Snow: Dataset development, NWS products evaluations, and its impact on CFS subseasonal to seasonal prediction

Xubin Zeng, Patrick Broxton, and Nick Dawson
University of Arizona

2 Mar 2017
NCEP/EMC
College Park, Maryland

THE UNIVERSITY OF ARIZONA

Outline

1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

UA model parameterizations and global datasets

EMC (implemented):
ocean surface turbulence (Zeng et al. 1998)
Noah land skin temperature (Zeng et al. 2012)

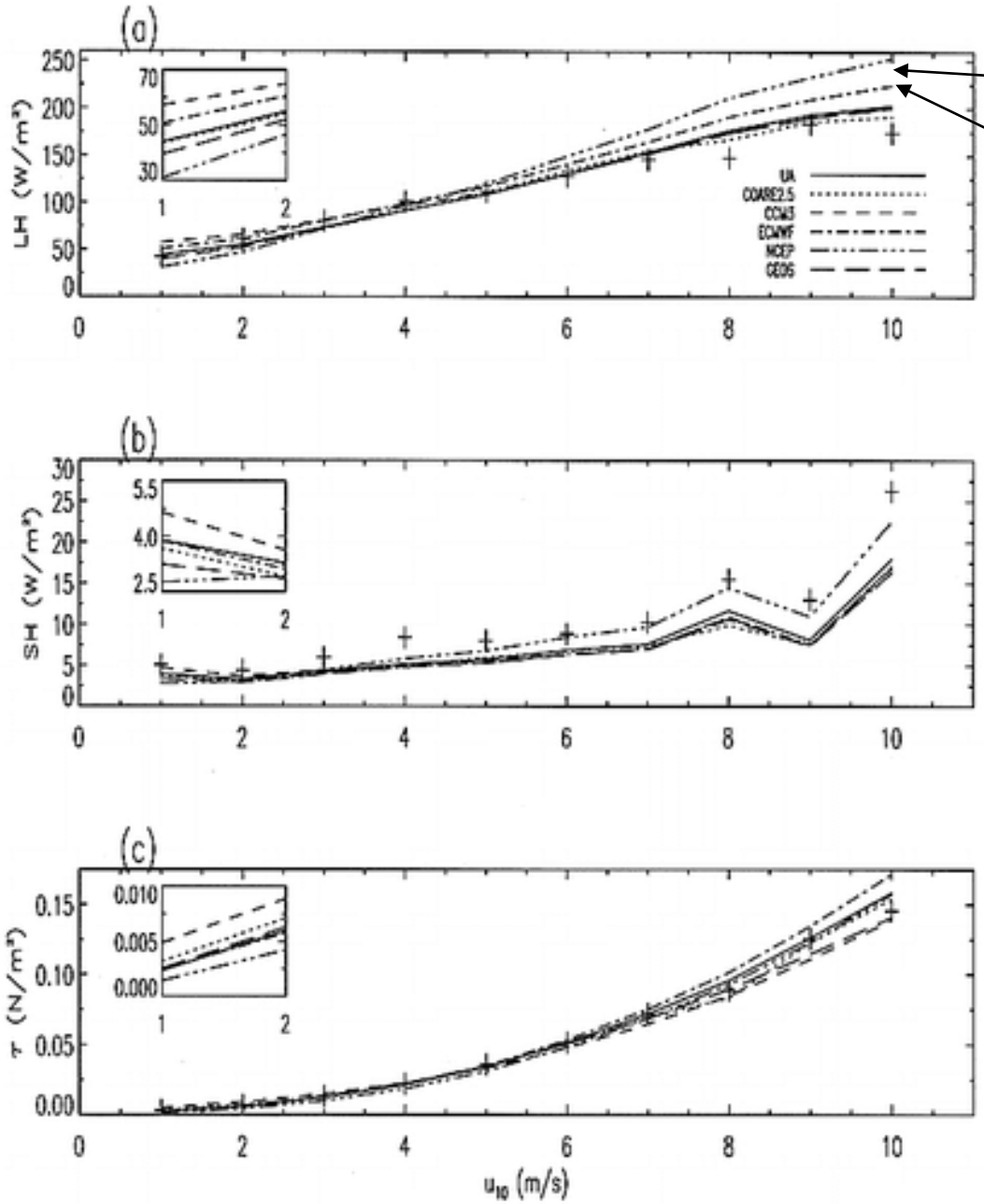
EMC (fully tested for implementation; but not yet):
Max snow albedo data (Barlage et al. 2005)
Noah snow model improvement (Wang et al. 2010)

CPC (scientists there informed):
Seasonal hurricane activity forecast (Davis et al. 2015)

ECMWF (implemented):
Ocean surface turbulence; vegetation root distribution data; ocean skin temperature

NCAR CESM (implemented):
Community Land Model; sea ice surface turbulence; soil moisture equation; dynamic vegetation; bedrock depth data

R2O success #1: Ocean Surface Fluxes



NCEP

ECMWF

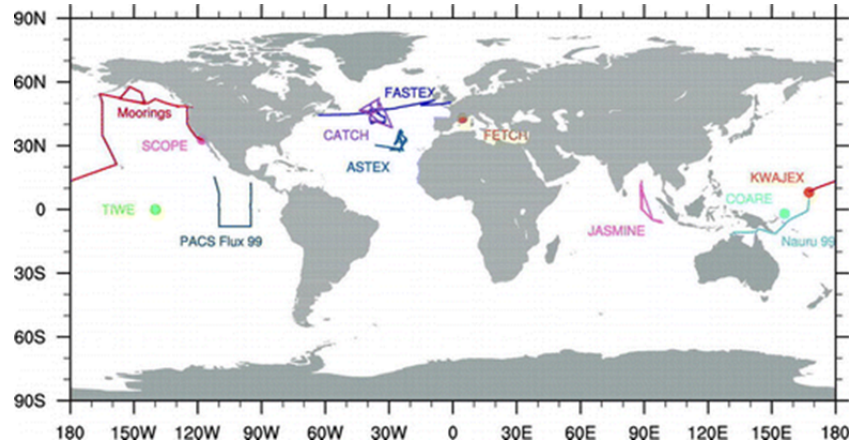
TOGA COARE Data (+)

Direct test of turbulence algorithms from NCEP, ECMWF, NCAR, GMAO, and the COARE and our UA algorithms

Zeng et al. (1998)

$$\overline{F_{prod} - F_{obs}} = \overline{F_{prod} - F_{algor}} - \overline{F_{algor} - F_{obs}}$$

Total bias | **Bulk variable uncert.** | **Residual uncert.** *includes algorithm uncert.*



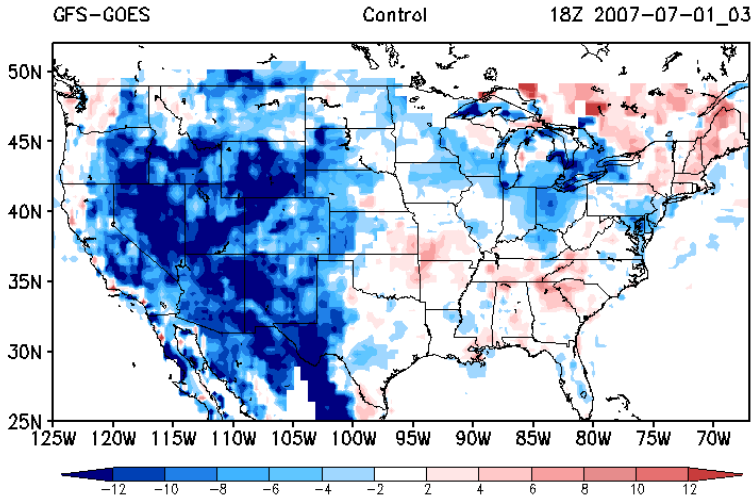
Product	Total bias	Bulk variable uncertainty	Residual uncertainty
LH flux (W m^{-2})			
NCEP/NCAR	11.2	-13.4	24.5
CFSR	19.3	8.2	11.0
SH flux (W m^{-2})			
NCEP-NCAR	6.0	-9.0	15.0
CFSR	-0.3	-12.0	11.7
Wind stress (10^{-3} N m^{-2})			
NCEP-NCAR	-7.6	-3.7	-3.9
CFSR	4.8	8.2	-3.5

CFSR residual uncertainty is reduced from earlier NCEP-NCAR reanalysis, due to the implementation of the UA algorithm.

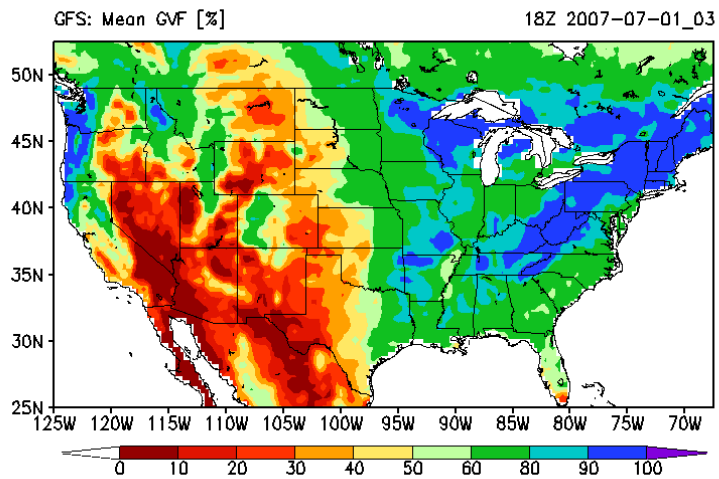
Brunke et al. (2011)

R2O success #2: Land Skin Temperature

July 2007



Land Skin T Diff



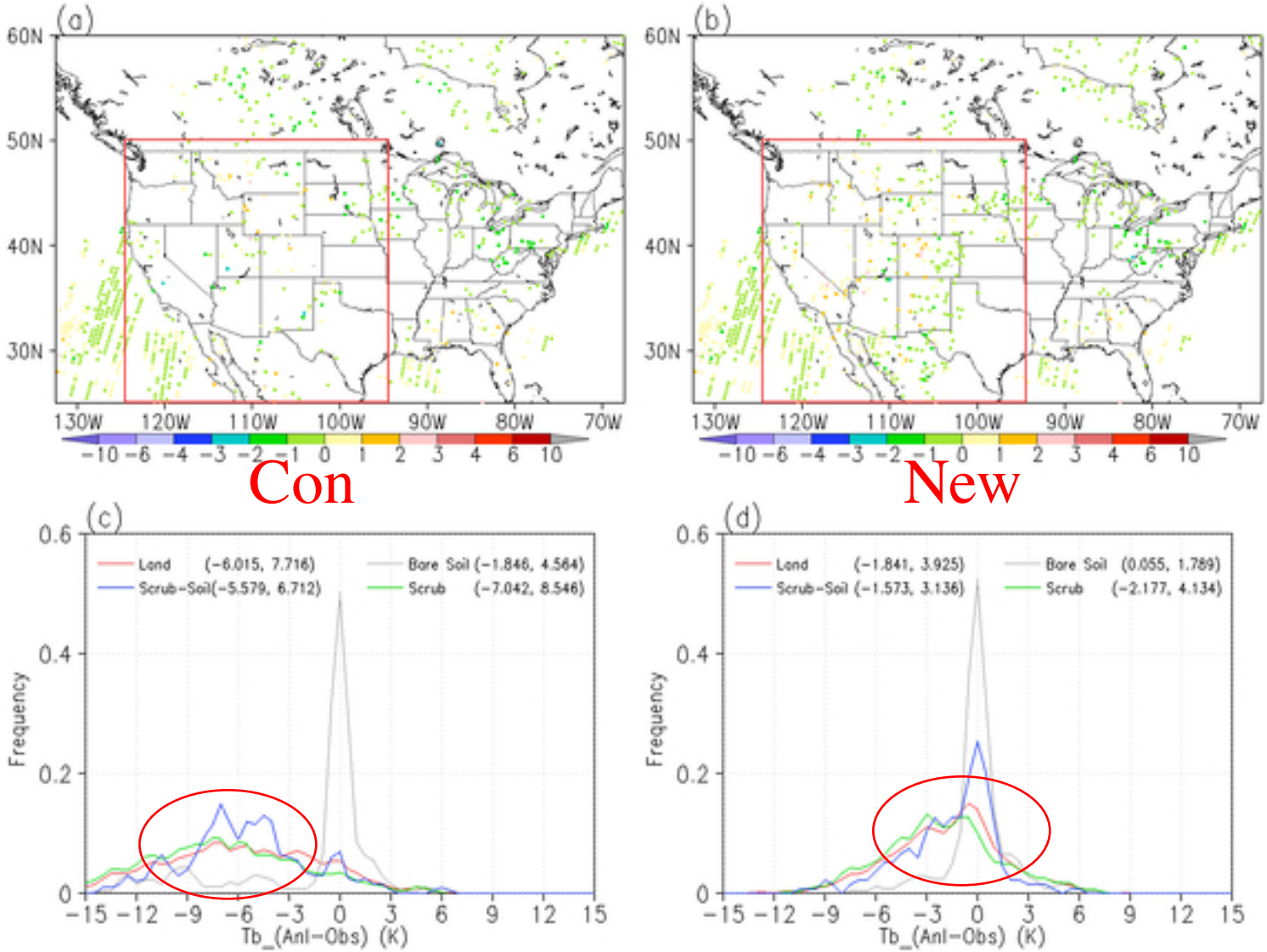
Green Vegetation Fraction

Zheng and Mitchell (2008)

Mean absolute error (K)

	Desert Rock Nevada	Gaize Tibet, China
Noah (Con)	2.8	5.8
Noah (New)	0.5	1.6
CLM (Con)	1.9	4.6
CLM (New)	0.7	1.8

Zeng et al. (2012)



Tb bias in satellite pixels used in GFS GSI (NOAA-17 HIRS-3 Ch. 8) (Zheng et al. 2012)

Similar improvements for NOAA-18 AMSU-A Ch.15

Outline

1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

Motivation for Snow Study

Snow affects the energy cycle (via albedo), water cycle (via snowmelt), and land-atmosphere coupling (via insulation of ground).

Snow cover is relatively easy to measure from space, and several global datasets exist; e.g., NESDIS/IMS, MODIS, Rutgers Univ

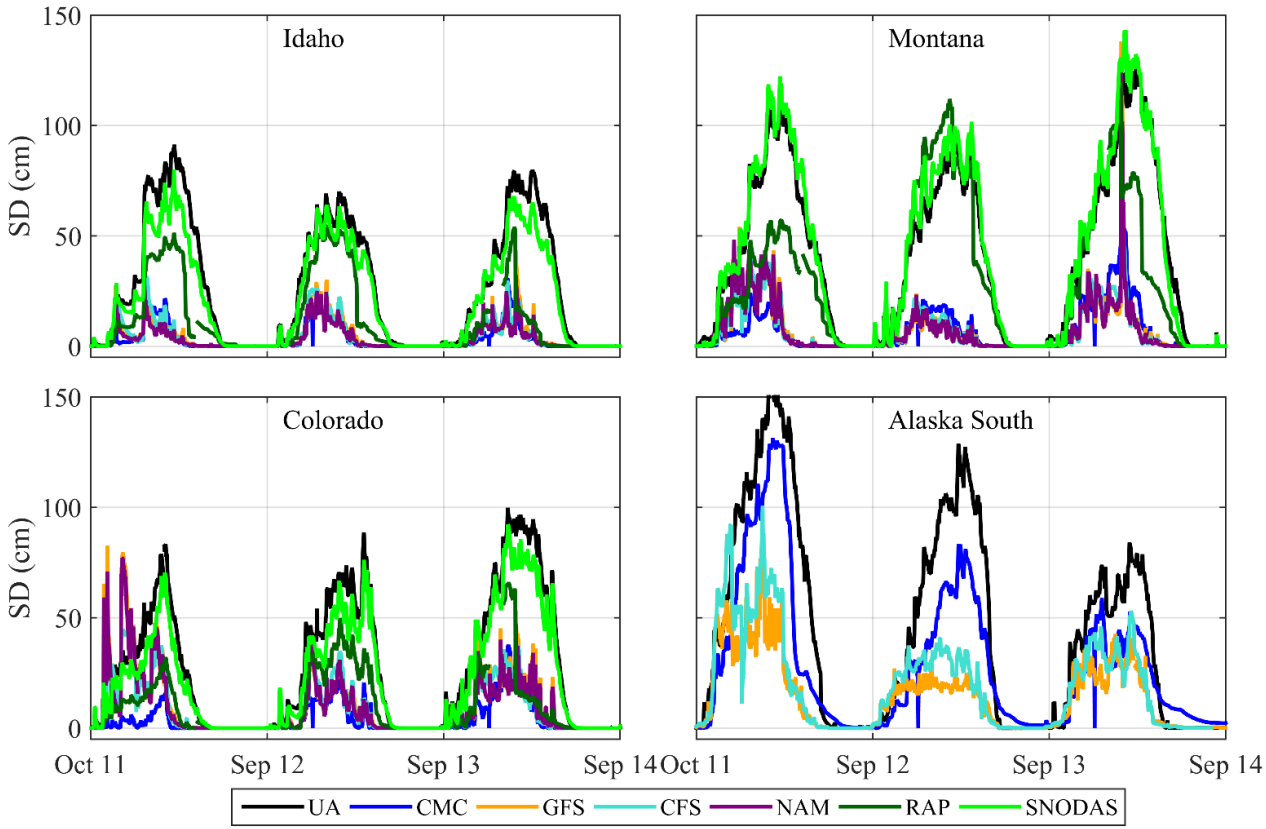
Snow water equivalent (SWE) and snow depth are much more challenging to measure from space or to upscale from in situ point measurements to area averages. But many datasets have also been produced; e.g.,

- Operational analysis, re-analysis, GLDAS, satellite (e.g., AMSR-E)
- Surface-based and satellite merged product,
- Merged product based on the above datasets

Q: How good are these SWE and snow depth products?

Q: How good are NCEP snow depth initializations?

Dawson et al. (2016)

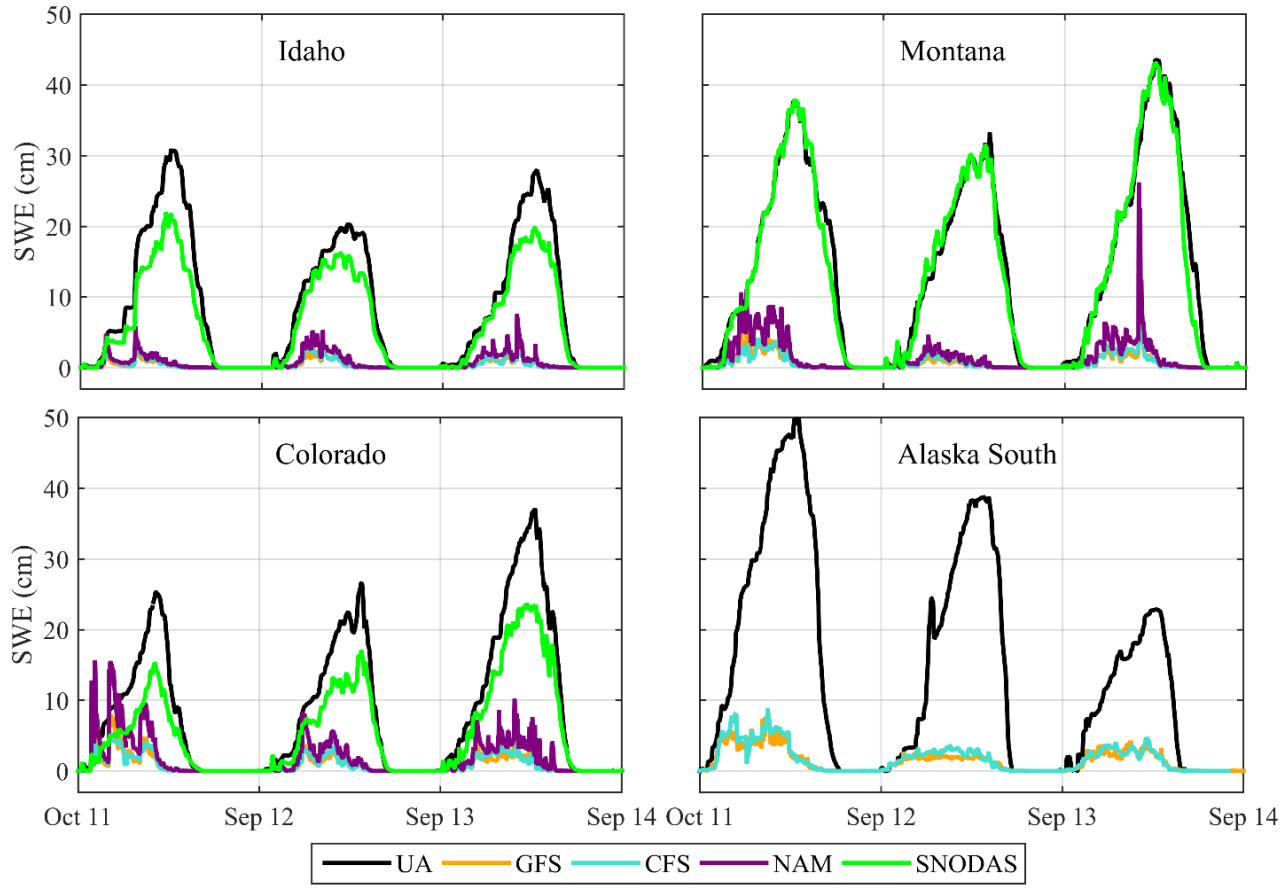


Deficiency: Snow depth (SD) initializations for GFS, CFS, and NAM are 77% below upscaled SD (UA) on average.

Reason: based on the poor AFWA snow depth analysis

Solution: develop a better snow depth data

Q: How good are NCEP SWE initializations?



Deficiency: SWE initialization is even worse than snow depth

Reason: use of constant snow density or very simple treatment

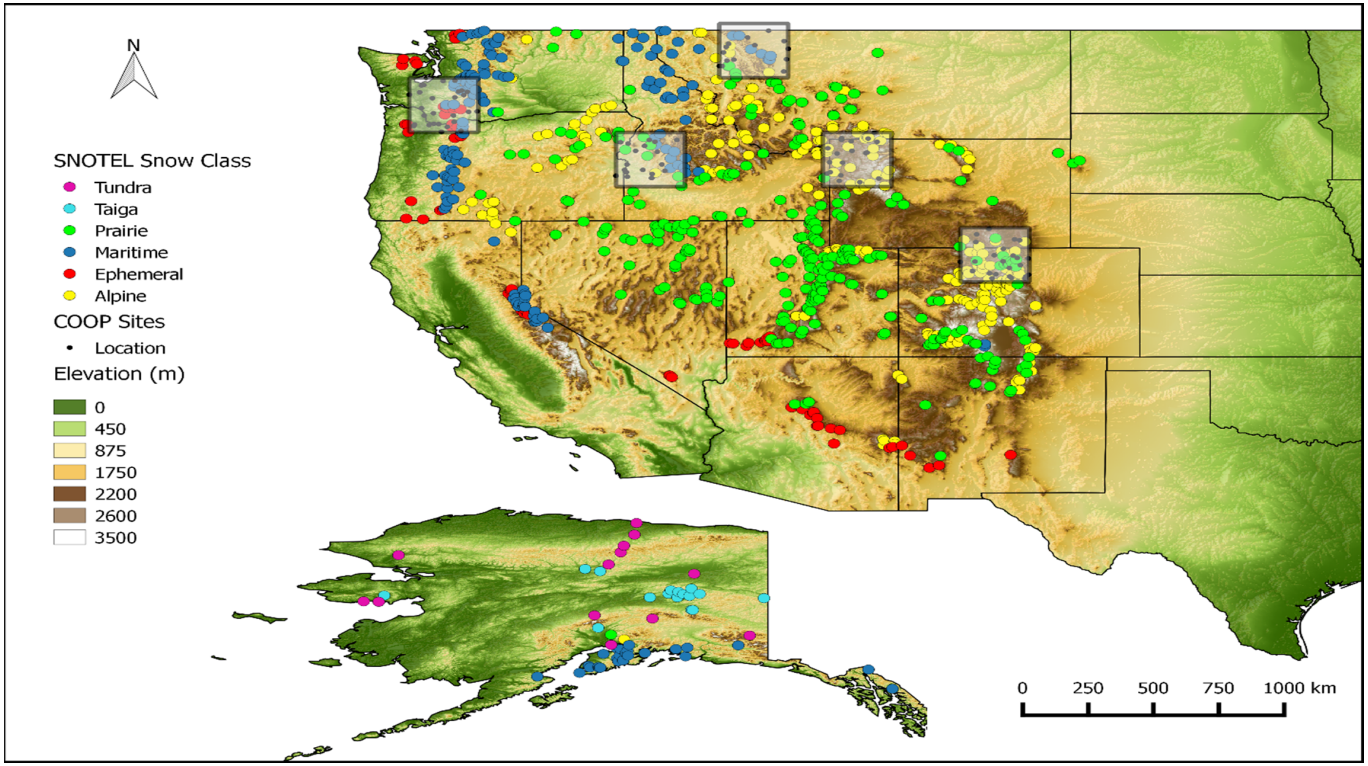
Solution: develop a better snow density parameterization

Better solution: develop consistent SWE and snow depth data

Outline

1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

A new snow density model (SNODEN)



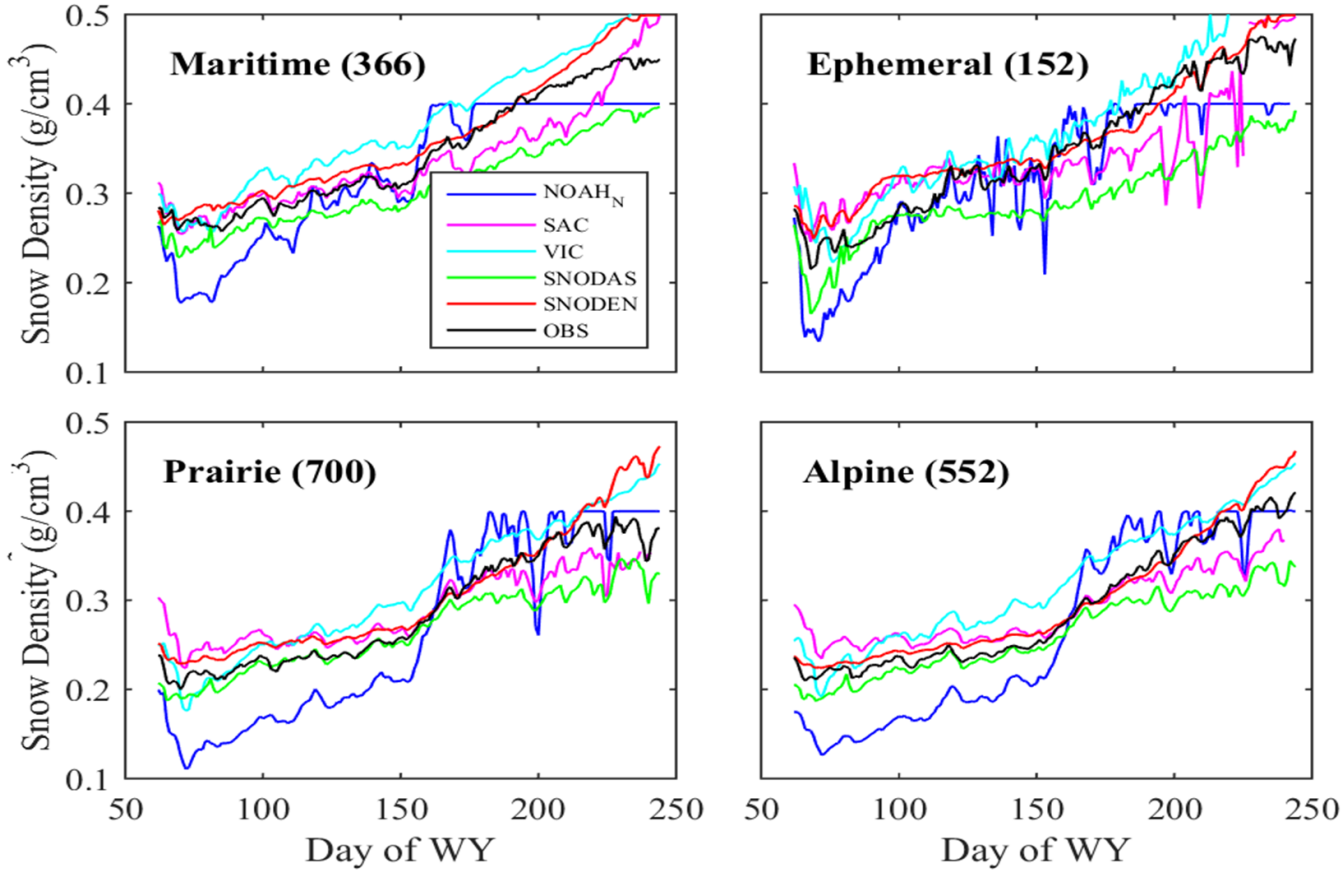
- Include up to 10 snow layers
- Driven by daily snowfall and T_{2m}
- Consider overburden and destructive metamorphism
- Consider melting pond
- Consider six snow classes

Dawson et al. (2017a)

snow density comparison

Using SNOTEL snow density to evaluate NLDAS values.

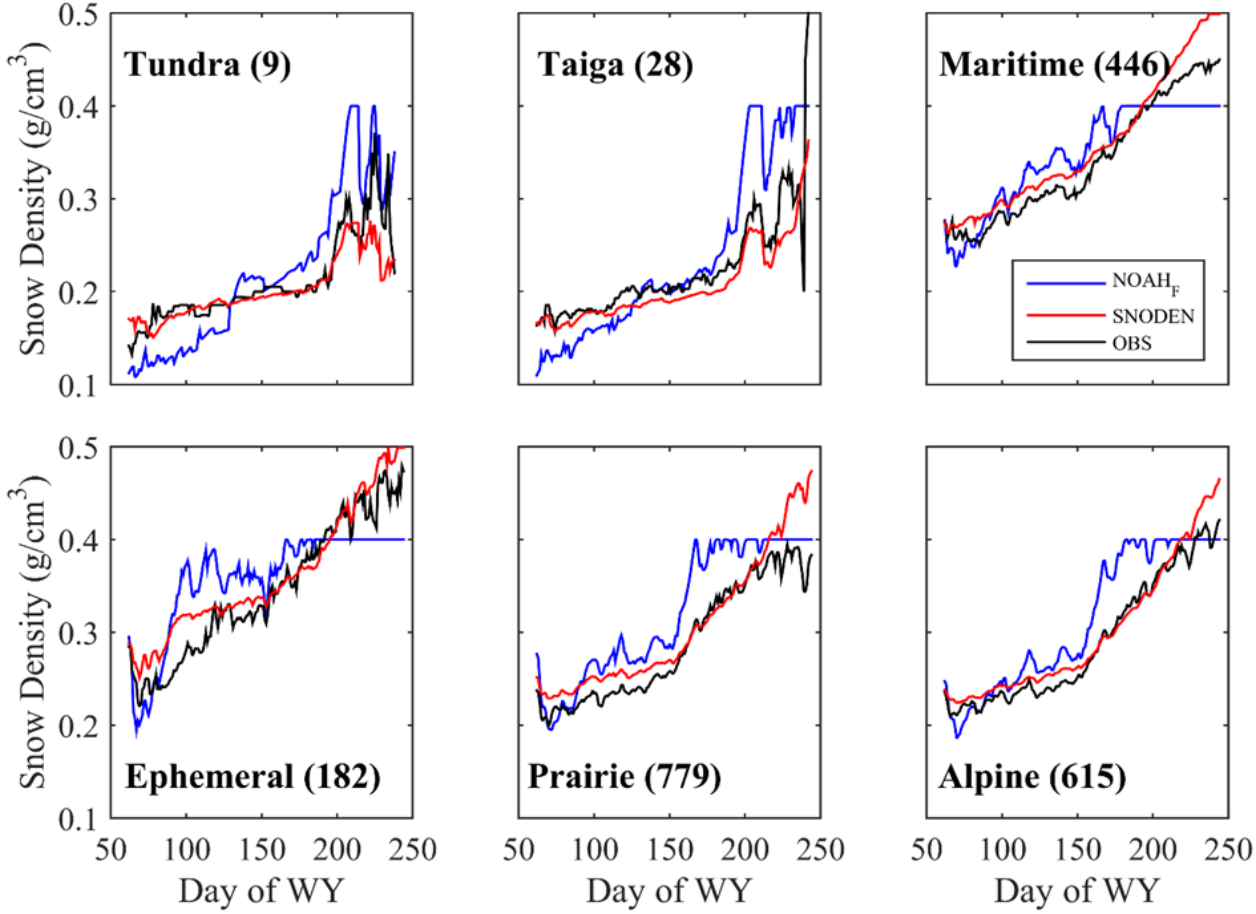
Our SNODEN performs best



12/1 5/31

NCEP Noah underestimates snow density early in the season but overestimates it later in the season

SNODEN compared to Noah formulation directly



Noah$_F$ and SNODEN are forced with identical SNOTEL T_{2m} and SWE.

Our SNODEN still performs better

Outline

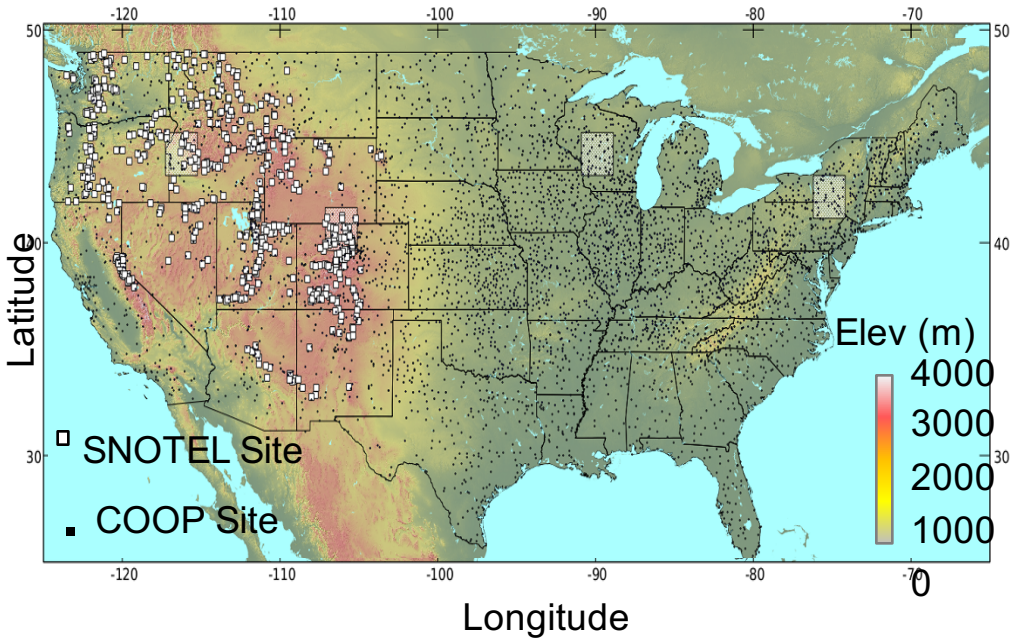
1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

Q: What are the “ground truth” data to evaluate these gridded products?

a) Surface networks with dense measurement sites over some regions:

- hundreds of SNOTEL sites: SWE and snow depth data;
- thousands of NWS COOP stations: snow depth data

Site representativeness is a concern



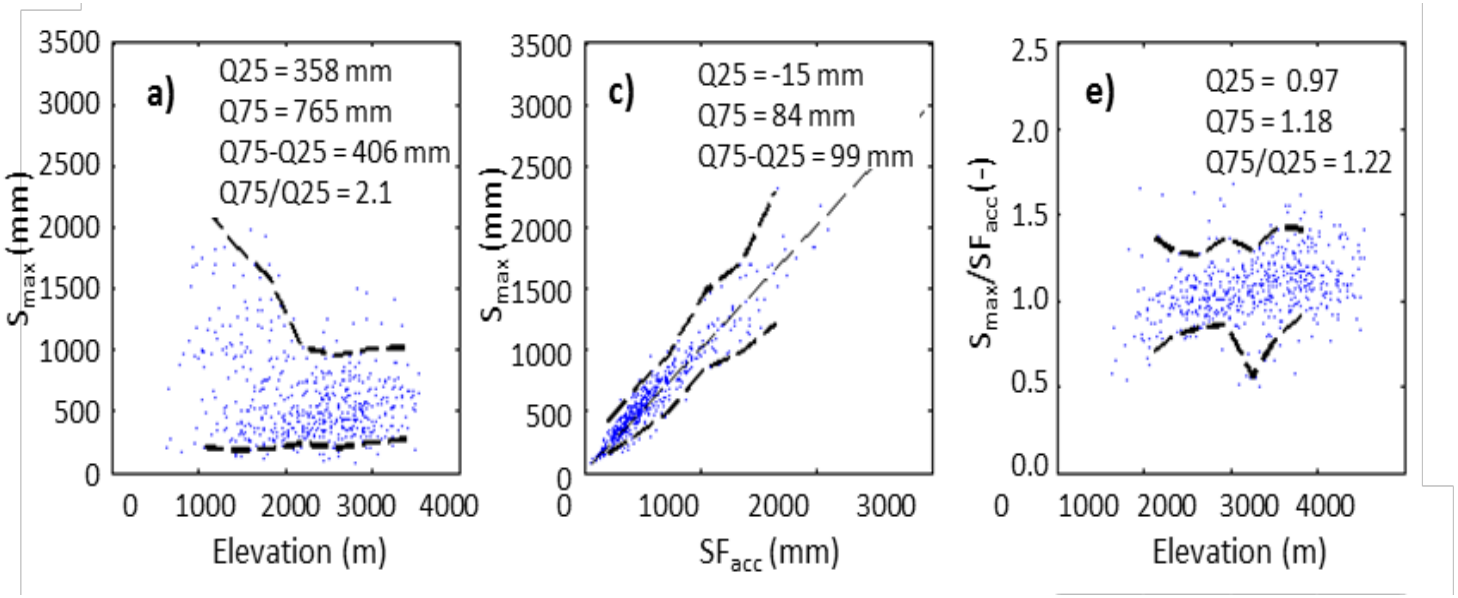
b) Airborne data: areas and periods are limited; airborne data themselves need to be calibrated

c) River discharge: integrated assessment; discharge is affected by other processes (e.g., rainfall, ET)

d) Satellite passive microwave (e.g., AMSR-E): provide global coverage; SWE retrieval has several deficiencies

Q: How do we upscale from in situ point measurements to area averages?

Step 1: compute the ratio of SWE over (accumulated snowfall minus snow ablation)



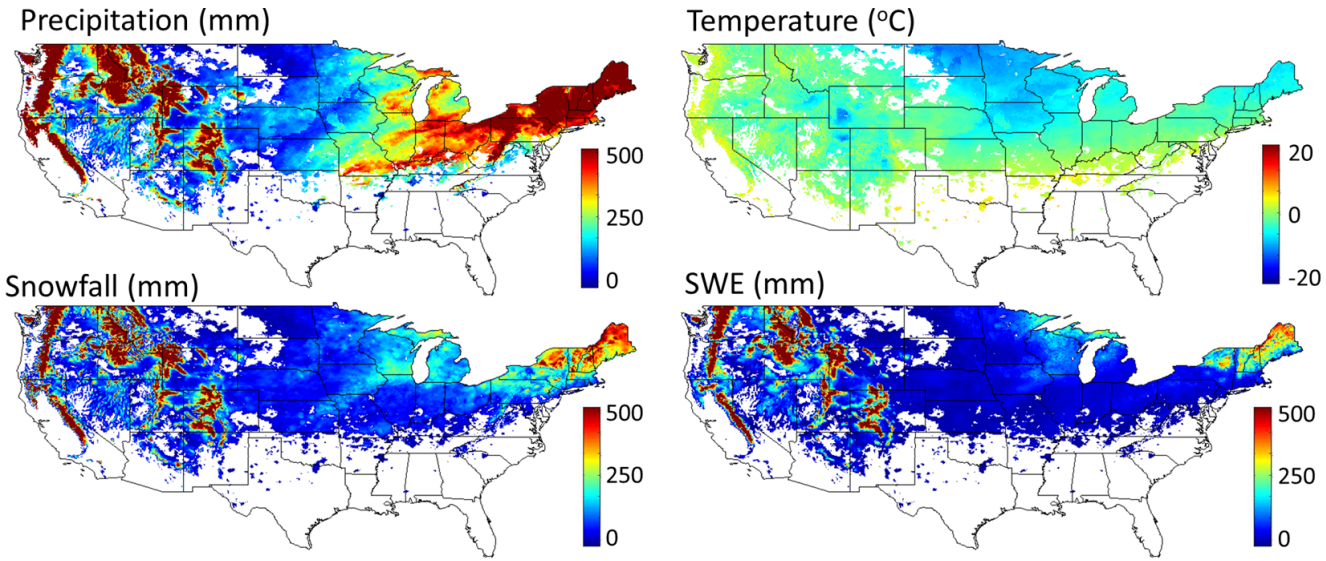
- Snowfall vs. rainfall: using a T_{2m} threshold based on station data
- Snow ablation: using T2m based on station data

Step 2: Use our new snow density model (SNODEN) to assimilate both SNOTEL SWE and COOP snow depth data

Broxton et al. (2016a)

Q: How do we upscale from in situ point measurements to area averages? ?

Step 3: Interpolate in situ normalized SWE (from Step 1) to 4 km grids;



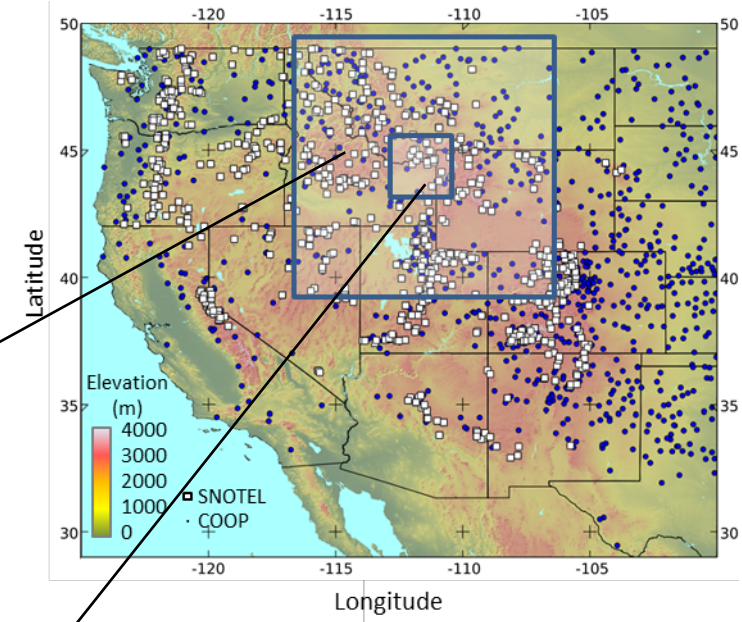
Step 4: Use PRISM daily 4 km P and T2m products to compute (accumulated snowfall minus ablation) (following Step 1)

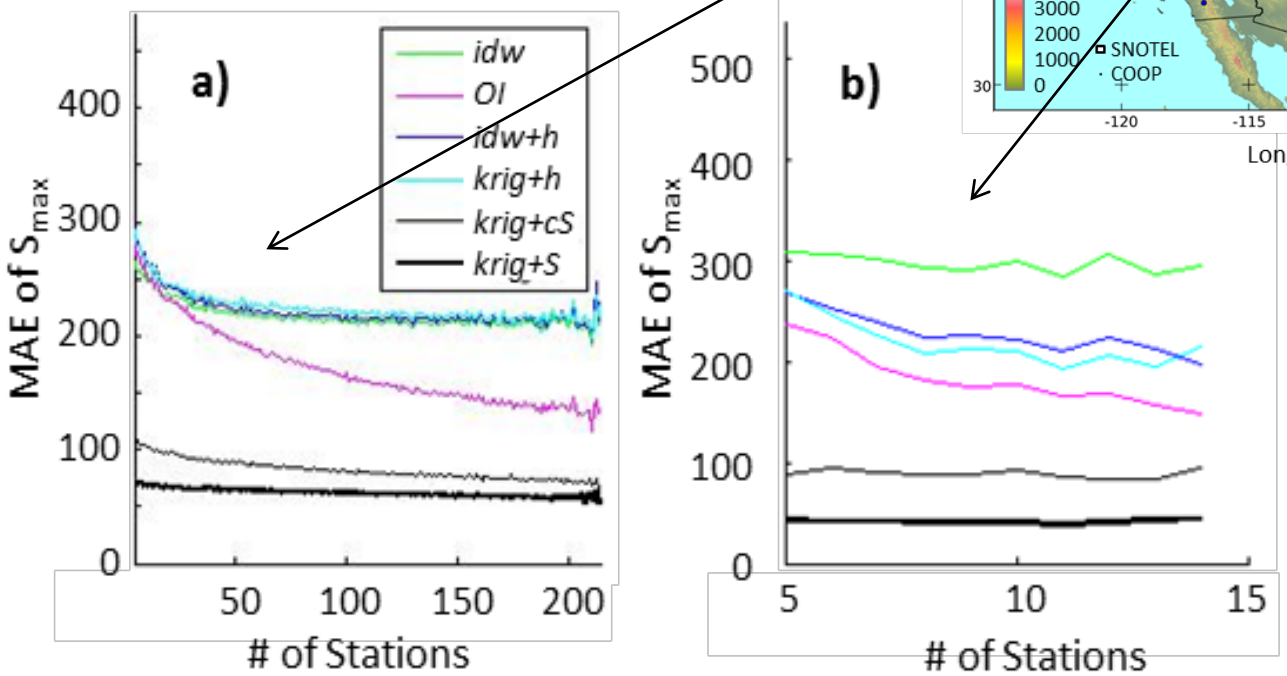
Step 5: use Steps 3 & 4 to obtain daily 4 km gridded SWE over ConUS

Step 6: use Steps 2 & 5 to obtain consistent snow depth

Test #1: Interpolation from point to point

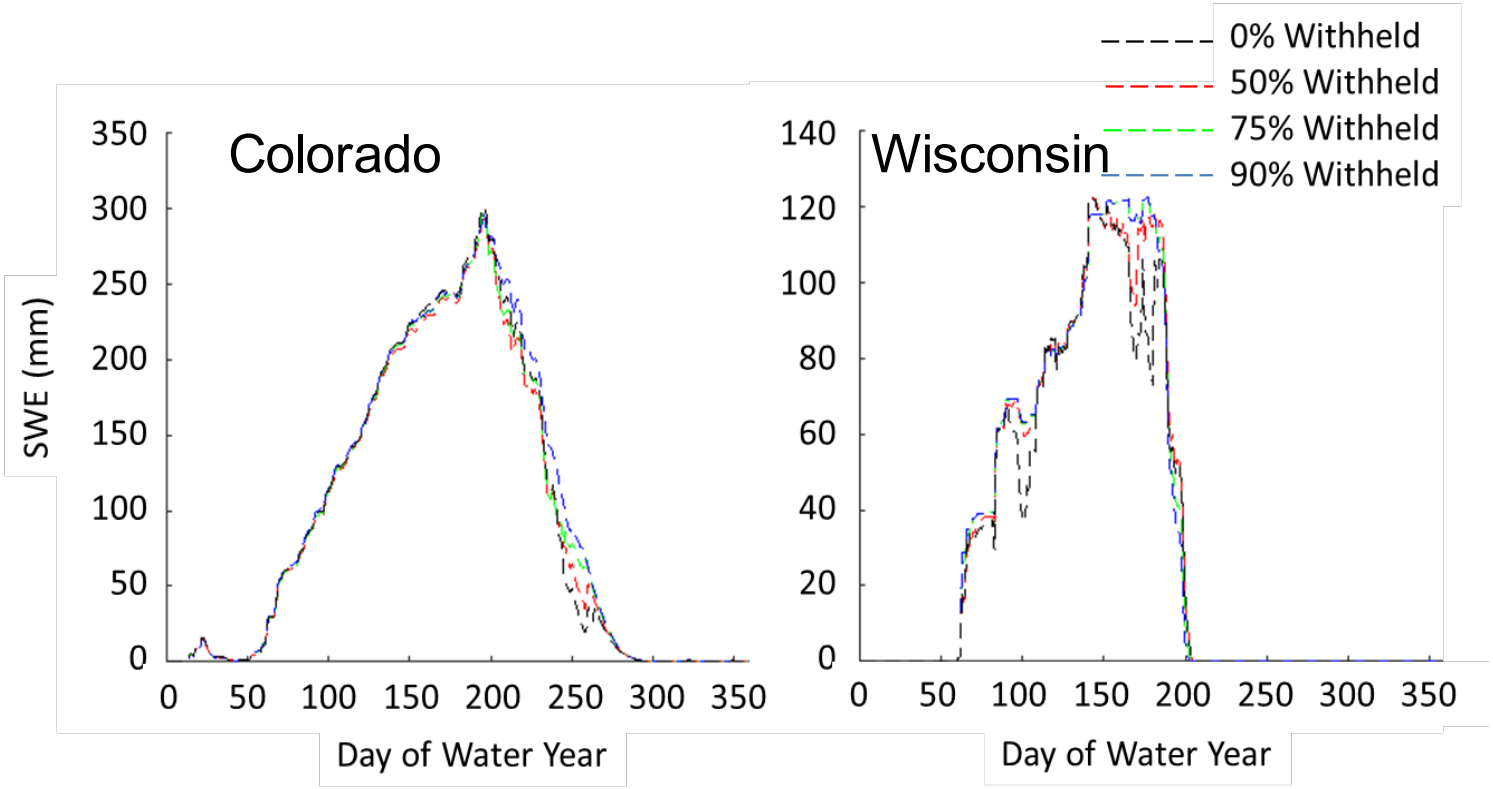
Q: How good is our method of spatial interpolation of normalized SWE compared with interpolation methods that use SWE itself?





- Our method has a much smaller error.
- Our method is very robust, as the errors are nearly the same if we use 5%, 10%, 30%, or 90% of the sites for interpolation

Test #2: Compare the average SWE over a 2°x2° area when 0%, 50%, 75%, and 90% of the station snow data are withheld during the generation of the UA data.



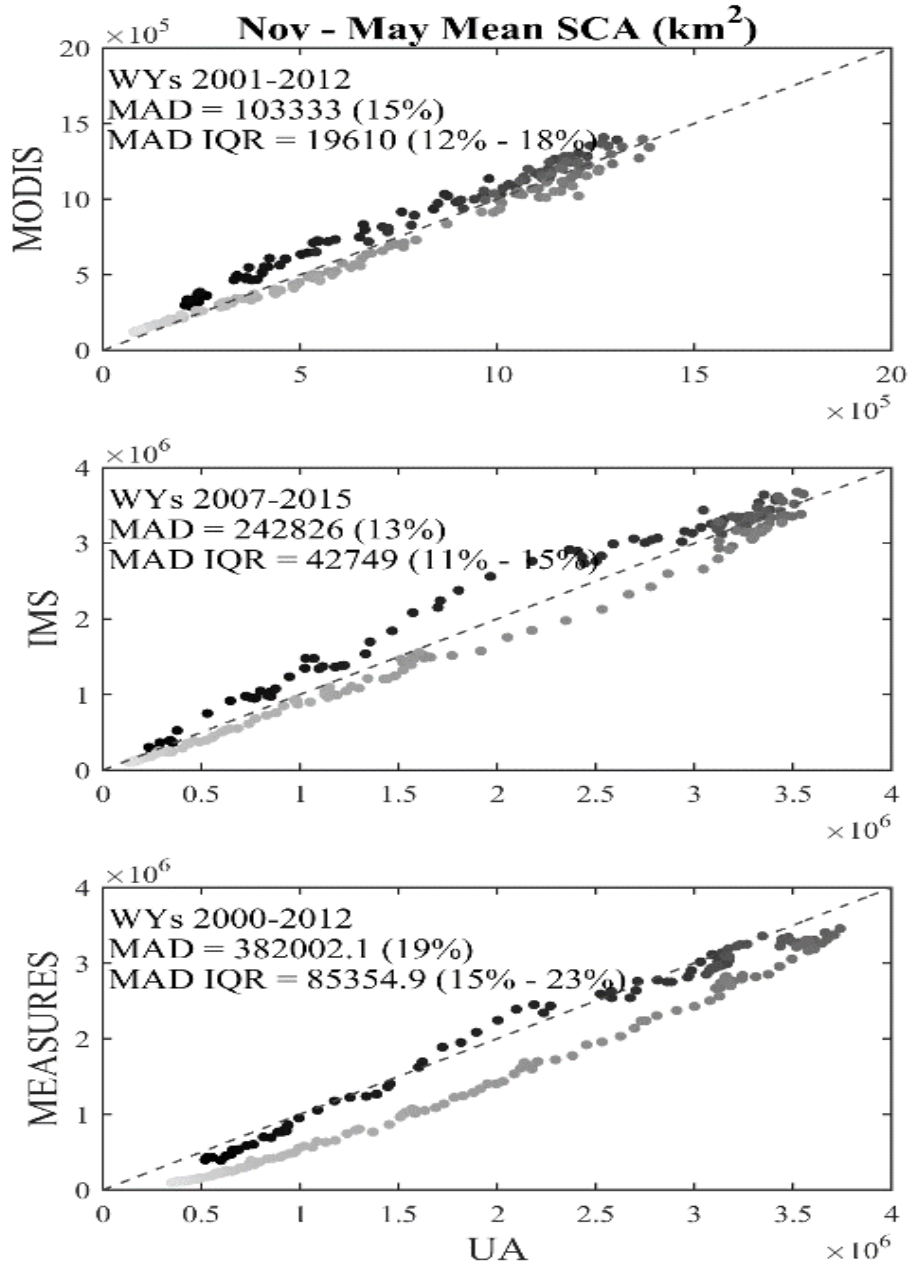
Our results are very robust, as using 10%, 25%, 50%, and 100% of the sites gives very similar area-averaged SWE seasonal cycle

Test #3: Compare daily snow cover (SWE > 3 mm) with other datasets

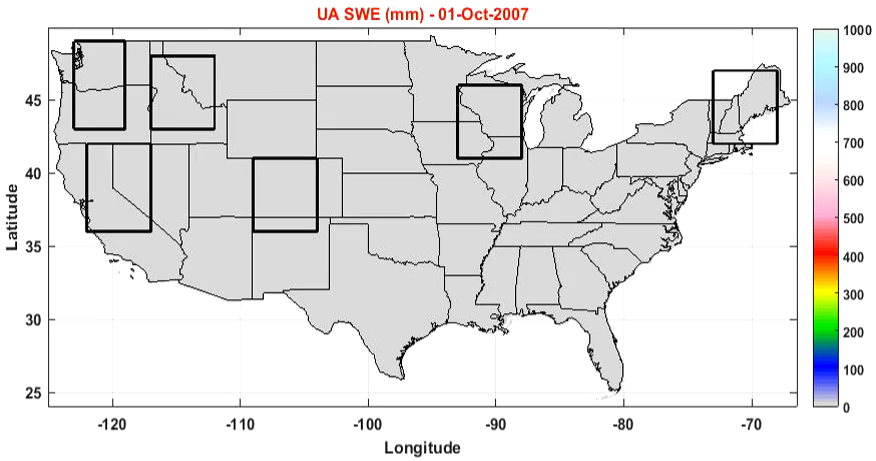
Our results agree well with other binary datasets (snow or no-snow), with the Mean Absolute Difference (MAD):

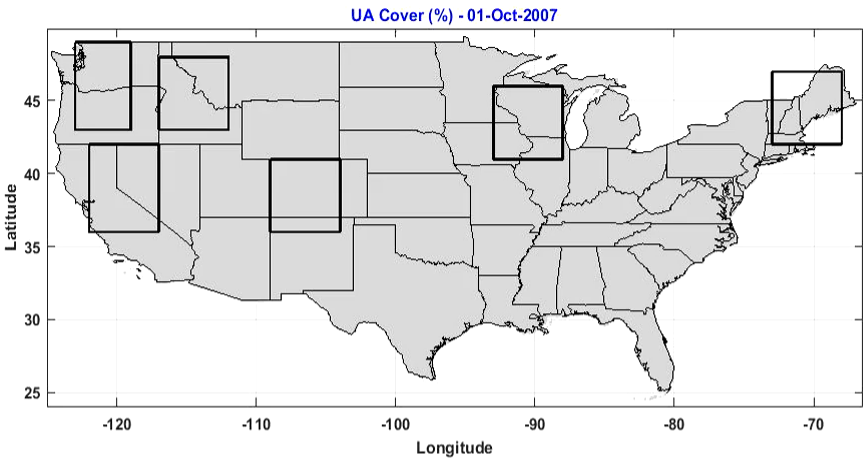
15% with MODIS (5km)
13% with IMS (4km)
19% with Rutgers Univ (25 km)

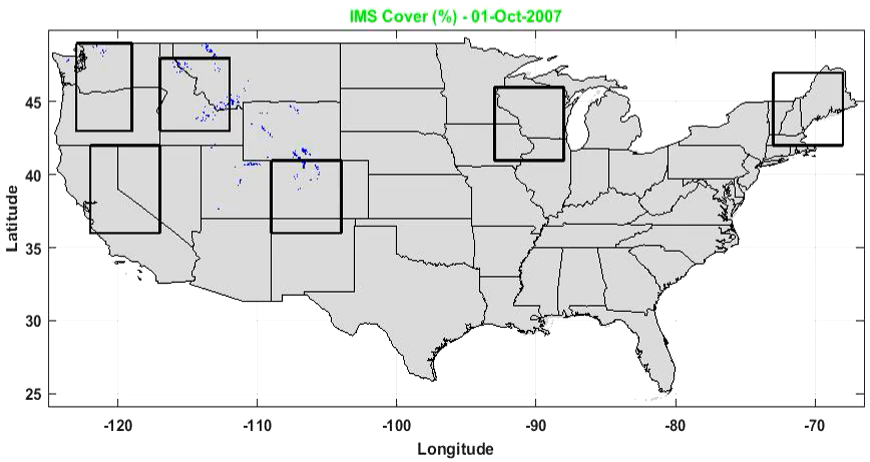
Dawson et al. (2017b, in preparation)

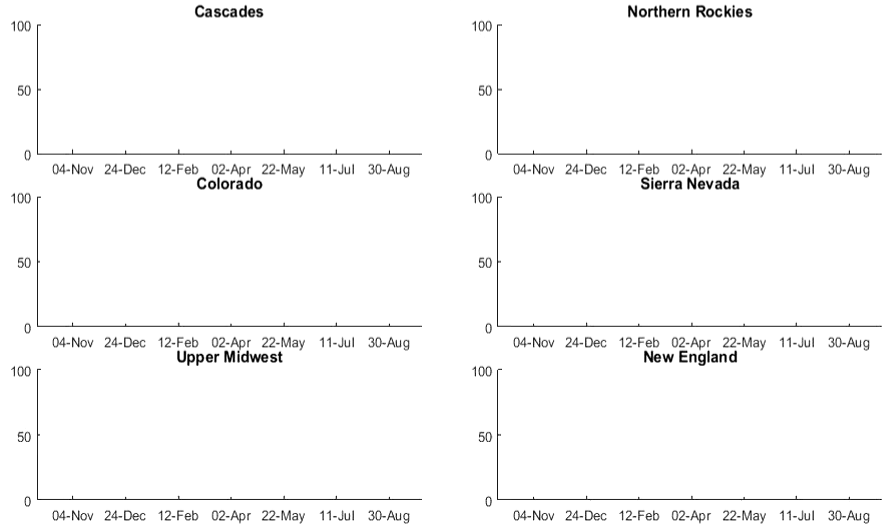


Comparison between UA SWE data and IMS product









Overall, our SWE data and IMS data are similar, though some inconsistencies in areas with shallow snow / near edges

Outline

1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

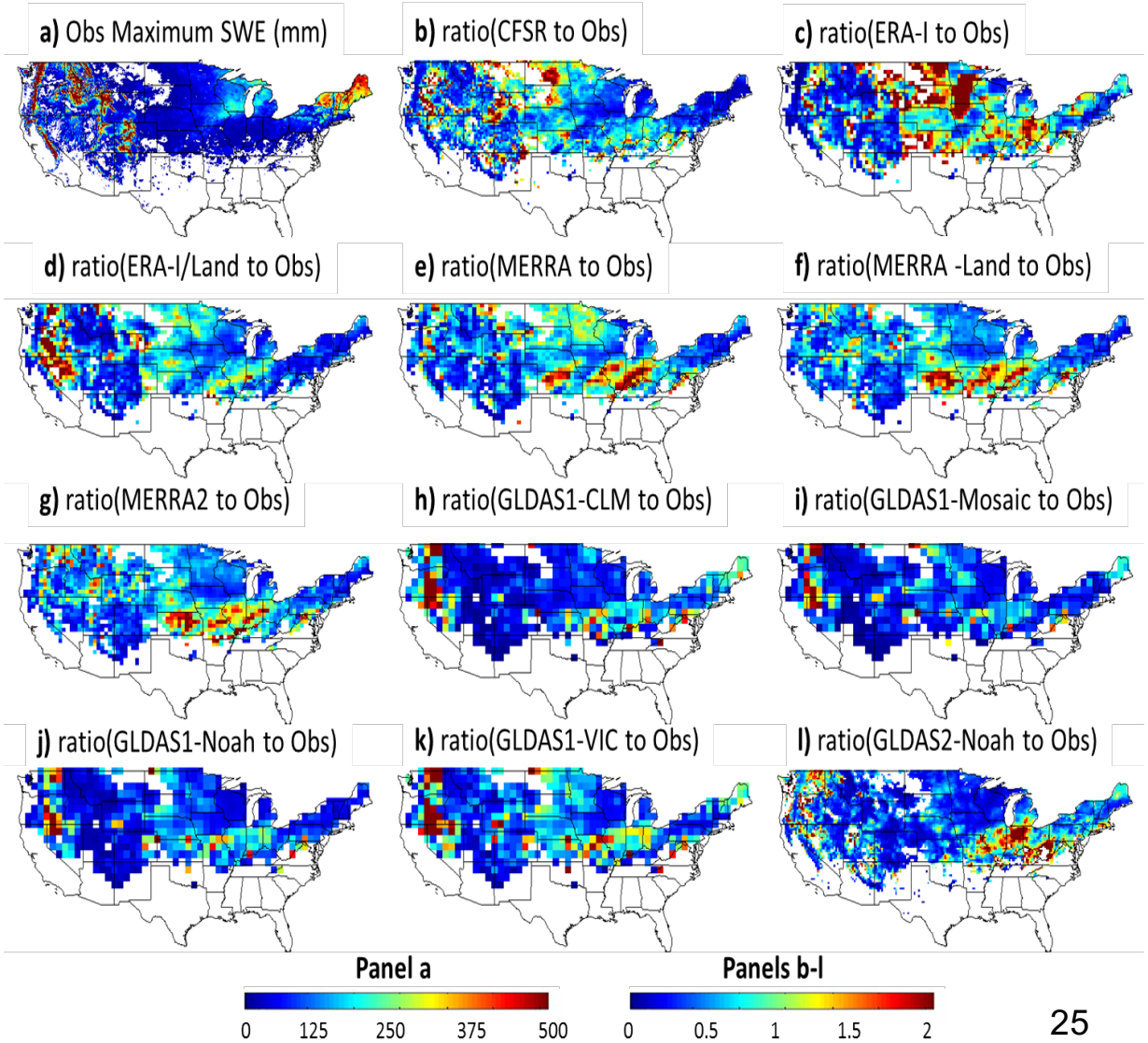
Application #1:

SWE in reanalyses and GLDAS is too low over much of ConUS

Q: What is the main reason for this underestimate?

- Atmospheric forcing deficiencies?
- deficiencies in land models and snow data assimilation?

Panel a) max SWE according to our dataset ("OBS"), Other panels: ratios between reanalysis and GLDAS max SWE and OBS for WY2008



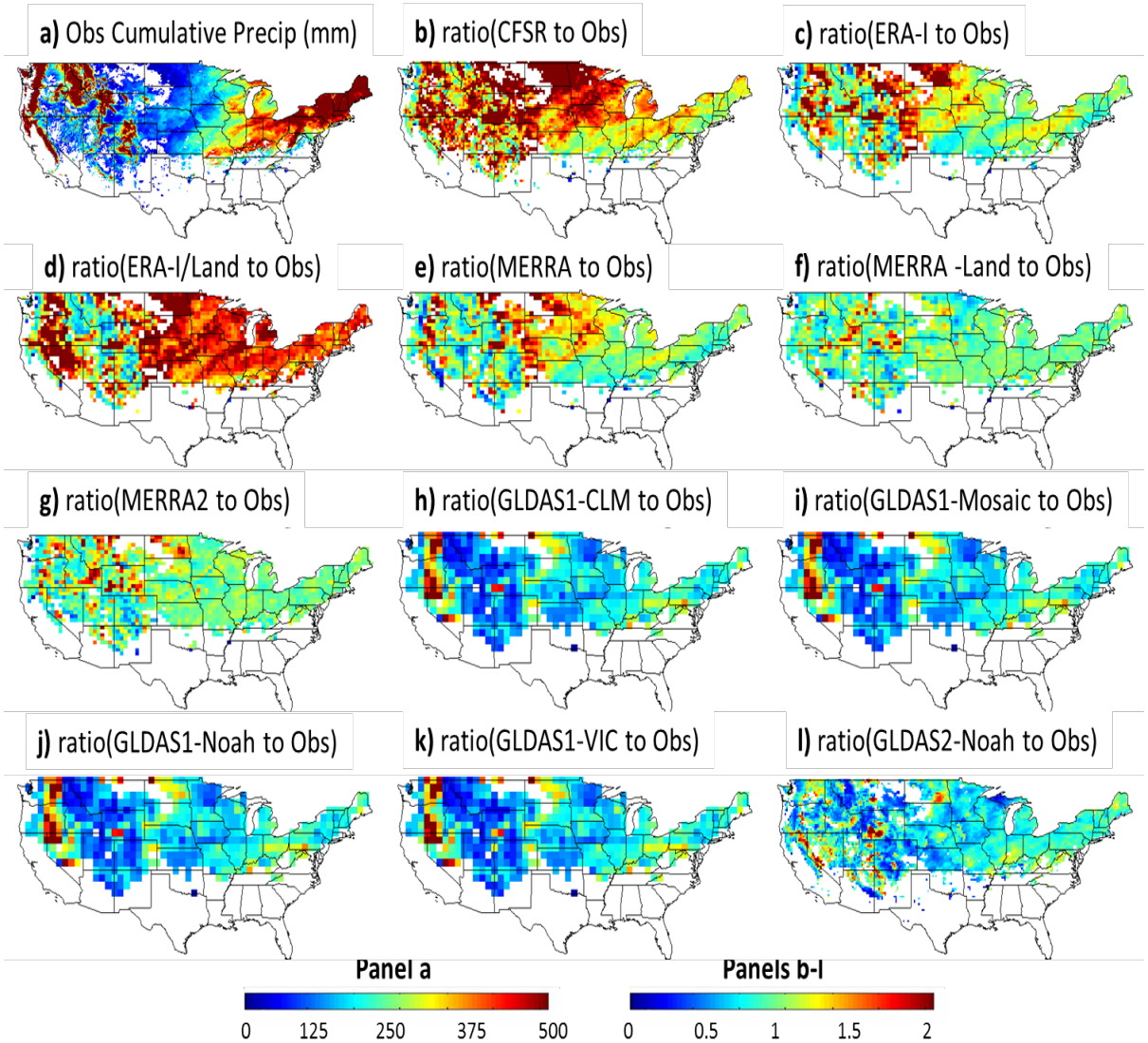
Broxton et al. (2016b)

Some products have too much precipitation or snowfall and some have too little

However, nearly all products have too little maximum SWE (previous slide)

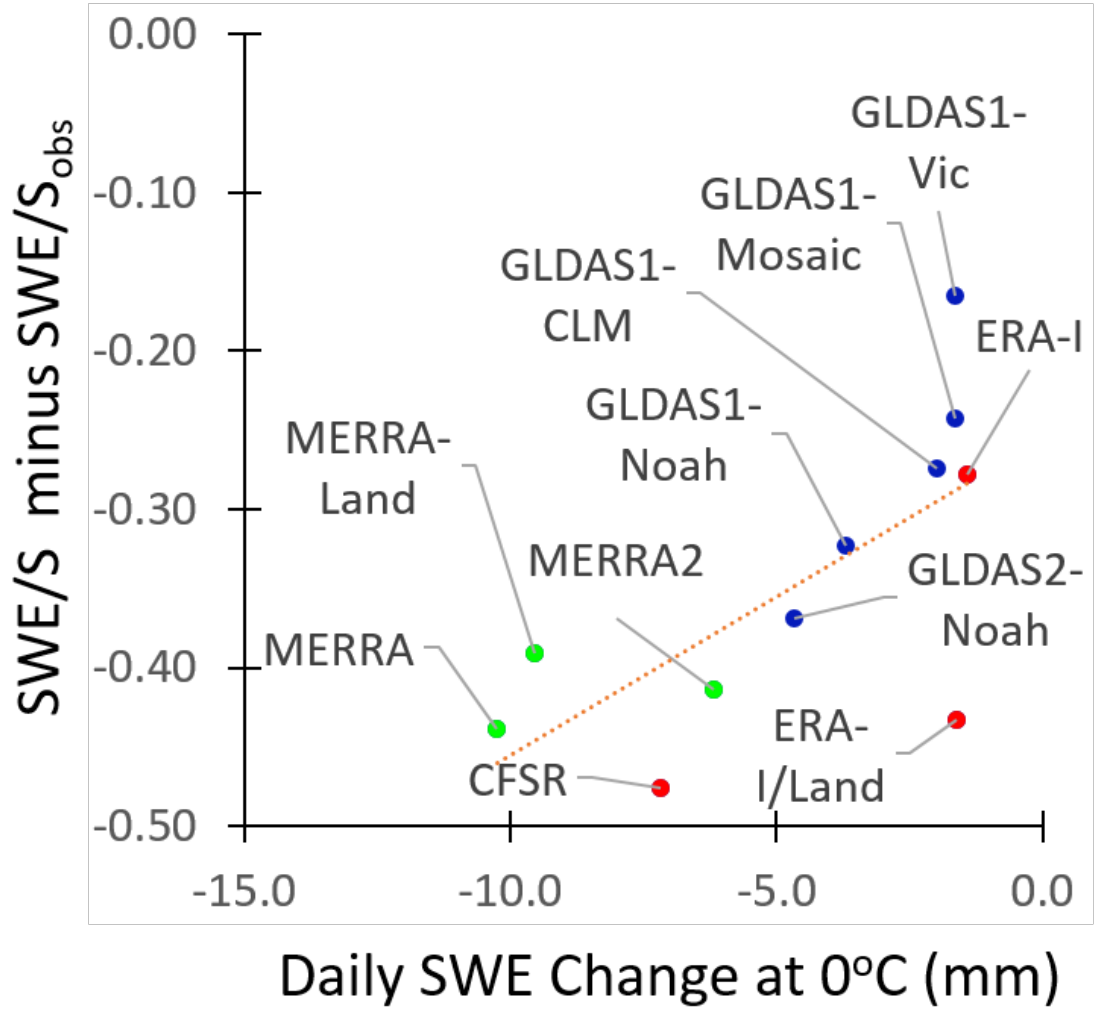
Point:

Deficiencies in atmospheric forcing data cannot explain this widespread underestimation of SWE.



a) Cumulative snow season precipitation ("OBS"), b-l) ratios between reanalysis/GLDAS cumulative snow season precipitation and OBS

SWE is under-predicted more severely for reanalysis products that ablate more snow near freezing point temperature



Point:

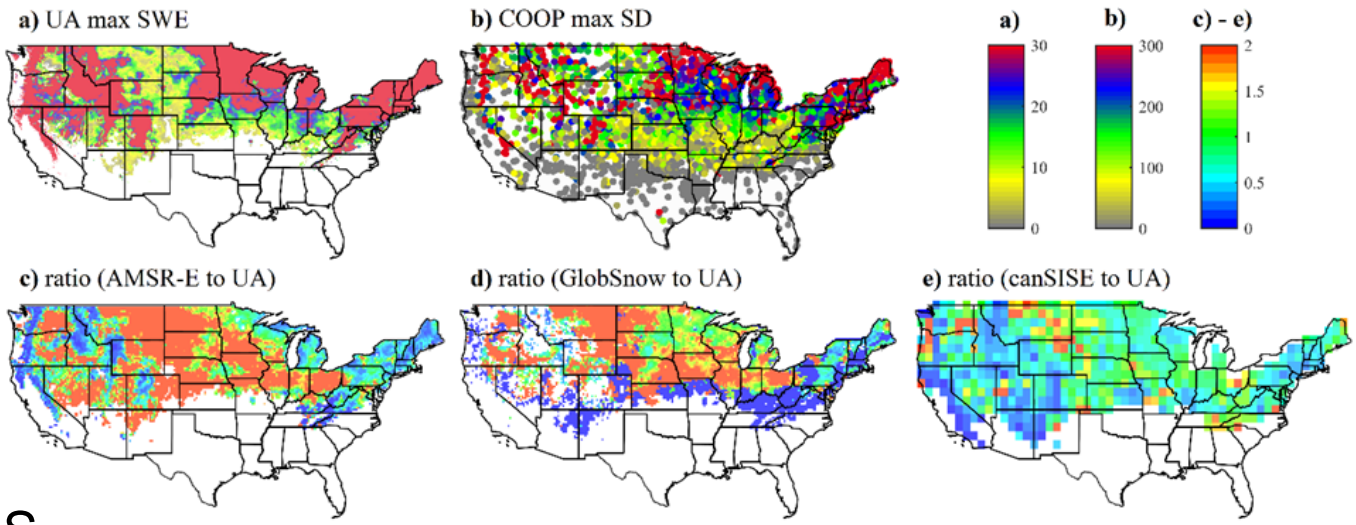
SWE underestimation in reanalysis/GLDAS is primarily caused by deficiencies in land model (particularly snow ablation near freezing point) and snow data assimilation

Application #2: remotely sensed products underestimate SWE over much of CONUS

AMSR-E (NASA);

GlobSnow (ESA): combine satellite and in situ data;

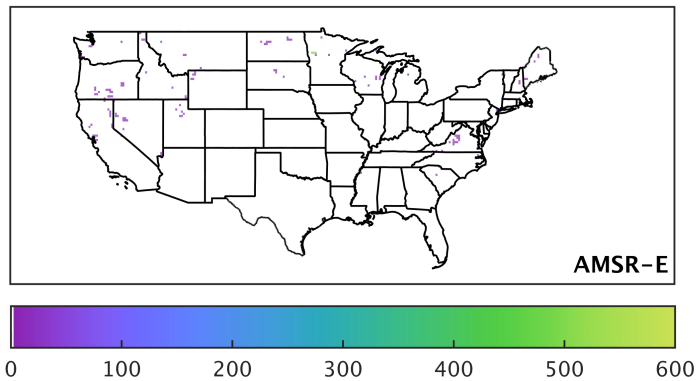
canSISE (Canada): combine GlobSnow, reanalyses, & GLDAS

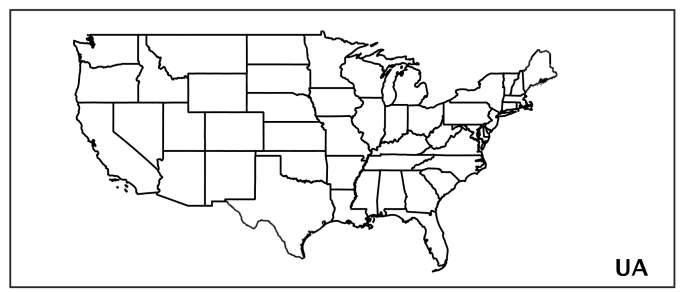


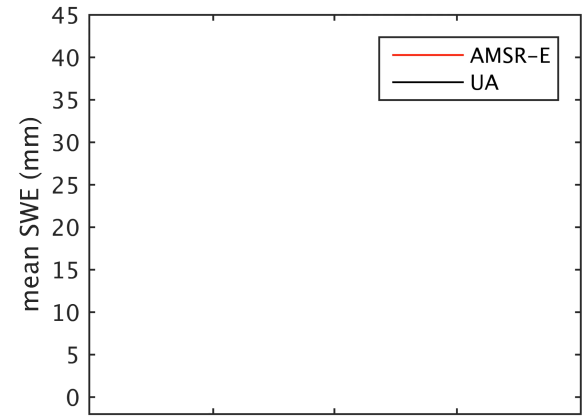
- AMSR-E (25 km) and GlobSnow (25 km) severely underestimate SWE over mountainous areas and heavily forested areas over flat areas
- AMSR-E and GlobSnow overestimate SWE in areas with SWE < 20 mm.
- canSISE SWE (1°x1^{o}) is generally underestimated everywhere.

Dawson et al. (2017b, in prepartion)

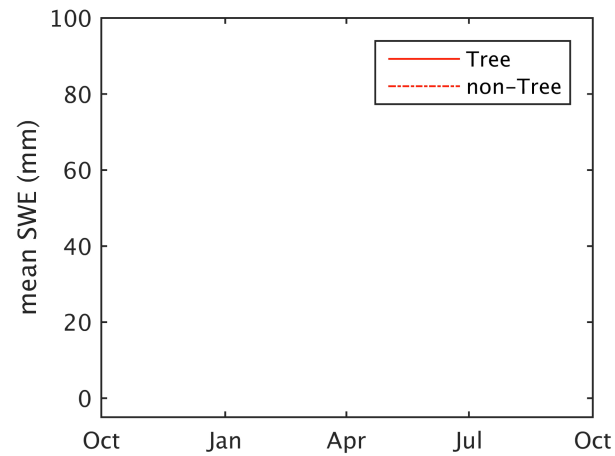
Daily AMSR-E versus UA SWE in WY 2007







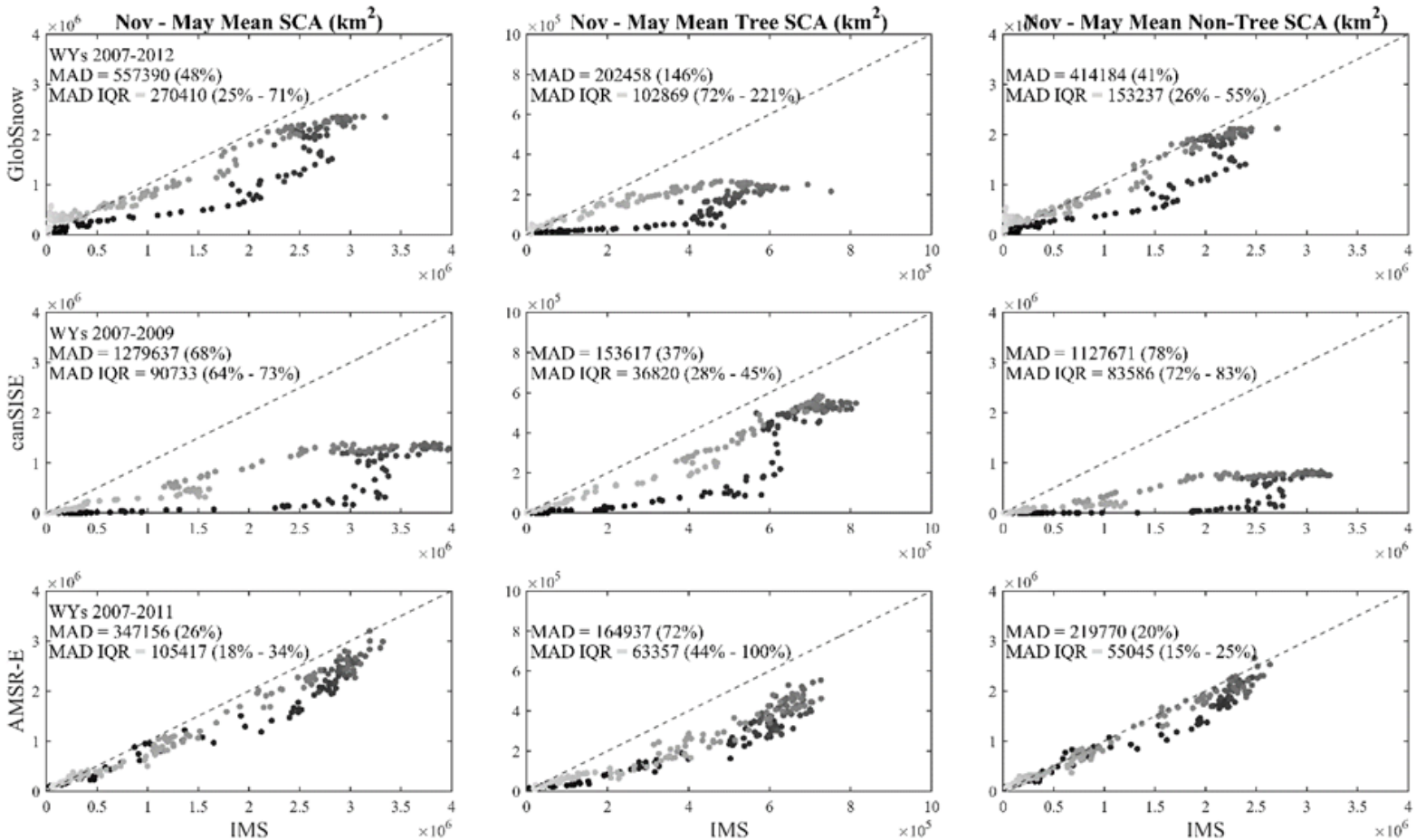
Mean SWE



Mean SWE over tree and non-tree grid boxes

AMSR-E SWE over tree-covered grids is even less than those over short-vegetation-covered grids

Derived snow cover compared to IMS

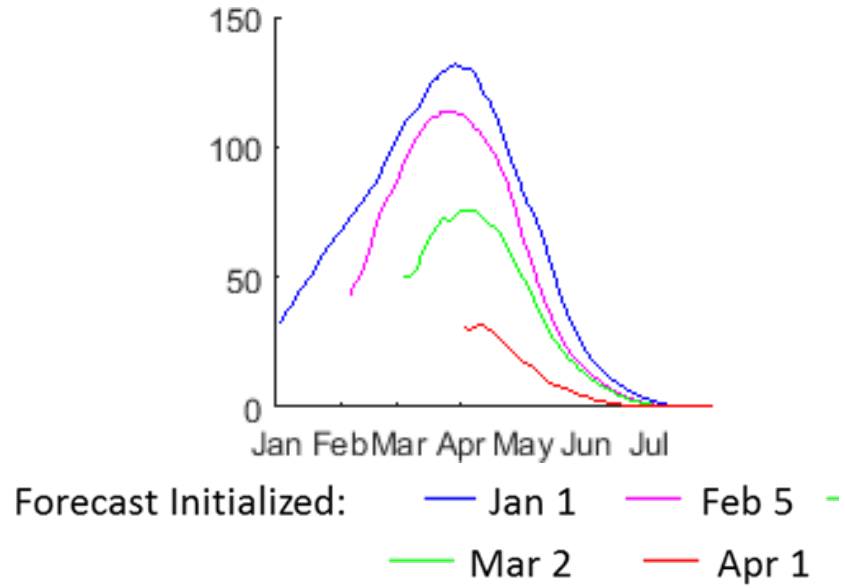


AMSR-E underestimates snow cover in Tree grid boxes, but performs well in non-Tree grid boxes.

Outline

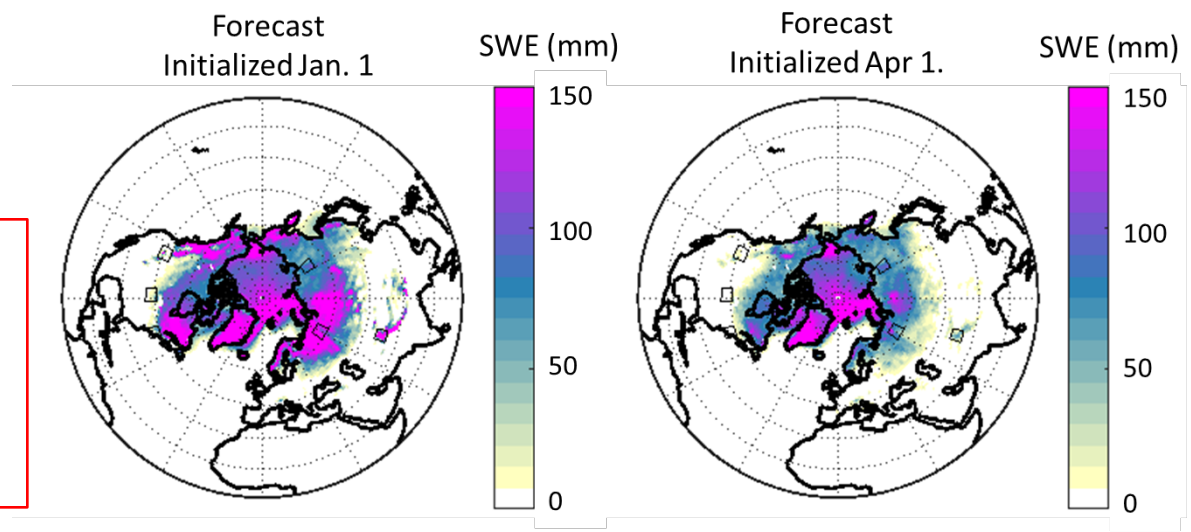
1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

CFS forecasted SWE (in mm) from different initialization times over a 10°x10° box in central Asia



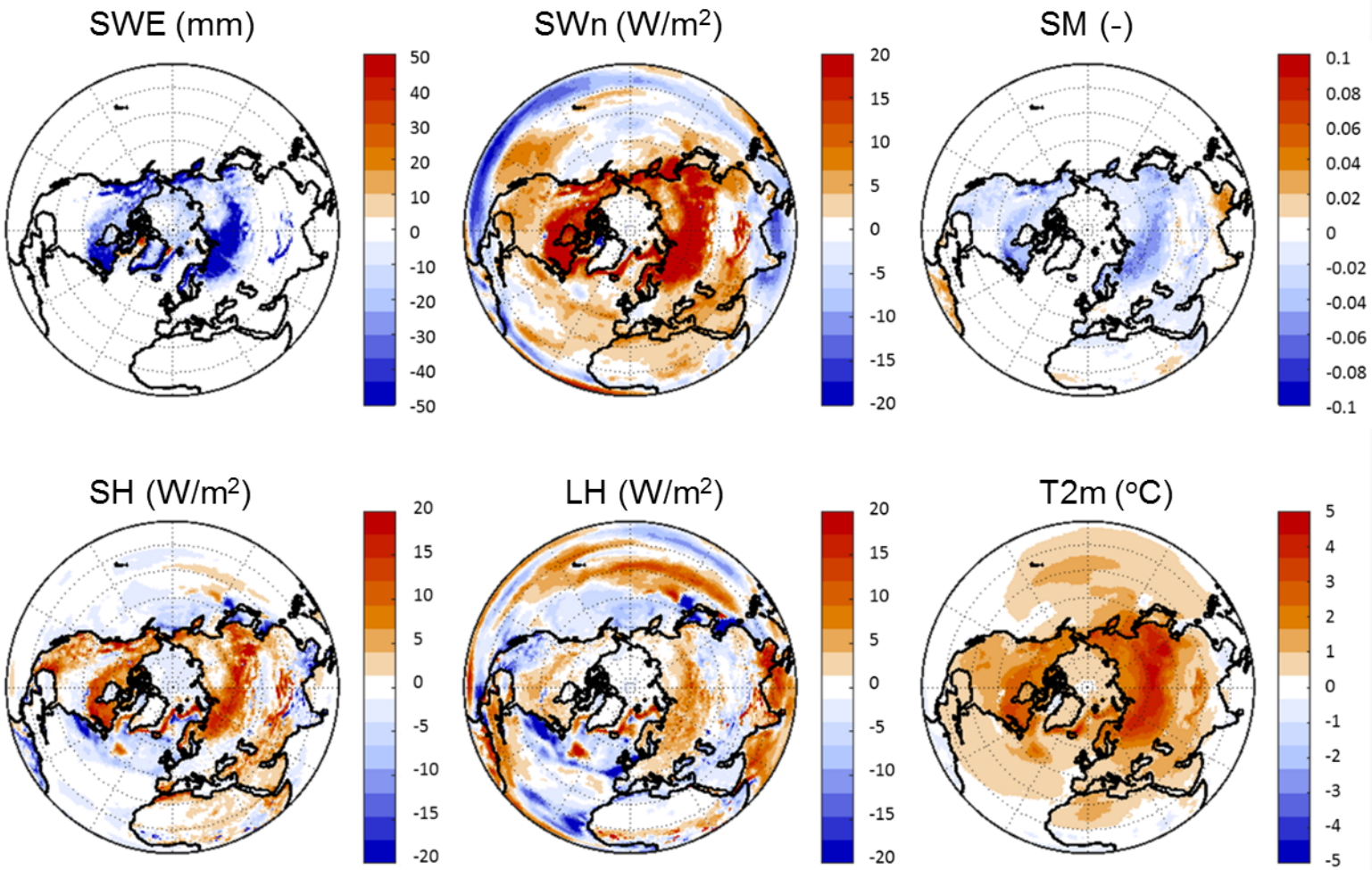
Poor CFS SWE initialization affects forecasts of SWE

Q: How does this affect other model forecast quantities during spring-summer transition



Predicted SWE for Apr 1 based on forecast issued in Jan 1 (left) vs forecast made Apr 1 (right)

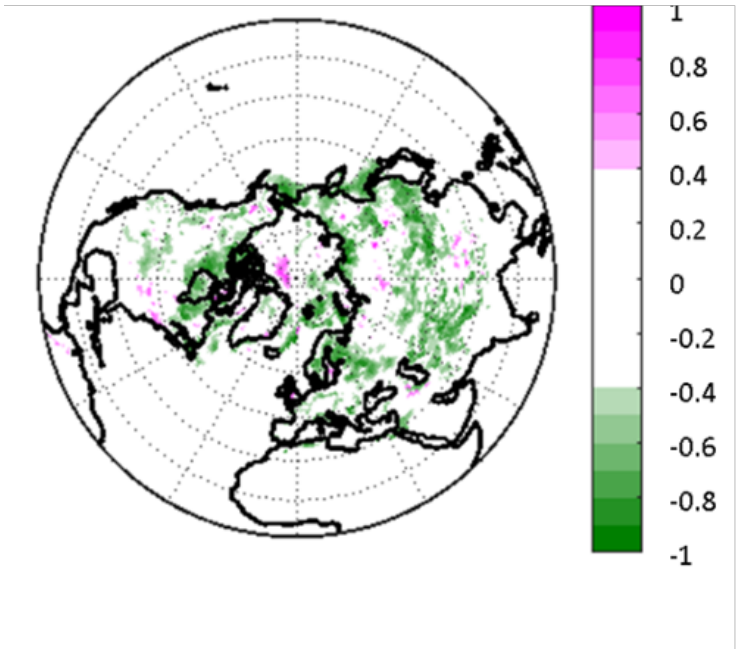
Broxton et al. (2017) (in review)

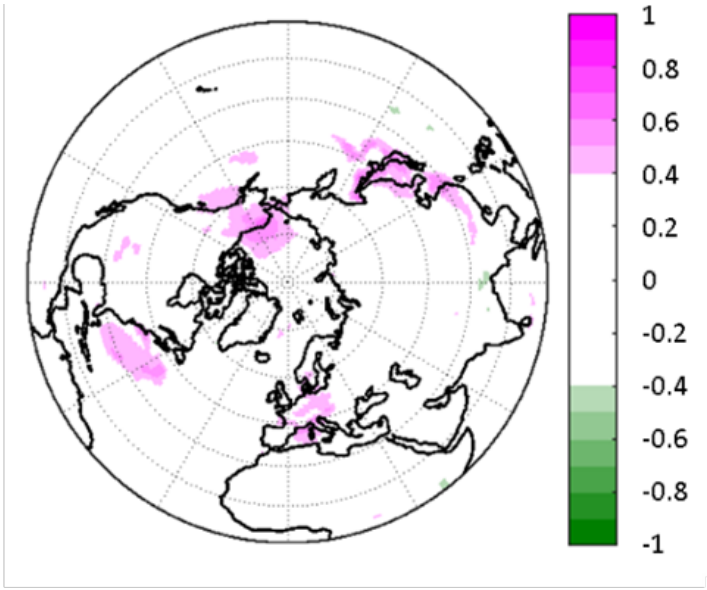


Apr 1st minus Jan 1st forecast of model quantities for spring months (Apr-Jun) averaged from 1982-2009.

Forecasts made later in the season have less SWE, more net solar radiation (SWn), less soil moisture (SM), more sensible heat (SH), less latent heat (LH), and higher T_{2M}

dSWE, dT2m, dSST – difference between Jan 1st and Apr 1st forecasts of SWE, T2m, and SST





Temporal correlation (from 1982-2009) between dSWE on Apr 1st and Apr-Jun dT2m (grid-to-grid);

correlation between Apr-Jun dSST (over oceans > 30°N) and Apr-Jun dT2m

Over Land, SWE influences other variables (e.g. T_{2M}) more strongly than do SSTs, whose influence is mostly felt on the edges of continents

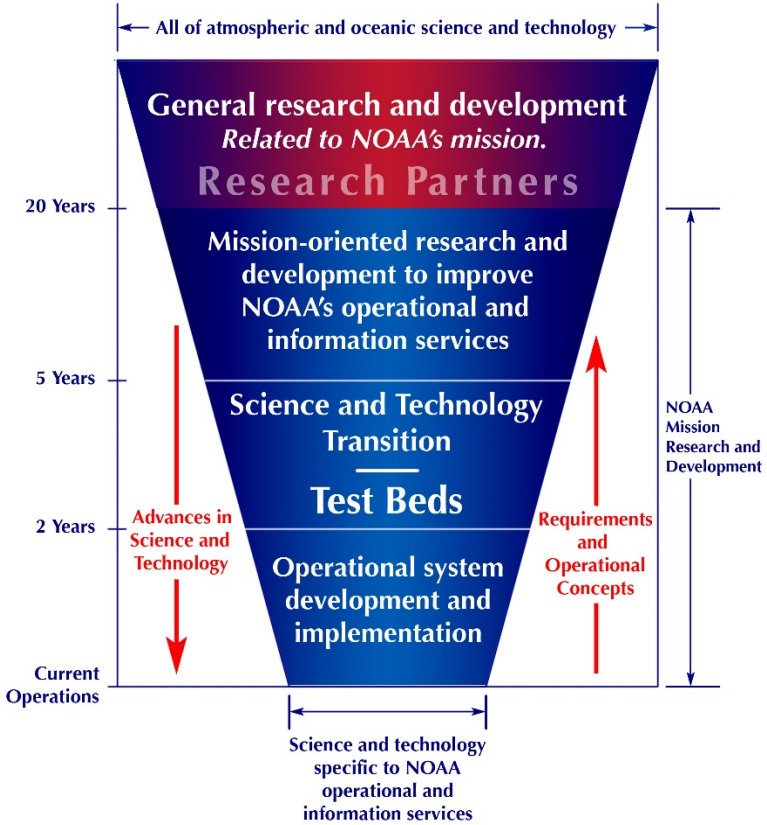
Outline

1. UA-EMC collaboration history
2. Evaluation of NCEP snow initialization
3. A new snow density parameterization for snow data assimilation
4. A new daily 4 km snow (water equivalent, depth, and fraction) dataset over ConUS from 1981 to present
5. Evaluation of reanalysis, GLDAS, and remote sensing snow products
6. Snow impact on CFS seasonal prediction
7. Implications for R2O

R2O issue

Assume:

- We get the funding to develop a better global SWE, snow depth, and snow fraction product (with our new snow density model, new data development methodology, potentially new data source);
- We work with EMC partners to implement the new data for snow data assimilation in CFS (or GFS, NGGPS);
- We work with EMC partners to finish the suite of operational tests

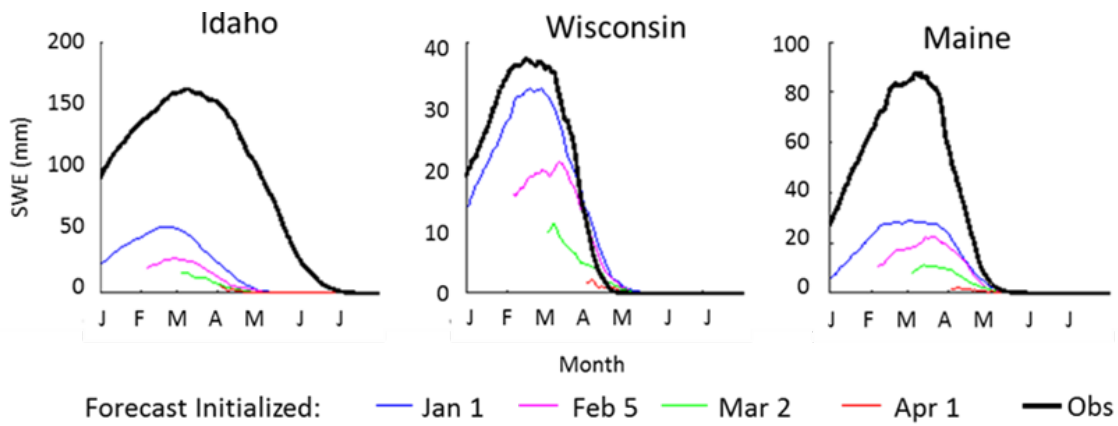


Based on the presentation so far,
Do you think

this will actually be implemented in CFS based on the NCEP criterion that the new parameterization or dataset reduces a known deficiency but does not degrade other aspects of the forecasting?

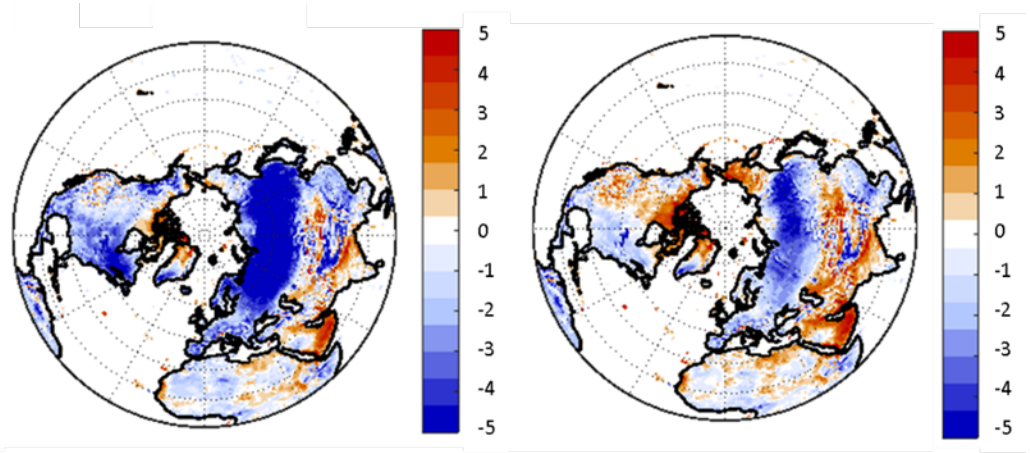
Earlier forecasts of SWE are more realistic (but still too little snow)

Later T_{2m} forecasts are more realistic, despite having less realistic SWE



Forecast SWE from different initialization times for three areas compared with our SWE data (Obs)

Point: More realistic SWE from Jan 1 forecast would lead to greater T_{2m} cold bias, because of the CFS deficiencies in the atmospheric processes (e.g., radiative transfer)



Left: Apr-Jun T_{2m} difference between CFS and Obs (forecasted from Jan 1st);
Right: difference between CFS and Obs (from Apr 1st)

R2O issue

Assume:

- We get the funding to develop a better global SWE, snow depth, and snow fraction product (with our new snow density model, new data development methodology, potentially new data source);
- We work with EMC partners to implement the new data for snow data assimilation in CFS (or GFS, NGGPS);
- We work with EMC partners to finish the suite of operational tests

Based on the presentation so far, do you think

this will actually be implemented in CFS based on NCEP criterion that the new parameterization or dataset reduces a known deficiency but does not degrade other aspects of the forecasting? No!

The more productive approach:

- improve snow initialization first,
- improve atmospheric radiative transfer (e.g. clouds and aerosols),
- finally improve land model

Conclusions

- Developed a new snow density parameterization for snow data assimilation
- Developed a robust method to obtain daily 4 km snow water equivalent (SWE), snow depth, and snow fractional coverage product over ConUS from 1981 – present
- Reanalyses and GLDAS products substantially underestimate SWE in the U.S., primarily because of the model deficiencies in the treatment of snow ablation especially near $0^{o}C$.
- NCEP global (CFS, GFS) and regional (NAM) operational model snow initialization substantially underestimates SWE
- SWE on Apr 1 is much more strongly correlated to the CFS Apr-Jun T_{2m} forecast over mid- and high-latitudes than SST is.
- Atmospheric model in CFS needs to be revised in order to have a successful R2O related to snow, because of compensating errors in CFS