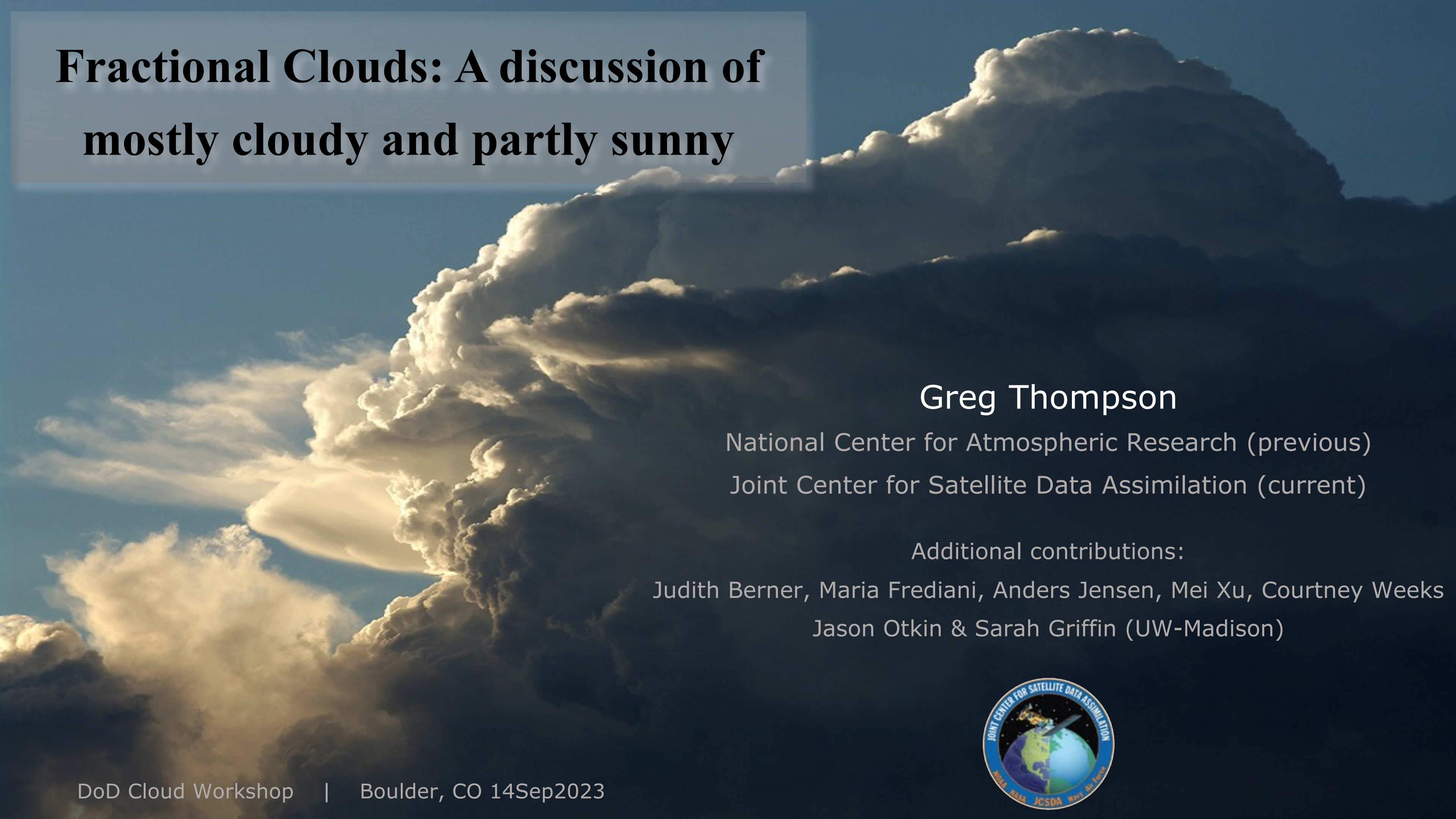


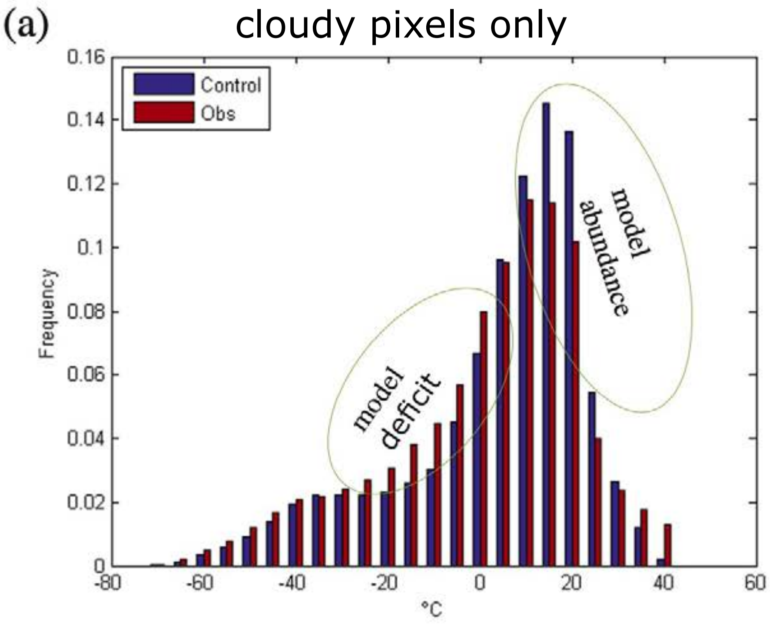
Fractional Clouds: A discussion of mostly cloudy and partly sunny

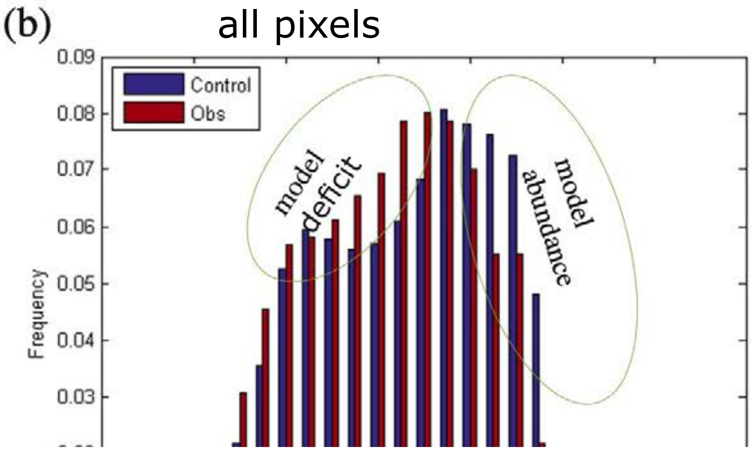
Greg Thompson
National Center for Atmospheric Research (previous)
Joint Center for Satellite Data Assimilation (current)

Additional contributions:
Judith Berner, Maria Frediani, Anders Jensen, Mei Xu, Courtney Weeks
Jason Otkin & Sarah Griffin (UW-Madison)

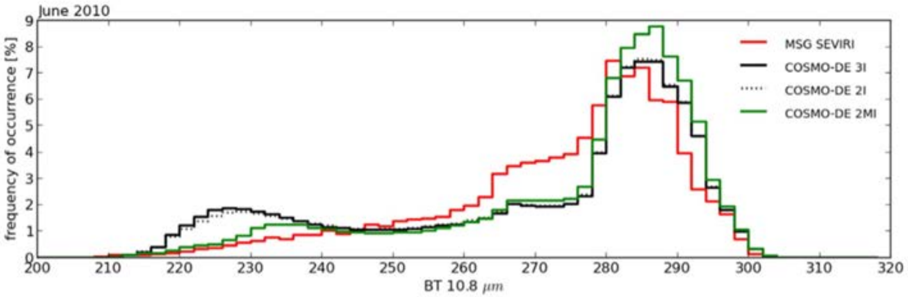
Motivation

G. Thompson et al. / Atmospheric Research 168 (2016) 92–104


(a) cloudy pixels only


(b) all pixels

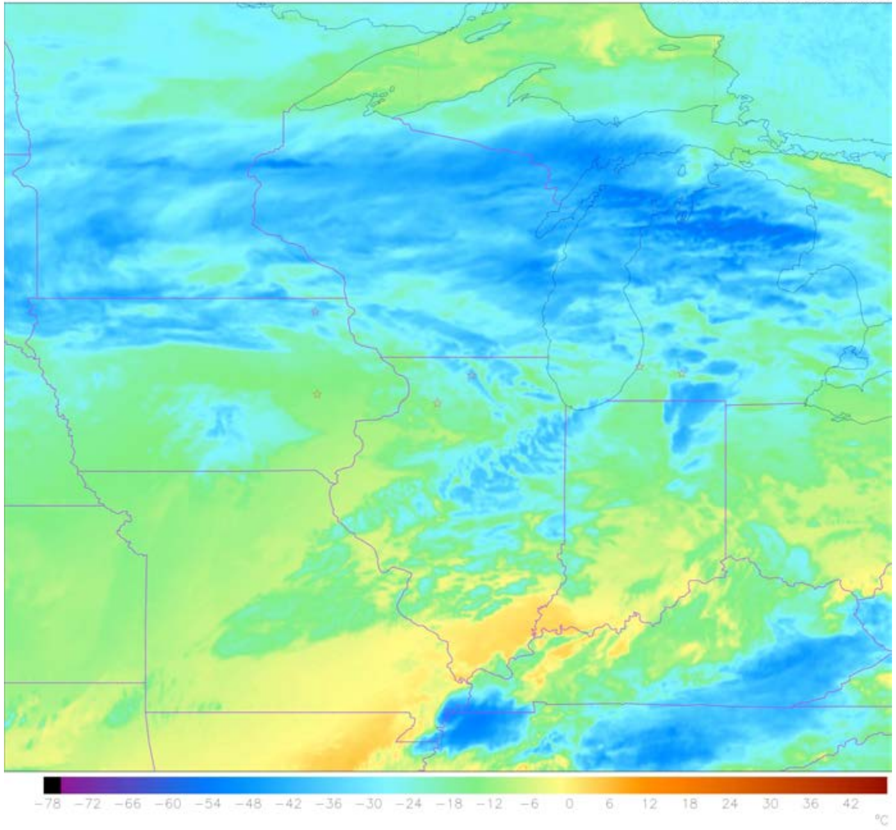
S. Eikenberg et al. / Atmospheric Research 156 (2015) 67–79



Motivation

GOES-16 channel 14 infrared (11 micron)

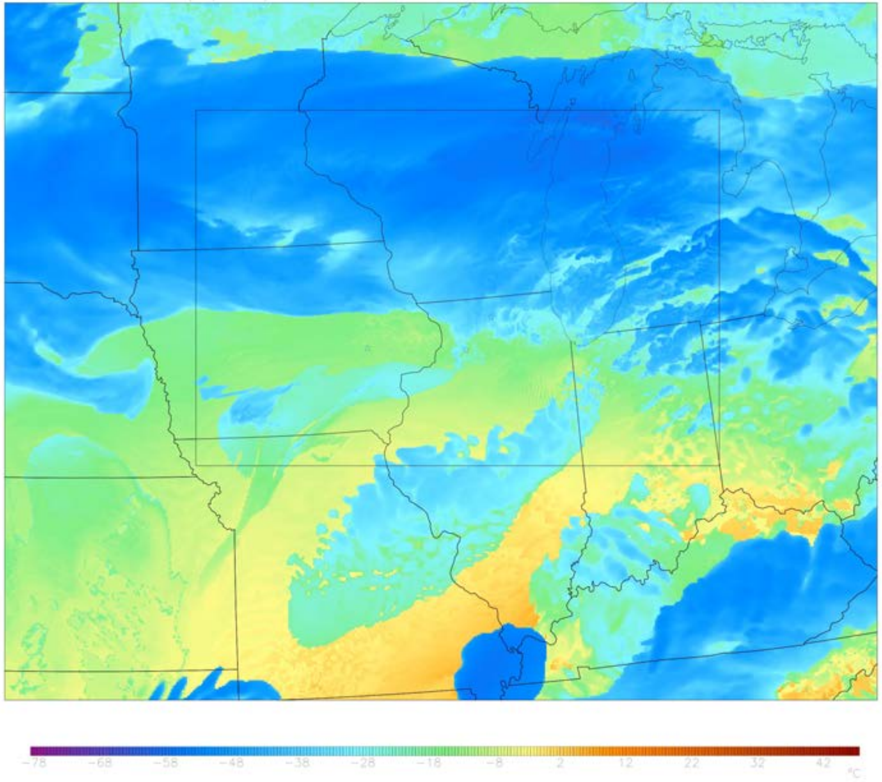
11:08:31 17 Feb 2019

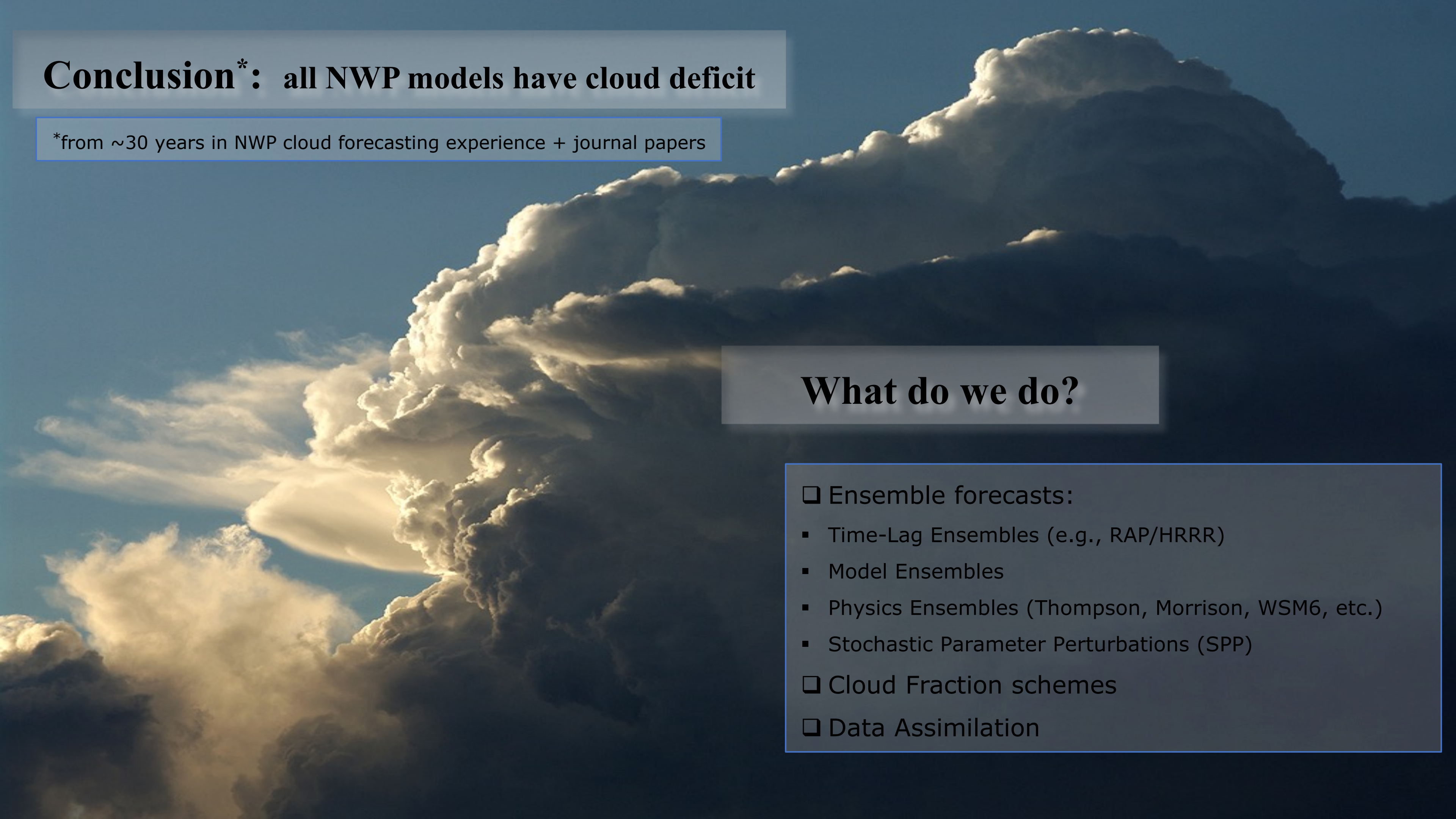


Synthetic infrared brightness temp (°C)

8-hour forecast valid 11:00:00 UTC 17 Feb 2019 initial time: 03z 17Feb

ICICLE WRF v4.0.3 (mp=28)





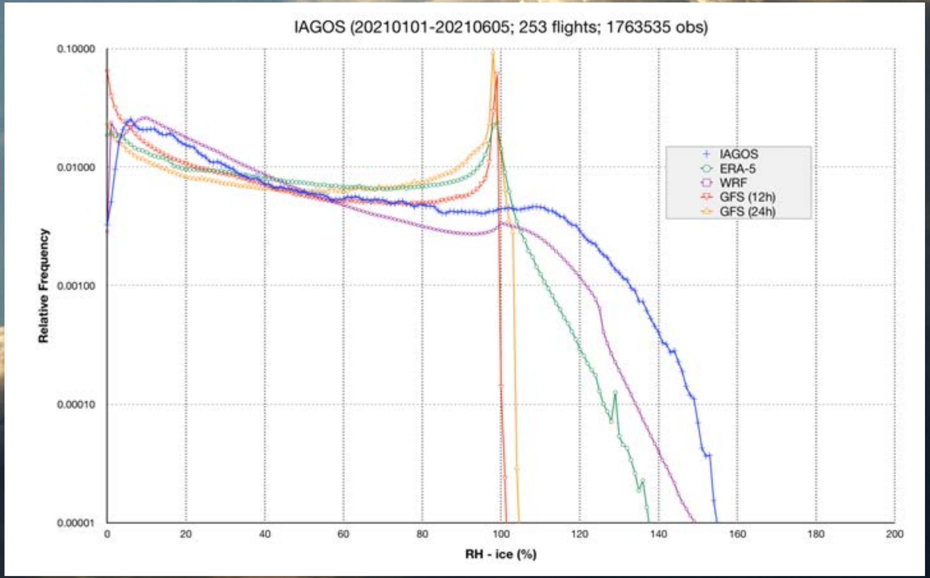
Conclusion[*]: all NWP models have cloud deficit

[*] from ~30 years in NWP cloud forecasting experience + journal papers

What do we do?

- Ensemble forecasts:
  - Time-Lag Ensembles (e.g., RAP/HRRR)
  - Model Ensembles
  - Physics Ensembles (Thompson, Morrison, WSM6, etc.)
  - Stochastic Parameter Perturbations (SPP)
- Cloud Fraction schemes
- Data Assimilation

Question: WHY do NWP models have cloud deficit?



Possibilities?

☐ Initial Conditions:

- Too dry?

☐ Physics

- Ice initiation?
- Hydrometeor fallout (rain/snow/hail)?
- Sub-grid-scale eddies (gray zone problem)?

What do we do?

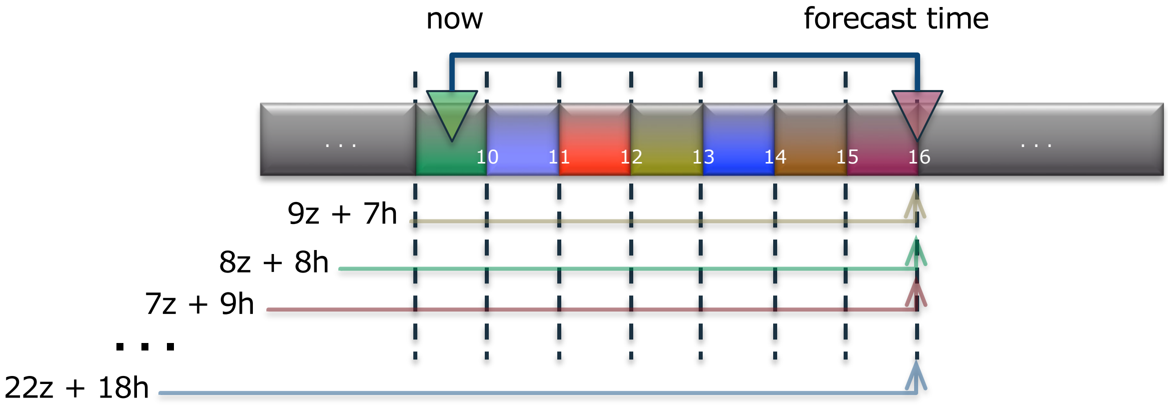
☐ Ensemble forecasts:

- ✓ Time-Lag Ensembles (e.g., RAP/HRRR)
- ▪ Model Ensembles
- ✓ Physics Ensembles (Thompson, Morrison, WSM6, etc.)
- ✓ Stochastic Parameter Perturbations (SPP)
- ▪ Cloud Fraction schemes
- ▪ Data Assimilation

High-Res Rapid Refresh (HRRR)

Time-lag-ensemble (TLE) average

- Hourly updates with hourly forecasts to 18 hours
- A traditional HRRR ensemble forecast system coming in a few years



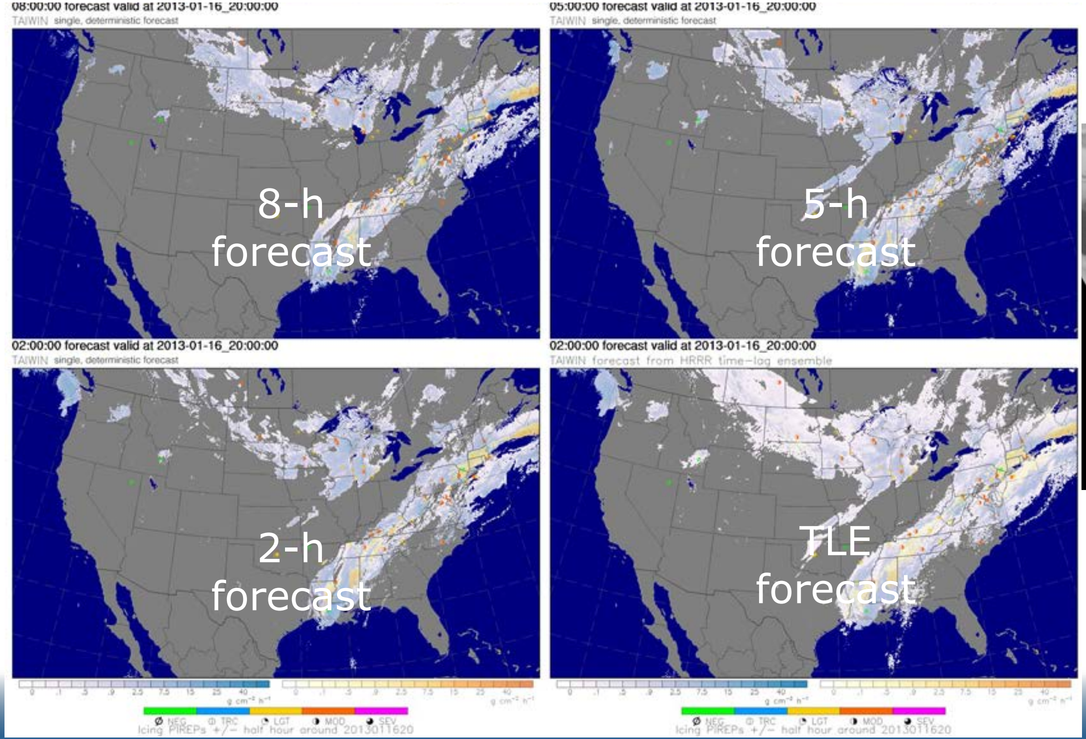
- If now is 09:30 and we consider a forecast valid at 16:00
- Then we could have as many as 12 forecasts all valid at this time.

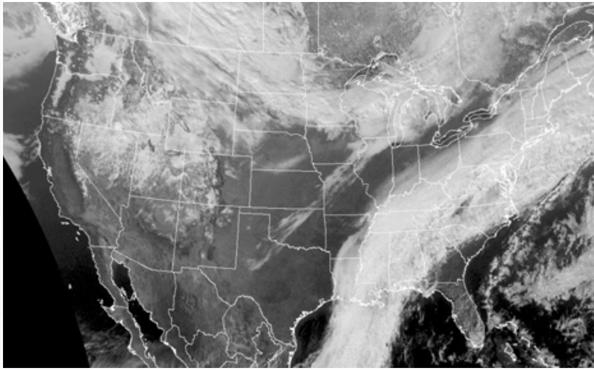
Time-lag-ensemble (TLE)

Simple weighted average of many HRRR forecasts valid at same time

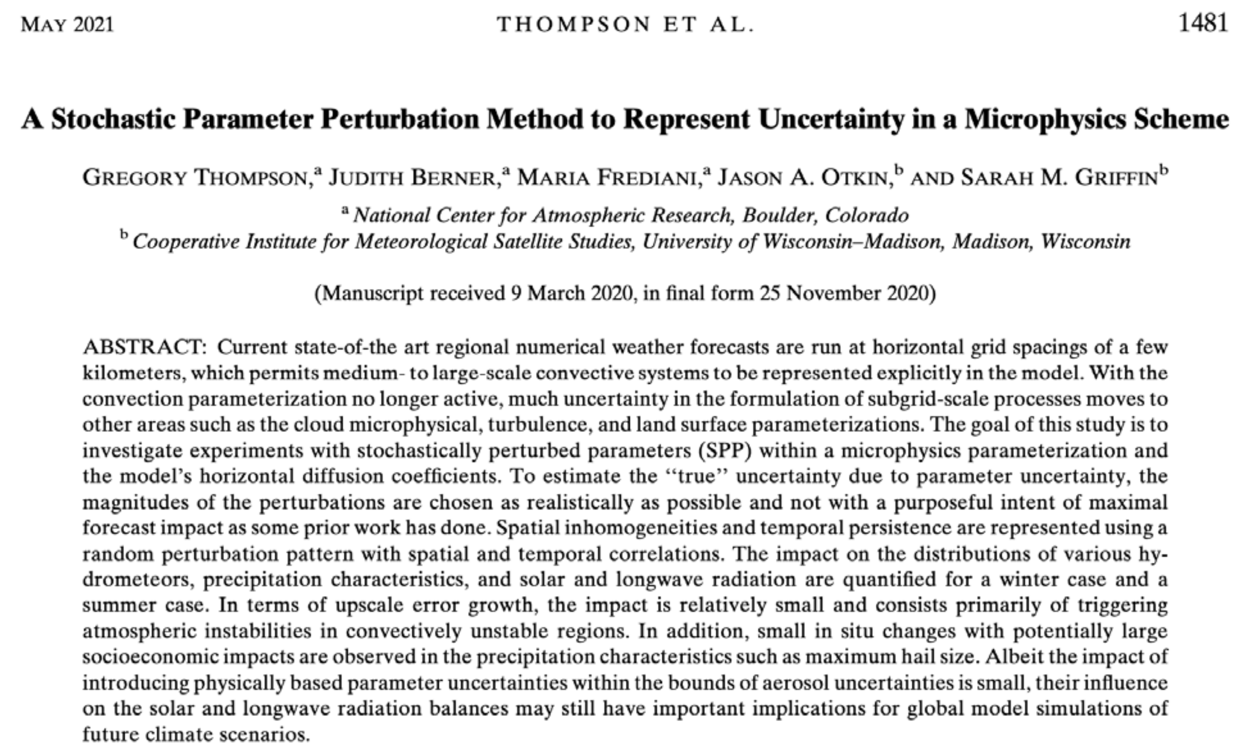
- Cloud water, rain, snow, etc.

Example max-in-column icing forecast valid 20z 16Jan2013





Stochastic Parameter Perturbations (SPP)



A Stochastic Parameter Perturbation Method to Represent Uncertainty in a Microphysics Scheme

Gregory Thompson,[a] Judith Berner,[a] Maria Frediani,[a] Jason A. Otkin,[b] and Sarah M. Griffin[b]

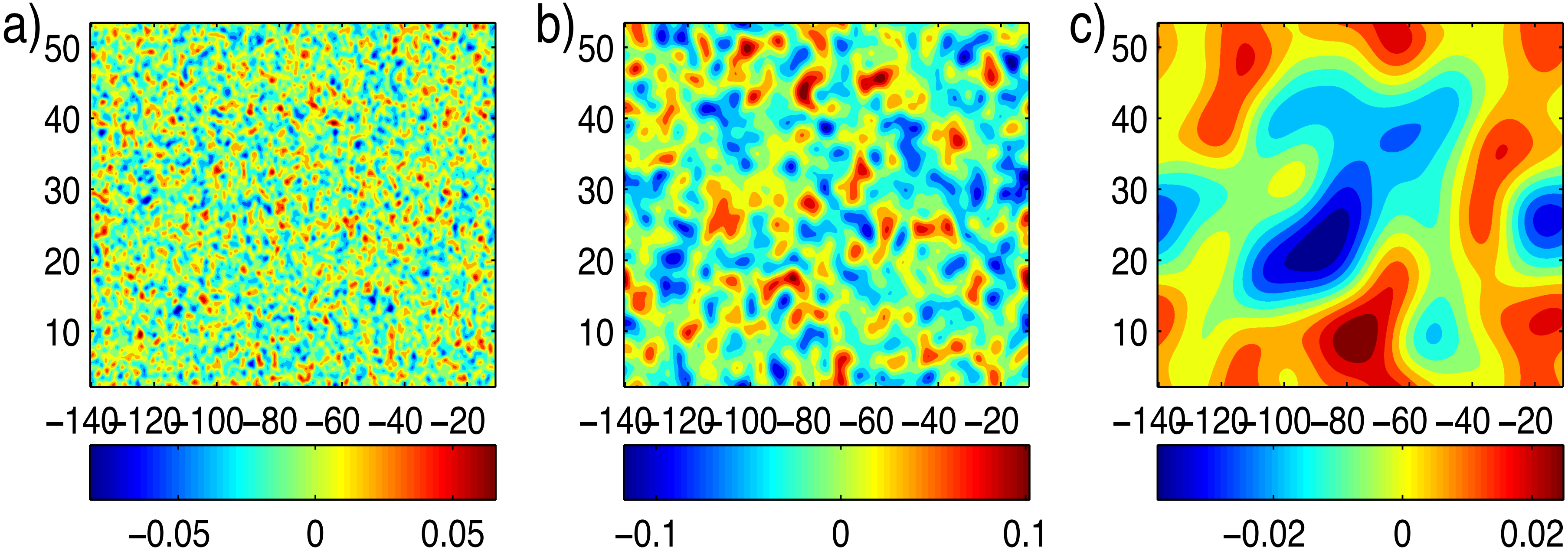
[a] *National Center for Atmospheric Research, Boulder, Colorado*
[b] *Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin–Madison, Madison, Wisconsin*

(Manuscript received 9 March 2020, in final form 25 November 2020)

ABSTRACT: Current state-of-the art regional numerical weather forecasts are run at horizontal grid spacings of a few kilometers, which permits medium- to large-scale convective systems to be represented explicitly in the model. With the convection parameterization no longer active, much uncertainty in the formulation of subgrid-scale processes moves to other areas such as the cloud microphysical, turbulence, and land surface parameterizations. The goal of this study is to investigate experiments with stochastically perturbed parameters (SPP) within a microphysics parameterization and the model's horizontal diffusion coefficients. To estimate the ''true'' uncertainty due to parameter uncertainty, the magnitudes of the perturbations are chosen as realistically as possible and not with a purposeful intent of maximal forecast impact as some prior work has done. Spatial inhomogeneities and temporal persistence are represented using a random perturbation pattern with spatial and temporal correlations. The impact on the distributions of various hydrometeors, precipitation characteristics, and solar and longwave radiation are quantified for a winter case and a summer case. In terms of upscale error growth, the impact is relatively small and consists primarily of triggering atmospheric instabilities in convectively unstable regions. In addition, small in situ changes with potentially large socioeconomic impacts are observed in the precipitation characteristics such as maximum hail size. Albeit the impact of introducing physically based parameter uncertainties within the bounds of aerosol uncertainties is small, their influence on the solar and longwave radiation balances may still have important implications for global model simulations of future climate scenarios.

Stochastic Parameter Perturbations (SPP)

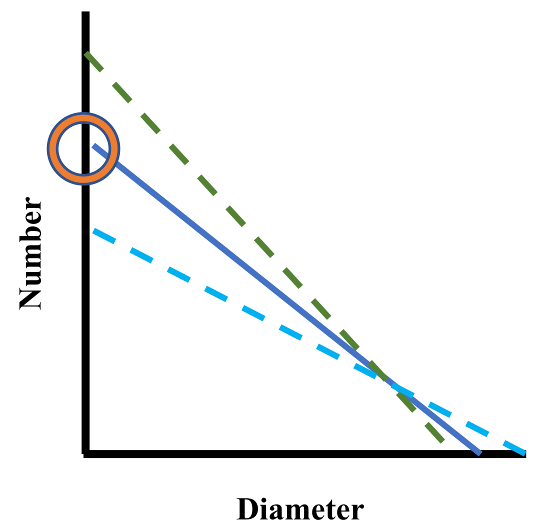
Example random perturbation patterns
User defined: magnitude, spatial, and temporal time scales



fine scale ⟷ broad scale

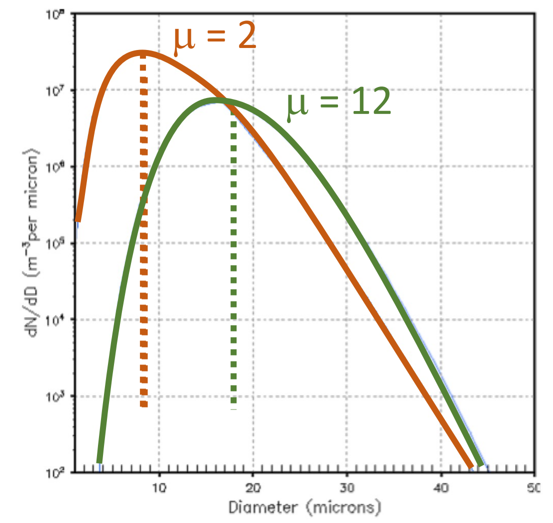
Alterations to microphysics scheme

A.) Graupel Y-intercept parameter



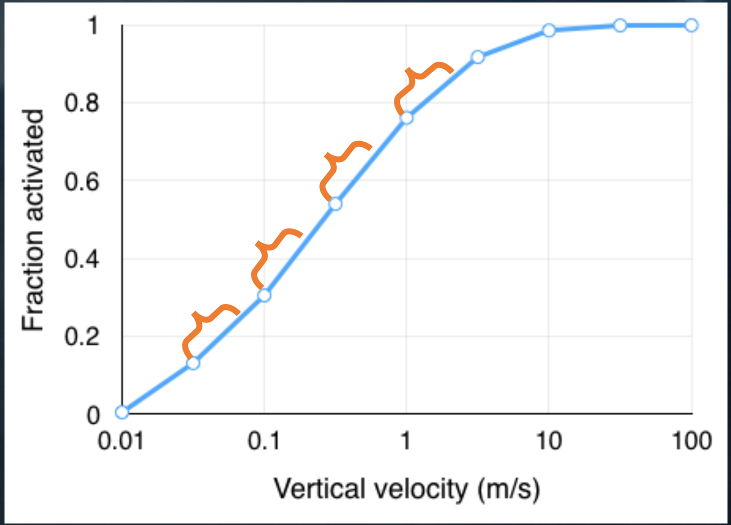
+/- 1.5 orders of magnitude (m^{-4})

B.) Cloud water shape parameter



+/- 3 always constrained [2,15]

C.) Cloud Condensation Nucleation



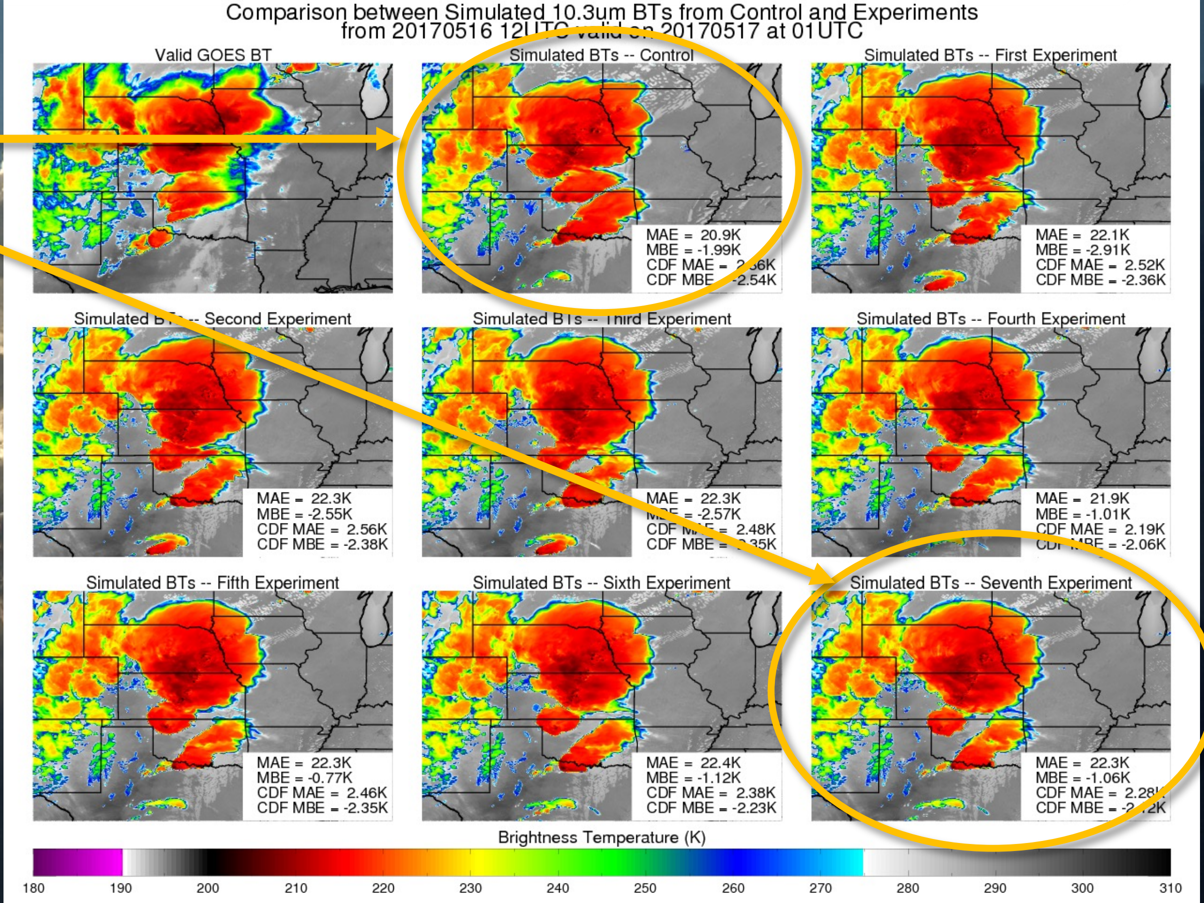
W perturbed up to + 0.35 m/s

Application Testing: Hazardous Weather Testbed

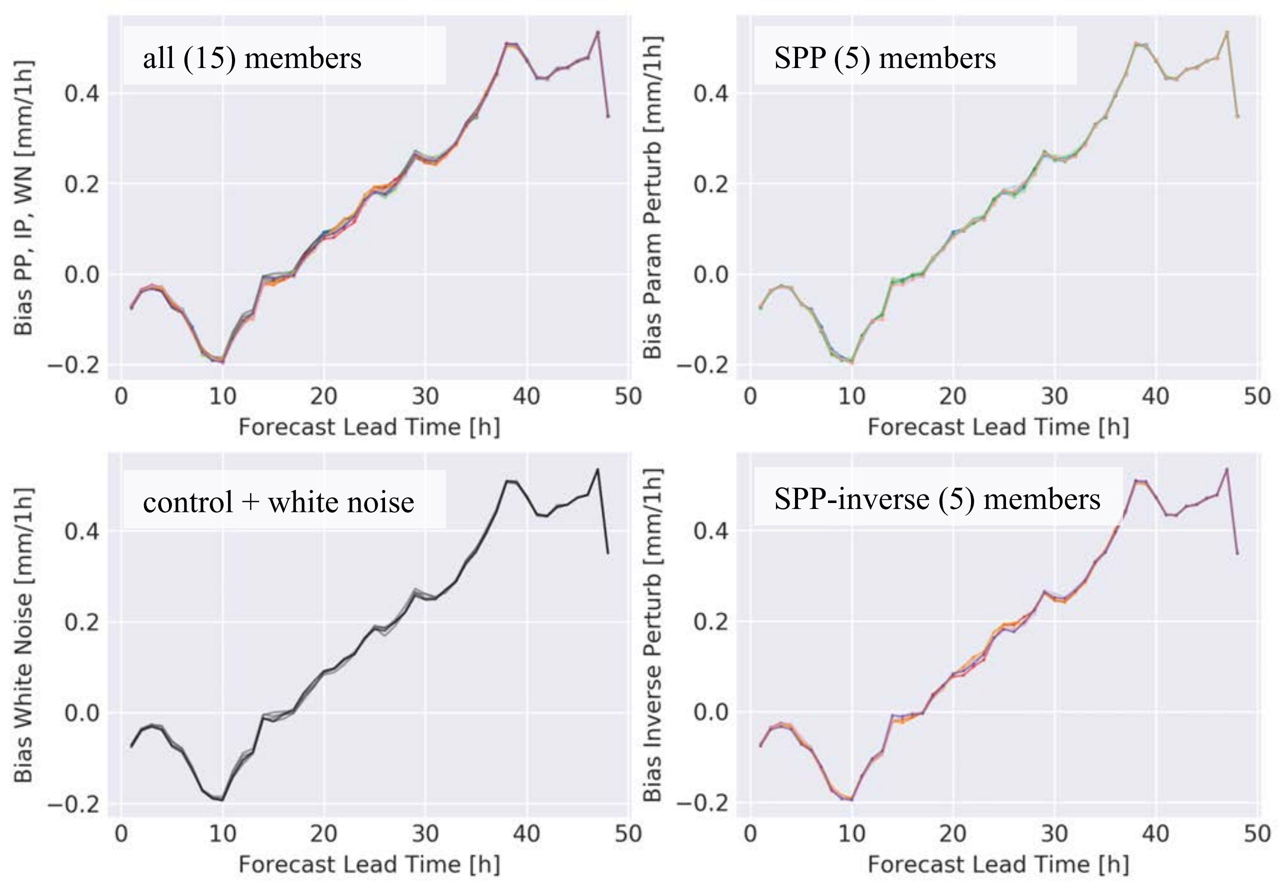
OU-CAPS 2017 Spring Experiment

Control: no SPP

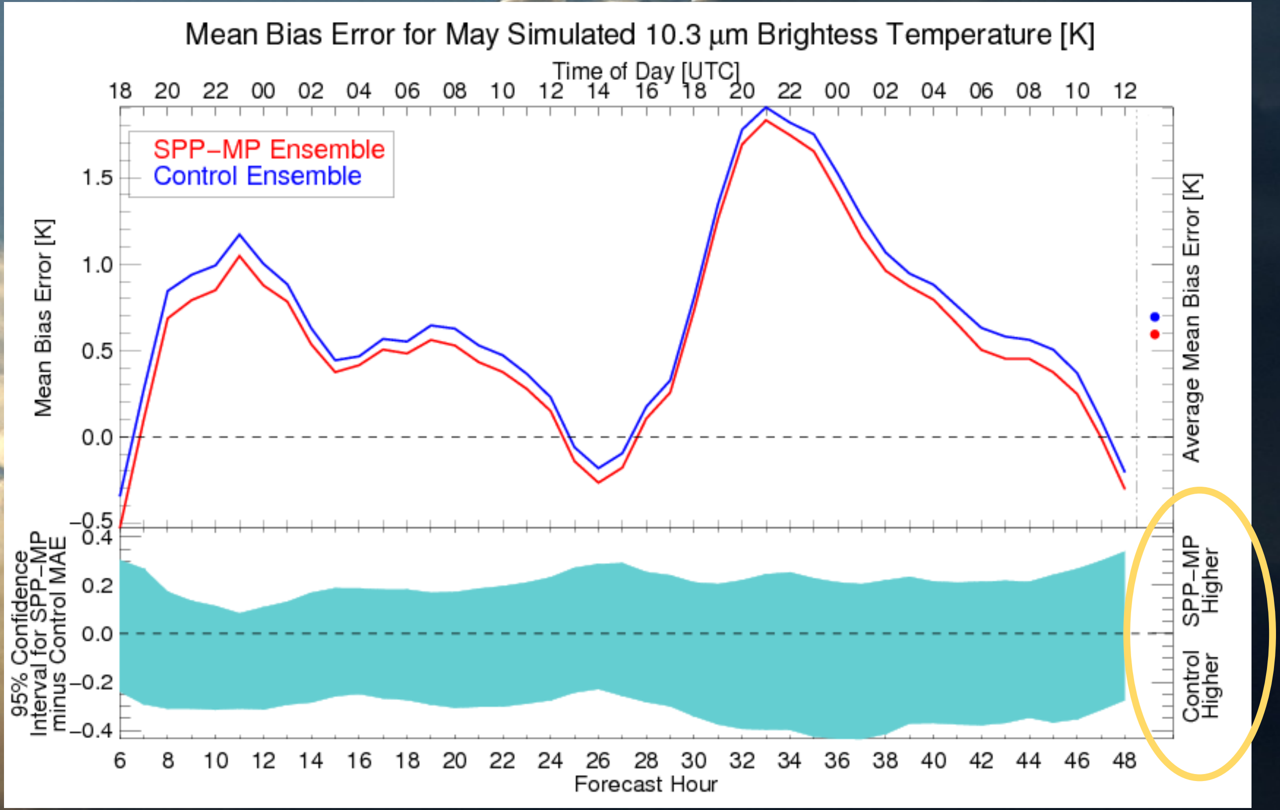
SPP_MP = 7 (all)



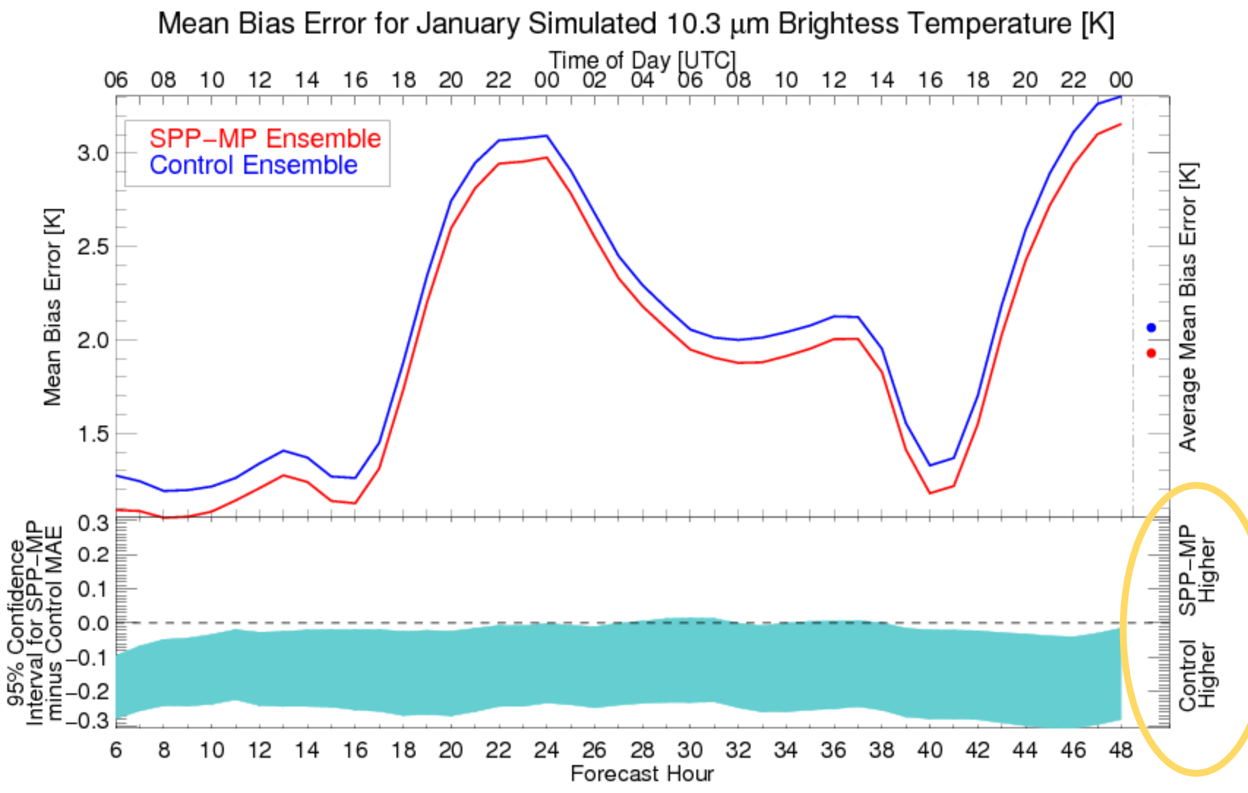
SPP, SPP-Inverse, White-noise



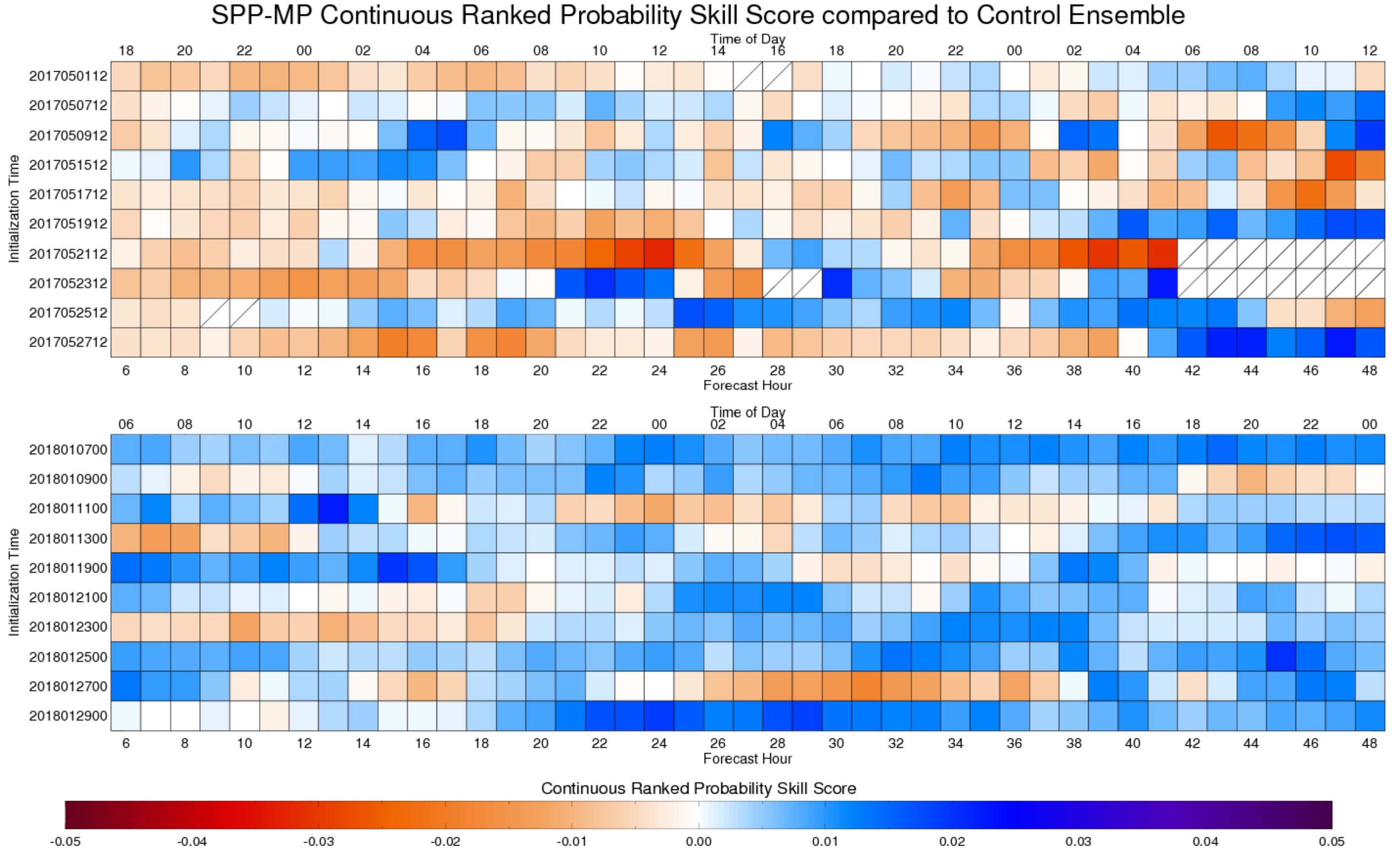
Analysis using GOES-16 IR (May2017, 5 dates)



Analysis using GOES-16 IR (Jan2018, 5 dates)



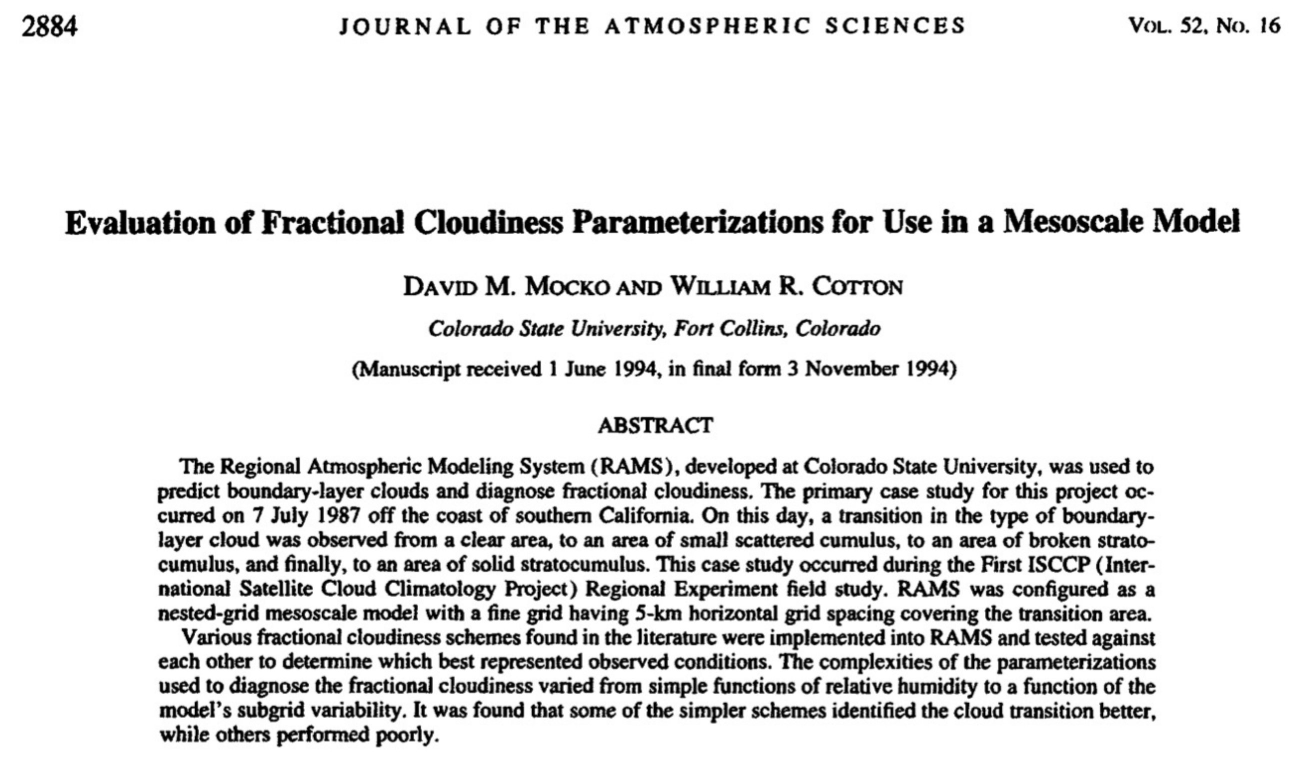
Skill scores May2017 and Jan2018 (GOES-16 IR)



What do we do?

❑ Ensemble forecasts:
- ✓ Time-Lag Ensembles (e.g., RAP/HRRR)
- ▪ Model Ensembles
- ✓ Physics Ensembles (Thompson, Morrison, WSM6, etc.)
- ✓ Stochastic Parameter Perturbations (SPP)
- ✓ Cloud Fraction schemes
- ▪ Data Assimilation

Generational knowledge gaps?



Evaluation of Fractional Cloudiness Parameterizations for Use in a Mesoscale Model

DAVID M. MOCKO AND WILLIAM R. COTTON

Colorado State University, Fort Collins, Colorado

(Manuscript received 1 June 1994, in final form 3 November 1994)

ABSTRACT

The Regional Atmospheric Modeling System (RAMS), developed at Colorado State University, was used to predict boundary-layer clouds and diagnose fractional cloudiness. The primary case study for this project occurred on 7 July 1987 off the coast of southern California. On this day, a transition in the type of boundary-layer cloud was observed from a clear area, to an area of small scattered cumulus, to an area of broken stratocumulus, and finally, to an area of solid stratocumulus. This case study occurred during the First ISCCP (International Satellite Cloud Climatology Project) Regional Experiment field study. RAMS was configured as a nested-grid mesoscale model with a fine grid having 5-km horizontal grid spacing covering the transition area.

Various fractional cloudiness schemes found in the literature were implemented into RAMS and tested against each other to determine which best represented observed conditions. The complexities of the parameterizations used to diagnose the fractional cloudiness varied from simple functions of relative humidity to a function of the model's subgrid variability. It was found that some of the simpler schemes identified the cloud transition better, while others performed poorly.

Obs vs. RAMS model @5km

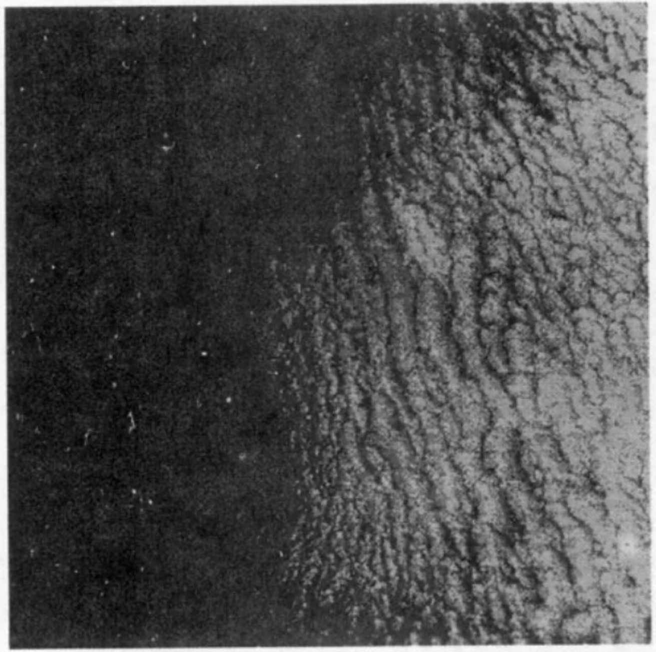
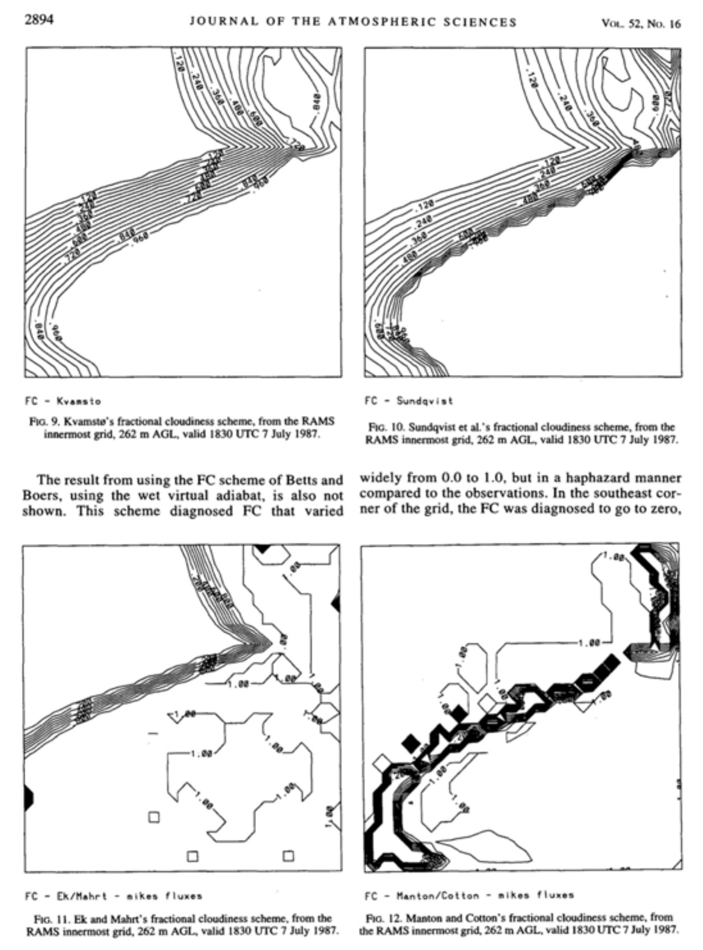


FIG. 5. Landsat scene at 1830 UTC 7 July 1987 with center coordinates 33°10′N, 121°44′W (from Betts and Boers 1990). Distance across is about 180 km.



2894 JOURNAL OF THE ATMOSPHERIC SCIENCES VOL. 52, NO. 16

FIG. 9. Kvamstø's fractional cloudiness scheme, from the RAMS innermost grid, 262 m AGL, valid 1830 UTC 7 July 1987.

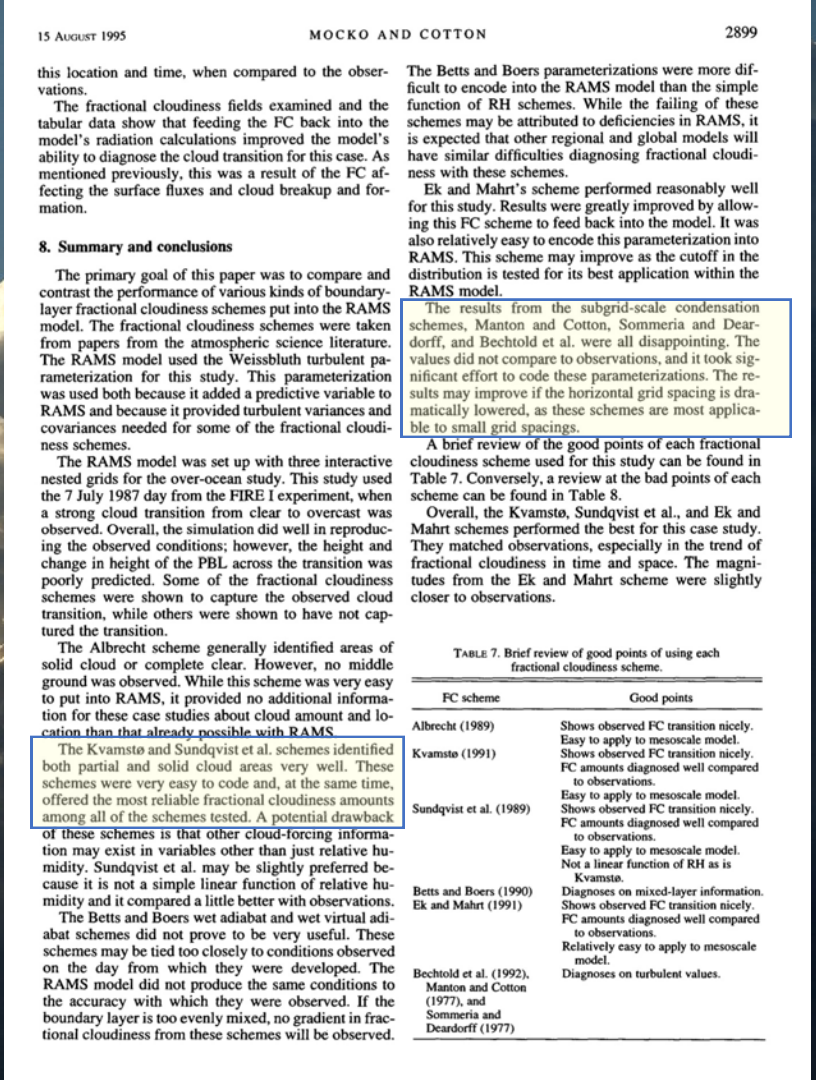
FIG. 10. Sundqvist et al.'s fractional cloudiness scheme, from the RAMS innermost grid, 262 m AGL, valid 1830 UTC 7 July 1987.

The result from using the FC scheme of Betts and Boers, using the wet virtual adiabat, is also not shown. This scheme diagnosed FC that varied widely from 0.0 to 1.0, but in a haphazard manner compared to the observations. In the southeast corner of the grid, the FC was diagnosed to go to zero,

FIG. 11. Ek and Mahrt's fractional cloudiness scheme, from the RAMS innermost grid, 262 m AGL, valid 1830 UTC 7 July 1987.

FIG. 12. Manton and Cotton's fractional cloudiness scheme, from the RAMS innermost grid, 262 m AGL, valid 1830 UTC 7 July 1987.

Tested numerous schemes



15 August 1995 MOCKO AND COTTON 2899

this location and time, when compared to the observations.

The fractional cloudiness fields examined and the tabular data show that feeding the FC back into the model's radiation calculations improved the model's ability to diagnose the cloud transition for this case. As mentioned previously, this was a result of the FC affecting the surface fluxes and cloud breakup and formation.

8. Summary and conclusions

The primary goal of this paper was to compare and contrast the performance of various kinds of boundary-layer fractional cloudiness schemes put into the RAMS model. The fractional cloudiness schemes were taken from papers from the atmospheric science literature. The RAMS model used the Weissbluth turbulent parameterization for this study. This parameterization was used both because it added a predictive variable to RAMS and because it provided turbulent variances and covariances needed for some of the fractional cloudiness schemes.

The RAMS model was set up with three interactive nested grids for the over-ocean study. This study used the 7 July 1987 day from the FIRE I experiment, when a strong cloud transition from clear to overcast was observed. Overall, the simulation did well in reproducing the observed conditions; however, the height and change in height of the PBL across the transition was poorly predicted. Some of the fractional cloudiness schemes were shown to capture the observed cloud transition, while others were shown to have not captured the transition.

The Albrecht scheme generally identified areas of solid cloud or complete clear. However, no middle ground was observed. While this scheme was very easy to put into RAMS, it provided no additional information for these case studies about cloud amount and location than that already possible with RAMS.

The Kvamstø and Sundqvist et al. schemes identified both partial and solid cloud areas very well. These schemes were very easy to code and, at the same time, offered the most reliable fractional cloudiness amounts among all of the schemes tested. A potential drawback of these schemes is that other cloud-forcing information may exist in variables other than just relative humidity. Sundqvist et al. may be slightly preferred because it is not a simple linear function of relative humidity and it compared a little better with observations.

The Betts and Boers wet adiabat and wet virtual adiabat schemes did not prove to be very useful. These schemes may be tied too closely to conditions observed on the day from which they were developed. The RAMS model did not produce the same conditions to the accuracy with which they were observed. If the boundary layer is too evenly mixed, no gradient in fractional cloudiness from these schemes will be observed. The Betts and Boers parameterizations were more difficult to encode into the RAMS model than the simple function of RH schemes. While the failing of these schemes may be attributed to deficiencies in RAMS, it is expected that other regional and global models will have similar difficulties diagnosing fractional cloudiness with these schemes.

Ek and Mahrt's scheme performed reasonably well for this study. Results were greatly improved by allowing this FC scheme to feed back into the model. It was also relatively easy to encode this parameterization into RAMS. This scheme may improve as the cutoff in the distribution is tested for its best application within the RAMS model.

The results from the subgrid-scale condensation schemes, Manton and Cotton, Sommeria and Deardorff, and Bechtold et al. were all disappointing. The values did not compare to observations, and it took significant effort to code these parameterizations. The results may improve if the horizontal grid spacing is dramatically lowered, as these schemes are most applicable to small grid spacings.

A brief review of the good points of each fractional cloudiness scheme used for this study can be found in Table 7. Conversely, a review at the bad points of each scheme can be found in Table 8.

Overall, the Kvamstø, Sundqvist et al., and Ek and Mahrt schemes performed the best for this case study. They matched observations, especially in the trend of fractional cloudiness in time and space. The magnitudes from the Ek and Mahrt scheme were slightly closer to observations.

TABLE 7. Brief review of good points of using each fractional cloudiness scheme.

FC scheme	Good points
Albrecht (1989)	Shows observed FC transition nicely. Easy to apply to mesoscale model.
Kvamstø (1991)	Shows observed FC transition nicely. FC amounts diagnosed well compared to observations. Easy to apply to mesoscale model.
Sundqvist et al. (1989)	Shows observed FC transition nicely. FC amounts diagnosed well compared to observations. Easy to apply to mesoscale model. Not a linear function of RH as is Kvamstø.
Betts and Boers (1990)	Diagnoses on mixed-layer information.
Ek and Mahrt (1991)	Shows observed FC transition nicely. FC amounts diagnosed well compared to observations. Relatively easy to apply to mesoscale model.
Bechtold et al. (1992), Manton and Cotton (1977), and Sommeria and Deardorff (1977)	Diagnoses on turbulent values.

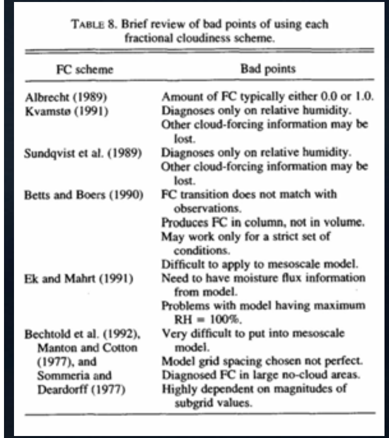
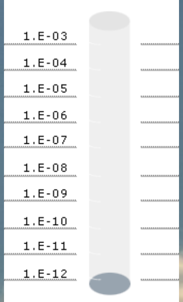


TABLE 8. Brief review of bad points of using each fractional cloudiness scheme.

FC scheme	Bad points
Albrecht (1989)	Amount of FC typically either 0.0 or 1.0.
Kvamstø (1991)	Diagnoses only on relative humidity. Other cloud-forcing information may be lost.
Sundqvist et al. (1989)	Diagnoses only on relative humidity. Other cloud-forcing information may be lost.
Betts and Boers (1990)	FC transition does not match with observations. Produces FC in column, not in volume. May work only for a strict set of conditions. Difficult to apply to mesoscale model.
Ek and Mahrt (1991)	Need to have moisture flux information from model. Problems with model having maximum RH = 100%.
Bechtold et al. (1992), Manton and Cotton (1977), and Sommeria and Deardorff (1977)	Very difficult to put into mesoscale model. Model grid spacing chosen not perfect. Diagnosed FC in large no-cloud areas. Highly dependent on magnitudes of subgrid values.

What amount of cloud water or cloud ice/snow constitutes 100% cloud fraction?



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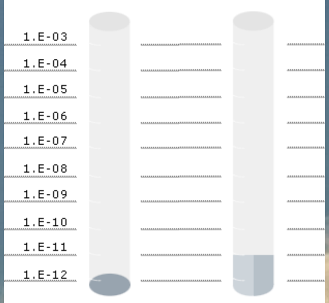

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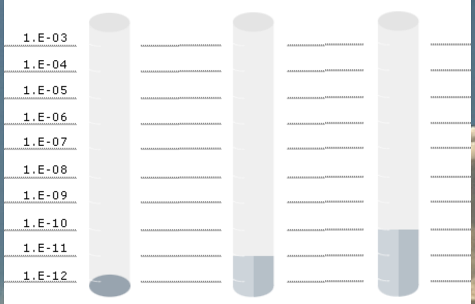

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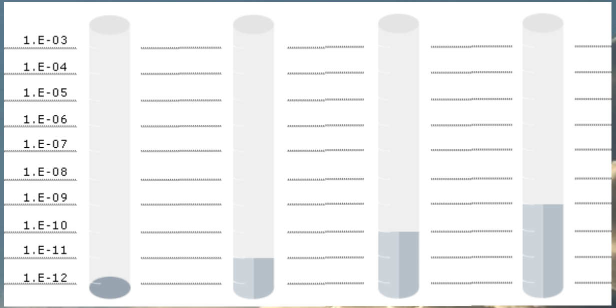

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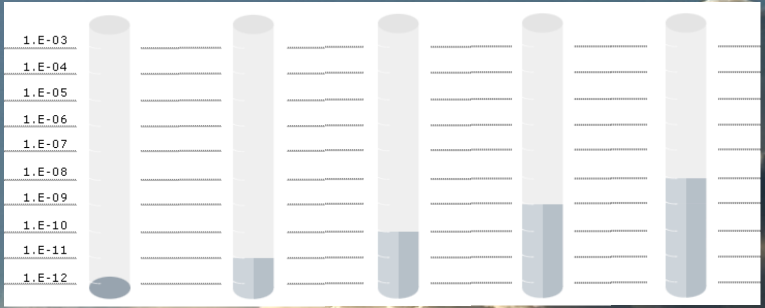

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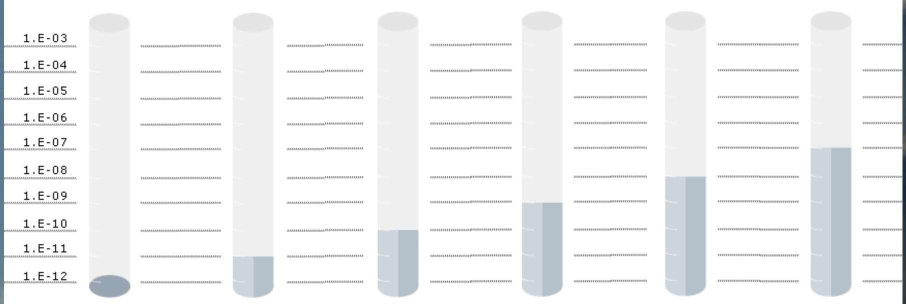

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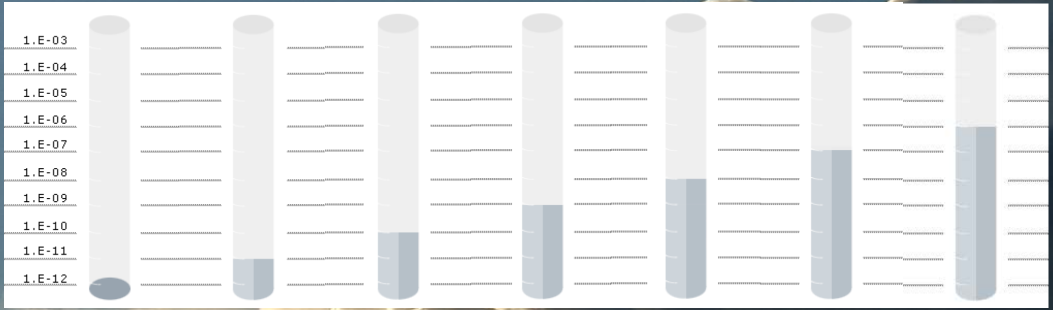

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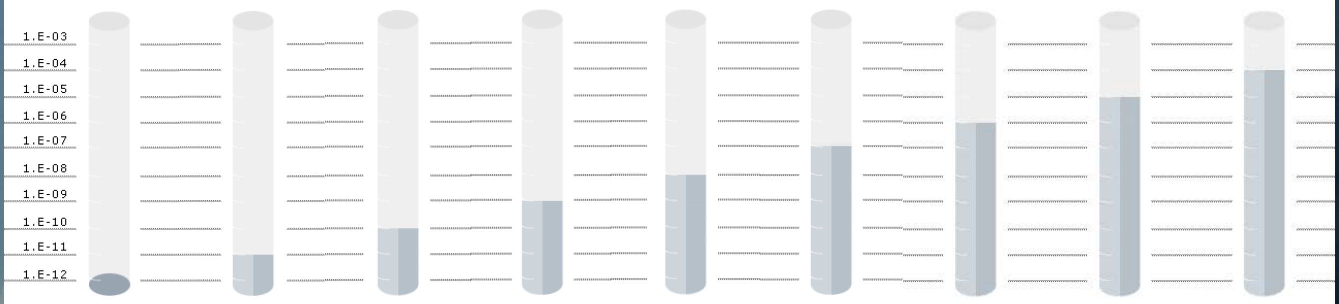

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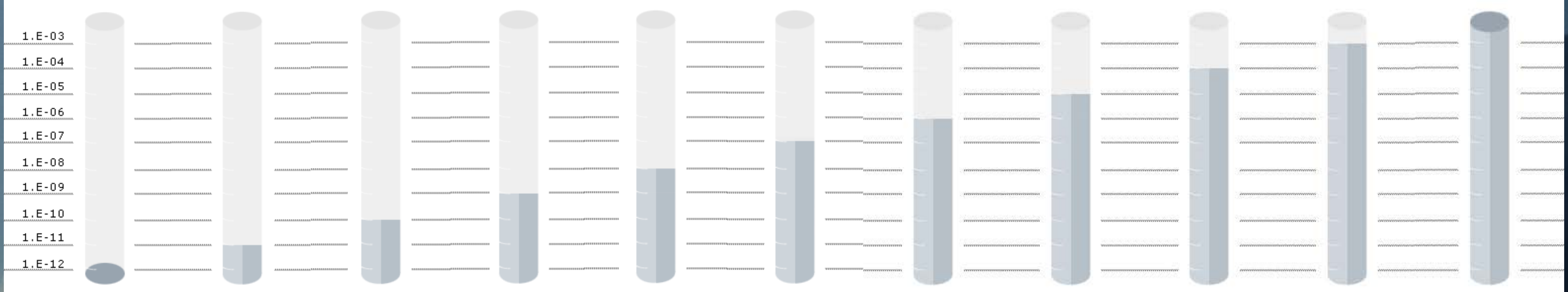
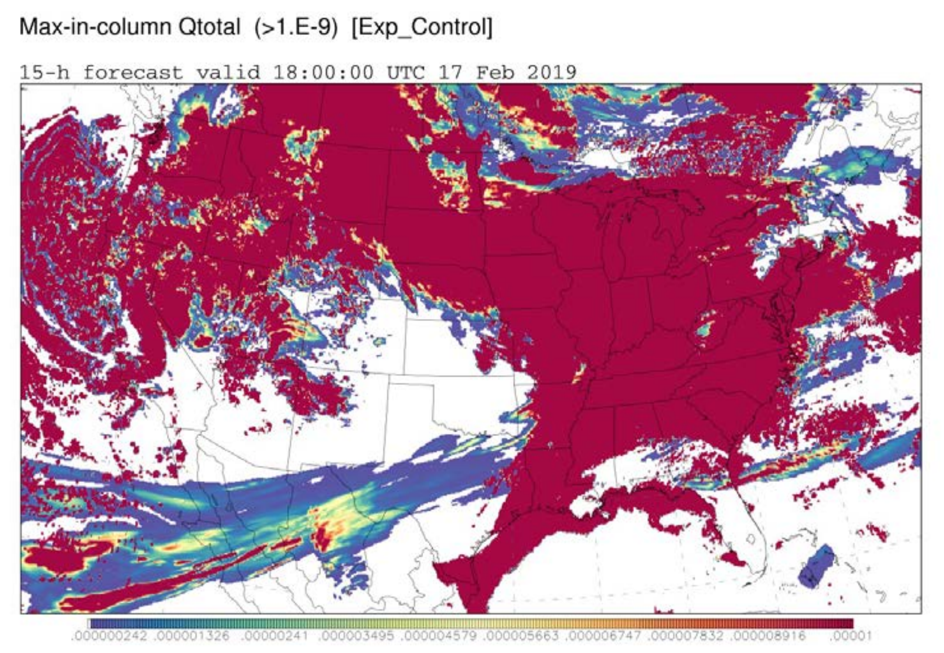


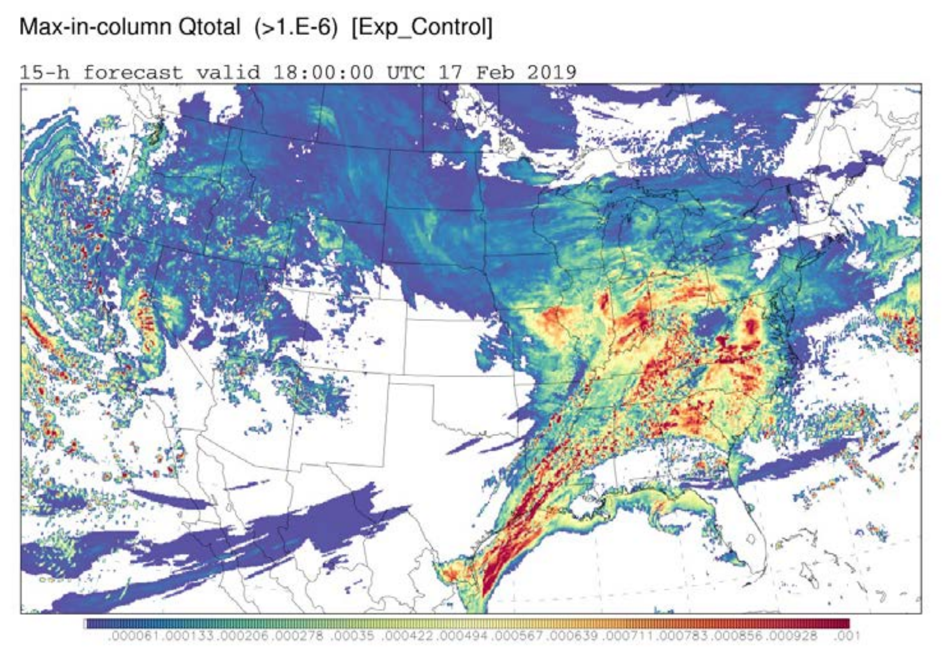
0.001 g/kg

1 g/kg

Small mixing ratios

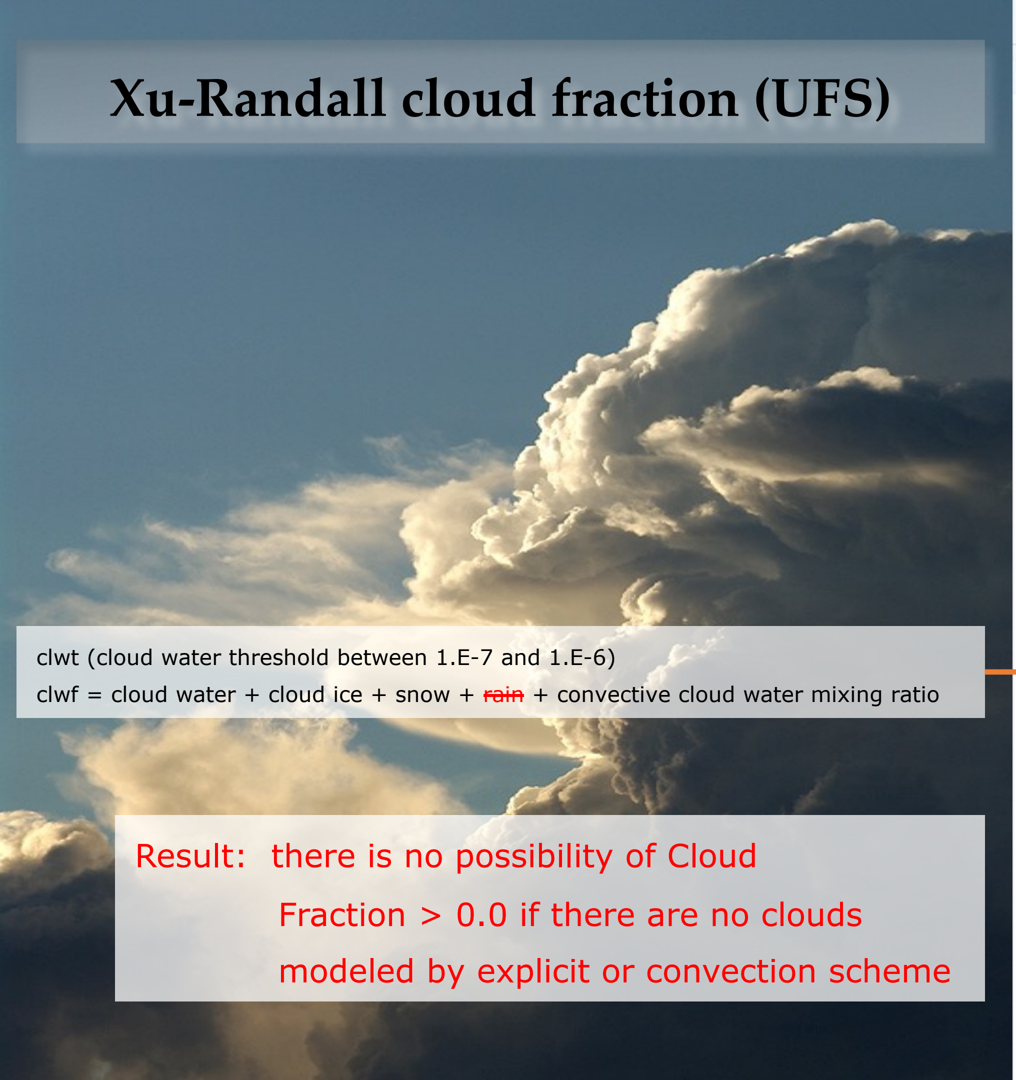

Max-in-column Qtotal (>1.E-9) [Exp_Control]

15-h forecast valid 18:00:00 UTC 17 Feb 2019


Max-in-column Qtotal (>1.E-6) [Exp_Control]

15-h forecast valid 18:00:00 UTC 17 Feb 2019

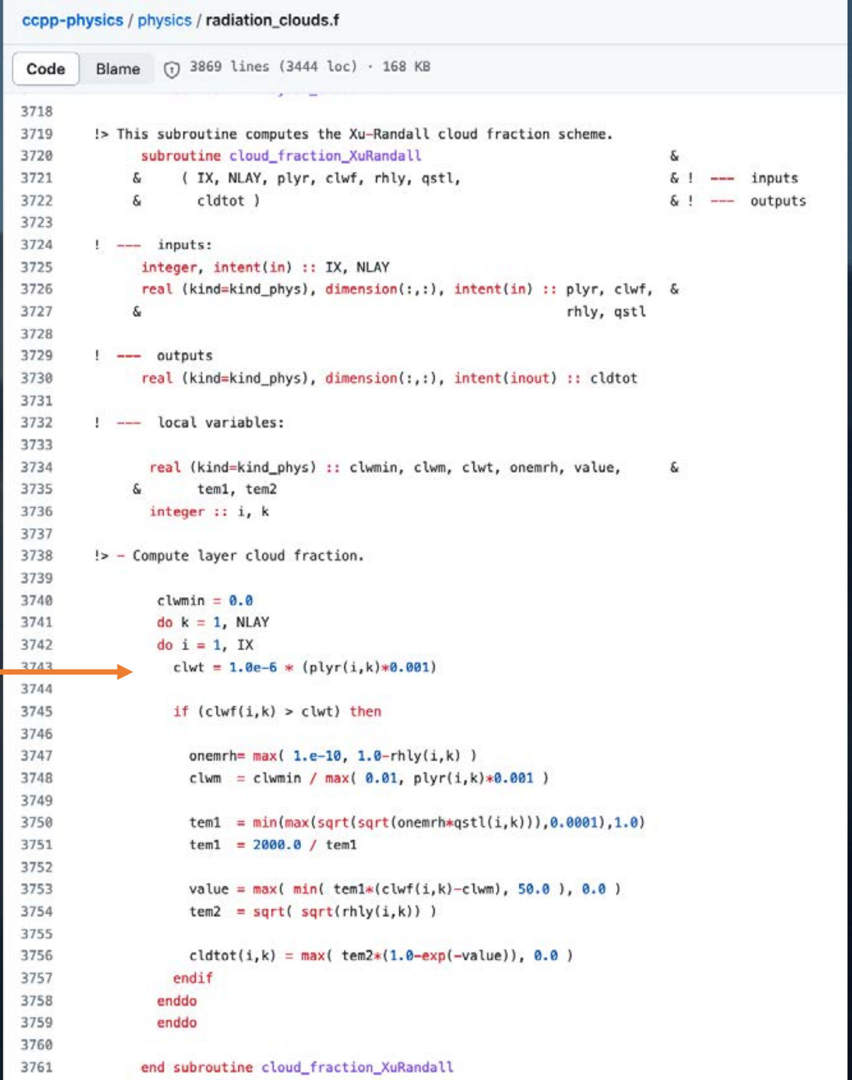
Xu-Randall cloud fraction (UFS)



clwt (cloud water threshold between 1.E-7 and 1.E-6)

clwf = cloud water + cloud ice + snow + ~~rain~~ + convective cloud water mixing ratio

Result: there is no possibility of Cloud
Fraction > 0.0 if there are no clouds
modeled by explicit or convection scheme



```fortran

!> This subroutine computes the Xu-Randall cloud fraction scheme.
      subroutine cloud_fraction_XuRandall                                &
     &     ( IX, NLAY, plyr, clwf, rhly, qstl,                           & !  ---  inputs
     &       cldtot )                                                    & !  ---  outputs

!  ---  inputs:
      integer, intent(in) :: IX, NLAY
      real (kind=kind_phys), dimension(:,:), intent(in) :: plyr, clwf,  &
     &                                                   rhly, qstl

!  ---  outputs
      real (kind=kind_phys), dimension(:,:), intent(inout) :: cldtot

!  ---  local variables:

       real (kind=kind_phys) :: clwmin, clwm, clwt, onemrh, value,      &
     &       tem1, tem2
       integer :: i, k

!> - Compute layer cloud fraction.

        clwmin = 0.0
        do k = 1, NLAY
        do i = 1, IX
          clwt = 1.0e-6 * (plyr(i,k)*0.001)

          if (clwf(i,k) > clwt) then

            onemrh= max( 1.e-10, 1.0-rhly(i,k) )
            clwm  = clwmin / max( 0.01, plyr(i,k)*0.001 )

            tem1  = min(max(sqrt(sqrt(onemrh*qstl(i,k))),0.0001),1.0)
            tem1  = 2000.0 / tem1

            value = max( min( tem1*(clwf(i,k)-clwm), 50.0 ), 0.0 )
            tem2  = sqrt( sqrt(rhly(i,k)) )

            cldtot(i,k) = max( tem2*(1.0-exp(-value)), 0.0 )
          endif
        enddo
        enddo

      end subroutine cloud_fraction_XuRandall
```

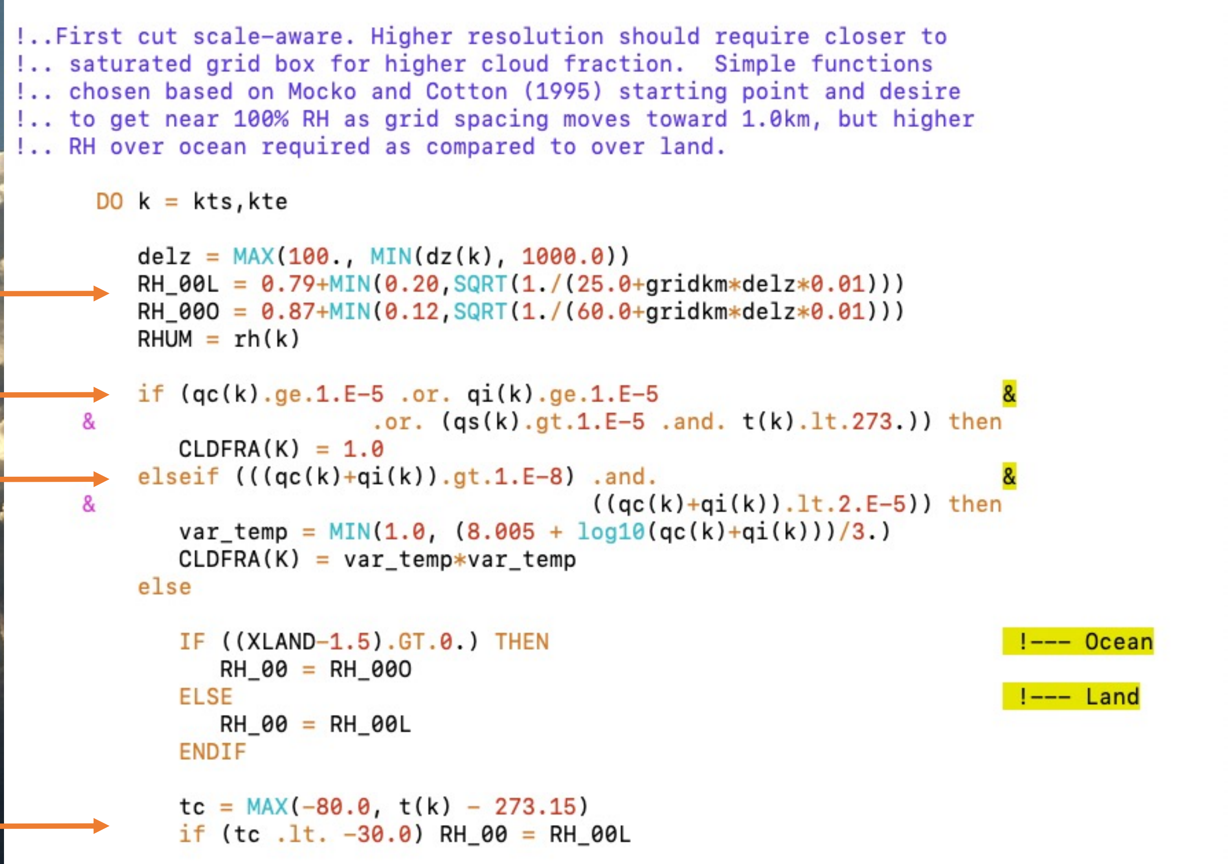
progcld_thompson (cal_cldfra3)

RH-critical depends on ocean v. land and has grid scale dependence

100% cloud fraction where $q_x > 0.01$ g/kg

where $1.E\text{-}5 > q_x > 0.01$ g/kg, cloud fraction scales with $\log_{10}$ of mixing ratio

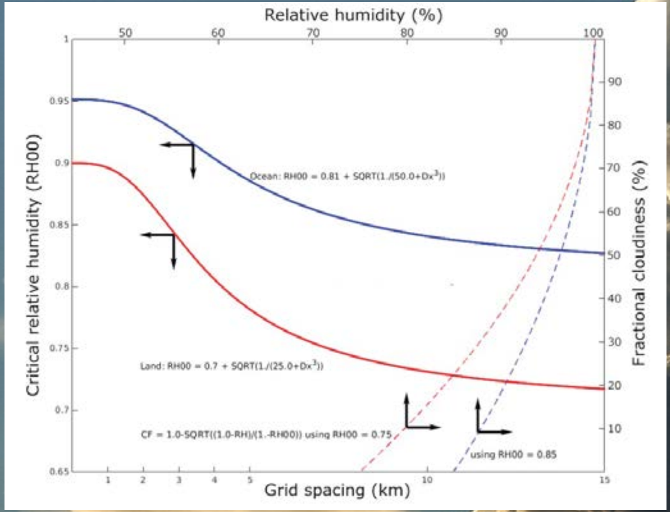
at high altitudes, ocean RH-critical reverts to the lower land value



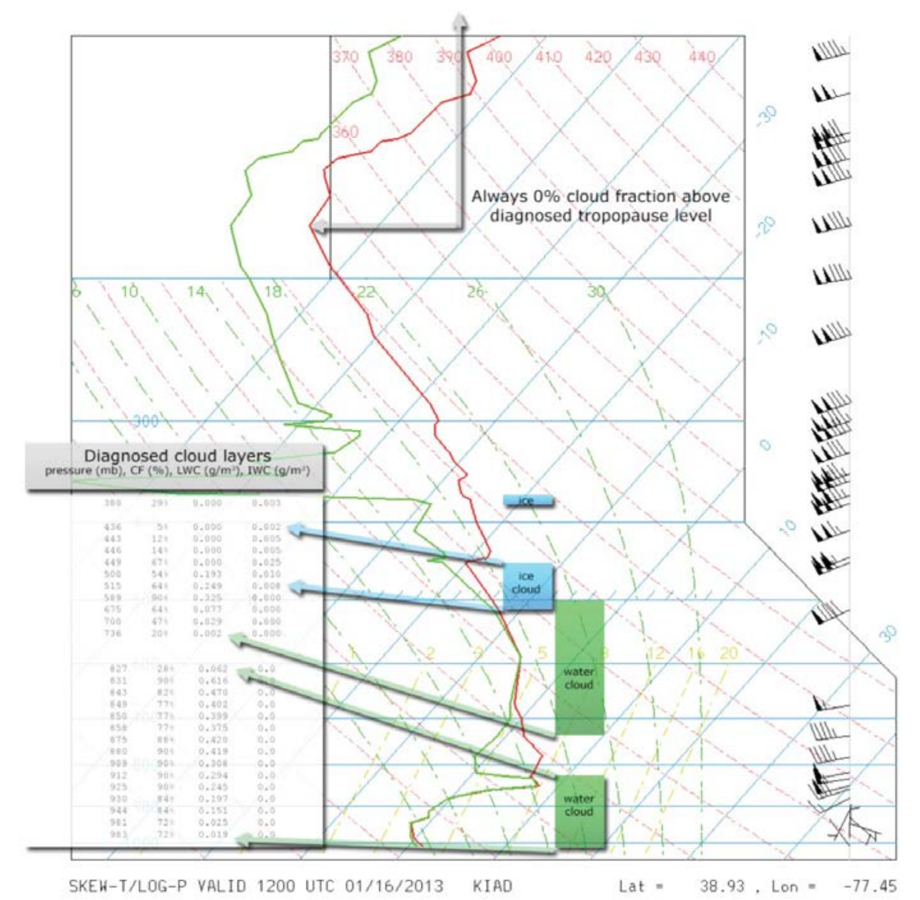
```
!..First cut scale-aware. Higher resolution should require closer to
!.. saturated grid box for higher cloud fraction.  Simple functions
!.. chosen based on Mocko and Cotton (1995) starting point and desire
!.. to get near 100% RH as grid spacing moves toward 1.0km, but higher
!.. RH over ocean required as compared to over land.

      DO k = kts,kte

         delz = MAX(100., MIN(dz(k), 1000.0))
         RH_00L = 0.79+MIN(0.20,SQRT(1./(25.0+gridkm*delz*0.01)))
         RH_00O = 0.87+MIN(0.12,SQRT(1./(60.0+gridkm*delz*0.01)))
         RHUM = rh(k)

         if (qc(k).ge.1.E-5 .or. qi(k).ge.1.E-5                         &
     &                    .or. (qs(k).gt.1.E-5 .and. t(k).lt.273.)) then
            CLDFRA(K) = 1.0
         elseif (((qc(k)+qi(k)).gt.1.E-8) .and.                         &
     &                                    ((qc(k)+qi(k)).lt.2.E-5)) then
            var_temp = MIN(1.0, (8.005 + log10(qc(k)+qi(k)))/3.)
            CLDFRA(K) = var_temp*var_temp
         else

            IF ((XLAND-1.5).GT.0.) THEN                                 !--- Ocean
               RH_00 = RH_00O
            ELSE                                                        !--- Land
               RH_00 = RH_00L
            ENDIF

            tc = MAX(-80.0, t(k) - 273.15)
            if (tc .lt. -30.0) RH_00 = RH_00L
```

progcld_thompson (cal_cldfra3)

cloud fraction increases with increasing RH (above RH-critical)



entire cloud layers are treated as adiabatic clouds with an entrainment factor, but the column sum of all water/ice clouds are kept from producing excessive LWP/IWP. No sub-grid clouds co-exist with explicit MP clouds



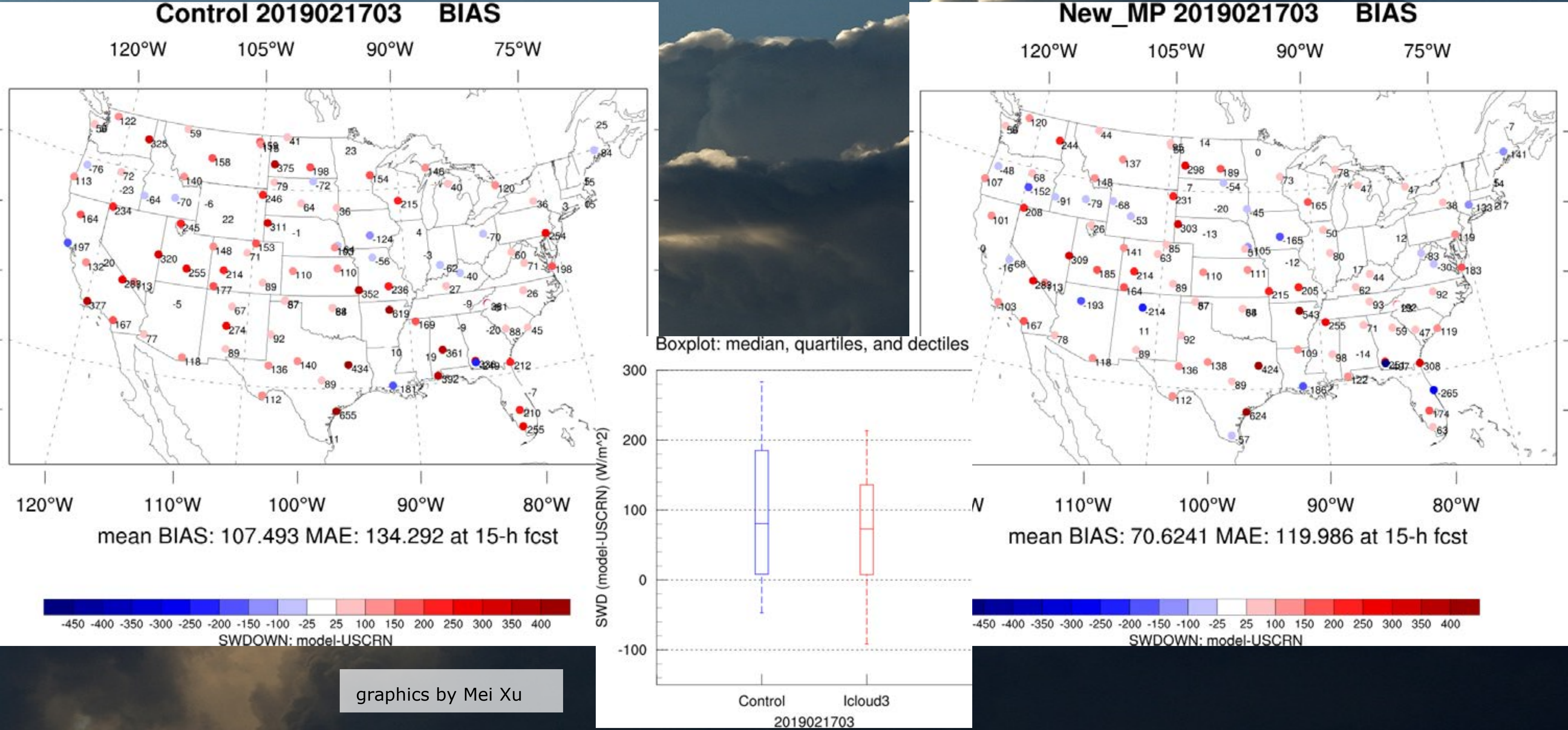
Diagnosed cloud layers

pressure (mb), CF (%), LWC (g/m³), IWC (g/m³)

300	29%	0.000	0.003
436	5%	0.000	0.002
443	12%	0.000	0.005
446	14%	0.000	0.005
449	47%	0.000	0.025
500	54%	0.193	0.010
515	64%	0.249	0.008
589	90%	0.325	0.000
675	64%	0.077	0.000
700	47%	0.029	0.000
736	20%	0.002	0.000
827	28%	0.062	0.0
831	90%	0.616	0.0
843	82%	0.470	0.0
849	77%	0.402	0.0
850	77%	0.399	0.0
858	77%	0.375	0.0
875	88%	0.420	0.0
880	90%	0.419	0.0
909	90%	0.308	0.0
912	98%	0.294	0.0
925	90%	0.245	0.0
930	84%	0.197	0.0
944	84%	0.151	0.0
981	72%	0.025	0.0
983	72%	0.019	0.0

SKEW-T/LOG-P VALID 1200 UTC 01/16/2013 KIAD Lat = 38.93 , Lon = -77.45

Verification: shortwave radiation at ground using USCRN data

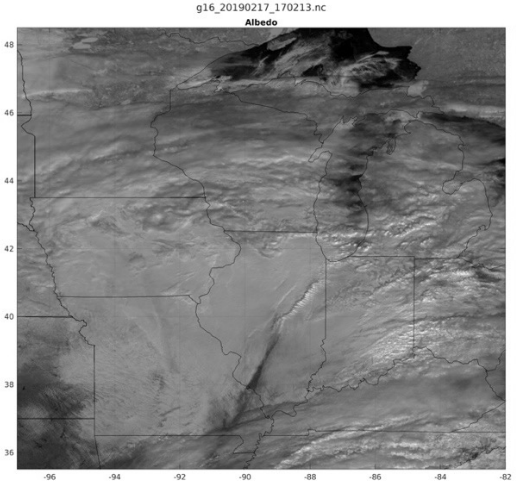


graphics by Mei Xu

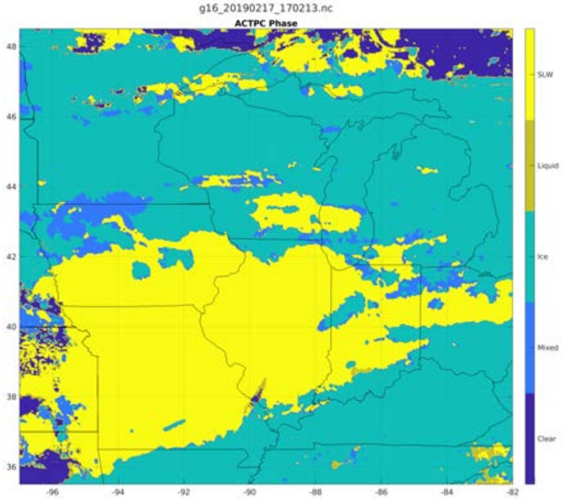
Cloud-top phase - OBS

Machine Learning: Principle Components Analysis (PCA)

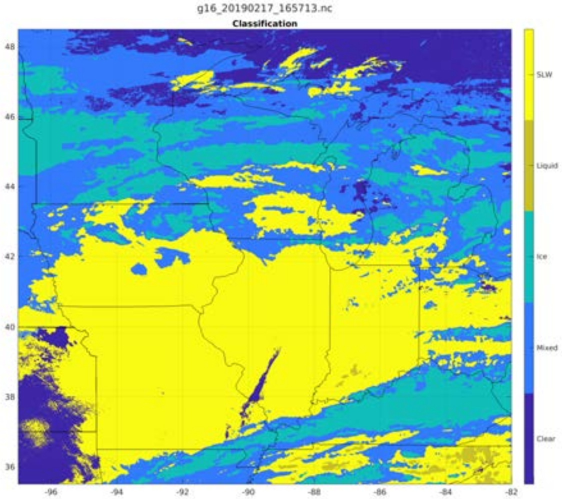
GOES-16 Visible



GOES-16 Level2 Cloud-top phase

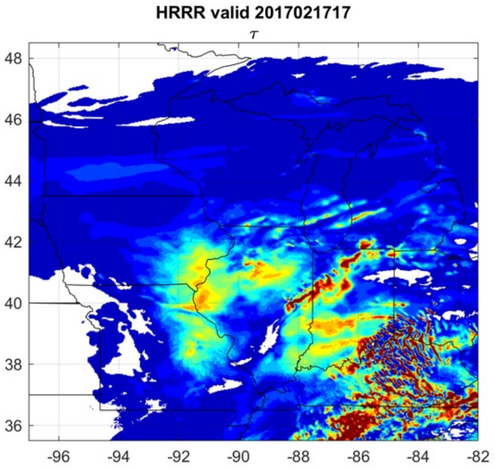


NCAR ML-PCA Cloud-top phase

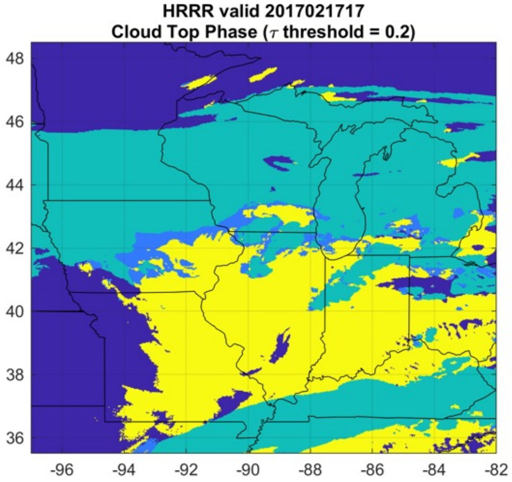


Cloud-top phase - Model

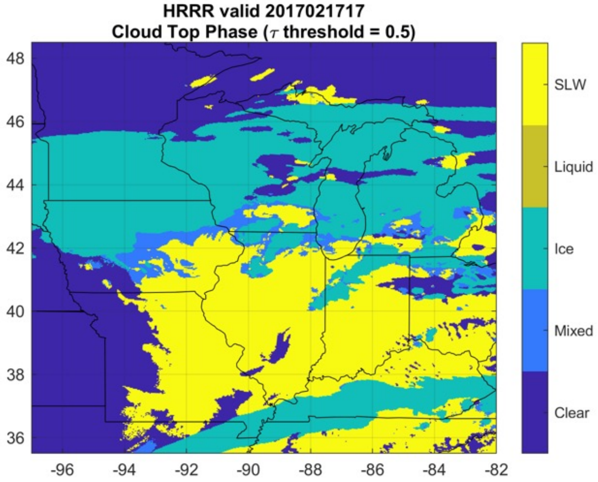
HRRR cloud optical depth (τ)



HRRR cloud-top phase (τ = 0.2)



HRRR cloud-top phase (τ = 0.5)



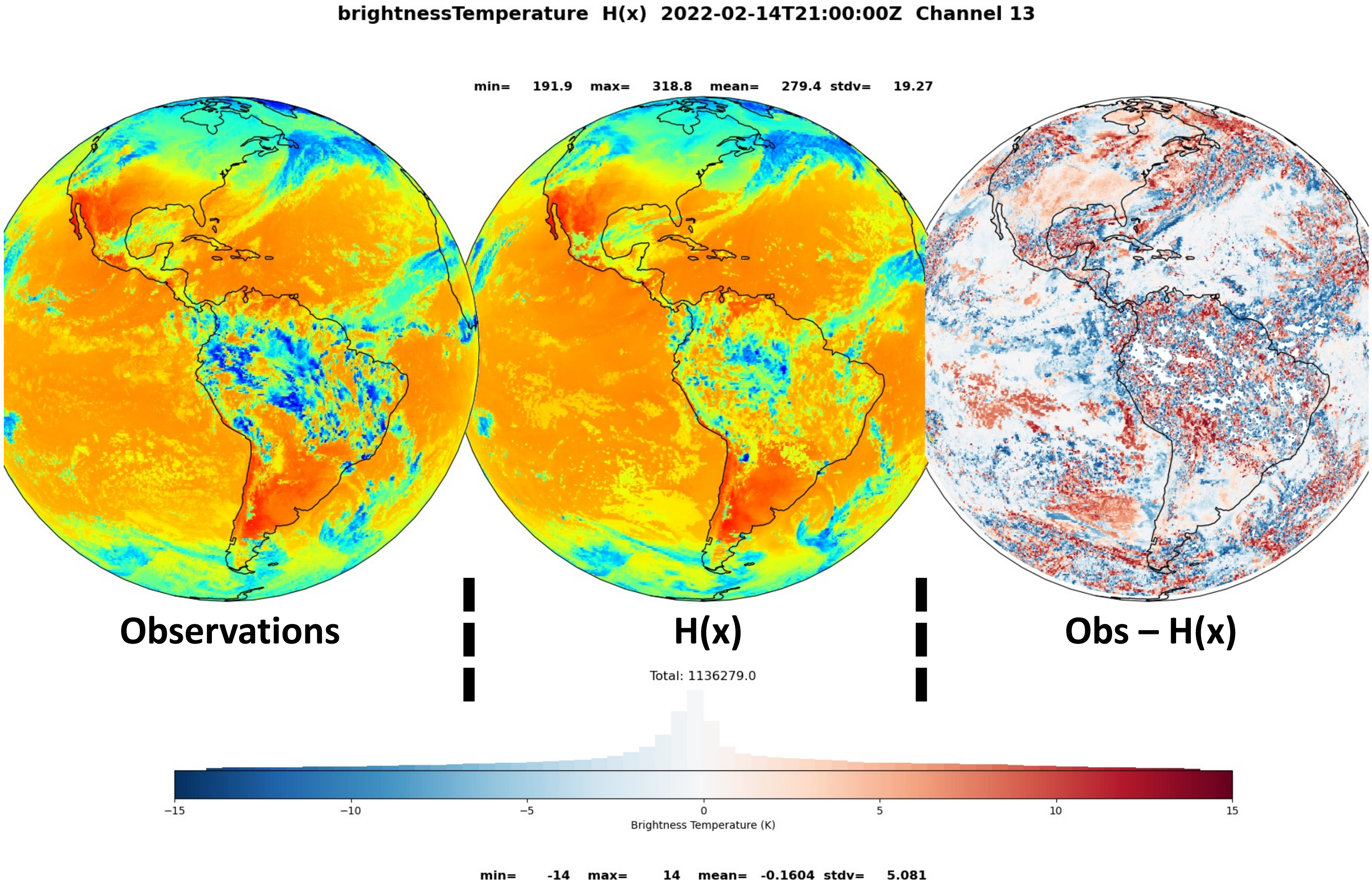
What do we do?

❑ Ensemble forecasts:

- ✓ Time-Lag Ensembles (e.g., RAP/HRRR)
- ▪ Model Ensembles
- ✓ Physics Ensembles (Thompson, Morrison, WSM6, etc.)
- ✓ Stochastic Parameter Perturbations (SPP)

✓ Cloud Fraction schemes

✓ Data Assimilation



Observations

H(x)

Obs – H(x)

Future Work

QC & BC

cloud mismatches: obs vs. first guess

correlated errors

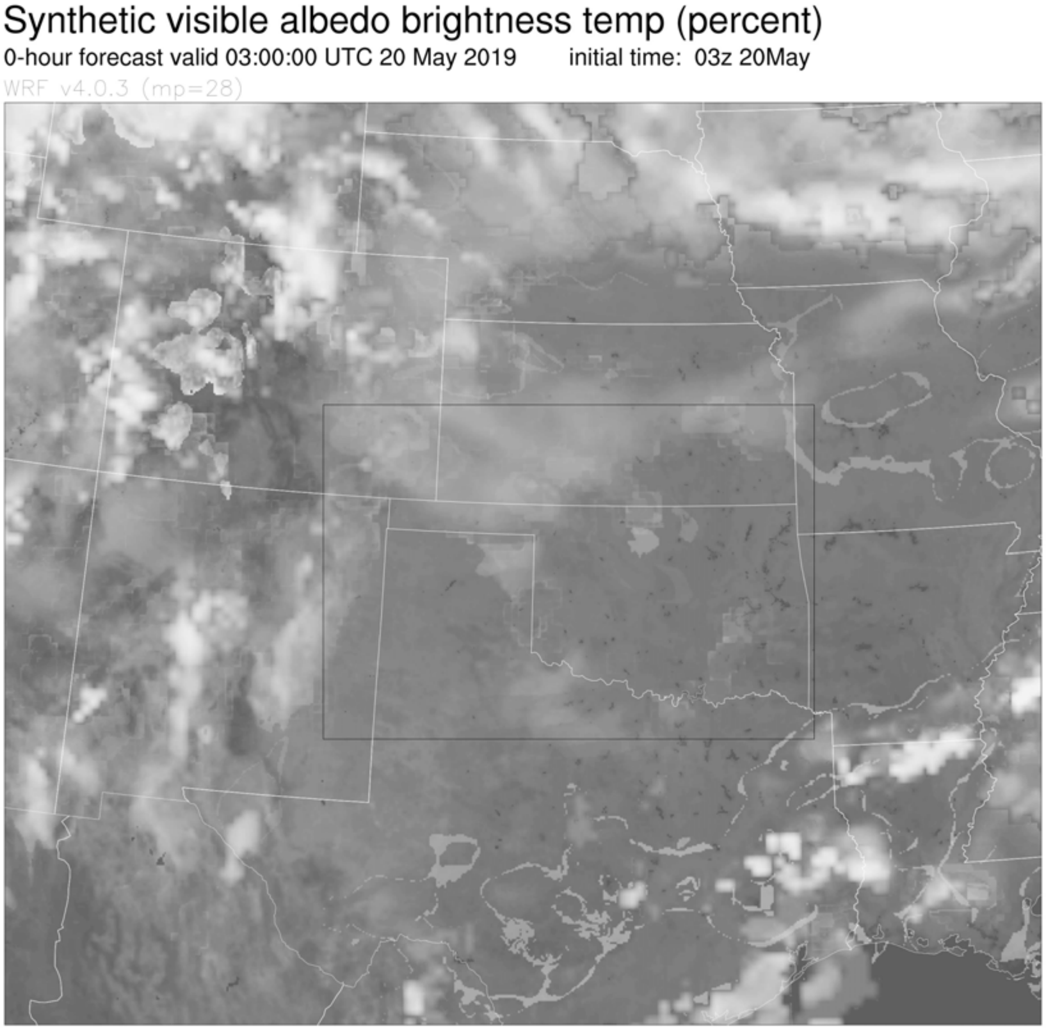
find cause of problem with solar-affected channels in CRTM

DA Sensitivity Experiments

- GOES-16 & GOES-17
- 15 Feb – 15 Mar 2022 and 01 – 31 Aug 2021
- 3-hourly vs. hourly
- 64 vs. 8 km subsampled data
- include visible wavelength

Coming soon:

DA with Visible reflectance channels



Is the future Mostly Sunny or Partly Cloudy?

- Microphysics schemes do not FIX all poor cloud forecasts; dynamics RULE baby!
- Stochastic parameter perturbations to **multiple** physical parameterizations are highly useful.
- Convective parameterizations are a nightmare. (Duh, convection is difficult.)
- Good data assimilation in cloudy regions should improve initial conditions as well as forecasts.
- More work needed in PARTLY to MOSTLY CLOUDY conditions.

Acknowledgements

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