Satellite Detection of Dust

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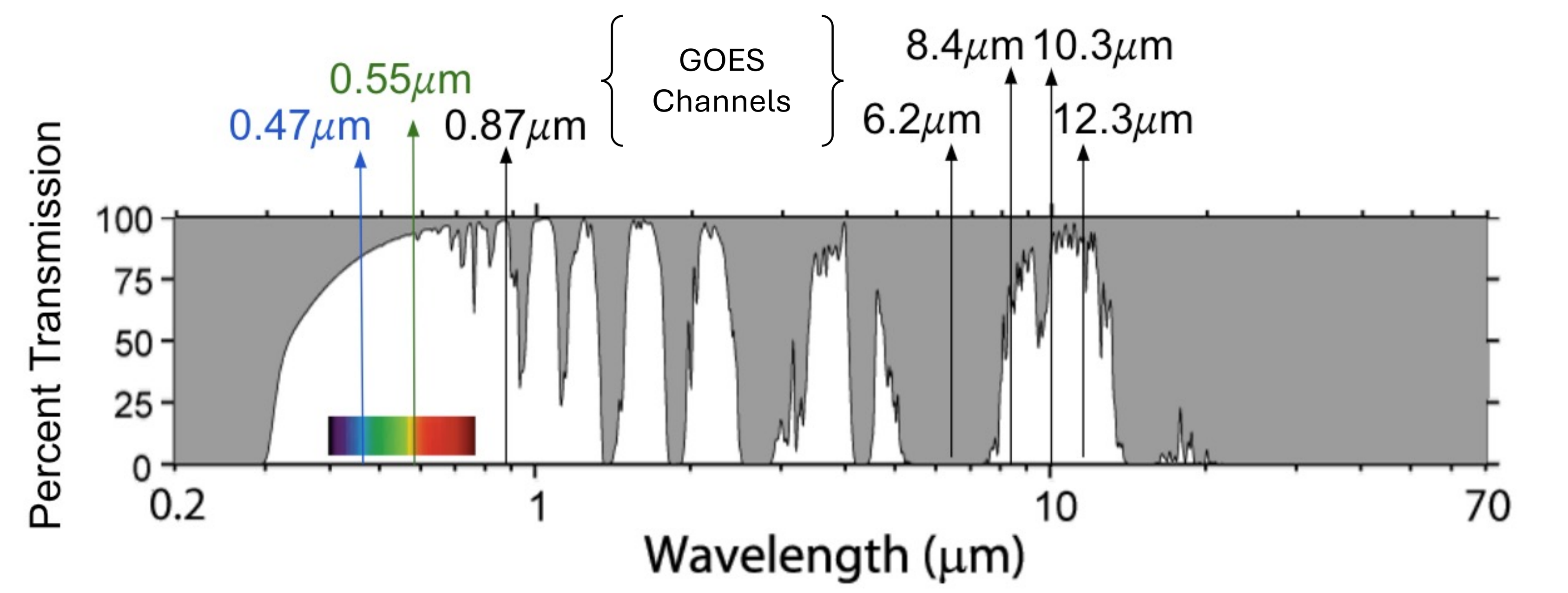
1) Motivation

Coarse particulate matter (PM_{coarse}, particulate matter with a diameter > 2.5 μm and < 10 μm) is a pollutant able to cause health problems, reduce visibility, and damage ecosystems. In most regions of the continental United States (CONUS), PM_{coarse} is predominantly dust; major sources include agricultural fields, arid land, deserts, unpaved roads, construction sites, sea spray, and industrial processes.[1,2] Since monitors are placed based on population density and sources of PM_{coarse} tend have a high spatiotemporal variability, monitors do not fully represent the extent of dust events. Satellite data can be used to bridge the data gap to detect dust events and estimate PM_{coarse} concentrations.

2) Satellite data offers information about aerosol size and composition.

- Aerosols interact differently with certain wavelengths of electromagnetic radiation based on their size and composition.
- Shorter wavelengths are used to calculate aerosol optical depth and Ångström exponents.
- Longer wavelengths offer more information about dust presence.
- Using the wavelengths that interact with dust the most, we can create a "Dust Confidence Factor" employing the DEBRA algorithm.[3]
- The ability to identify dust using specific wavelengths can be used to estimate PM_{coarse} concentrations.



3) Data products and methods

Dataset	Retrieval Method	Spatial Resolution	Temporal Resolution
Brightness Temperatures at 0.47, 0.55, 0.87* 6.2, 8.4, 10.3, and 12.3 μm	ABI sensor aboard GOES-16 satellite	2 km	5 minutes
Surface Temperature	MERRA-2	50 km	1 hour
University of Wisconsin-Madison Baseline Fit Emissivity	MODIS sensor coupled with a conceptual model	5km	Monthly

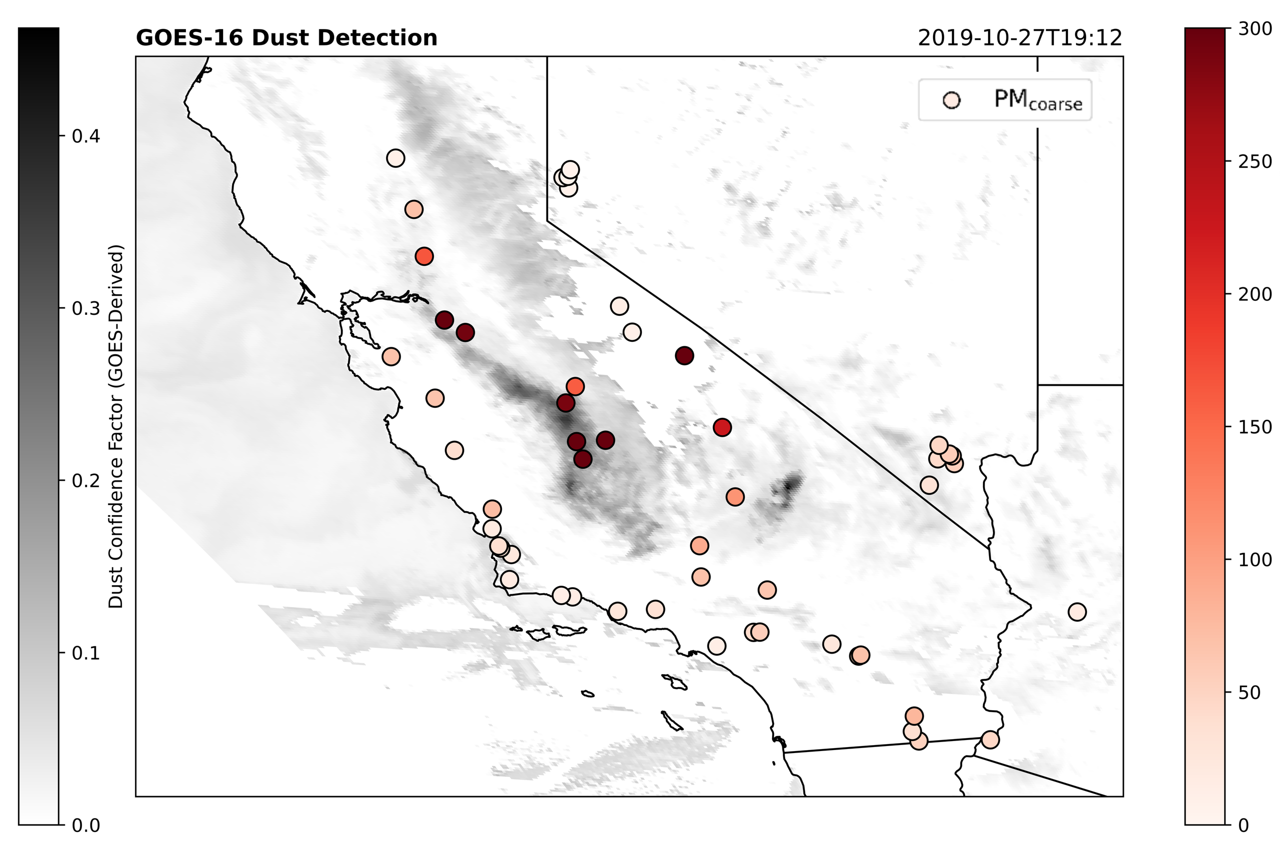
*visible channels not used in the case studies

- Surface temperature and emissivity are used to calculate background brightness temperatures.
- Background brightness temperatures are compared with GOES brightness temperatures at 6.2, 8.4, 10.4, and 12.3 μm to develop a Dust Confidence Factor using the DEBRA algorithm.

4) Dust presence can be identified from a satellite-derived confidence factor.

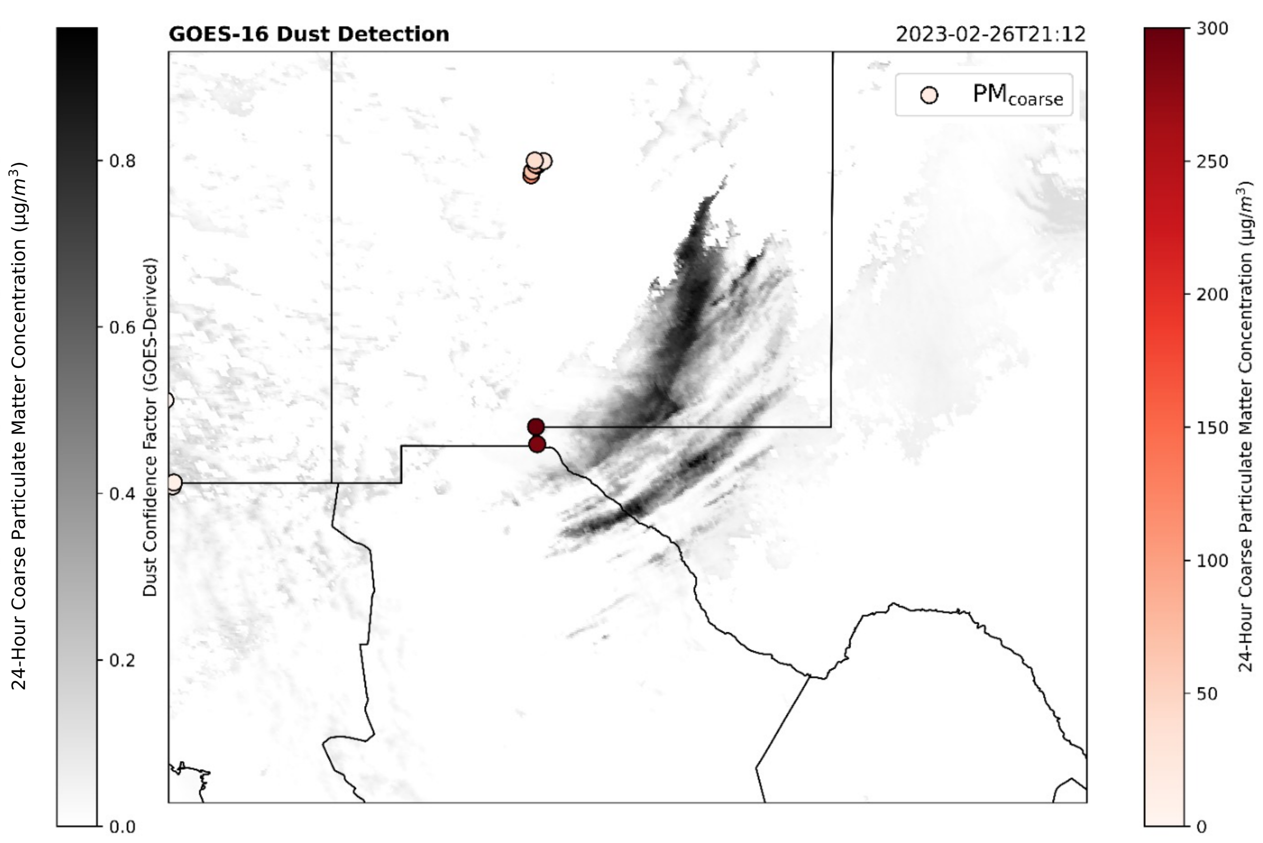
- Plotted below is a dust Confidence Factor developed from GOES-16 instantaneous data and PM_{coarse} concentrations from co-located EPA 24-hour PM_{10} and $PM_{2.5}$ monitors.

October 27, 2019: Optically thin dust over California.



- High density of monitors able to detect PM from dust.
- High concentrations of PM where the DEBRA algorithm identifies the presence of dust.

February 26, 2023: Optically thick dust over southern New Mexico.



- Low density of monitors leaves spatial extent of the dust event unknown without satellite data.

5) Materials interact with specific wavelengths in unique ways.

- The complex refractive index of a material provides information about its scattering and absorbing properties at a specific wavelength.
- Dust absorbs more strongly at 10.3 μm versus 11.2 and 12.3 μm aiding with screening dust from clouds.

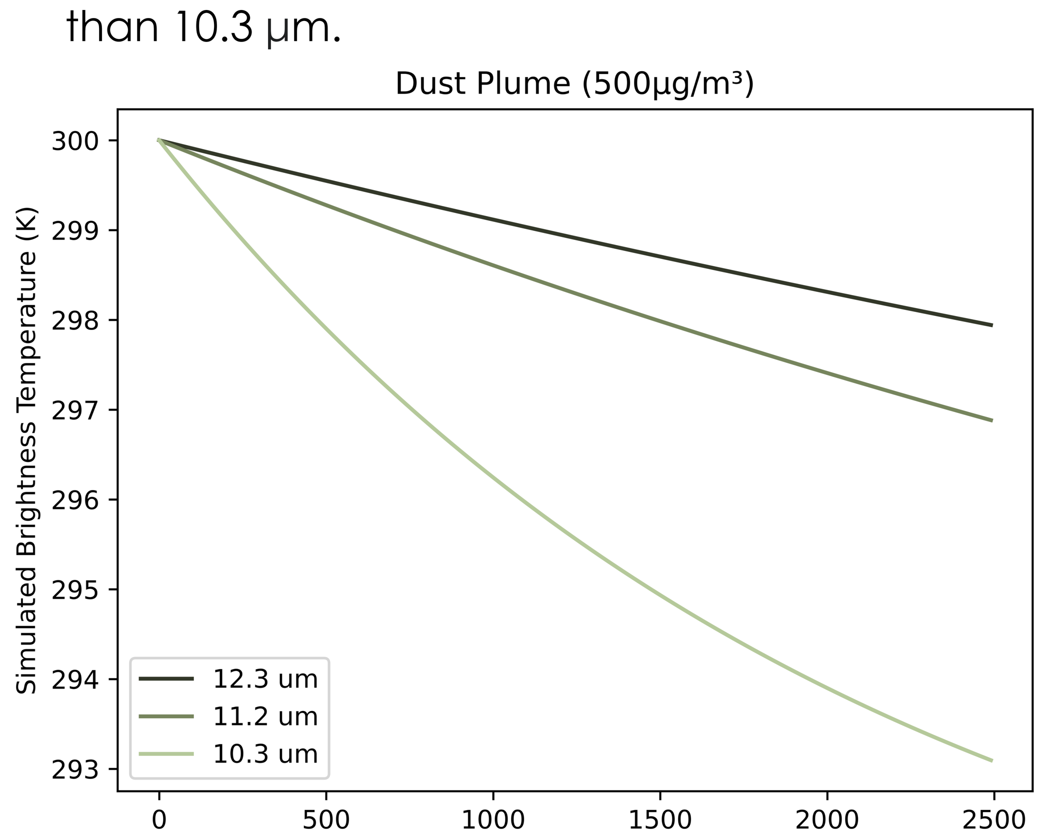
Complex Refractive Index (m) = n - ki
Scattering Absorbing

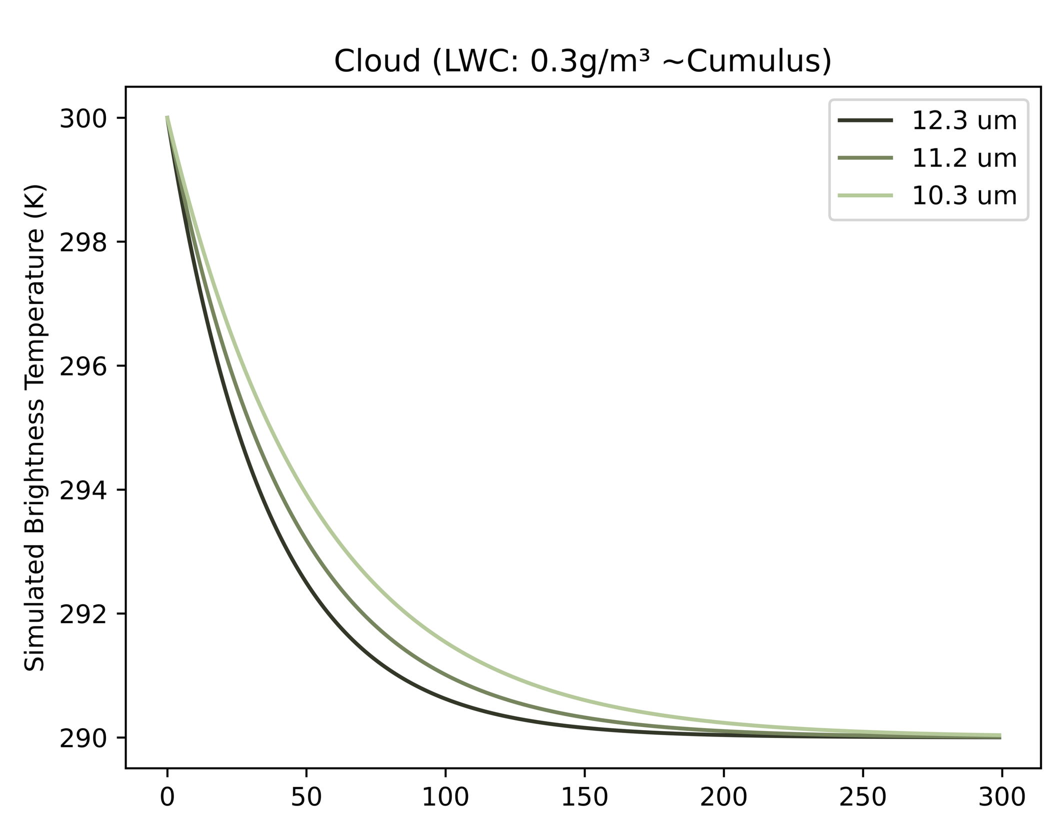
Decreasing Scattering and Decreasing Absorbing

Wavelength of Radiation	10.3 μm	11.2 μm	12.3 μm
Refractive Index of Dust[4]	1.8 + 0.5i	1.6 + 0.06i	1.5 + 0.04i
Refractive Index of a Cloud (Water)[5]	1.2 +0.06i	1.1 + 0.1i	1.1 + 0.2i

Decreasing Scattering and Increasing Absorbing

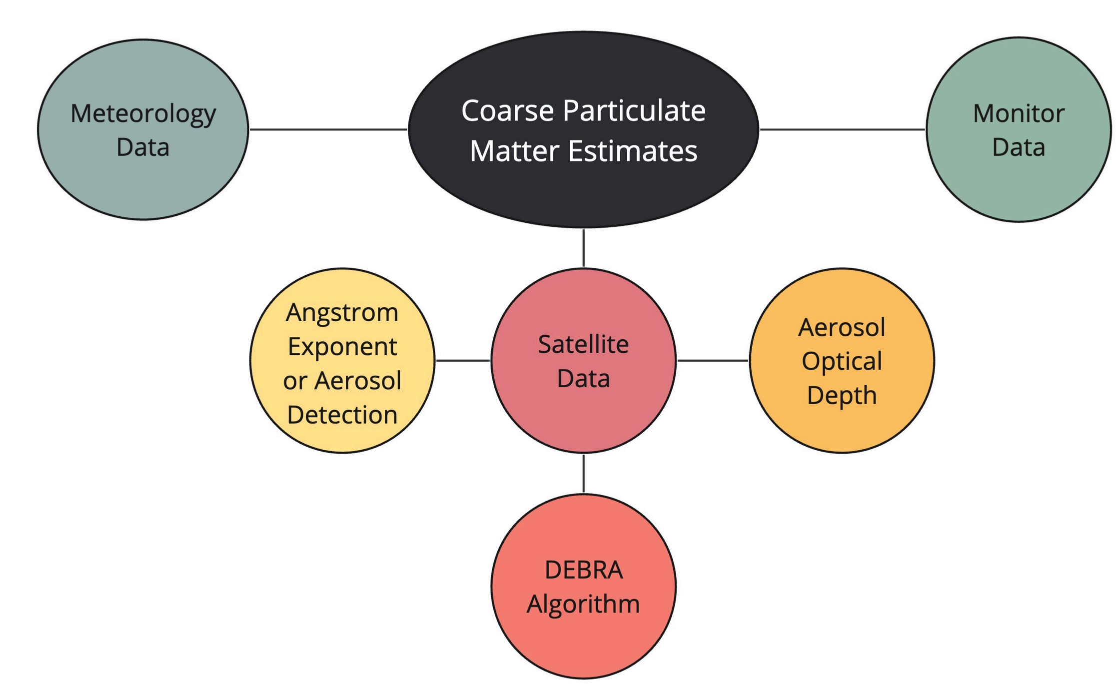
- For a dust plume, the brightness temperature is colder at 10.3 μm than 12.3 μm due to a larger absorption at 10.3 μm. This is opposite for clouds where 12.3 μm has a colder brightness temperature than 10.3 μm.





6) Future work

- Combine satellite, meteorological, and monitor data to create continuous, CONUS PM_{coarse} estimates.



- Determine how other PM_{coarse} aerosols (e.g. sea spray) behave at specific wavelengths of radiation.

7) References

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