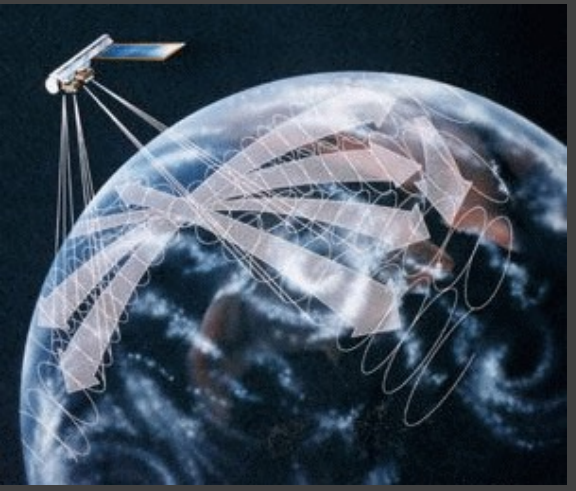

CERES Angular Distribution Model Working Group Report

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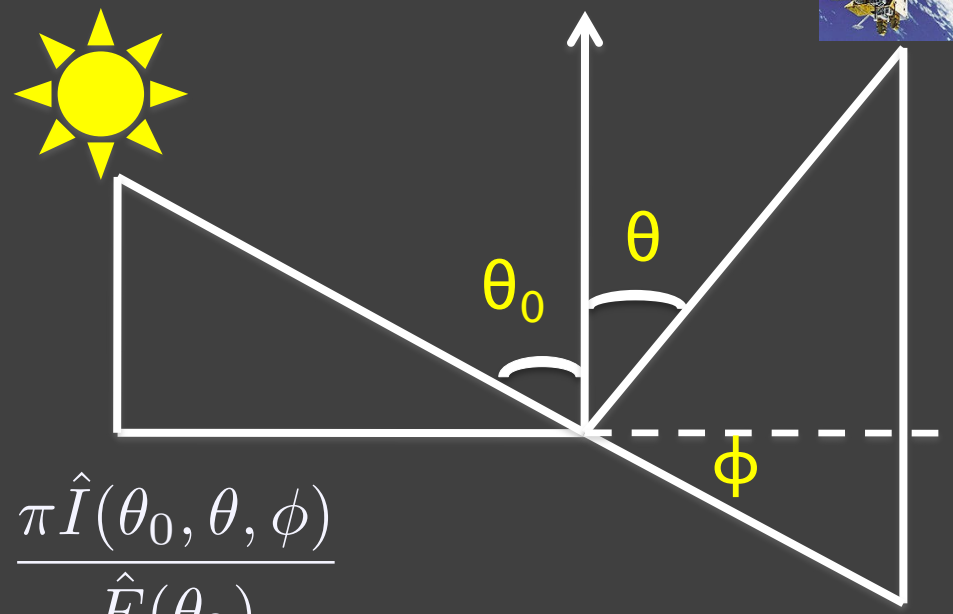
From radiance to flux: angular distribution models

- Sort observed radiances into angular bins over different <u>scene types</u>;
- Integrate radiance over all θ and ϕ to estimate the anisotropic factor for each scene type:



$$R(\theta_0,\theta,\phi) = \frac{\pi \hat{I}(\theta_0,\theta,\phi)}{\int_0^{2\pi}\int_0^{\frac{\pi}{2}} \hat{I}(\theta_0,\theta,\phi) cos\theta sin\theta d\theta d\phi} = \frac{\pi \hat{I}(\theta_0,\theta,\phi)}{\hat{F}(\theta_0)}$$

- For each radiance measurement, first determine the <u>scene type</u>, then apply scene type dependent anisotropic factor to observed radiance to derive TOA flux:

$$F(\theta_0) = \frac{\pi I_o(\theta_0,\theta,\phi)}{R(\theta_0,\theta,\phi)}$$

SW ADMs over different scene types

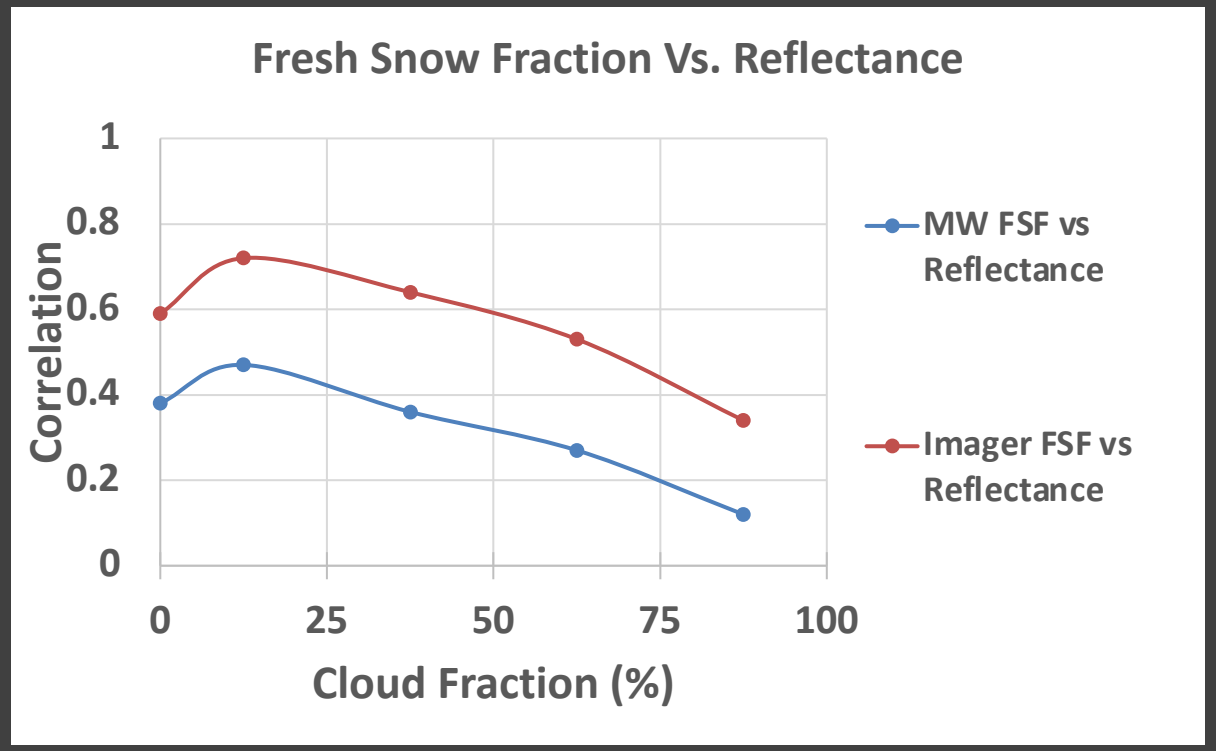
Scene	Ed4
Clear Land	1° regional monthly ADM using modified Ross-Li 3-parameter fit for different NDVI (0.1), cosθ (0.2), and surface roughness;
Clear Ocean	Function of wind speed, AOD, and aerosol type;
Cloud Ocean	Continuous 5-parameter sigmoid function of ln(fτ) for three phases;
Cloud Land	Continuous 5-parameter sigmoid function of ln(fτ) for three phases; background albedo from clear land;
Fresh Snow	Clear: 1° regional monthly ADM using Ross-Li 3-para fit for different NDVI (0.1), cosθ (0.2), and surface roughness;
	Cloudy: function of cloud fraction and snow fraction; for overcast consider surface brightness and cloud optical depth
Perm. Snow	Clear Antarctica: use MISR data to develop ADMs that account for the effect of sastrugi Clear Greenland: one ADM
	Partly cloudy: 4 cloud fraction bins
	Overcast: cloud phase (2), and log optical depth bin (4)
Sea ice	Clear: sea ice fraction (6), for 100% sea ice coverage use sea ice brightness index (3) to classify surface brightness
	Partly cloudy: cloud fraction (4), for 100% sea ice coverage use sea ice brightness index (3) to classify surface brightness
	Overcast: sea ice brightness index (5), phase (2), linear function of ln(tau)

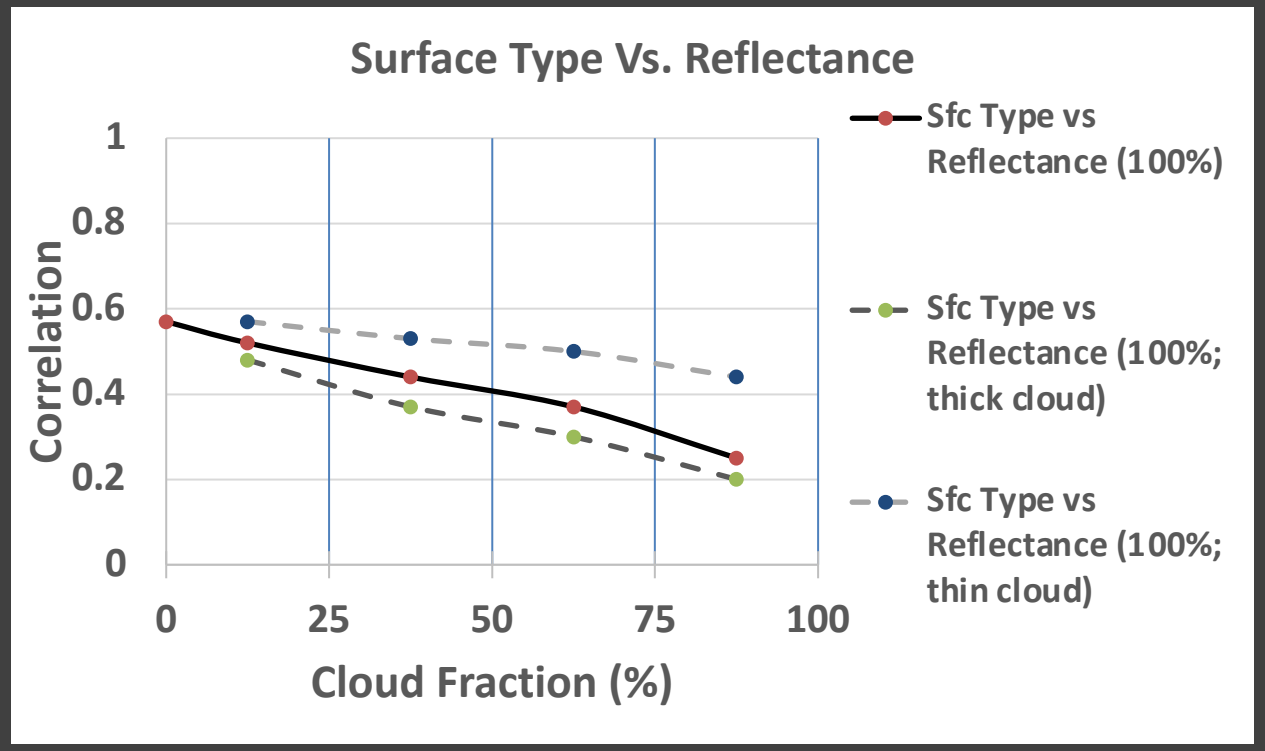
LW ADMs over different scene types

Scene	Ed4
Clear Ocean/Land	Discrete bins of precip. water, lapse rate, skin temp. for six surface types, with interpolation in skin temperature;
Cloudy Ocean/Land	Average radiance for each 1 W m^{-2} sr^{-1} pseudoradiance Ψ bin is used to estimate radiance at each VZA. Ψ is a function of surface skin temperature, surface emissivity, cloud top temp, and cloud emissivity. In addition, scenes are defined by intervals of precipitable water, cloud fraction, surface skin temperature, and surface-cloud top temperature difference;
Fresh Snow	Clr: Discrete bins of skin temperature, with interpolation in skin temperature;
	Cld: Similar to Cloudy Ocean/Land, but no precipitable water categories;
Permanent Snow	Clr: Discrete bins of skin temperature, with interpolation in skin temperature;
	Cld: Similar to Cloudy Ocean/Land, but no precipitable water categories;
Sea-Ice	Clr: Discrete bins of skin temperature, with interpolation in skin temperature;
	Cld: Similar to Cloudy Ocean/Land, but no precipitable water categories.

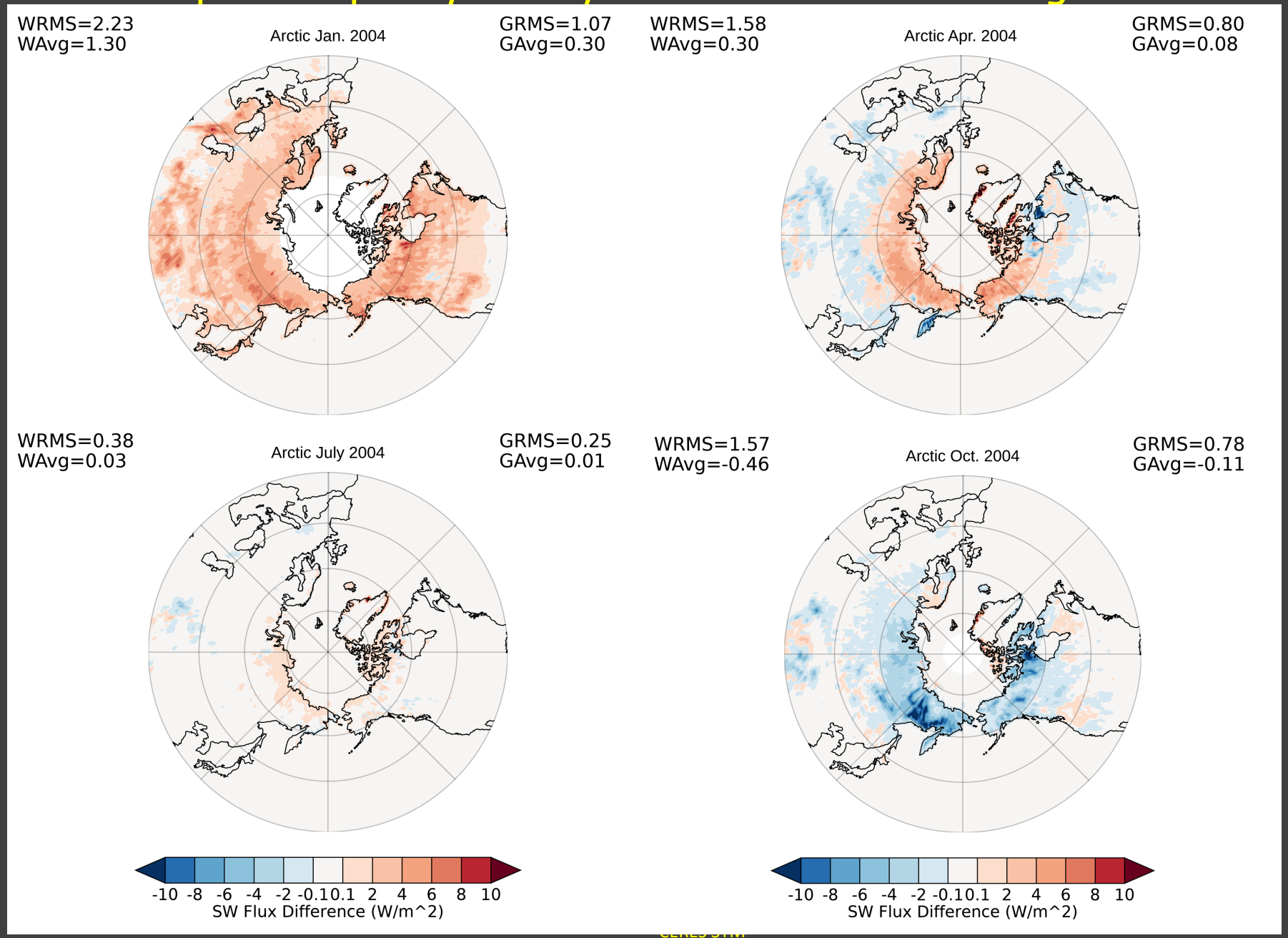
Partly cloudy fresh snow ADMs

- Ed4: ADMs are derived for discrete intervals of cloud fraction and snow fraction.
- Proposed Ed5:
  - Using imager-based fresh snow fraction, and assuming snow coverage under clouds is the same as cloud-free portion of the footprint
  - Adding dependency on surface type when fresh snow fraction equals 100%
  - Adding dependency on cloud thickness when cloud fraction is greater than 50%
- New ADMs increase flux consistency by ~3.5% for partly cloudy fresh snow scenes.





Impact of partly cloudy fresh-snow ADM change on fluxes

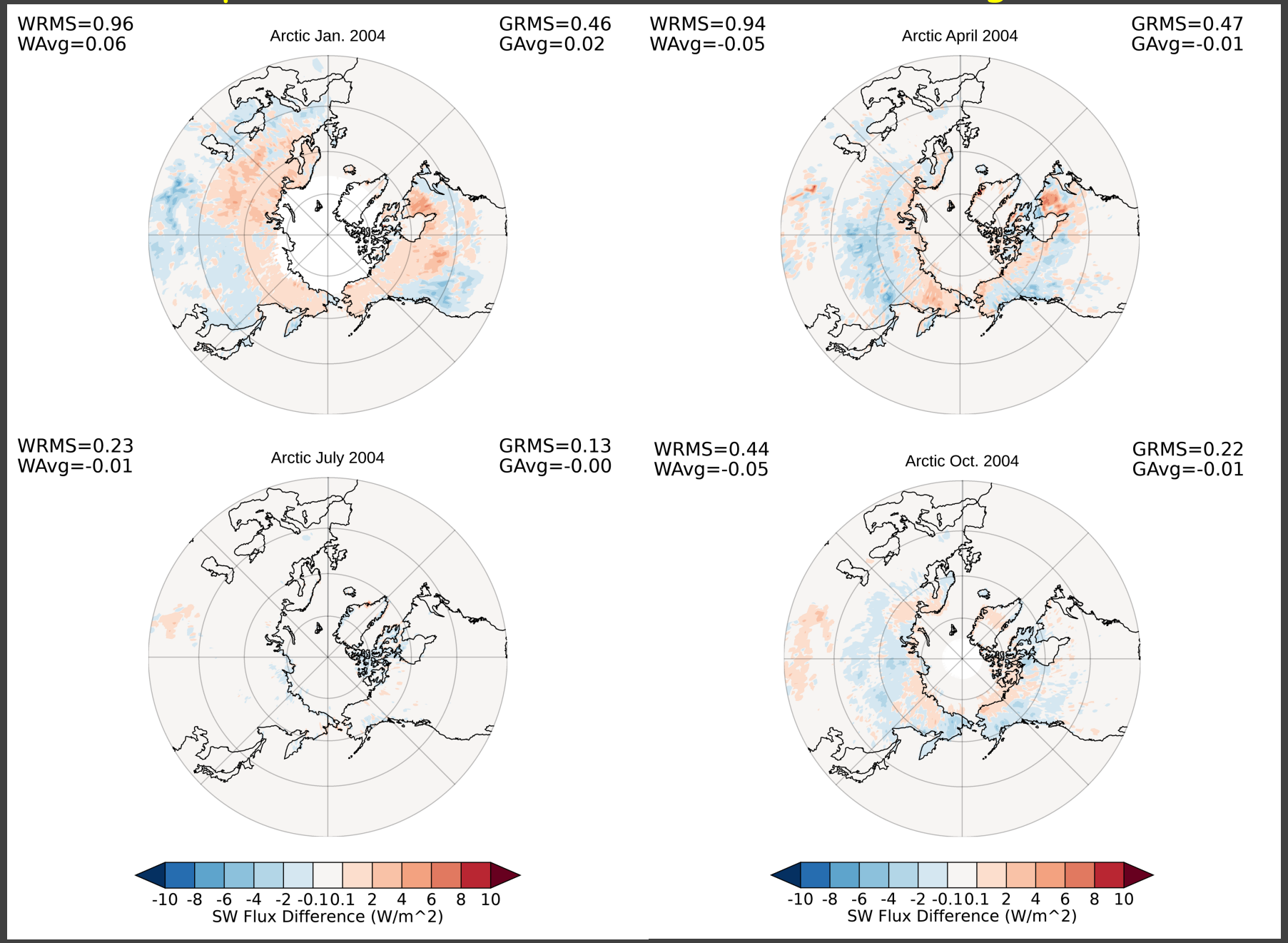


WAvg = Arctic Avg
WRMS = Arctic RMS
GAvg = Global Avg
GRMS = Global RMS

Overcast fresh snow ADMs

- Ed4: Overcast ADMs are derived separately for bright and dark surfaces and for thin (tau<10) and thick (tau>10) clouds.
- Proposed Ed5 ADMs are constructed for:
  - 4 surface type categories: low-to-mod tree shrub, mod-to-high tree shrub, dark desert, bright desert
  - 6 log(tau) bins
  - 2 cloud phase
- New ADMs increase flux consistency by ~1.7% for overcast fresh snow scenes.

Impact of overcast fresh-snow ADM change on fluxes



WAvg = Arctic Avg
WRMS = Arctic RMS
GAvg = Global Avg
GRMS = Global RMS

How resilient are ADMs to climate variability and change

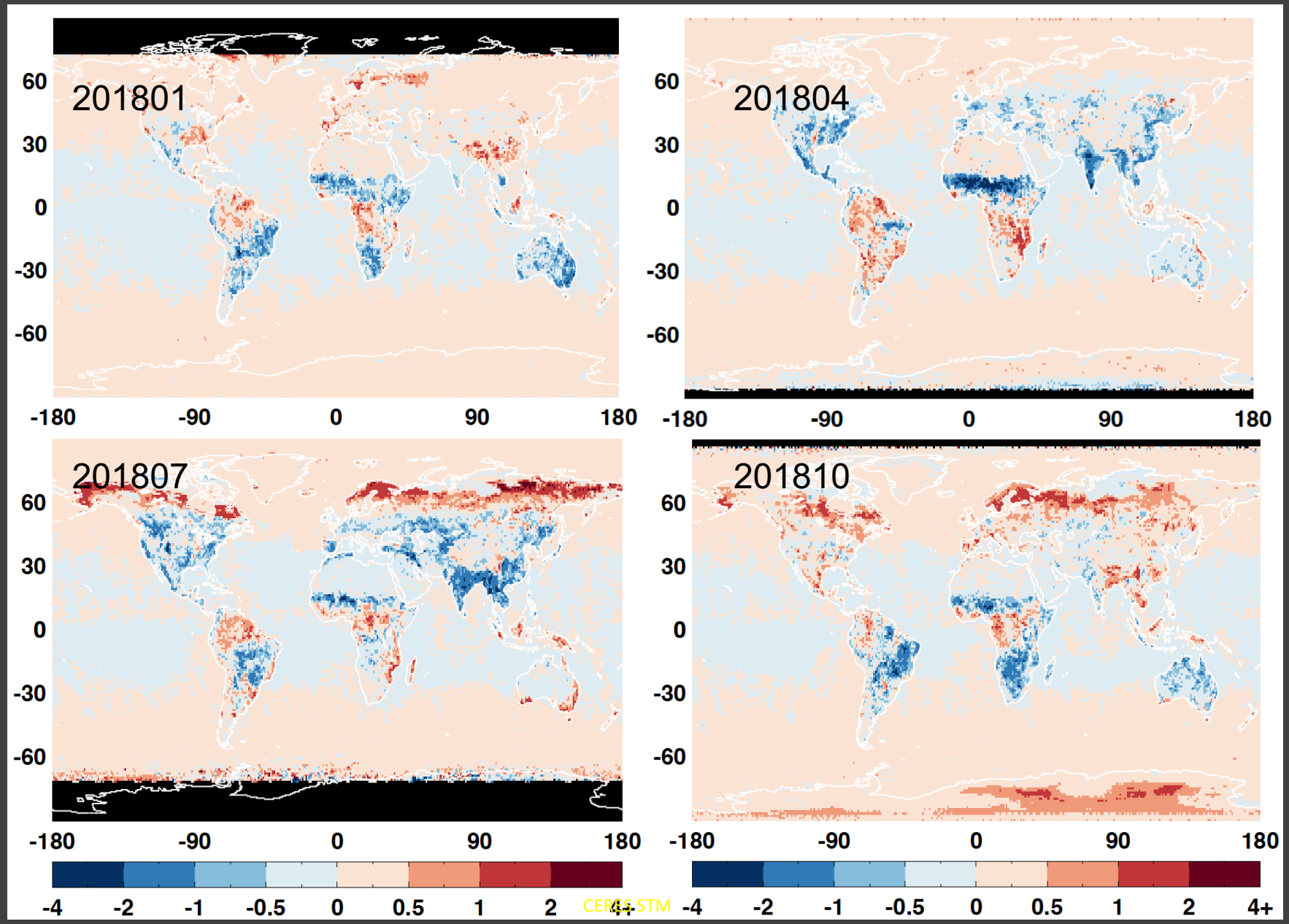
- As climate change and the mean climate state shifts, can the ADMs constructed using data taking in the early 2000s be used for flux inversion now and in the coming decades?
- Using data taken during different phase of ENSO to test LW ADM sensitivity to climate variability:
  - Used the NOAA Physical Sciences Laboratory Multivariate ENSO Index (MEI) v2 to characterize ENSO phase.
  - Used 36 cool (MEI < 0) cross-track months and the 12 coolest (MEI < 0.14) RAPS months to construct clear- and cloudy-sky LW ADMs, called "La Niña ADMs".
- The Ed4 inversion code was run with these La Niña ADMs and the fluxes were compared with those on the SSF.
- Note that most of the RAPS period was in warm ENSO conditions, so if ENSO has a large impact, it should show up here.

Daytime LW fluxes (La Niña- SSF)
Global average differences

	All-sky bias ($W\ m^{-2}$, %)	All-sky RMS	Clear-sky bias	Clear-sky RMS
201801	-0.03 (-0.01%)	1.20 (0.50%)	0.01 (~0.00%)	0.45 (0.16%)
201804	0.01 (~0.00%)	1.30 (0.54%)	0.08 (0.03%)	0.39 (0.14%)
201807	-0.01 (~0.00%)	1.38 (0.55%)	0.08 (0.03%)	0.44 (0.15%)
201810	-0.03 (-0.01%)	1.30 (0.53%)	0.04 (0.01%)	0.43 (0.16%)

Biases and RMS Differences are calculated by averaging all flux differences within each grid cell when both the SSF and La Niña fluxes are valid. Both clear-sky and all-sky fluxes are very close on average, and the RMS differences are within roughly 1.4 $W\ m^{-2}$. Note that 2018 went from cool ENSO conditions (Jan and Apr) to roughly neutral conditions (Jul) to warm conditions (October).

Daytime LW flux difference (La Niña– SSF)
Use footprints that both sets of ADMs produce valid fluxes



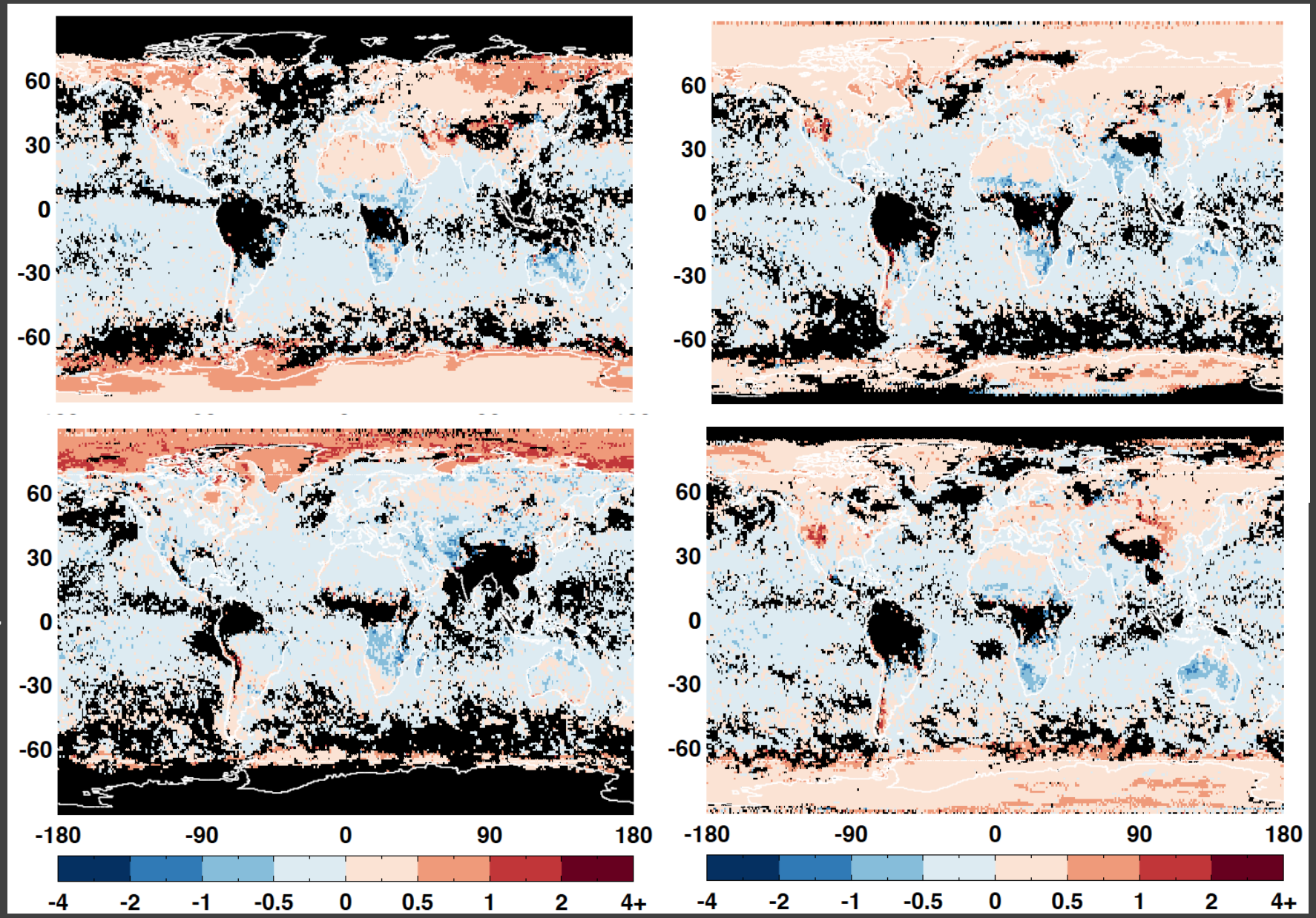
Daytime clear-sky LW fluxes difference (La Niña-SSF)

201801

201804

201807

201810



Surface emissivity

- The LW emissivity is an input for the cloudy-sky LW ADMs, which are most scenes.
- For Edition 4 and earlier editions, a single value of emissivity was assigned to each IGBP type for both the LW and WN channels.
- With Edition 5, we will use 10-year climatology of surface emissivity based on IASI hyperspectral data (Zhou et al. 2011, 2013), which will allow for the emissivity to change with season and vary within each IGBP type. This is especially important for arid and semi-arid land areas.

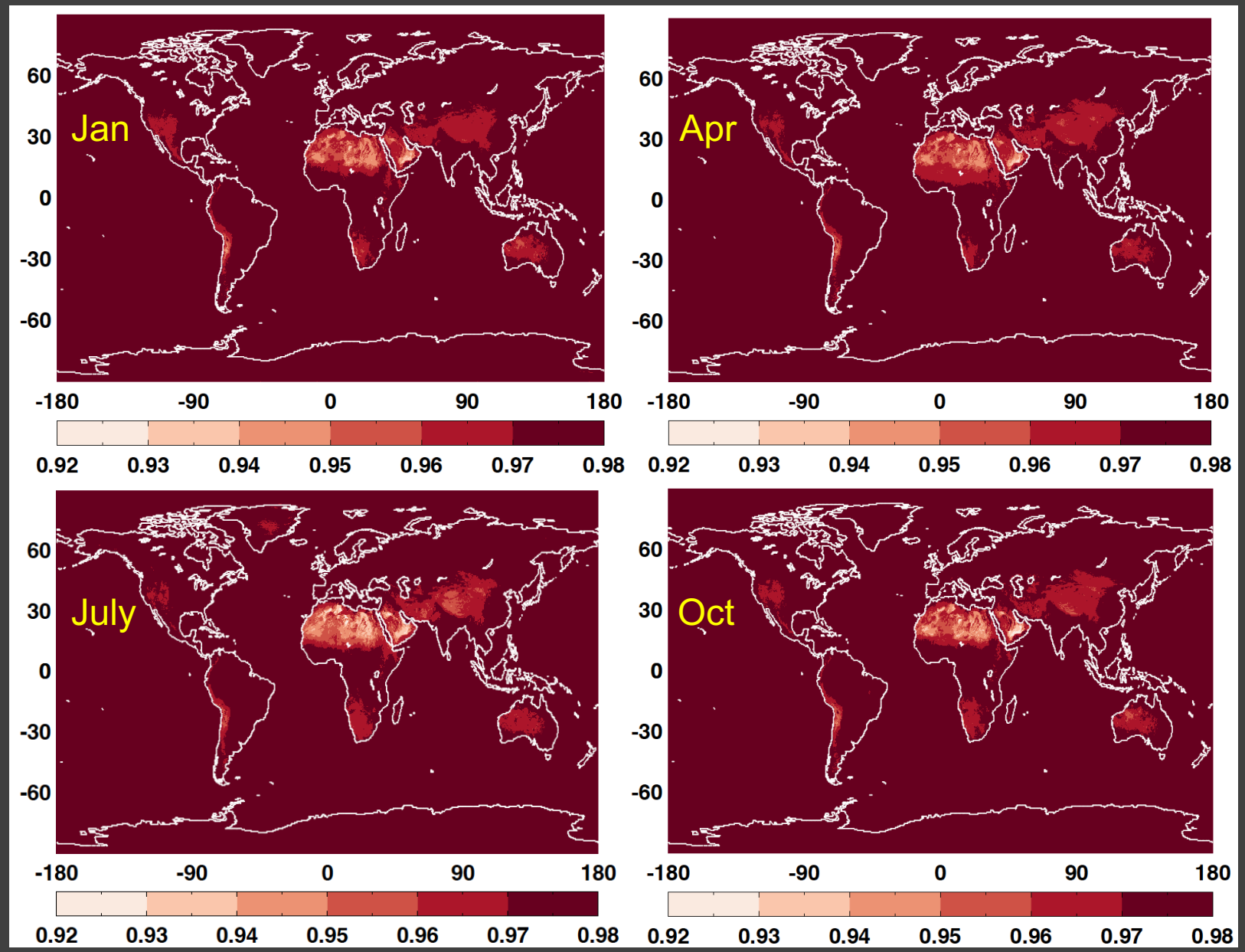
Surface emissivity

- The Zhou 10-year climatology of surface emissivity based on IASI hyperspectral data gives monthly 0.25° x 0.25° values of emissivity at 0.25 cm^{-1} resolution from 645 cm^{-1} to 2760 cm^{-1}. This was converted to LW channel emissivity by first calculating average emissivity over the 12 Fu-Liou bands, and then averaging the band averages over the LW, using a weighting factor:

$$wf_i = \frac{\int_{\omega_{(i,\,lower)}}^{\omega_{(i,\,upper)}} B_\omega \, d\omega}{\int_0^{2200} B_\omega \, d\omega},$$

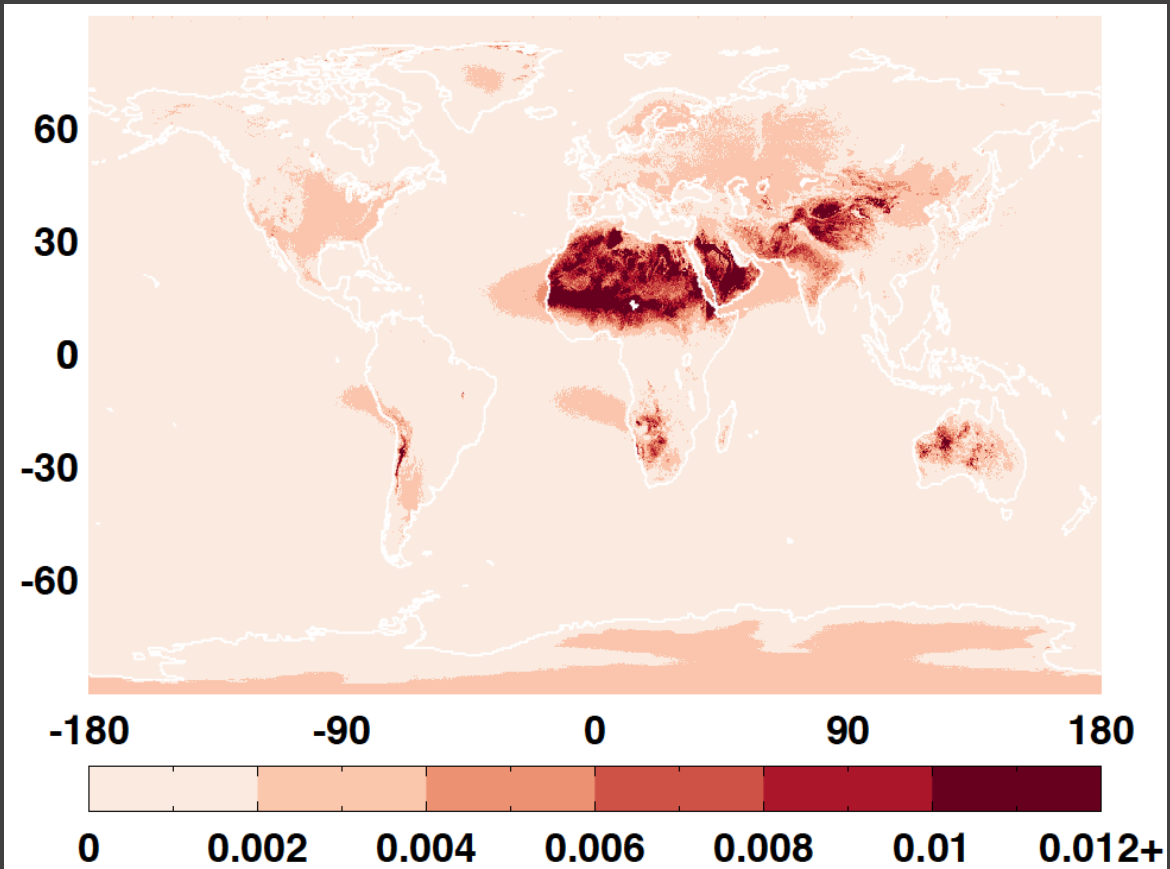
$$\varepsilon_{bb} = \sum_{i=1}^{i=12} wf_i \varepsilon_i .$$

LW emissivity from IASI

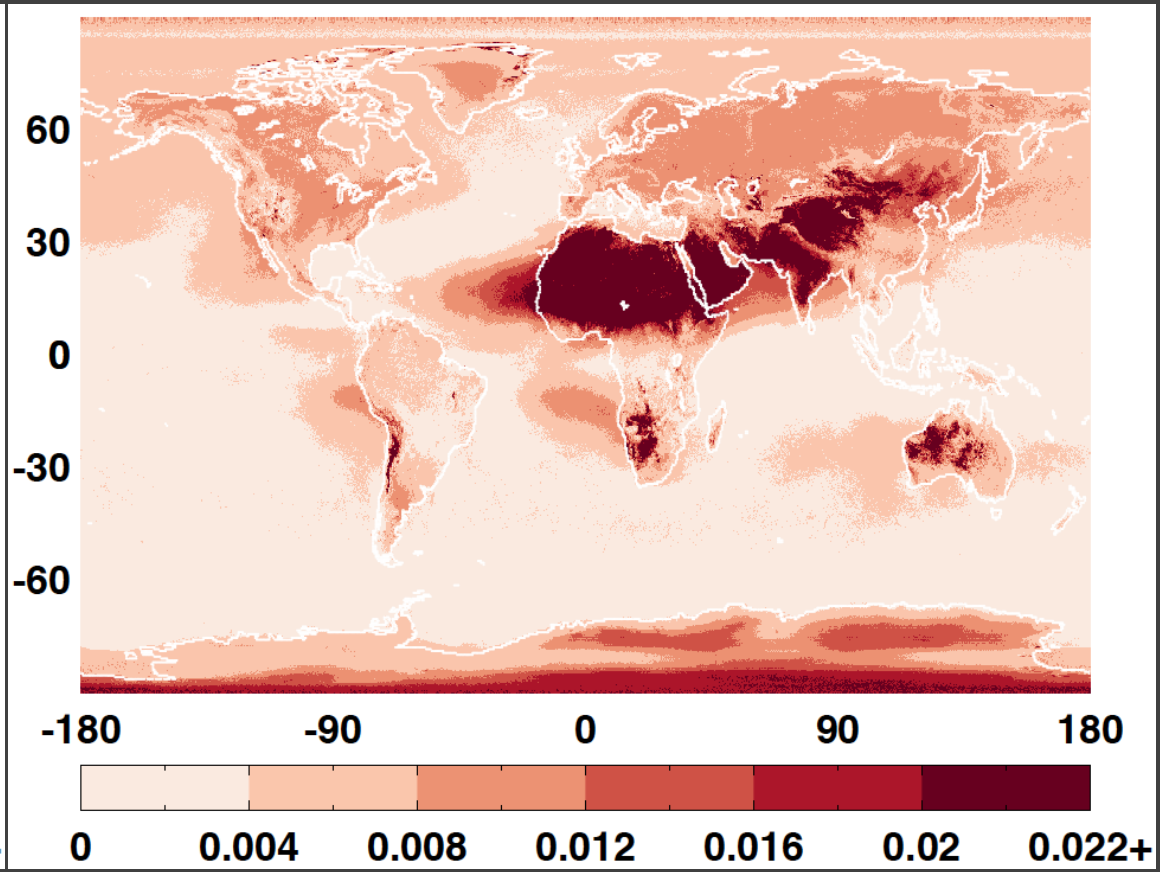


Maximum seasonal difference in LW and WN emissivity

LW

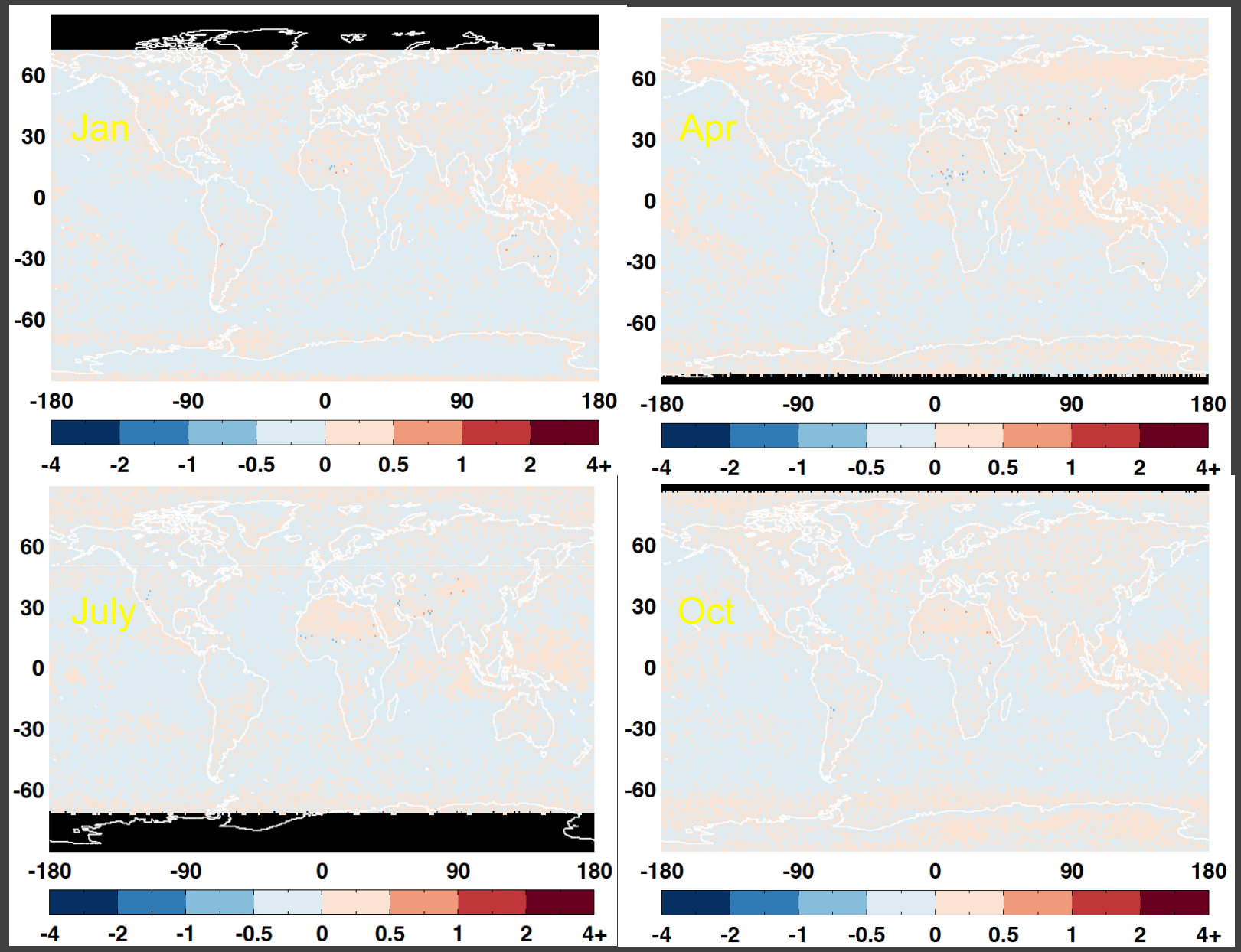


WN



(Note scale change)

Impact of changed LW emissivity on LW fluxes (new emissivity – SSF)



Summary

- Proposed cloudy fresh-snow ADMs adding surface type and cloud properties for scene classification increase flux consistency by 3.5% for partly cloudy skies and by 1.7% for overcast skies.
- RMS error of LW flux using ADMs developed with data taken during La Niña and El Niño phase is equivalent to LW ADM uncertainty, indicating small sensitivity of LW ADMs to climate variability.
- Developed monthly surface LW and WN emissivity based on IASI spectral emissivity. Large seasonal variability is observed over arid and semi-arid regions. From a preliminary experiment, it appears that the impact on LW flux is small on both the global and regional scale.

Daytime LW fluxes (La Niña - SSF)
Global average differences

	All-sky bias ($W\ m^{-2}$, %)	All-sky RMS	Clear-sky bias	Clear-sky RMS
201801	-0.02 (-0.01%)	0.97 (0.40%)	0.05 (0.02%)	0.40 (0.15%)
201804	-0.01 (-0.01%)	1.01 (0.41%)	0.09 (0.03%)	0.36 (0.13%)
201807	0.01 (<0.01%)	1.01 (0.40%)	0.13 (0.04%)	0.40 (0.14%)
201810	-0.02 (-0.01%)	0.97 (0.39%)	0.08 (0.03%)	0.37 (0.14%)

Biases and RMS Differences are calculated by averaging all flux differences within each grid cell when both the SSF and La Niña fluxes are valid and not produced by neural networks, and then area-weighting grid cells with valid differences. Both clear-sky and all-sky fluxes are very close on average, and the RMS differences are within roughly 1 $W\ m^{-2}$. Note that 2018 went from cool ENSO conditions (Jan and Apr) to roughly neutral conditions (Jul) to warm conditions (October).

Daytime LW flux difference (La Niña– SSF)
Use footprints that both sets of ADMs produce non-ANN-based fluxes