Snowfall Detection and Rate Retrieval from ATMS

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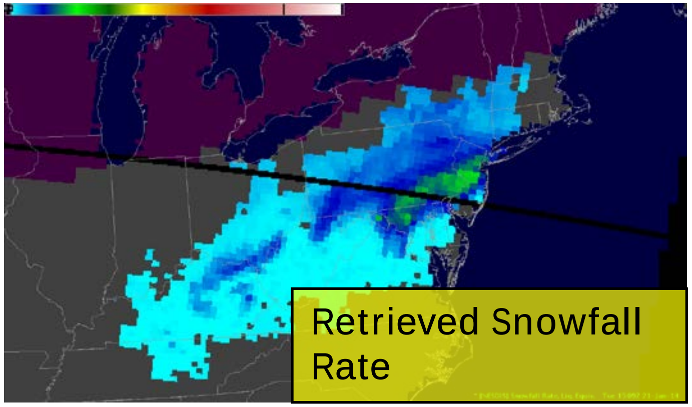
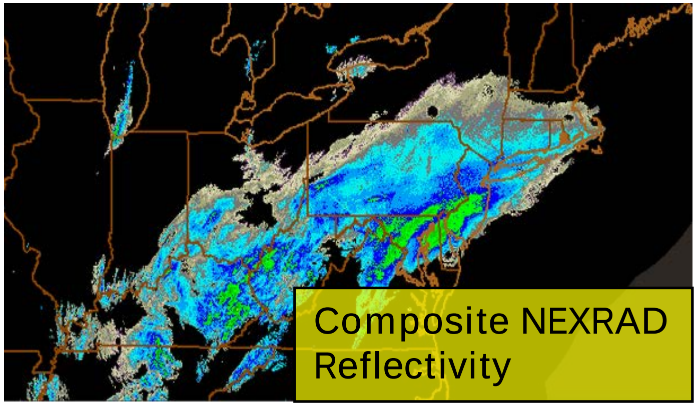
Background

- The NESDIS Snowfall Rate (SFR) product is water equivalent snowfall estimate and has been in NOAA operation since 2012
- Passive microwave sensors: AMSU/MHS pair and ATMS (in transition to operation)
- Satellites: NOAA-18, NOAA-19, Metop-A, Metop-B, and S-NPP (and future JPSS satellites)
- The five satellites provide ~10 snowfall rate estimates daily in mid-latitudes





SFR Algorithm

- Snowfall Detection (embedded in SFR, C. Kongoli, H. Meng)
  - ✓ Logistic regression model
  - ✓ New development: combined SD method
- Snowfall Rate retrieval
  - ✓ 1DVAR-based retrieval
  - ✓ New development: incorporating the effect of cloud liquid water in the simulation

Snowfall Detection

- Satellite-based module
  - ✓ Coupled principal components and logistic regression model (Kongoli et al., 2015)
  - ✓ Model output is snowfall probability
  - ✓ Training dataset are composed of matching satellite and ground snowfall observation data
- NWP model-based module
  - ✓ Logistic regression model
- Final SD is the combination of the two modules
- NWP model-based screening

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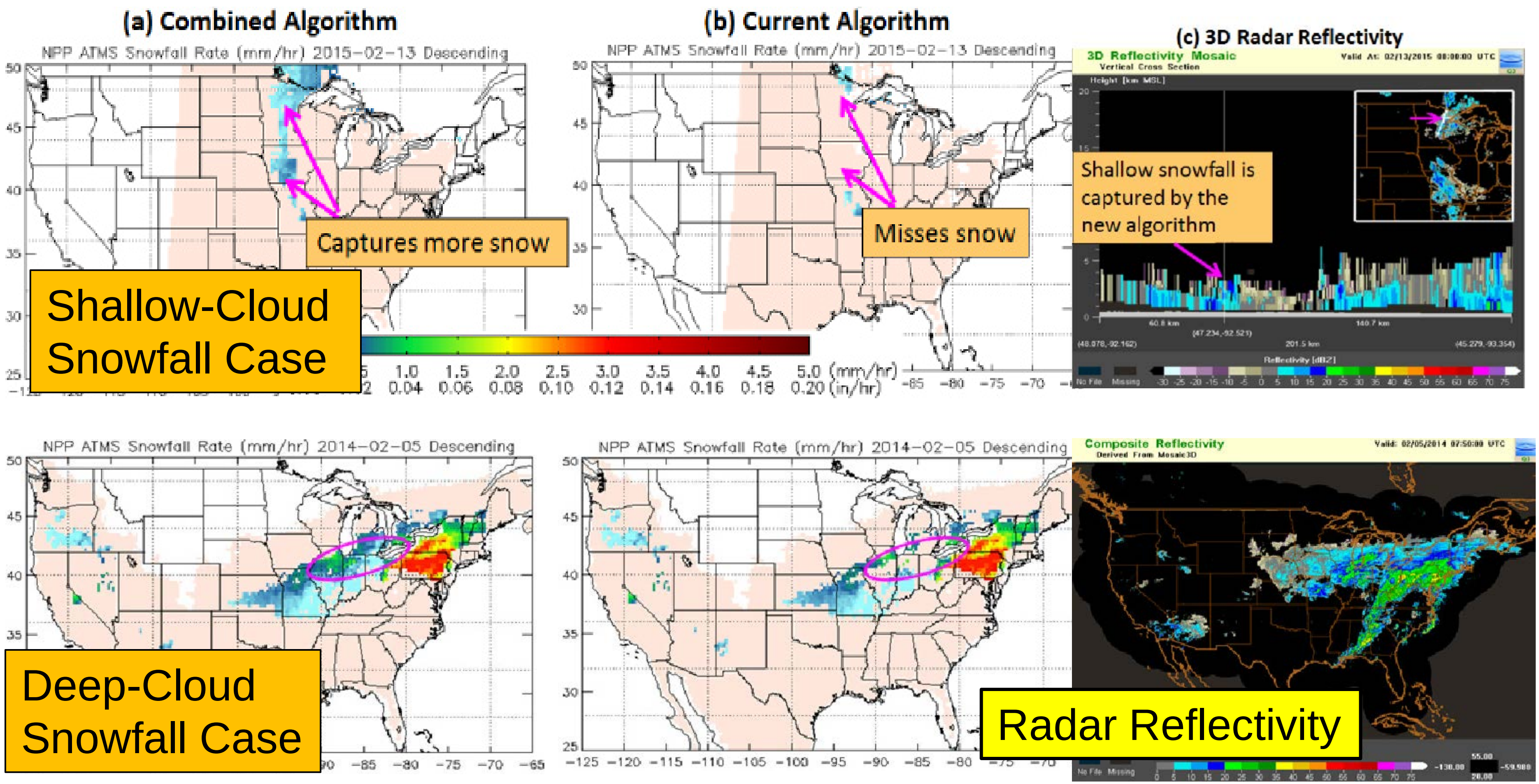
Validation:

Probability of Detection (%)	False Alarm Rate (%)	Heidke Skill Score
51	9.5	0.45

62% of ground truth data is ‘trace’, i.e. very light snowfall – very challenging to detect from satellite observations

SD Improvement

- The combined SD improves detection for both shallow and thick-cloud snowfall



SFR - Retrieval of Cloud Properties

- 1D variational method
  - ✓ Forward simulation of Tb's with a radiative transfer model (RTM) (Yan *et al.*, 2008)

$$\begin{vmatrix} \Delta I_c \\ \Delta D_e \\ \Delta \varepsilon_{23} \\ \Delta \varepsilon_{31} \\ \Delta \varepsilon_{89/88} \\ \Delta \varepsilon_{157/165} \\ \Delta \varepsilon_{190/176} \end{vmatrix} = \left| (A^T A + E)^{-1} A^T \right| \begin{vmatrix} \Delta T_{B23} \\ \Delta T_{B31} \\ \Delta T_{B89/88} \\ \Delta T_{B157/165} \\ \Delta T_{B190/176} \end{vmatrix}$$

I_c: ice water path

D_e: ice particle effective diameter

ε_i: emissivity at 23.8, 31.4, 89(MHS)/88.2(ATMS), 157/165.5, and 190.31/183±7 GHz

T_{Bi}: brightness temperature at 23.8, 31.4, 89/88.2, 157/165.5, and 190.31/183±7 GHz

A: Jacobian matrix, derivatives of T_{Bi} *over IWP,* D_e*, and* ε_i

E: error matrix

- ✓ Iteration scheme with ΔT_{Bi} thresholds
- ✓ IWP and De are retrieved when iteration stops

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$$\begin{vmatrix} \Delta Lw \\ \Delta Dw \end{vmatrix}$$

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Snowfall Rate

- Terminal velocity is a function of atmospheric conditions and ice particle properties, Heymsfield and Westbrook (2010):

$$v(D) = \frac{\eta R_e}{\rho_a D}$$

- Snowfall rate model (Meng et al., 2016):

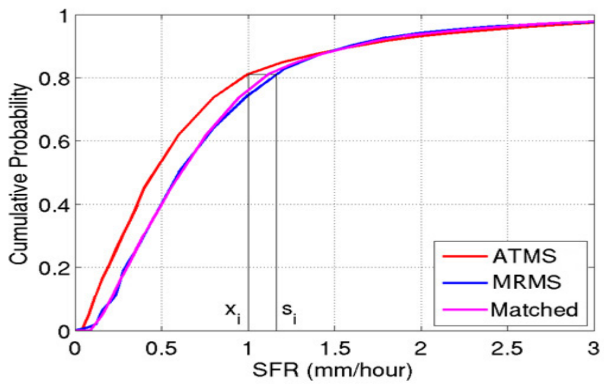
$$SR = A \int_{D_{min}}^{D_{max}} D^2 e^{-D/D_e} \left[\left(1 + BD^{3/2}\right)^{1/2} - 1 \right]^2 dD$$

$$A = \frac{\alpha I_c \delta_0^2 \eta}{24 H \rho_w \rho_a D_e^4}, \qquad B = \frac{8}{\delta_0^2 \eta} \sqrt{\frac{g \rho_a \rho_I}{3 C_0}}$$

- An adjusting factor, α, to compensate for non-uniform ice water content distribution in cloud column; derived from collocated satellite and radar data

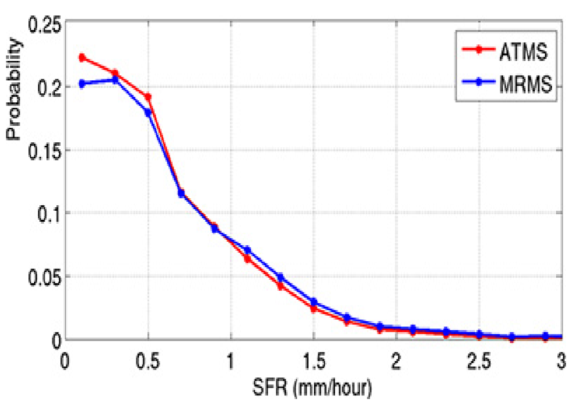
SFR Calibration & Validation

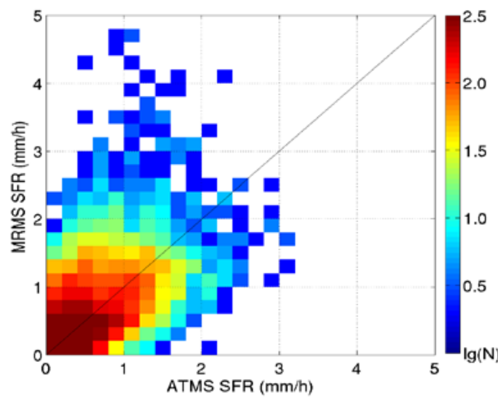
- Calibration using Multi-Radar Multi-Sensor (MRMS) instantaneous snowfall rate data to reduce bias - histogram matching to adjust SFR CDF towards MRMS



	Correlation Coefficient	Bias (mm/hr)	RMS (mm/hr)
Original	0.55	-0.30	0.77
Calibrated	0.56	-0.10	0.73

- Validation against MRMS:

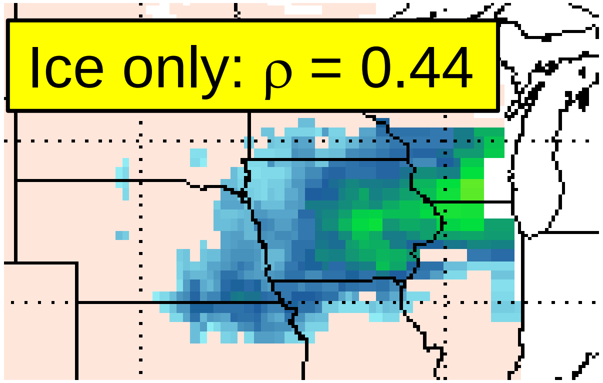


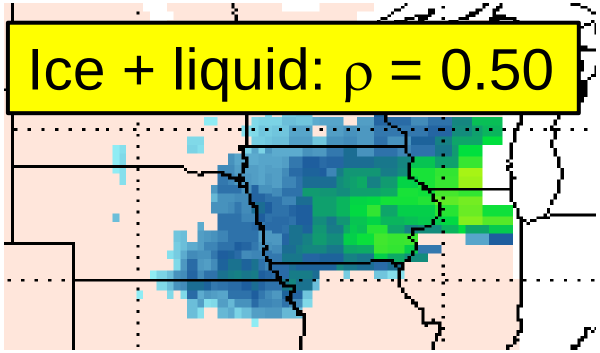


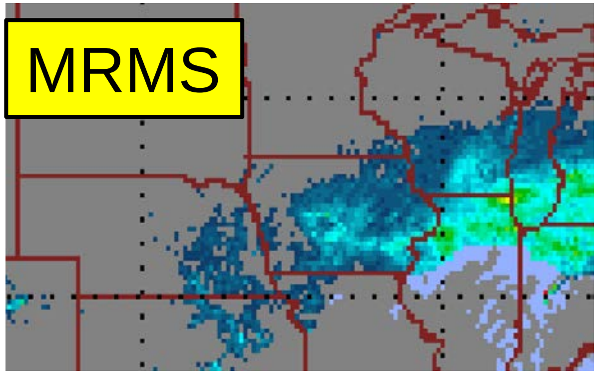
Correlation Coefficient	Bias (mm/hr)	RMS (mm/hr)
0.52	-0.07	0.55

Snowfall Rate Improvement

- The radiative transfer model (RTM) in the current SFR algorithm does not include the effect of cloud liquid water
- The RTM has been modified to include CLW
  - ✓ Leading to increased SFR in most cases – mitigate the dry bias in SFR
  - ✓ Developing more robust initialization of cloud properties





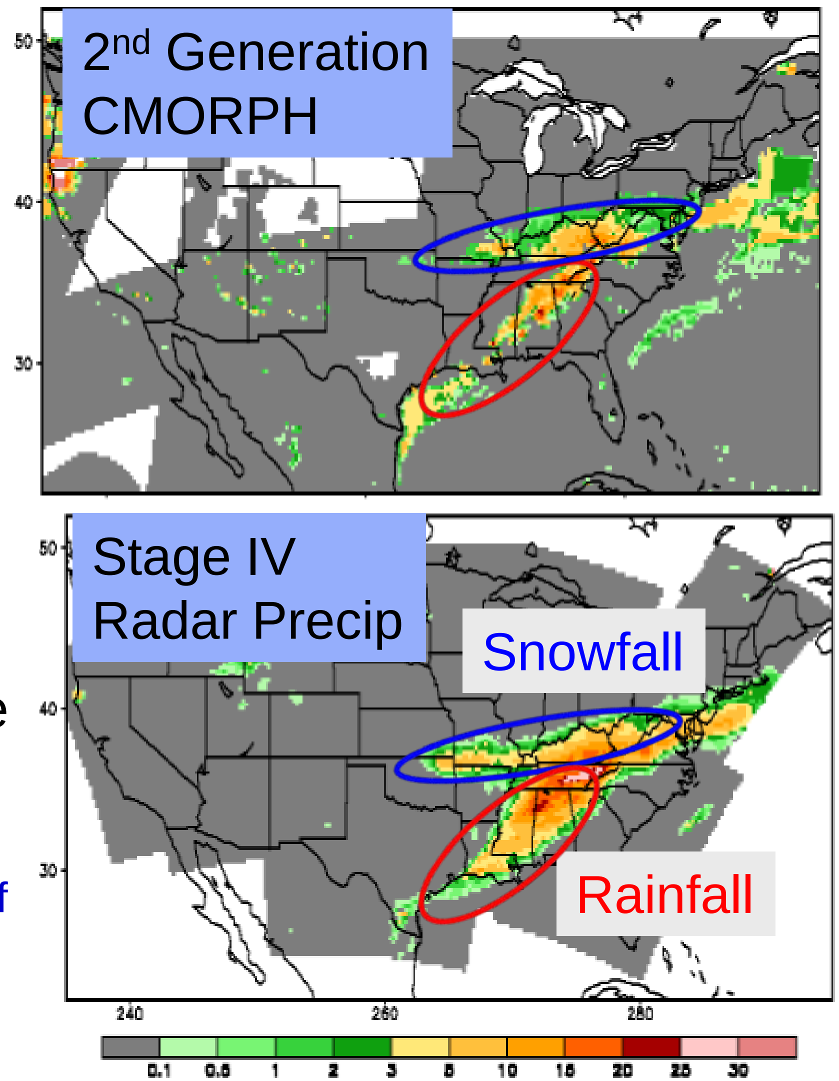


Application in Hydrology
Blended Satellite Precipitation Product

- Most blended satellite precipitation datasets do not include satellite snowfall rate product – use other data sources (model, ground observations, etc.)
- CMORPH is a NOAA global blended precipitation analysis product with wide-ranging applications
- The first generation CMORPH only has rain rate. The SFR product is integrated in the second generation CMORPH
- A sample for a major snowstorm over the east coast of US in March 2014 (right)

✓ Stage IV radar precipitation image (bottom) shows a warm band (rainfall) and a cold band (snowfall) of precipitation from a frontal system

✓ The second generation CMORPH (top) captures both bands after integrating SFR

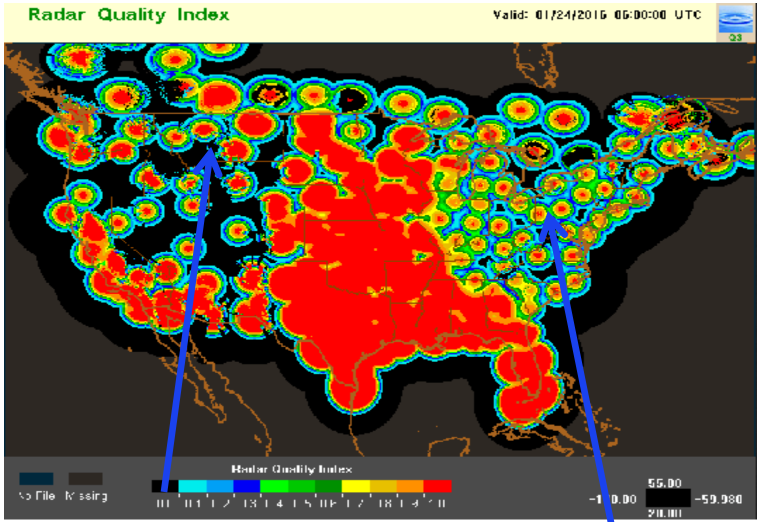


(Xie and Joyce, NOAA/NCEP/CPC)

Application in Weather Forecasting

- SFR assessment at several NWS Weather Forecast Offices. User feedback indicates that SFR is a useful product for weather forecasting operations
- SFR is especially useful for filling observational gaps in mountains and remote regions where radar and weather stations are sparse or radar blockage and overshooting are common
- SFR also provides quantitative snowfall information to complement snowfall observations or estimations from other sources (stations, radar, GOES etc.)
- A radar and SFR combined product, mSFR, with 10-min interval

MRMS Precip Quality Index during 2016 East Coast Blizzard



poor coverage

quality degradation during snowfall

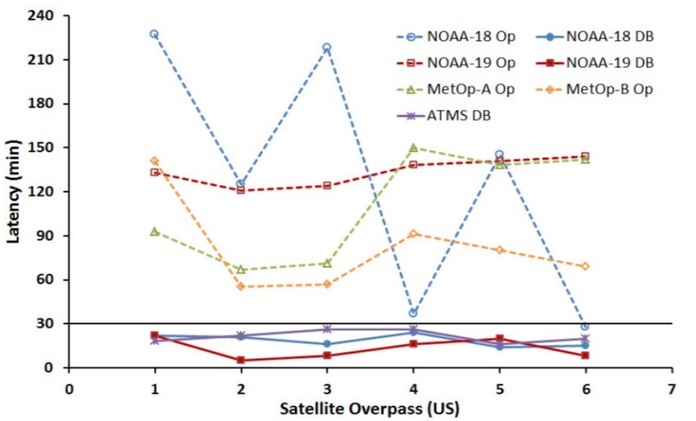
SFR Applications
Using Direct Broadcast Data

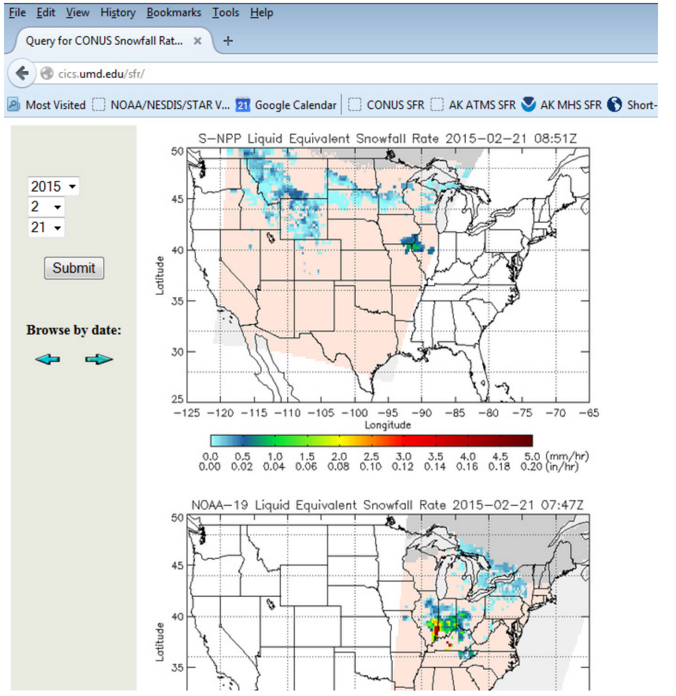
- Reduce latency to meet requirement for weather forecasting – forecasters' feedback
- Retrieve DB CONUS and Alaska L1B data from Univ. of Wisconsin, Madison/CIMSS
- Generate SFR within 30 min of observation; SFR with operational L1B data has 30 min ~ 3 hr delay
- Output:
  - ✓ Data made available to NASA/SPoRT, reformat to AWIPS, and disseminate to WFOs and WPC
  - ✓ Images posted on SFR webpage at near real-time
- Webpage:
  - ✓ NESDIS/CICS:

  http://cics.umd.edu/sfr

  http://www.star.nesdis.noaa.gov/corp/scsb/mspps_backup/sfr_realtime.html
  - ✓ SPoRT:

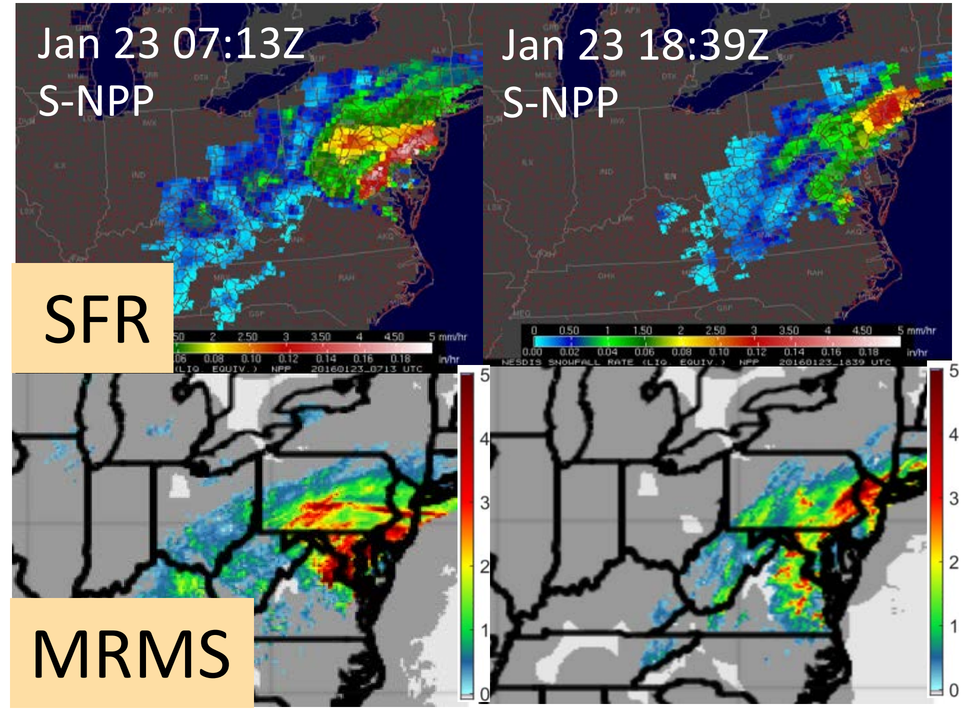
  http://weather.msfc.nasa.gov/cgi-bin/sportPublishData.pl?dataset=snowfallrateconus&product=conus_snowrate



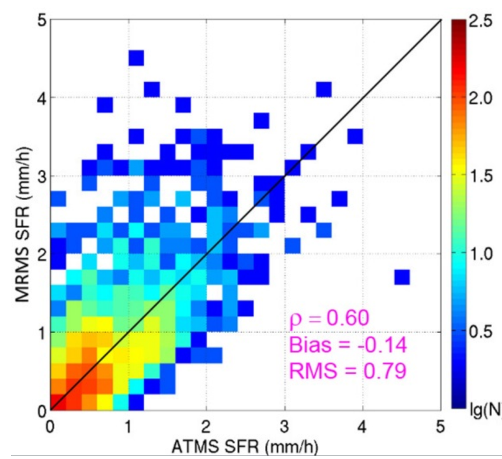


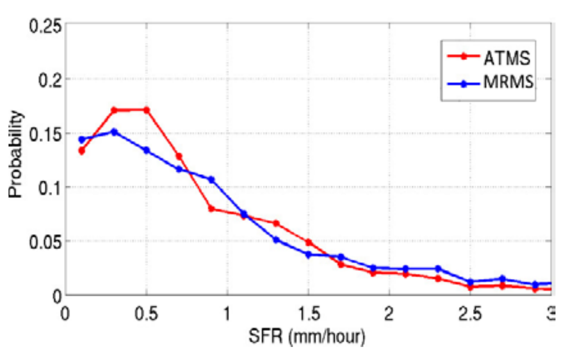
2016 East Coast Blizzard

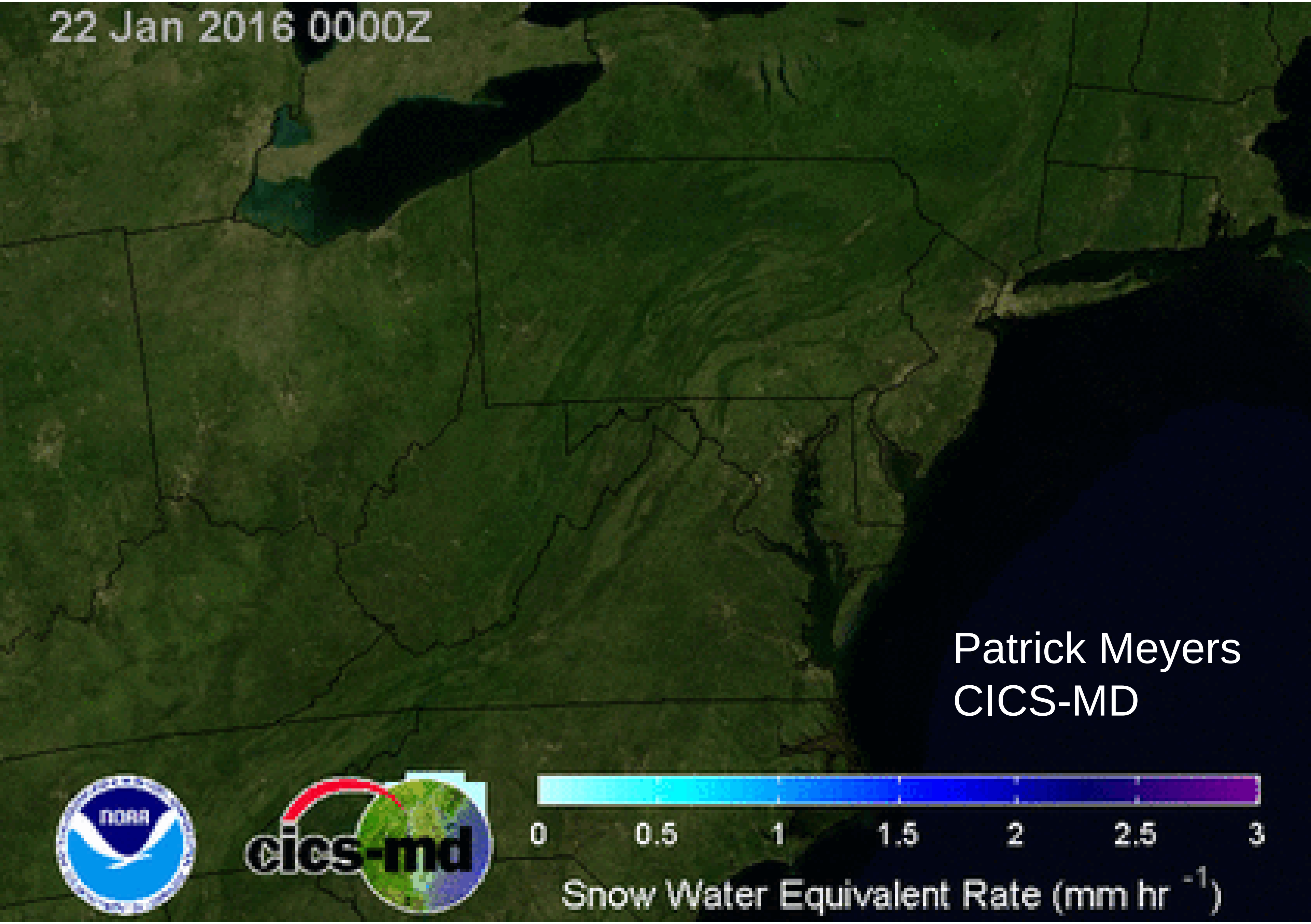
- The 2016 Blizzard hit the Mid-Atlantic region on 22-24 January 2016 and produced record snowfall in many local areas
- The ATMS and MHS SFR products captured the evolution of the blizzard with five satellites including S-NPP, POES and Metop.



	Correl. Coeff.	Bias (mm/hr)	RMS (mm/hr)
ATMS	0.60	-0.14	0.79
MHS	0.54	-0.53	0.88

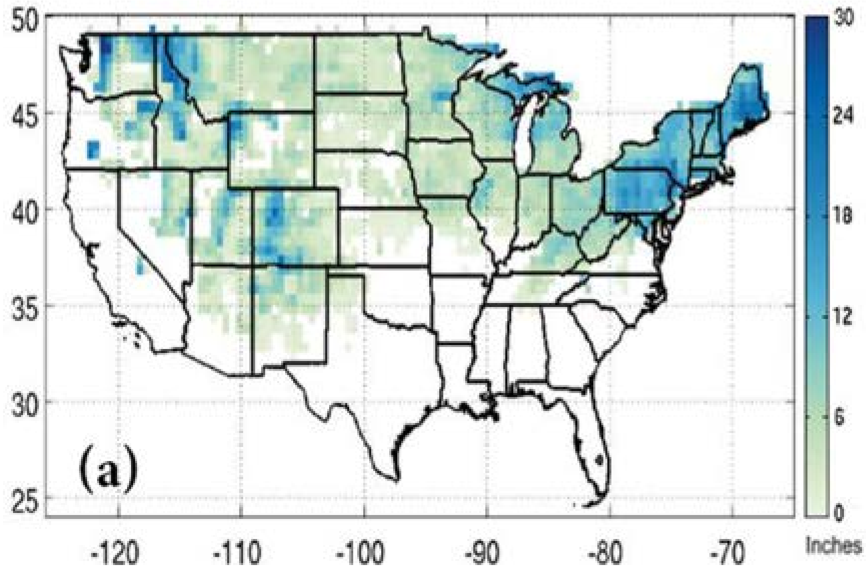




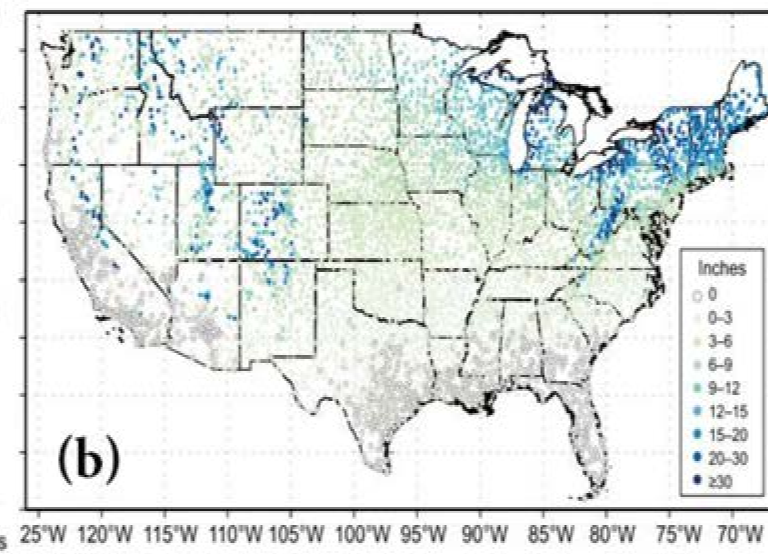

22 Jan 2016 0000Z
Patrick Meyers
CICS-MD
0 0.5 1 1.5 2 2.5 3
Snow Water Equivalent Rate (mm hr $^{-1}$)

SFR Climatology

ATMS "Accumulated Snowfall"
January Average, 2015-2016



Gauge Accumulated Snowfall
January Average, 1981-2010



(Durre, 2013)

- Not the same quantity or time period; comparing snowfall patterns
- Patterns generally match well (Rockies, Great Plains, northeast, etc.)
- Issues with shallow and convective snowfall: lake effect, shallow orographic snow (Great Lakes, Sierra Nevada, Appalachians, etc.)

Summary

- Building on the operational AMSU/MHS SFR product, an ATMS SFR algorithm has been developed
- The ATMS SFR algorithm includes two components: Snowfall Detection and Snowfall Rate Estimation. Validation study showed good agreement between SFR and ground observations (for detection) and radar snowfall rate (for rate)
- The SFR product has applications in hydrology and weather forecasting
- Both ATMS and AMSU/MHS SFR are generated within 30 min using direct broadcast data

Future Plan

- Development of DMSP SSMIS SFR algorithm
- Development of GPM GMI SFR algorithm

Acknowledgement

- JPSS Proving Ground and Risk Reduction Program
- NASA SPoRT
- NOAA/NESDIS

Thank you!