The GEOS-5 Neural Network Retrieval (NNR) for AOD

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Remote Sensing of Aerosols

AOD
- Column integrated value (top of the atmosphere to surface)
- Optical measurement of aerosol loading – unitless.
- AOD is function of shape, size, type and number concentration of aerosols

Figure: NASA ARSET Program
GEOS-5 Aerosol Data Assimilation

The aerosol data assimilation problem requires a homogenized dataset of AOD across different platforms.

Biases between datasets can propagate in the model forecast.
Empirical Retrievals

Satellite Sensor Observation $[S]$ 

Transfer Function $[f]$  
$G = f(S, A)$

Geophysical Parameter of Interest $[G]$ 

- $f$ is a continuous function that maps $S$ to $G$
- Represent $f$ with a mathematical function that contains a set of empirical parameters, $A$
- $A$ are determined from a training dataset of pairs of $G$ and $S$ observations.

Physically Based Retrievals

Satellite Sensor Observation $[S]$ 

Forward Model $[F]$  
$S = F(G)$

Geophysical Parameter of Interest $[G]$ 

- $F$ is a physical model derived from first principles (e.g. radiative transfer model)
- $F$ is not easily inverted
- The objective of the retrieval algorithm is to search for a $G^*$ that minimizes $||S - F(G)||$
### Observations

**Satellite Sensor Observation [S]:**

**MODIS MOD04 /MYD04 Level 2 Reflectance**

- Cloud masked, quality controlled, 10 km data
- Deep Blue Land
  - 3 channels over bright surfaces
  - 412 nm, 470 nm, and 670 nm
- Dark Target Land
  - 9 channels over dark surfaces
  - 412-2100 nm
- Dark Target Ocean
  - 7 channels over ocean
  - 470-2100 nm

**Geophysical Parameter of Interest [G]:**

**550 nm AOD**

- Aerosol Robotic Network (AERONET) observations of AOD
  - Global network of sunphotometers
  - 15 minute sampling
  - Low uncertainty (±0.01)

[Image of satellite sensor and AERONET network]
MODIS-AERONET Data Pairs

- 15 years of data (2000-2015)
- ~150K Deep Blue data pairs
- ~100K DT-Land data pairs
- ~40K DT-Ocean data pairs

Additional Data Screening
- Outlier removal
- Cloud Fraction < 0.7
- Used MERRA-2 to “balance” the dataset by aerosol type
- Reduces number of data pairs by half

Petrenko, et al. AMT (2012)
Neural Networks

- A set of nodes connected by numerical weights.
- The weights are tuned based on a specific training dataset containing input-output data pairs.
- The superposition of many nonlinear transfer functions (nodes) allow NN’s to approximate extremely nonlinear functions.

\[
\sigma(w, x) = \frac{1}{1 + \exp(-w \cdot x - c)}
\]

Fig. 1. A taxonomy of neural network architectures (after Jain et al., 1996).

Fig. 2. A multilayer perceptron with two hidden layers.

Fig. 3. The logistic function \( y = \frac{1}{1 + \exp(-x)} \).

The superposition of many nonlinear transfer functions (nodes) allow NN’s to approximate extremely nonlinear functions.
5.1. Selection of “Dark Pixels”

Figure 4 illustrates the main steps of our new land algorithm. Each individual MODIS scene, called a granule, consists of a 5-min swath of data, measuring approximately 1340 km by 2030 km. The relevant Level 1 B (L1B) data include calibrated spectral reflectance in eight wavelength bands at a variety of spatial resolutions, as well as the associated geolocation information. The spectral data include the 0.66 and 0.86 μm channels (MODIS channels 1 and 2 at 250 m resolution), the 0.47, 0.55, 1.24, 1.64, and 2.12 μm channels (channels 3, 4, 5, 6, and 7 at 500 m), and the 1.38 μm channel (channel 26 at 1 km). The geolocation data are at 1 km and include angles (q₀, q₈, a, and Q), latitude, longitude, elevation, and date. L1B reflectance values are corrected for water vapor, ozone, and carbon dioxide (described in ATBD-2006) before proceeding.

The first step is to organize the measured reflectance into nominal 10 km by 10 km boxes (corresponding to 20 by 20, or 40 by 40 pixels, depending on the channel). The 400 pixels in the box are evaluated pixel by pixel to identify whether the pixel is suitable for aerosol retrieval. Clouds [Martins et al., 2002], snow/ice [Li et al., 2005], and inland water bodies (via NDVI tests) are considered not suitable and are discarded. Details of this masking are also described in ATBD-2006.

The nonmasked pixels are checked for their brightness. Pixels having measured 2.12 μm reflectance between 0.01 and 0.25 are grouped and sorted by their 0.66 μm reflectance. The brightest (at 0.66 μm) 50% and darkest 20% are discarded, in order to reduce cloud and surface contamination and scale toward darker targets in the visible wavelengths. If there are at least 12 pixels remaining (10%), proceed.

Do Inversion

For 13 values of η (-0.1,0.0,0.1,...,0.9,1.0,1.1,...)
Find t₉₆6 and pʰ₉²₁ such that
pʰ₉₂₁(0.047) = pʰ₉₆₆(0.047) = 0,
where pʰ₉₆₆ = η(ρʰ₉₆₆) + (1-η)(ρ煌₉₆₆)
Choose η such that
pʰ₉₆₆(0.066) = pʰ₉₆₆(0.066) = ϵ is minimized
Primary products: t₉₆₆, pʰ₉₂₁.

Do Single Channel Retrieval

Find t₀₅₅ and pʰ₅₂ such that
pʰ₅₂(0.047) = pʰ₅₂(0.047) = 0,
where pʰ₅₂ = pʰ₅₂.
Primary products: t₀₅₅, pʰ₅₂.

Calculate t₀₅₅, M₀, tₜ₅₅, Mₜ₅₅, tₜ₅₅ = Fill

If t₀₅₅ ≤ 0.0 then set αₜ₅₅ = Mₜ₅₅ = tₜ₅₅ = 0
If 0.1 < t₀₅₅ ≤ 0.05, then set tₜ₅₅ = 0.05
If t₀₅₅ > 0.1, then set tₜ₅₅, Mₜ₅₅, tₜ₅₅ = Fill

Report: tₜ₅₅, αₜ₅₅, Mₜ₅₅, tₜ₅₅, QA, etc.
GEOS-5 NNR for AOD

INPUT LAYER

- MxD04 L2 Reflectance
  - 9-channel DT-Land: 412-2100 nm
  - 3-channel Deep Blue: 412,470,660 nm
  - 7-channel DT Ocean: 470-2100 nm
- Scene Geometry
  - Scattering Angle
  - \( \cos(SZA) \)
  - Glint Angle
- Surface Reflectance
  - DT-Land: MCD43C1 BRDF
  - Deep Blue: MxD04 Assumed Surface Reflectance
- Aerosol Type
  - GEOS-5 Aerosol Composition
    - \( f_{\text{dust}}, f_{\text{BC+OC}}, f_{\text{sulfate}}, f_{\text{sea-salt}} \)
    - For training we use MERRA-2

HIDDEN LAYER

OUTPUT LAYER

- N-Nodes = 2xN-Inputs
- \( \log(550 \text{ nm AOD}) \)
NNR Training, Testing, Validation

- **Train & Test**
  - Iteratively train and test adjusting input variables, architecture, etc. to optimize neural network
  - Cross Validation
    - K-folding: create K subsets of data, using K-1 for training, and 1 for testing. Iterate K times.

- **Validate**
  - Use a separate dataset, not used to train/test
  - Observations after 2015
NNR Training & Testing

Error bars indicate the spread in the k-folds

Level 2 MODIS Observation
- Geometry
  - SolarZenith
  - ScatteringAngle
  - GlintAngle
- Reflectance
  - mRef412
  - mRef470
  - mRef660

MYD04 Assumed Surface Reflectance
- mSre412
- mSre470
- mSre660

GEOS-5 Aerosol Type
- fco
- fcc
- fsu

AQUA DEEP BLUE NNR RMSE
NNR Testing

LAND - Dark Surface

LAND - Bright Surface

OCEAN

MODIS Standard Retrievals

Neural Network Retrievals

GMAO Global Modeling and Assimilation Office
gmao.gsfc.nasa.gov

dark target land

dark target ocean

9-Channel NNR

3-Channel NNR

7-Channel NNR

log(MODIS AOD + 0.01) - log(AERONET AOD + 0.01)

log(NNR AOD + 0.01) - log(AERONET AOD + 0.01)
LAND - Bright Surface

NNR Testing

TERRA DEEP MOD04 MRMSE

TERRA DEEP Relative Change in RMSE

NNR RMSE < MODIS Standard Retrieval

NNR RMSE > MODIS Standard Retrieval

[%]
**LAND - Dark Surface**

**NNR Testing**

**OCEAN**

TERRA LAND Relative Change in RMSE

TERRA OCEAN Relative Change in RMSE

NNR RMSE < MODIS Standard Retrieval

NNR RMSE > MODIS Standard Retrieval
NNR Testing at Some Individual Sites

LAND - Bright Surface

USURRYSK
Outliers at high AOD

LAND – Dark Surface

DHAKA UNIVERSITY

TERRA LAND (0.17)
NRR (0.23)

OCEAN

CROZET ISLAND

TERRA OCEAN (0.05)
NRR (0.04)

HALIFAX

TERRA DEEP (0.06)
NRR (0.03)

BEIJING

TERRA LAND (0.24)
NRR (0.16)

DAKAR

TERRA OCEAN (0.11)
NRR (0.09)
NNR Validation (Observations after 2015)

LAND - Dark Surface

DARK TARGET LAND

Probability Density

-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

log(MODIS AOD + 0.01) - log(AERONET AOD + 0.01)

- Terra
- Aqua

LAND - Bright Surface

DEEP BLUE LAND

Probability Density

-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

log(MODIS AOD + 0.01) - log(AERONET AOD + 0.01)

- Terra
- Aqua

OCEAN

DARK TARGET OCEAN

Probability Density

-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

log(MODIS AOD + 0.01) - log(AERONET AOD + 0.01)

- Terra
- Aqua

MODIS Standard Retrievals

9-Channel NNR

Probability Density

-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

log(NNR AOD + 0.01) - log(AERONET AOD + 0.01)

- Terra
- Aqua

3-Channel NNR

Probability Density

-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

log(NNR AOD + 0.01) - log(AERONET AOD + 0.01)

- Terra
- Aqua

7-Channel NNR

Probability Density

-1.5 -1.0 -0.5 0.0 0.5 1.0 1.5

log(NNR AOD + 0.01) - log(AERONET AOD + 0.01)

- Terra
- Aqua

Neural Network Retrievals
LAND - Dark Surface

NNR Validation

LAND - Bright Surface

TERRA LAND Relative Change in RMSE

TERRA DEEP Relative Change in RMSE

NNR RMSE < MODIS Standard Retrieval

NNR RMSE > MODIS Standard Retrieval
NNR Applied to Entire MODIS Time Series: TERRA
NNR Applied to Entire MODIS Time Series: TERRA Climatology

MODIS Standard Retrieval

Neural Network Retrieval

DJF

MAM

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NNR Applied to Entire MODIS Time Series: TERRA

MODIS Standard Retrieval

Neural Network Retrieval

JJA

SON
Summary & Outlook

- The NNR provides a way to homogenize the AOD observing system for data assimilation
- Validation with independent data indicates that the error characteristics of the NNR are stable [for the most part]

Future Work
- Validate over open ocean with Marine Aerosol Network (MAN) Observations
- Periodic retraining for near real-time application
  - Do calibration drifts require multiple networks?
- Improve training data set
  - More QA filtering, balancing
- Multiple targets
  - Multi-channel AOD
  - SSA
  - Angstrom Exponent
- Geostationary observations

{[Image] 440 nm AOD

{[Image] 660 nm AOD

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