

# European Satellite Products: What do we need?

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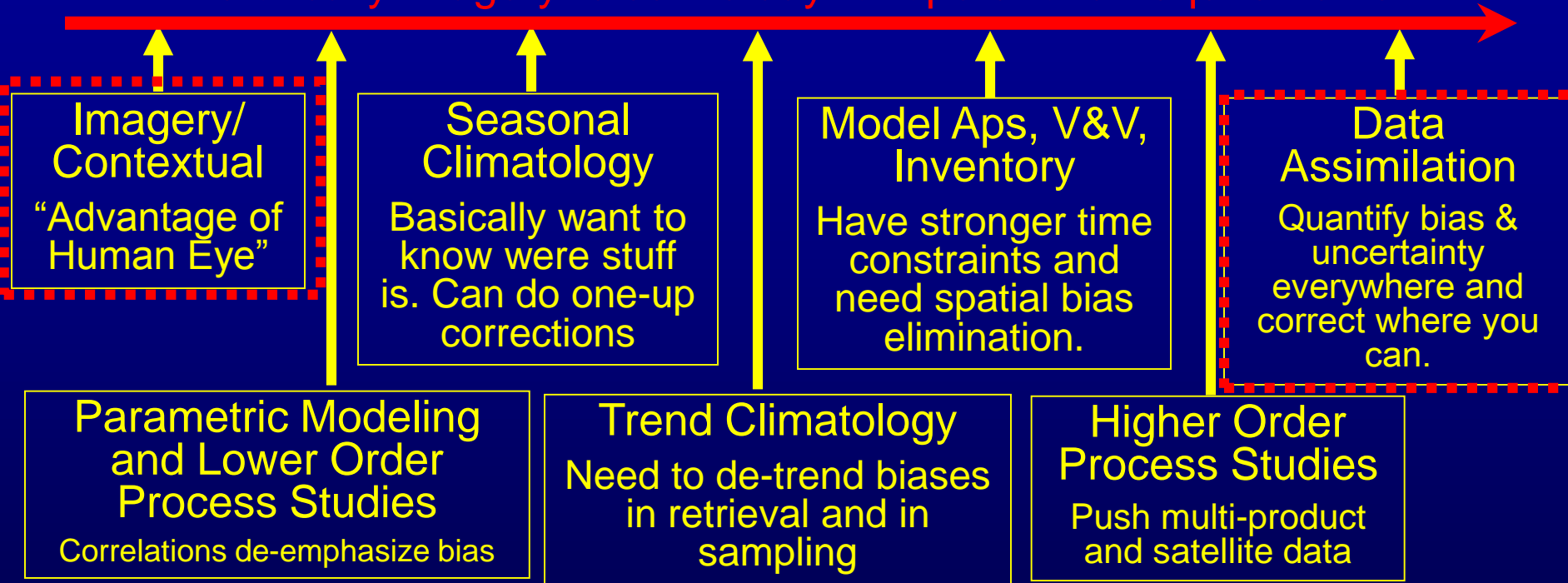
<http://www.nrlmry.navy.mil/flambe/>



# Relative Levels of Efficacy and Error Characterization Required

(Approximate and not meant to offend...)

**Operational Agencies Focus on the Extremes**  
Historically imagery rules the day for operational requirements



- Inverse modeling is sensitive to spatially and temporally correlated error.
- Forecasting is even more sensitive, as anomalously high data will create a “plumes” in the forecast fields. Forecasters are not used to this.
- Non-linear transfer function between AOD and model mass complicates error propagation, particularly at low AODs.



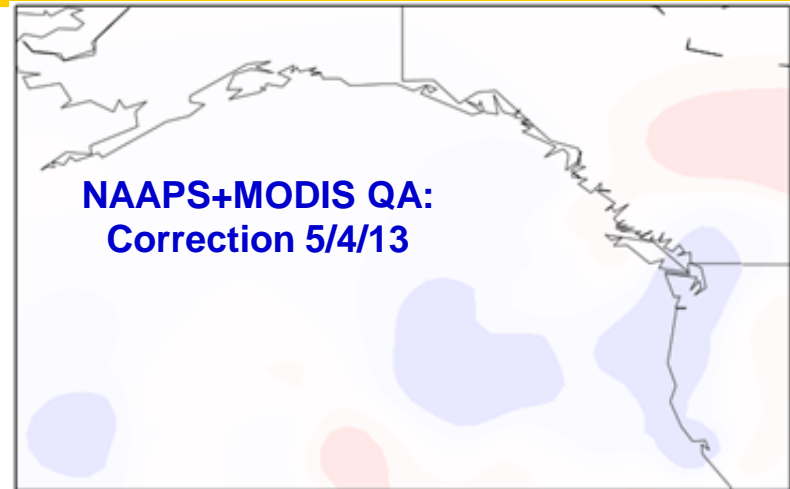
# Types of Bias

Each a talk in themselves.

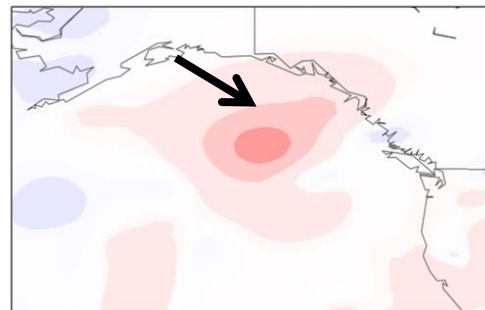
- **Method Bias**: Biases related to shortcomings in the method itself.
- **Calibration Bias**: Unaccounted for drift in the instrument response characteristics.
- **Sampling/Contextual Bias**: Biases related to where a retrieval is/is not performed or contextually related uncertainty in a scene. This leads to a skewed data population relative to what is thought to have been collected.
- **Aggregation/Data Reduction Bias**: Loss of required information during conversion to higher level products or during analysis.
- **Cognitive Bias**: We, the investigators, misinterpret, withhold, or frame data/results without consideration of the full nature of the data.
- **Other Considerations for multi-sensor work**:
  - a) **Correlated error**-“Independent” products that share similar biases;
  - b) **Tautology** -Circular reasoning or treating non-independent data as independent during data reduction.

# Impact of QA process: Ocean example of a comparison of two methodologies

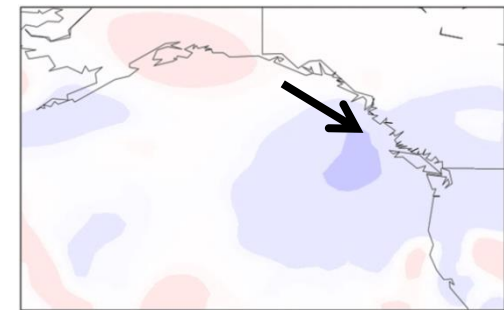
Statistically, using the NASA neural net product versus ours does not make a significant difference in bulk AOT statistics, but data assimilation dipoles in biases are there which change interpretation in individual places and time. This said, NASA has stronger inline QA and can assimilate more data. So it is always a trade off



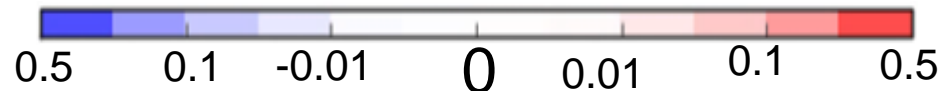
NAAPS+MODIS QA:  
Correction 5/4/13



NAAPS+ Neural Net  
Correction 5/4/13

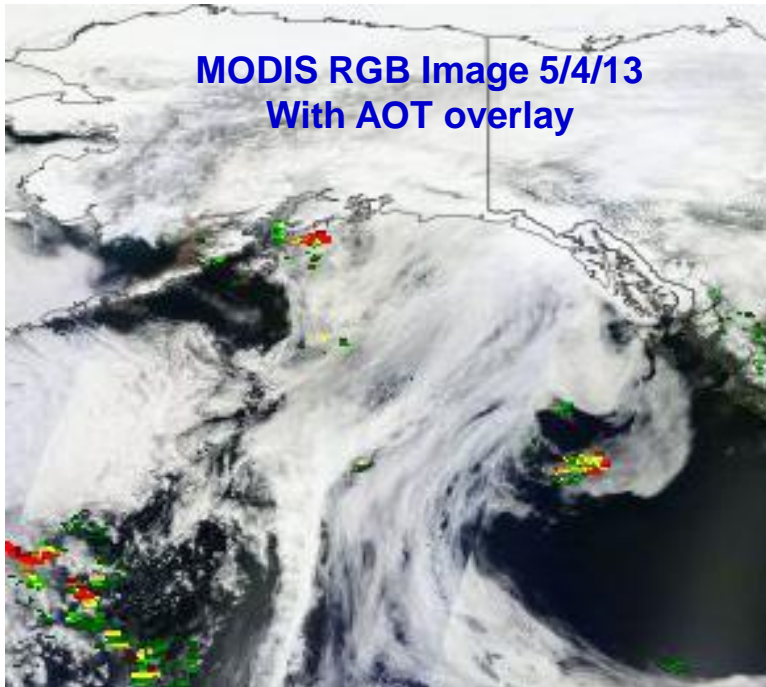


NAAPS+ Neural Net  
Correction 5/5/13



NAVDAS AOT Corrections

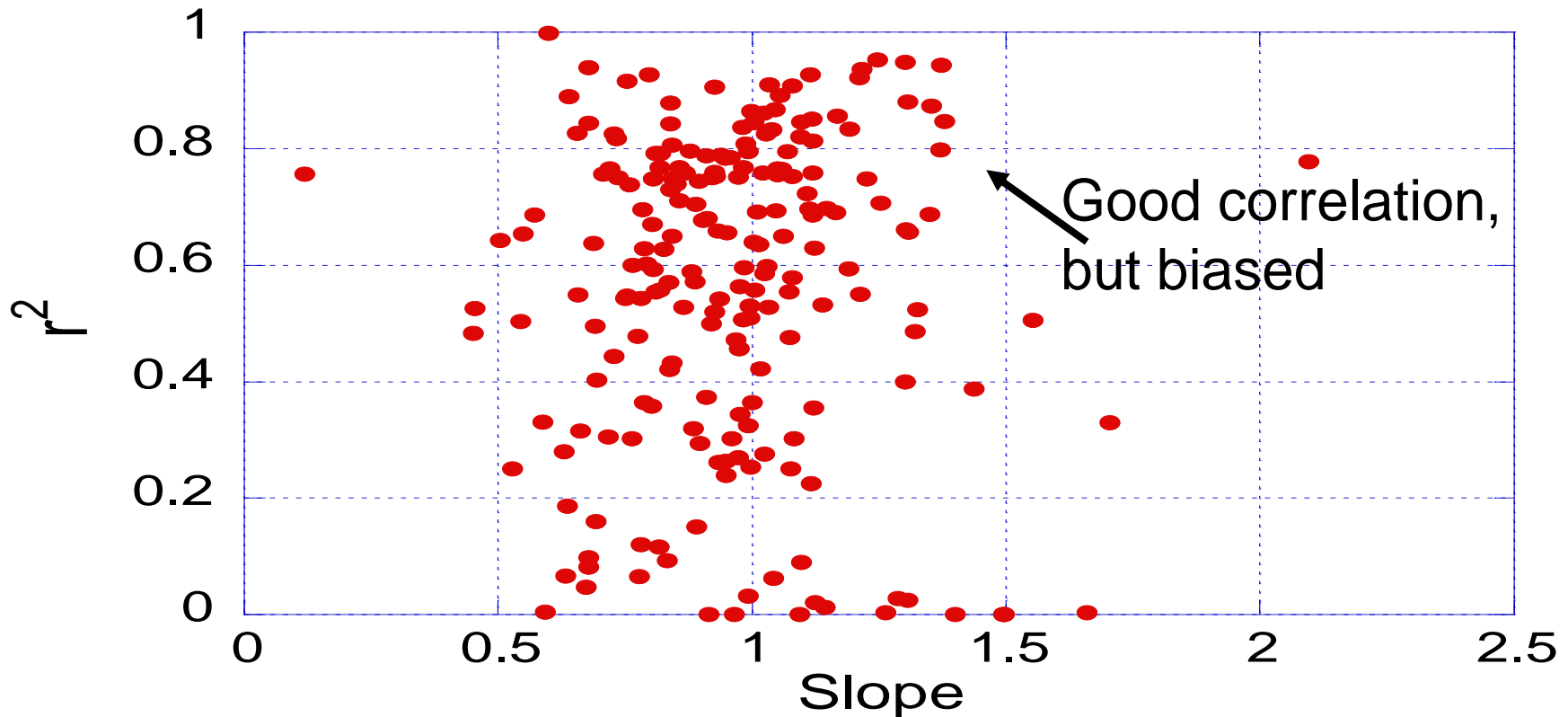
MODIS RGB Image 5/4/13  
With AOT overlay



# Harder biases to model: Correlated bias-particularly over land

- The core retrieval biases related to clouds, lower boundary condition, and microphysics are non-random, but spatially and temporally correlated- invalidating most commonly used V&V methods and data assimilation assumptions.

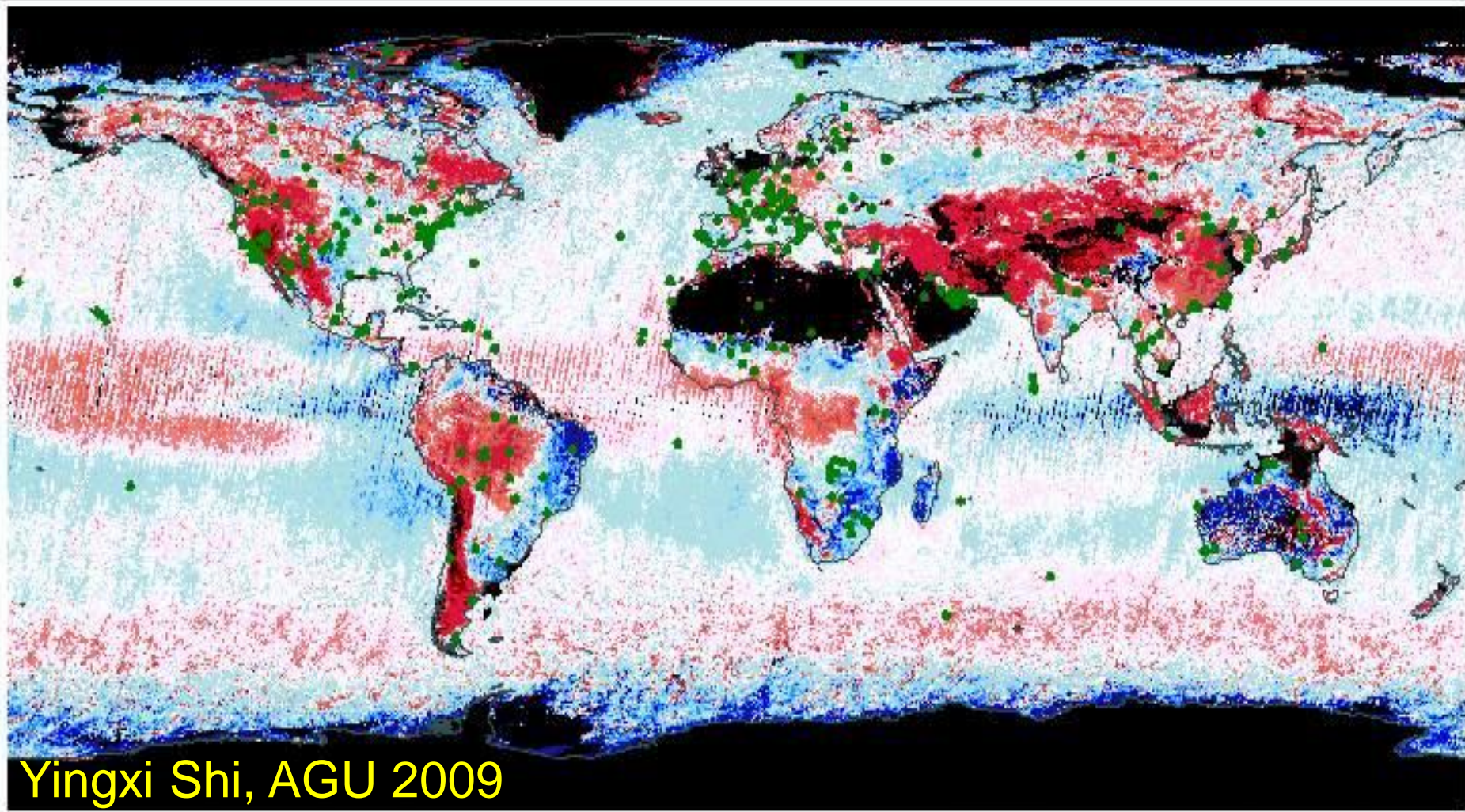
## MODIS Versus AERONET Summary Statistics, AOD>0.2



# Correlated bias in lower boundary condition, microphysics, cloud masking.

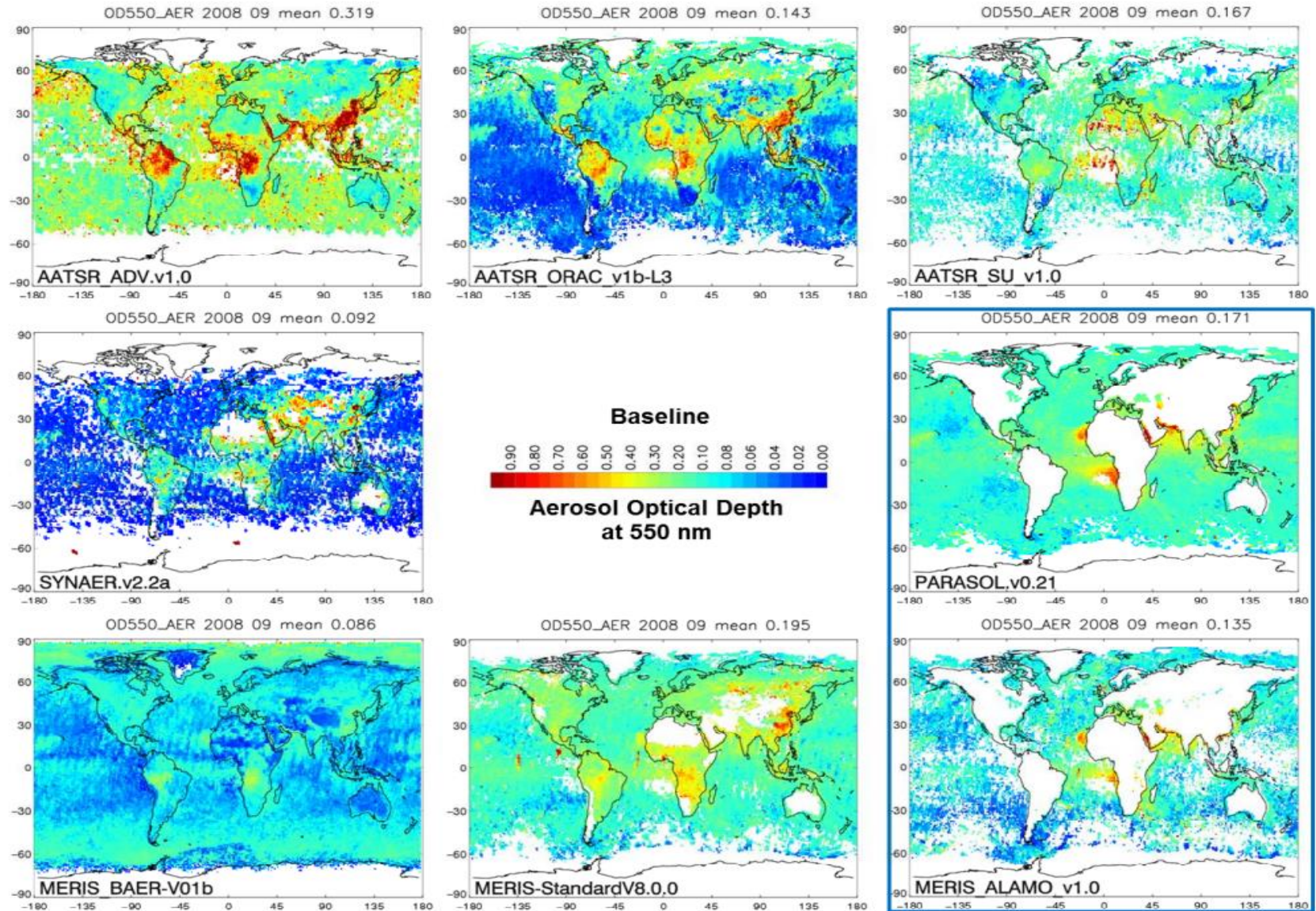


Ratio of MODIS to MISR. These features dominate innovation vectors and hence any inverted quantity.



Yingxi Shi, AGU 2009





**Fig. 6.** September 2008 unweighted monthly mean ADO550 for eight total column precursor algorithms: baseline datasets (experiment number 0 in Table 1). From top left to bottom right: AATSR ADV, AATSR ORAC, AATSR SU, SYNAER, MERIS BAER, MERIS STANDARD, MERIS ALAMO (ocean only), PARASOL (ocean only).



# What we want

(and some friendly advice)



- Most importantly be honest with yourself and the community in regard to what your objective are and how good your product really is. Big errors are ok, as long as when we know they are big.
- For data assimilation we need a de-biased products with a residual point wise error estimate. That is, we need an error model for bias and root mean square deviation.
- Feel free to pack in as much metadata as is reasonable (cloud fraction, snow, aggregated radiance or reflectances). It helps us develop our own error models and select the right data to use.
- Categorical aerosol models such as "dust, polluted dust, etc." can be difficult to implement in data assimilation. Index of refraction of a complex mixture is not easily relatable. More generally, unless we can clearly define an observation operator, an observable cannot be effectively assimilated. Great uncertainties in observation operators --> specification of large observation errors --> less impact.
- Data needs to be easy to get and parse. Be consistent with a few major upgrades being preferable to lots of incremental changes.
- Consider the niche market and keep the global constellation in mind. Every product does not need to do everything.





# Components of Level 2 Error Model

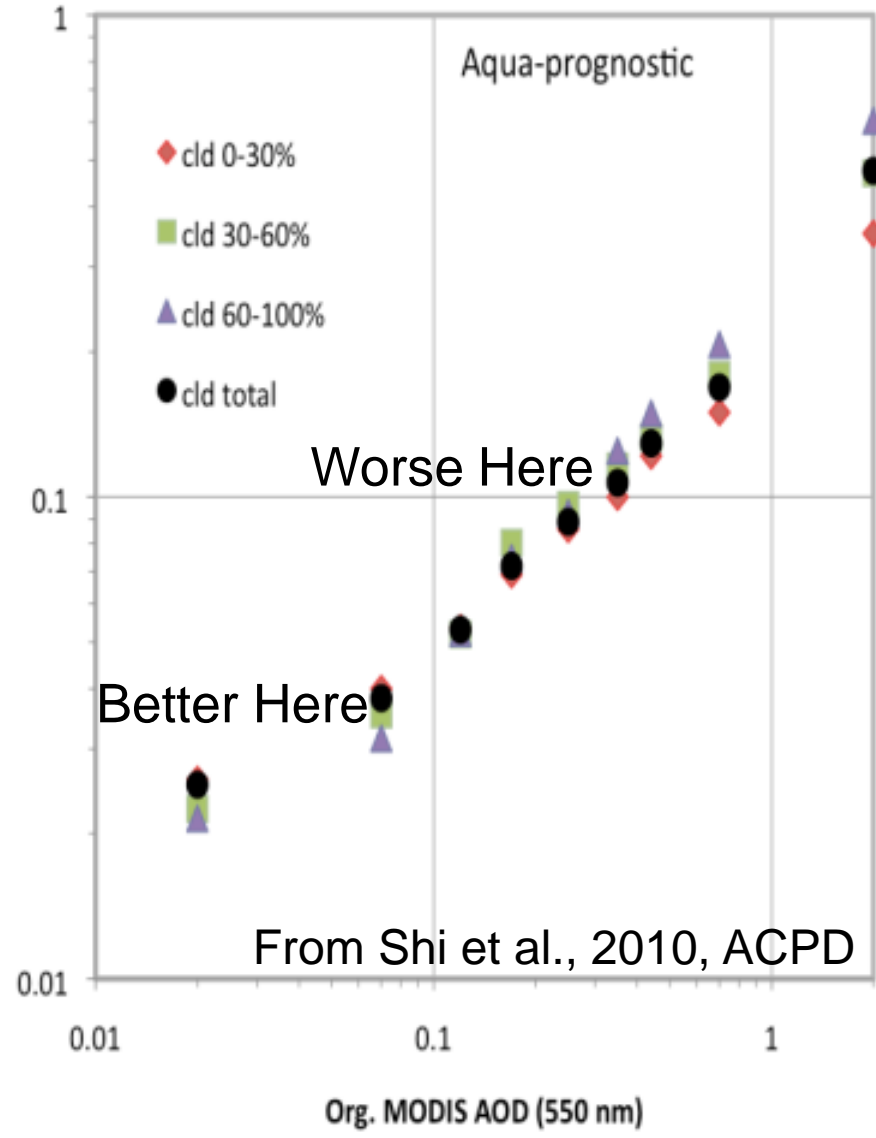
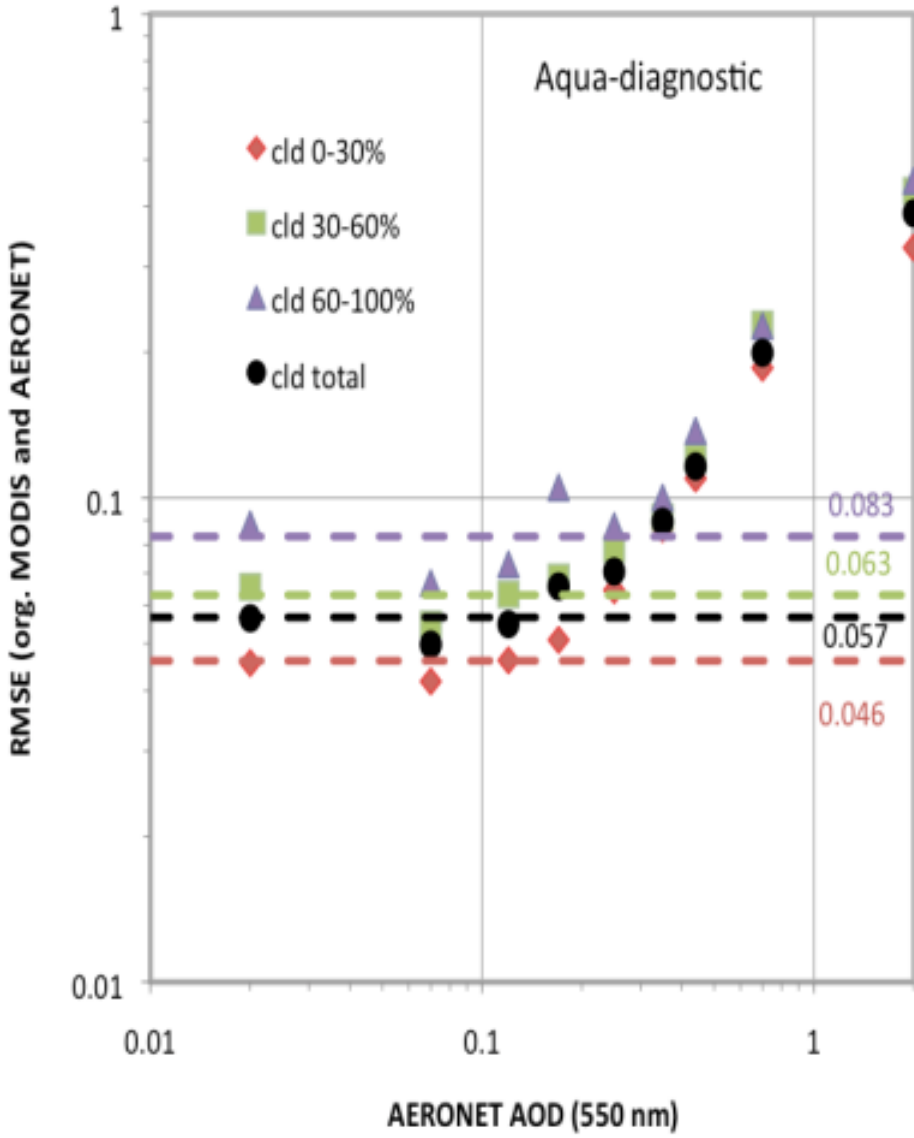
(requires lots of data to pull out)



- **Can be as simple as RMSE as a function of AOD**
  - AOD can be from AERONET (diagnostic) or own AOD (prognostic).
  - But, RMSE is symmetric nor does it address massive outliers which are often the problem
- **Terms include:**
  - Differential Signal to Noise: Lower boundary minus total, including view angle/optical path length.
  - Lower Boundary Condition:
    - Ocean: Wind/glint/whitecap, class 2 waters, sea ice
    - Land: Surface reflectance model, snow, view angle/BRDF/hotspot
  - Cloud mask
  - Microphysical: Fine coarse/partition,  $P(\theta)/g$ ,  $\omega_0$ , AOD
- **Biases are often folded into “random” error models. If they are known, why not correct for them?**
- **Radiance Calibration: Individual wavelengths propagate non-linear through retrievals and are not easy to incorporate.**
- **Verification! You need to verify your error model so we believe you.**

# Diagnostic versus prognostic error models: A MODIS over ocean example

(Shi et al., 2011)





# Research to Operations, or, Operations to Research?????



- One of the greatest myths is that operational data records require less fidelity than climate data records. Nothing is further from the truth, although agency leadership still has not fully recognized this.
- This can be proven when one has concrete metrics. The current “one size fits all” approach to products in the end fits none.
- The second greatest myth is that only Operations wants data in near real time. The future is moving to towards multiple sensor and sensor-model products. GMAO looks a lot like an operational center too...
- Don't exclusively think like an engineer or climate scientist. Also think like all of your potential customers.
- The fusion of multiple sensors with models is inevitable and positive. Don't fight it. Be part of the process.