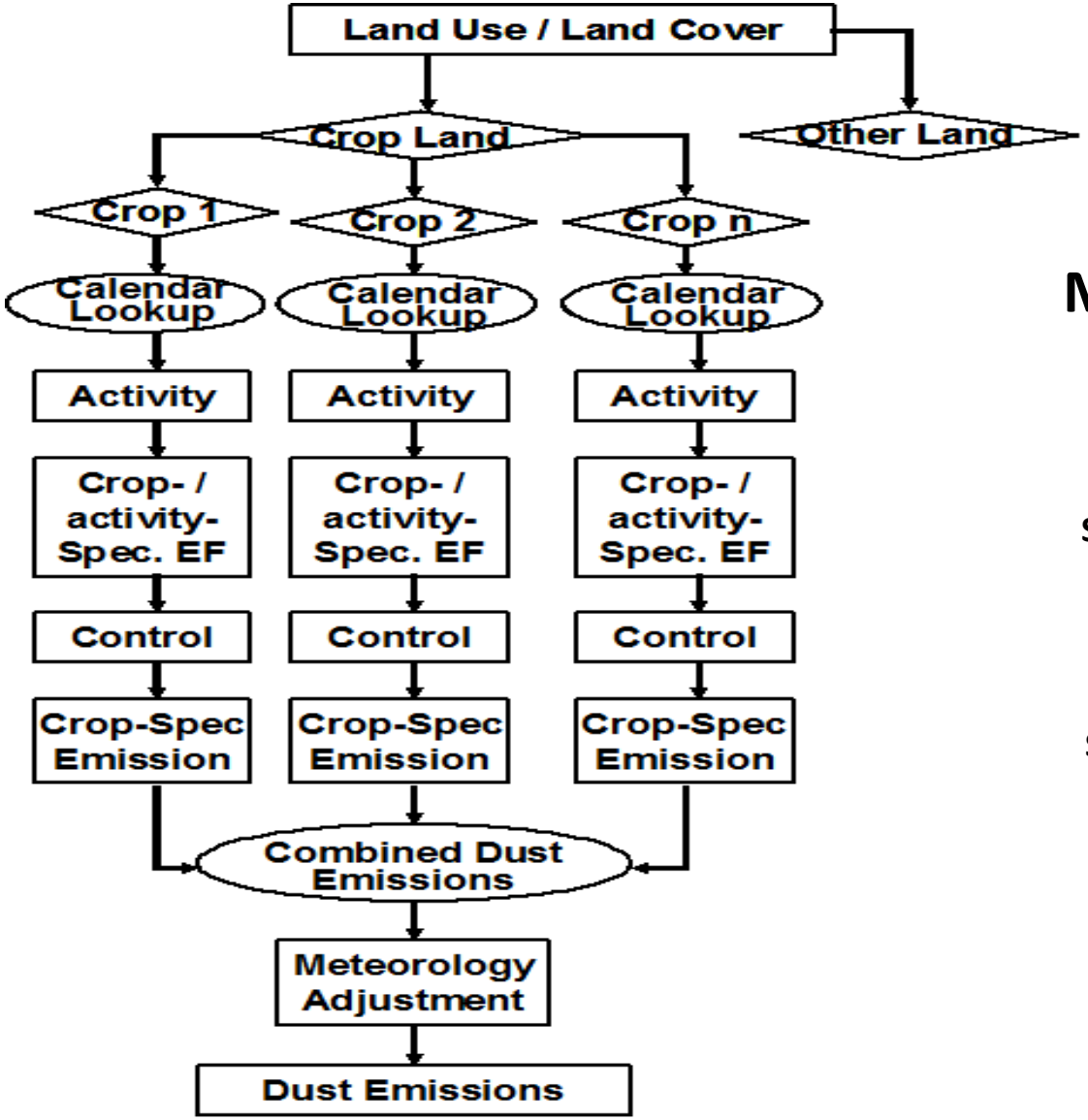
Three components for an emission forecasting model:

a)Emission algorithms;

b)Near-real-time (NRT) data hub;

c)A computer model to integrate a and b;

Agricultural Dust Emission Forecasting Conceptual Design



Major Crops in U.S.

Crop	Acreage (10^6 acres)	Revenues ($ billion)
Corn	72.7	15.1
Soybeans	72.7	12.5
Hay	59.9	3.4
Wheat	53.0	5.5
Cotton	13.1	4.6
Sorghum	7.7	0.82
Rice	3.0	1.2

How to Move towards Emission Forecasting?

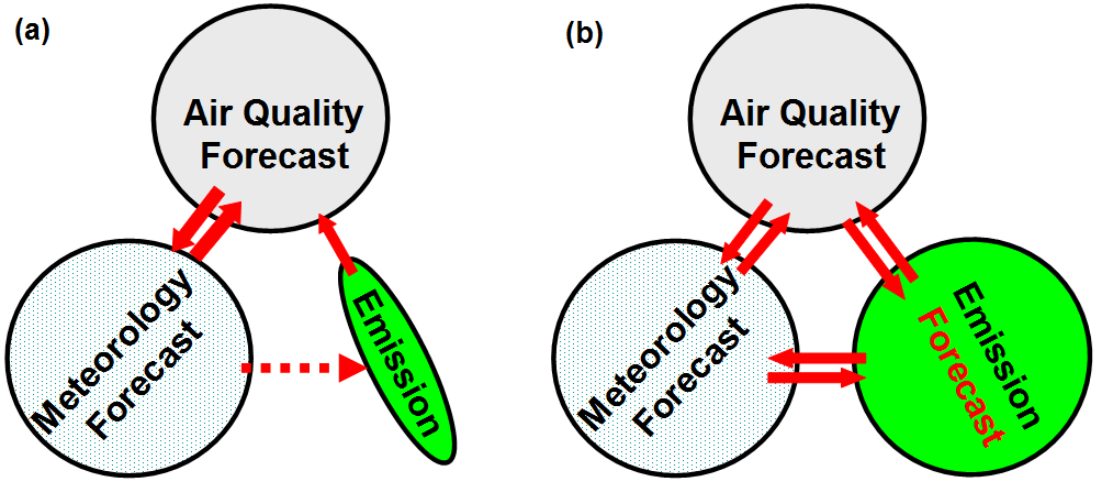
- **Stage I. Emission activity and process modeling:**

  Reproducing emission inventory data through emission modeling;
  - **Careful review of emission inventory documentation;**
  - **Develop emission models to reproduce emission data;**

- **Stage II. Improving emissions through incorporation of near-real-time data;**

- **Stage III. New emission algorithms and parameterization;**

- **Stage IV. Emission-Meteorology-Air Quality three way coupling;**



Past Future

Benefits of Emission Forecasting

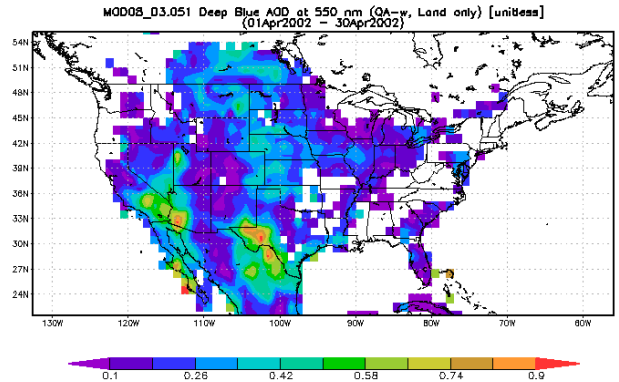
- **Capability to forecast emissions of tomorrow;**
- **Bring new emission sources into the domain:**
  - **Wildfires (M. Prank; J. Chen; P. Lee; J. Vaughan);**
  - **Marine isoprene (M. Wang);**
  - **Windblown dust (X. Zhang; M. Cope; D. Tong);**
  - **Lightning (D. Allen);**
  - **Pollen (M. Sofiev);**
  - **Volcanic emission (S. Lu);**
- **Increased transparency of emission data generation:**
  - **Transparency along the data flow from input data to emission algorithm to model-ready emissions;**
  - **Traceability of uncertainties and their propagation;**
  - **Scientifically measureable improvements (data, algorithms, or parameterization);**
- **Less expensive way to update emission inventories;**
- **Increased flexibility for forecasters and air quality managers;**

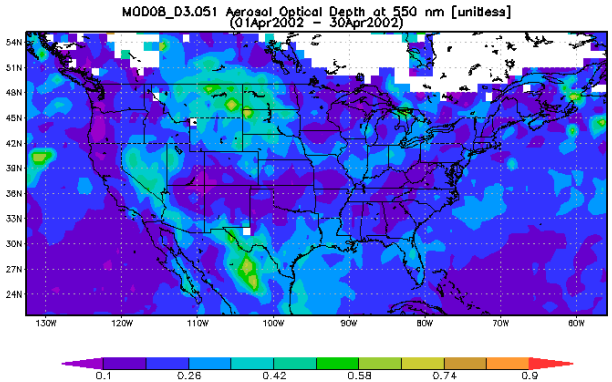
Challenge: Which Dataset to use

Data Source: NASA Giovanni: *http://disc.sci.gsfc.nasa.gov/giovanni*

MODIS Deep Blue | **MODIS Collection 5**

April





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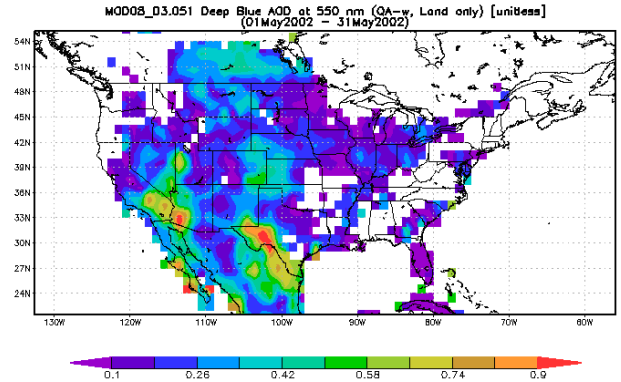
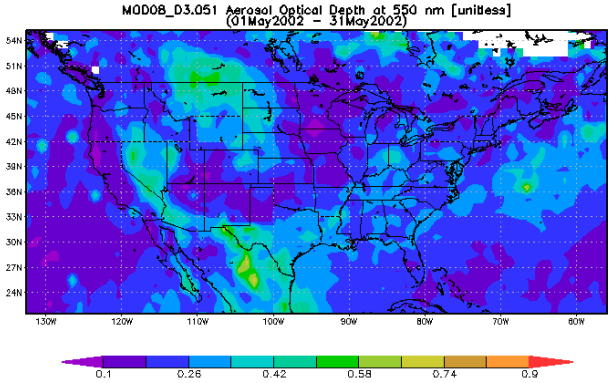




Same Sensor;

Same period;

Same location;

Same color scale;

But

Distinct values;

Distinct spatial variations;

The remote sending community needs to build Consensus for users;

Marine Isoprene Emissions

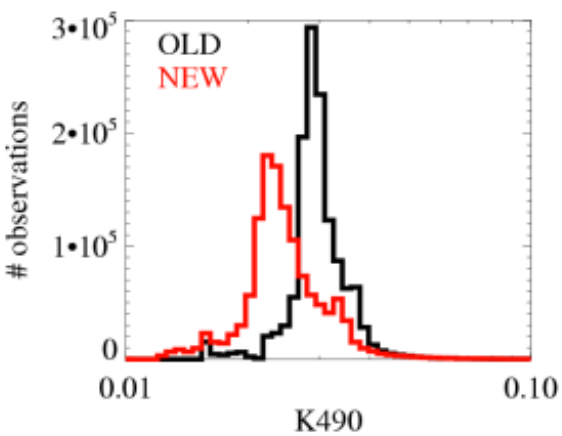
- **Isoprene emissions very sensitive to diffuse coefficient K_{d490}:**

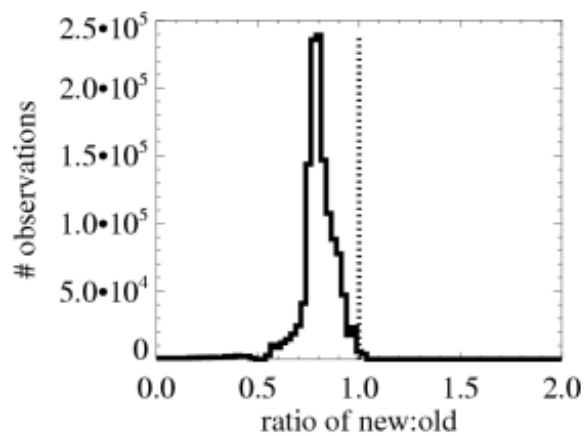
$$H\max = (-\ln(\frac{2.5}{I_0})/K_{490})$$

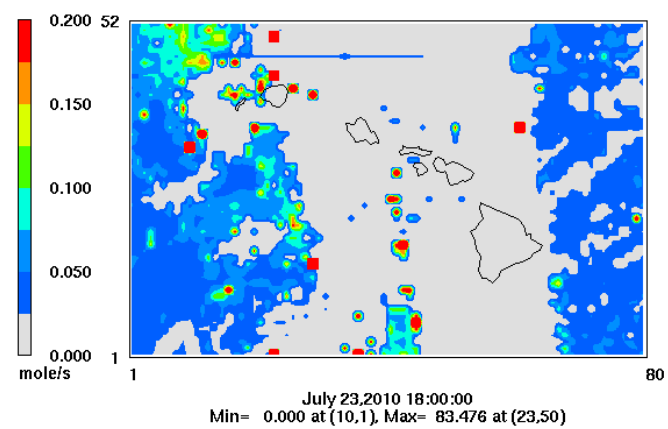
$$P = SA * H\max * [Chl-a] * EF * \int_0^{H\max} \ln(I)^2 dh$$

- **Some existing K_{d490} algorithms:**

1. NASA previous operational algorithm (Mueller, 2000);
2. Revised Mueller algorithm (J. Werdell, online 2005);
3. NASA current operational algorithm (Morel et al., 2007);
4. NOAA's new Kd490 algorithms: (Wang et al., 2009).







<u>Work closely with data providers to understand theeuncertainty in the input data.</u>

New Direction Article
Atmospheric Environment (in press)

Atmospheric Environment xxx (2011) 1–2

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New Direction: The need to develop process-based emission forecasting models

Air quality forecasting, also known as chemical weather forecasting, is a rapidly expanding science and technological discipline. Traditionally, weather forecasting predicts the *physical* state and tendency of the weather in the near future. Since the beginning of the industrial revolution, human impacts on the atmosphere have increased to such a high level that the composition of the atmosphere is distinctly different from that in the past (Horowitz, 2006). Most noticeably, the use of fossil fuels has spewed millions of tons of waste gases and particles into the atmosphere. These gases and particles are chemically transformed in the presence of sunlight to form secondary pollutants that, together with directly emitted pollutants, pose serious threats to human health and to the well-

individual sources are no long available in the emission inventories. Instead, emission processing is used to reconstruct such characteristics based on precompiled profiles. Such practices not only leave large uncertainties unknown and unexplored for years, but also delay advances in emissions science.

In light of these current realities, emissions science needs to be brought to a higher level to meet the specific requirements of air quality forecasting. Meteorological and chemical models are built by using a physically based approach for all known and computationally implementable processes that control the evolution of physical or chemical states of the atmosphere. Such a process-based modeling approach has been used to generate emission data for

Emission Forecasting WorkGroup

Collaboration essential to the success!

Want to contribute or be kept in loop? Email us:

Daniel.Tong@noaa.gov

Pius.Lee@noaa.gov

Rick.Saylor@noaa.gov