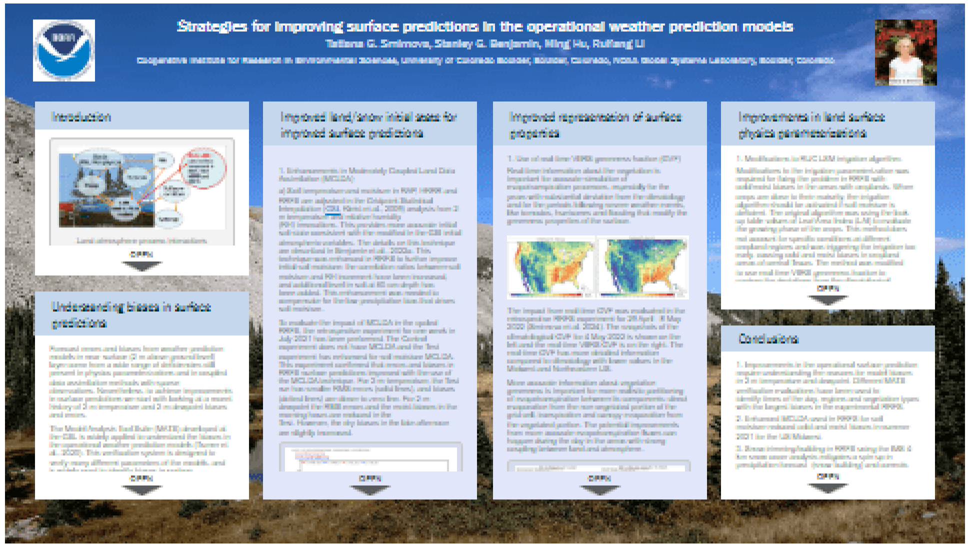
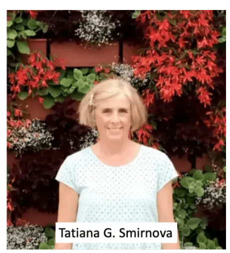
Strategies for improving surface predictions in the operational weather prediction models



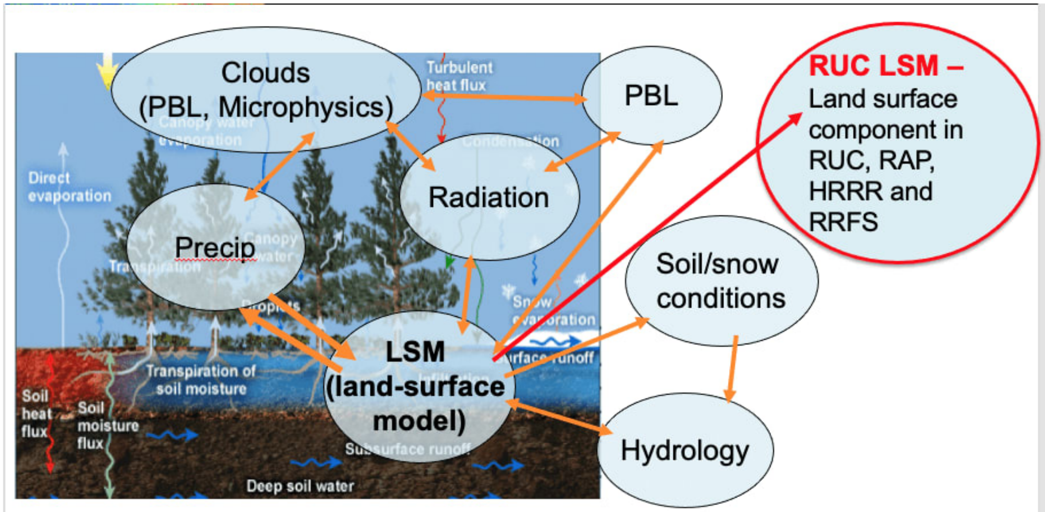
Tatiana G. Smirnova, Stanley G. Benjamin, Ming Hu, Ruifang Li

Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, Colorado, NOAA Global Systems Laboratory, Boulder, Colorado



PRESENTED AT:

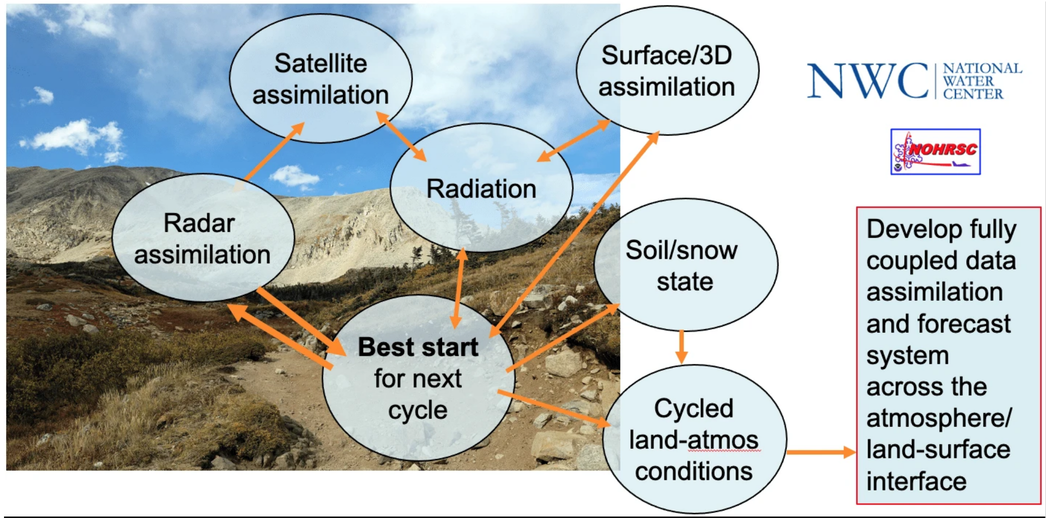
INTRODUCTION



Land-atmosphere process interactions

To fulfill our goal of providing guidance to the public about severe weather events or other weather conditions, the complicated interactions between the land-surface subsystem and overlaying atmosphere shown on the diagram need to be quantified with good accuracy in the physics parameterizations of boundary layer, clouds, precipitation and surface feedback into the atmosphere. Improving these physics parameterizations is a great challenge that the physics development branch of the National Oceanic and Atmospheric Administration (NOAA) Global Systems Laboratory (GSL) addresses.

Parameterizations of surface processes are included in the weather forecast models by specifying different lower boundary conditions, depending on surface characteristics. Over land, where there are often significant diurnal changes of temperature and moisture near the interface with the atmosphere, heat and moisture budgets and fluxes are solved within the land surface models (LSMs). An accurate representation of soil moisture, soil temperature and snow cover is critical for obtaining successful predictions of heat and moisture exchanges between the ground and the atmospheric boundary layer, frequently the dominant driving mechanisms for mesoscale circulations. The initialization of these poorly observed surface variables is one more challenge that has to be solved in weather prediction models.



Data Assimilation for Improved Surface State

Assimilation of some land-water-vegetation-related observations must accompany parameterizations of land-water processes to improve their initial conditions. The new version of the diagram roughly depicts such observations. For example, assimilation of radar reflectivity is important for better precipitation prediction and surface observations are critical for better boundary layer representation. Hourly assimilation of all available observations can help to improve atmospheric predictions that drive the evolution of soil moisture and temperature, and thus it helps to avoid significant drifts in the evolving land states. Also, to maintain the consistency of atmosphere and land initial conditions, soil/snow temperature and soil moisture are adjusted in the moderately coupled land data assimilation system (MCLDA) from the analysis increments of 2-m moisture and temperature (Benjamin et al. 2022a). Similarly, an initialization method is also applied to provide much more accurate lake temperatures (Benjamin et al 2022b) also improving heat and moisture fluxes from the surface.

Altogether, improving physics parameterizations and assimilation techniques helps to produce the best possible initial land/snow state and more accurate surface heat/moisture fluxes in the operational weather prediction models. However, the current weather models are still far from being perfect, and the work to develop strategies for identifying and reducing their biases is still needed. This presentation will be focused on describing such strategies for improved surface predictions within the short-range regional models being developed at NOAA GSL and utilizing Rapid Update Cycle (RUC) LSM as a surface component.

RUC LSM was first implemented at NCEP in the operational Rapid Update Cycle (RUC, Benjamin et al., 2004) weather prediction model in 1998, and later in the Weather Research Forecasting Model (WRF)-based Rapid Refresh (RAP, Benjamin et al., 2016) and High-Resolution Rapid Refresh (HRRR, Dowell et al, 2022, James et al., 2022). A matured over years version of RUC LSM has been implemented in the Unified Forecast System (UFS) via the Common Community Physics Package (CCPP, Heinzeller et al. 2023) in 2020. The experiments with the UFS-based Rapid Refresh Forecasting System (RRFS) will be used to illustrate proposed strategies for improved surface predictions.

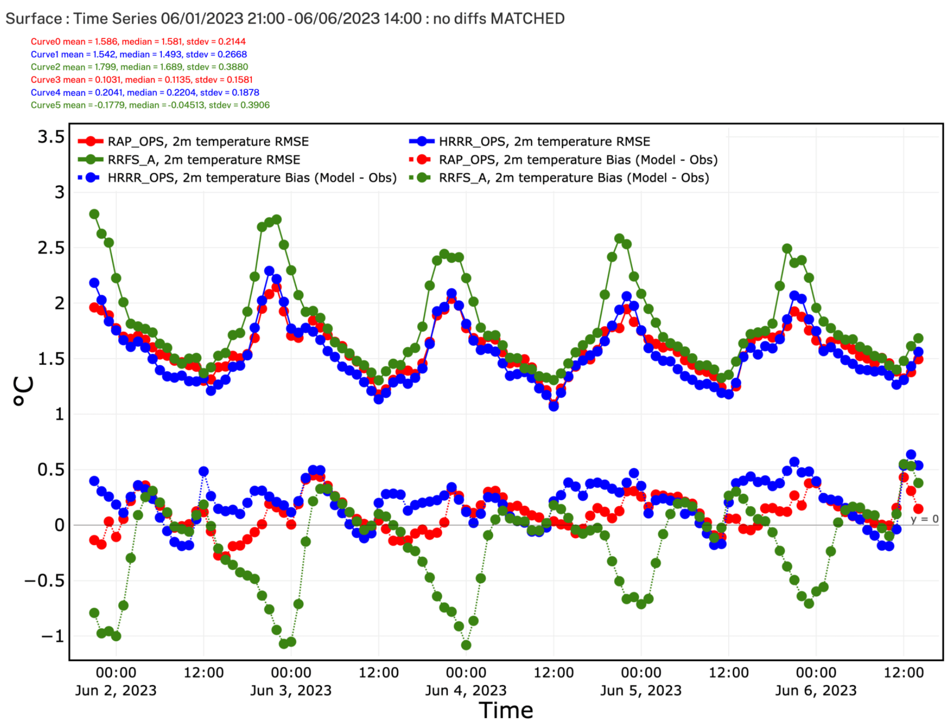
UNDERSTANDING BIASES IN SURFACE PREDICTIONS

Forecast errors and biases from weather prediction models in near-surface (2 m above ground level) layer come from a wide range of deficiencies still present in physics parameterizations and in coupled data assimilation methods with sparse observations. Nevertheless, to achieve improvements in surface predictions we start with looking at a recent history of 2-m temperature and 2-m dewpoint biases and errors.

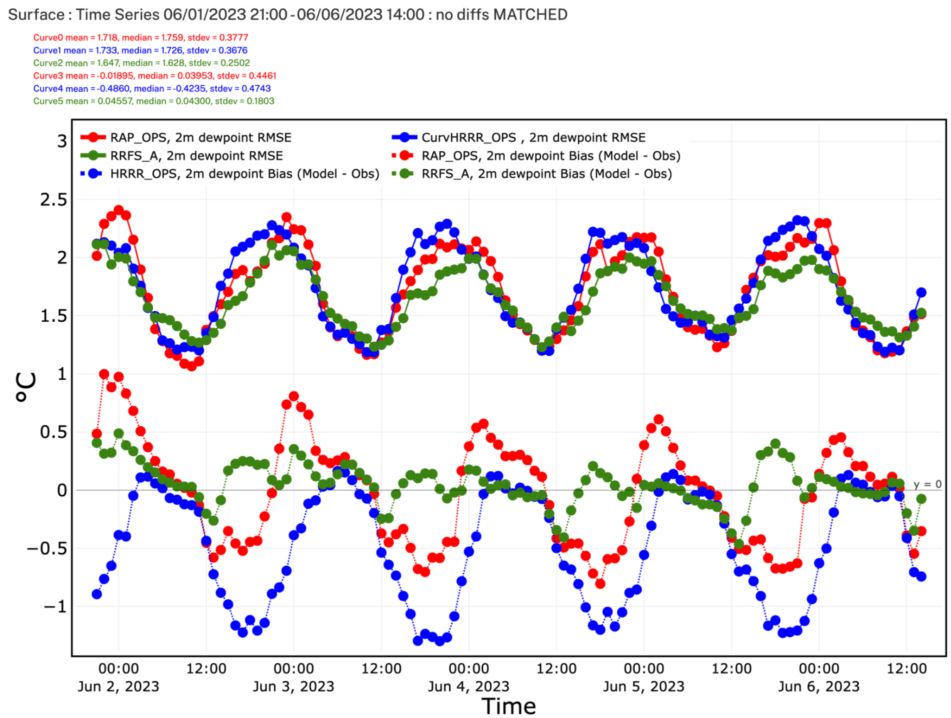
The Model Analysis Tool Suite (MATS) developed at the GSL is widely applied to understand the biases in the operational weather prediction models (Turner et al., 2020). This verification system is designed to verify many different parameters of the models, and is widely used to identify biases in surface predictions.

1. Time series of surface errors and biases.

Time series of biases and errors of surface variables is the first step towards identifying the periods when the errors and biases are the largest.



RMS errors (solid) and biases (dotted) for 2-m temperature, 3-h forecast, Eastern US. red - 13-km RAP, blue - 3-km HRRR, green - 3-km RRFS. Verification is against METAR surface stations for 1-6 June 2023.

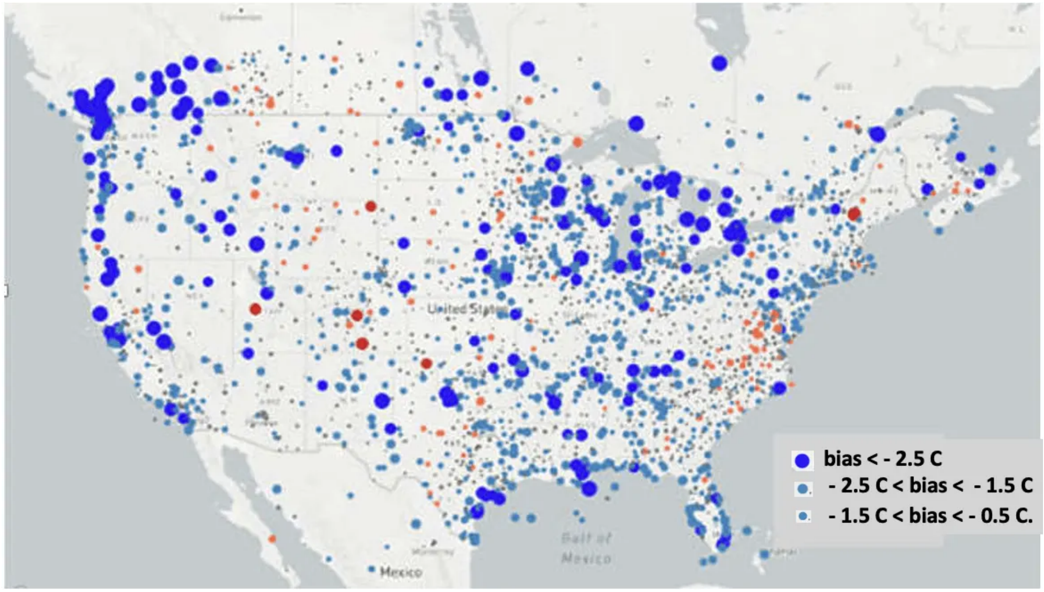


RMS errors (solid) and biases (dotted) for 2-m dewpoint, 3-h forecast, Eastern US
red - 13-km RAP, blue - 3-km HRRR, green - 3-km RRFS. Again, verification is against METAR surface stations for 1-6 June 2023

Examples of diurnally averaged errors for the period from 1-6 June 2023 are shown on the above figures for operational RAP and HRRR and the next-generation RRFS model. These figures demonstrate comparisons of the RMS errors (solid lines) and biases (dotted lines) for 2-m temperature (top) and for 2-m dewpoint (bottom) from different forecast models. To exclude the impact of elevation mis-match between the model and the stations, only observations over Eastern US are included in these statistics. The red and blue curves show the verification for operational 13-km RAP and 3-km HRRR, respectively, and the green curves are for the experimental version of the RRFS model, the successor for RAP and HRRR.

The main goal of such comparisons is to evaluate the experimental RRFS modeling system compared to already operational weather prediction models. The plots show that for 2-m dewpoint in this period, RRFS (green) is a superior model. However, for 2-m temperature 3-km RRFS is close to 13-km RAP and 3-km HRRR at night but has significant cold bias during the day. The daytime cold bias in RRFS needs to be reduced to match or even improve over the performance of the HRRR model. To achieve this goal, the regions with highest biases should be identified.

2. Spatial distribution of biases and RMS errors for different surface variables.

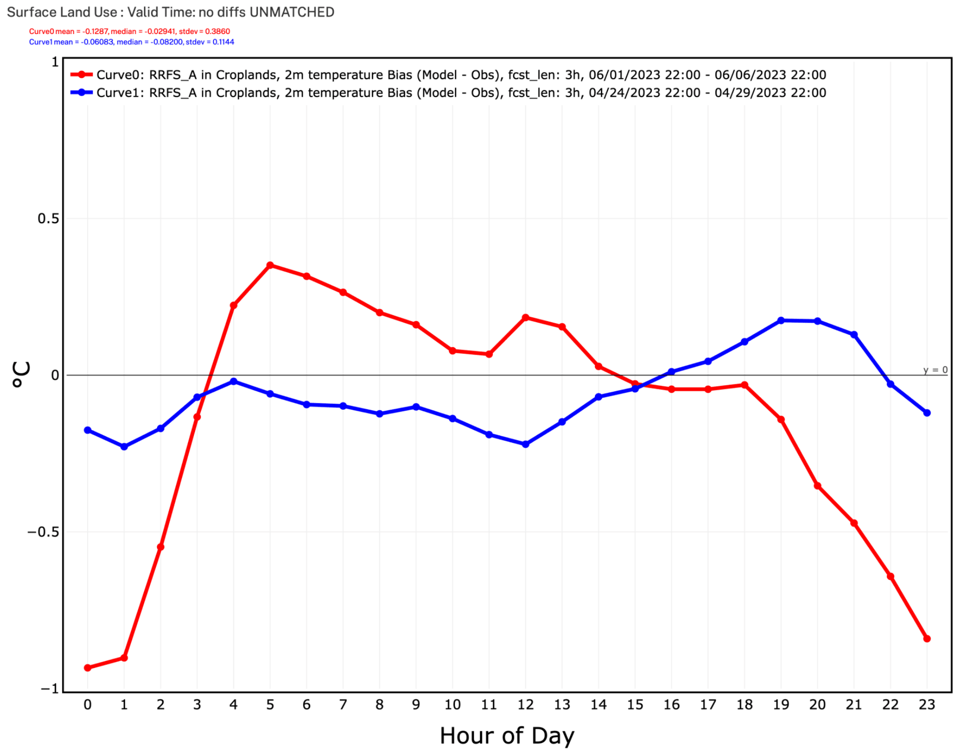


RRFS, bias of 2-m temperature forecasts,
3-h forecasts valid at 00 UTC, 1-6 June 2023. Blue indicates that forecast minus observation is negative.

Spatial distribution of biases allows to identify the problematic regions. The above figure demonstrates spatial distribution of 2-m temperature bias in 3-h RRFS forecast averaged for a period 1-6 June 2023. Larger blue circles show that the worst cold biases are related to the agricultural areas in the Eastern US. This was a hint to plot Individual statistics for cropland vegetation category in the RRFS domain to more information helping in understanding the problem.

3. Diurnally averaged surface verification for land use types.

On 30 May 2023 an upgrade to the RRFS system has been implemented. It included changes to soil and vegetation classifications with an addition of fractional information for soil and vegetation categories in the grid cell. Fractional information allowed to activate irrigation parameterization in RUC LSM for cropland fractions.

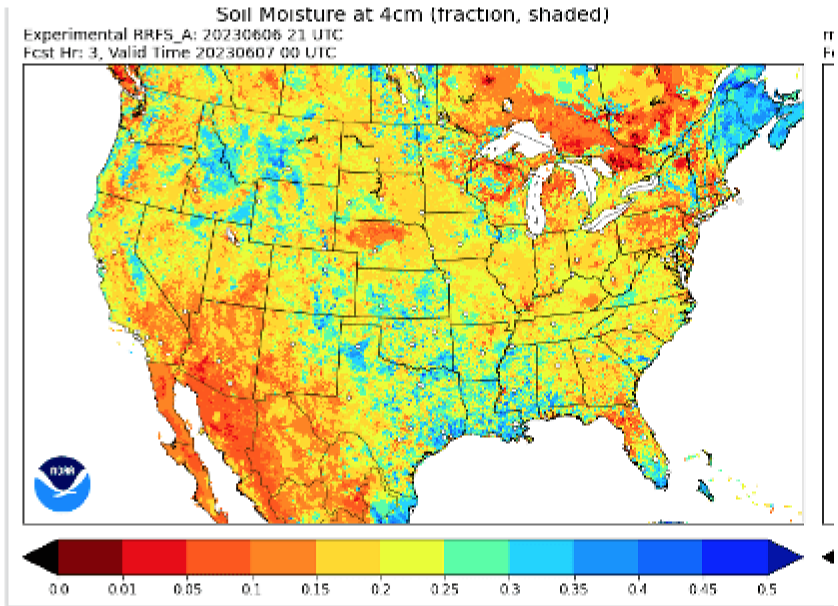


RRFS, bias of 2-m temperature for croplands, 3-h forecast.
Red - 1-6 June 2023, Blue - 24-29 April 2023

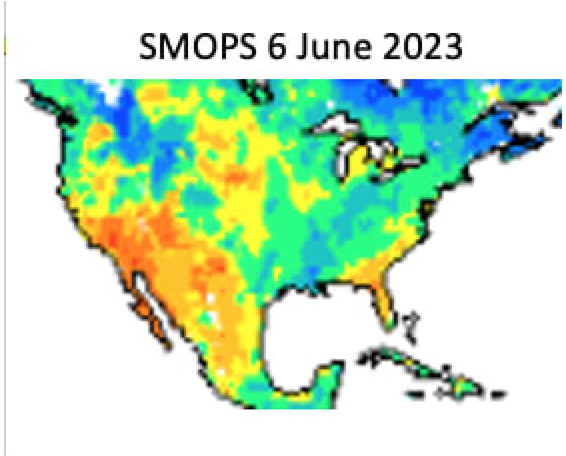
Diurnal variations of 2-m temperature bias for the cropland category for two different periods: before the upgrade of the RRFS system (blue) and after the upgrade (red) are shown on the above figure. It demonstrates that system upgrade introduced the problem. In-depth analysis of code upgrade tracked down the problem to the use of look-up table values for leaf area index (LAI) in the irrigation algorithm. The look-up table values of LAI were much higher than the climatological LAI used in RAP/HRRR for many regions, as a result the irrigation was turned on unrealistically early in the year introducing cold and moist biases for croplands. The solution to this problem is described in the section of the iPoster entitled "Improvements in land surface parameterizations".

4. Soil moisture evaluation.

Important parameter for surface predictions is evolving soil moisture driven by 1-h forecast of atmospheric forcing: precipitation, snowfall, clouds, radiation, surface layer parameterization. Qualitative soil moisture evaluation against the satellite information can help to find the regions where soil moisture drifted from reality and to further isolate the cold bias problem.



RRFS volumetric soil moisture at 4-cm depth,
6 June 2023



Cut-out from the global SMOPS (https://www.ospo.noaa.gov/Products/land/smops/) (Yin et al., 2022) volumetric soil moisture for CONUS, the color table is the same as in the above figure.

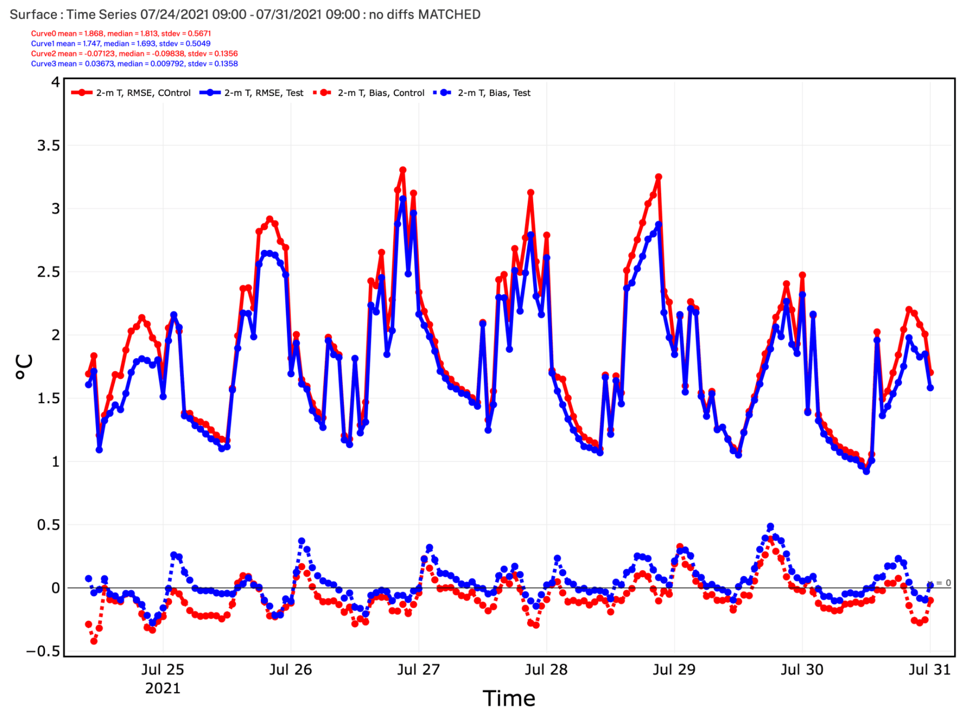
As shown on the above figure for 6 June 2023, soil moisture in RRFS is drier than the SMOPS blended soil moisture product (Yin et al, 2022), including in the areas with large cold biases. Drier soil moisture usually leads to daytime warm bias and cannot explain cold 2-m temperature biases after the RRFS upgrade. However, for improved surface fluxes the technique in the moderately coupled land data assimilation (MCLDA, Benjamin et al. 2022a), developed for RAP and HRRR, has to be enhanced to avoid long-term soil moisture drifts from reality.

IMPROVED LAND/SNOW INITIAL STATE FOR IMPROVED SURFACE PREDICTIONS

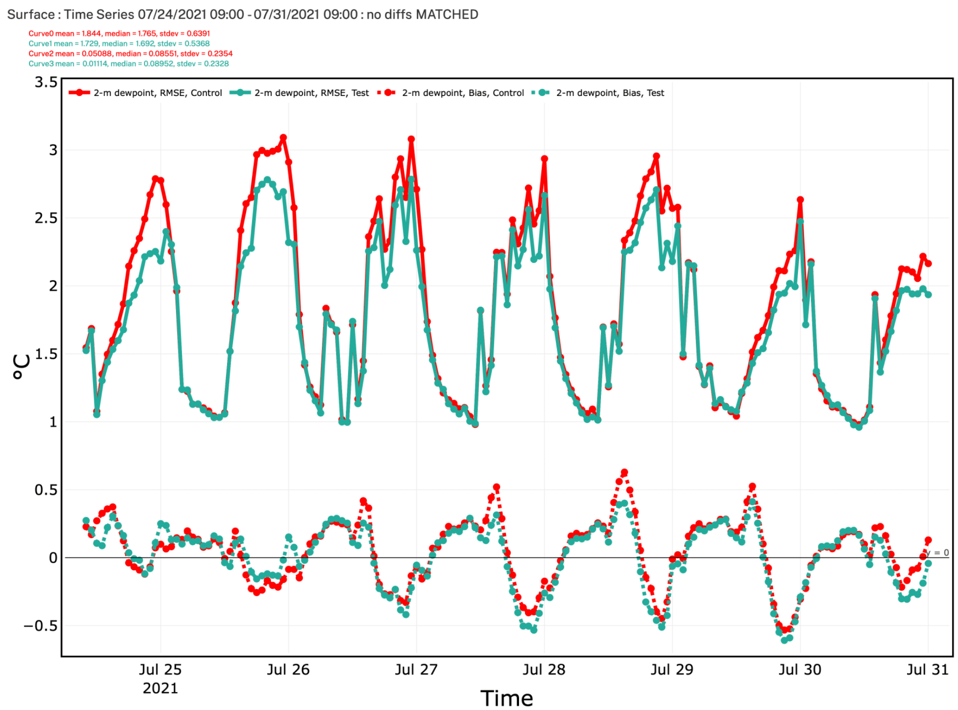
1. Enhancements in Moderately Coupled Land Data Assimilation (MCLDA)

a) Soil temperature and moisture in RAP, HRRR and RRFS are adjusted in the Gridpoint Statistical Interpolation (GSI, (https://ral.ucar.edu/solutions/products/gridpoint-statistical-interpolation-gsi) Kleist et al., 2009) analysis from 2-m temperature and relative humidity (RH) innovations. This provides more accurate initial soil state consistent with the modified in the GSI initial atmospheric variables. The details on this technique are described in Benjamin et al., 2022a. This technique was enhanced in RRFS to further improve initial soil moisture: the correlation ratios between soil moisture and RH increment have been increased, and additional level in soil at 60-cm depth has been added. This enhancement was needed to compensate for the low precipitation bias that drives soil moisture.

To evaluate the impact of MCLDA in the cycled RRFS, the retrospective experiment for one week in July 2021 has been performed. The Control experiment does not have MCLDA and the Test experiment has enhanced for soil moisture MCLDA. This experiment confirmed that errors and biases in RRFS surface predictions improved with the use of the MCLDA technique. For 2-m temperature, the Test run has smaller RMS errors (solid lines), and biases (dotted lines) are closer to zero line. For 2-m dewpoint the RMS errors and the moist biases in the morning hours are reduced in the Test. However, the dry biases in the late afternoon are slightly increased.

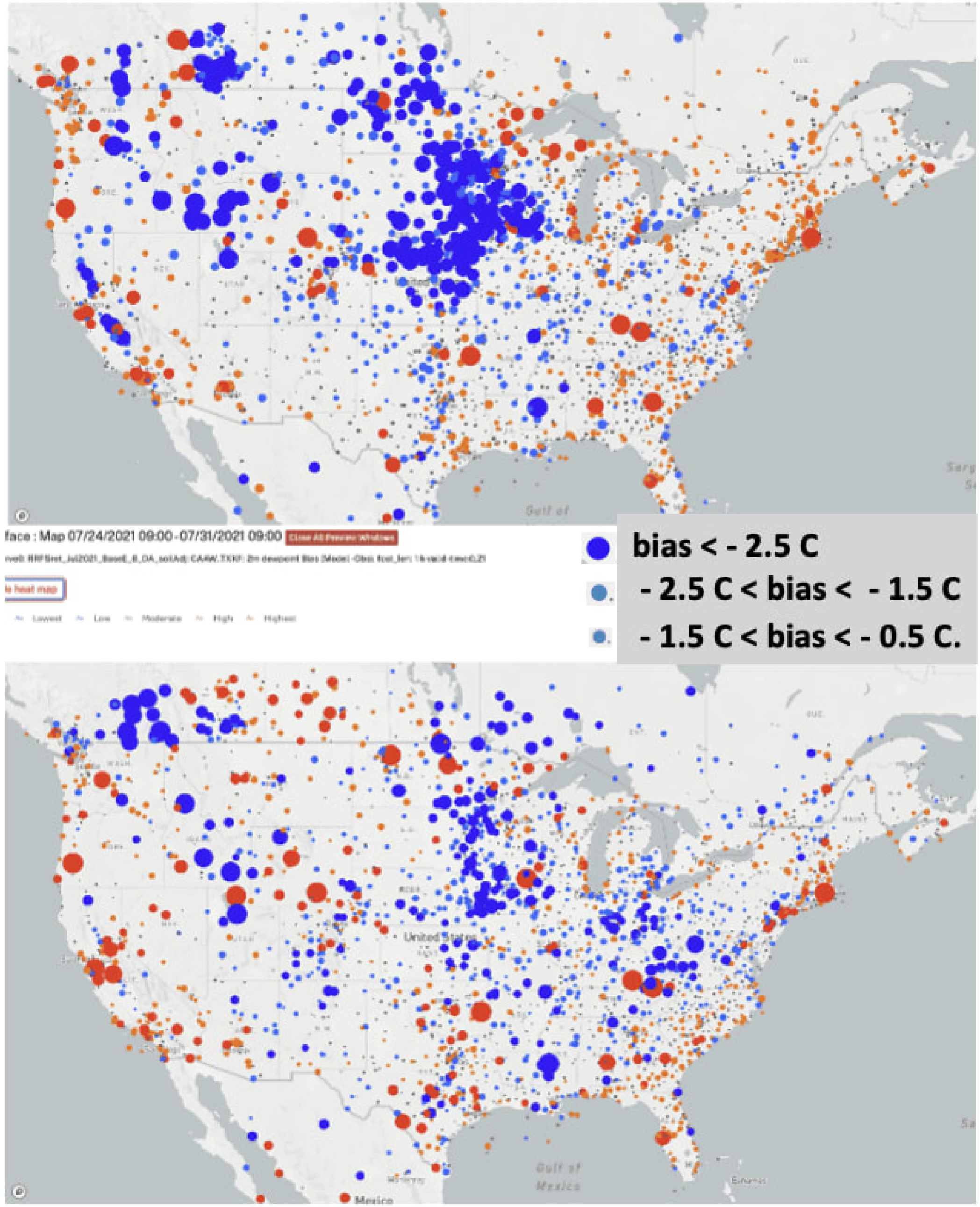


RRFS RMS errors and biases for 2-m temperature, 1-h forecast, Eastern US.
red - Control - no MCLDA, blue - Test with MCLDA



RRFS RMS errors and biases for 2-m dewpoint, 1-h forecast, Eastern US.
red - Control (no MCLDA), green - Test (with MCLDA)

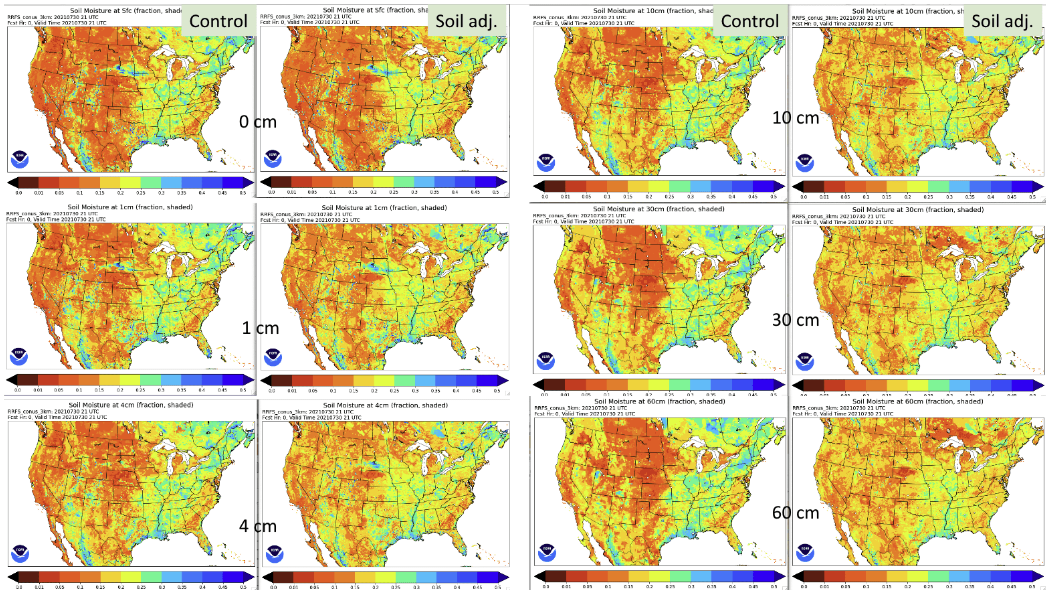
To understand better the differences between the two runs in the daytime, it is useful to look at the spatial distribution of daytime dewpoint biases.



RRFS 2-m daytime dewpoint bias, 1-h forecast,
24-31 July 2021.
Top - Control (no MCLDA),
Bottom - Test (with MCLDA)

Blue - dry bias, Red - moist bias

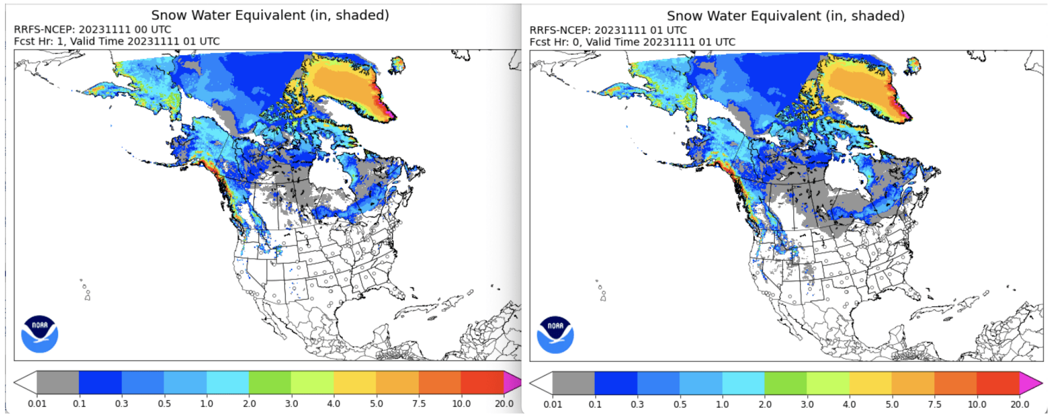
The figure above demonstrates that Test (bottom) significantly improves the dry biases in the Midwest of US over Control (top). But in some other areas Test has turned small moist biases into very small dry biases, and thus, the area-averaged bias shows as slightly drier than in the Control. The sample of soil moisture in the Control and Test experiments is shown below.



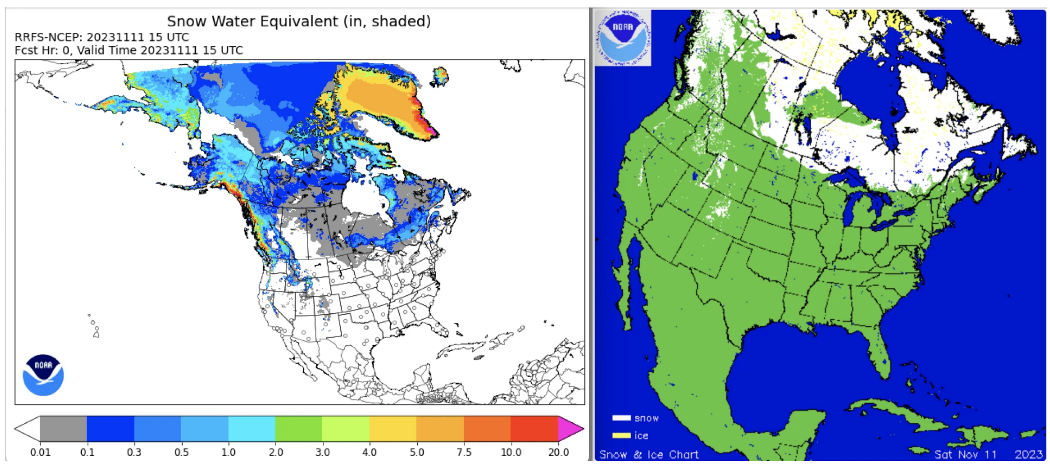
Comparison of volumetric soil moisture between the Control (left) and Test (right).
Valid at 21 UTC, 30 July 2021

b) Snow building/trimming to compensate for a spin-up issue in 1-h forecast of snow precipitation

In the cold season it is important to represent snow cover on the ground correctly. The snow in the RRFS is cycled driven by the model precipitation and snow physics in the RUC LSM. There are the possibilities to get snow on the ground in the wrong places from misplaced snow storms, or deficient snow accumulation from not sufficient snow precipitation or overestimation of snow melting processes depending on the near-surface temperature. Therefore, snow cover is evaluated daily from Interactive Multisensor Snow and Ice Mapping System (IMS) snow cover analysis, and snow is trimmed or built if needed.



Cycled in RRFS snow water equivalent before snow update (left) and after snow update (right), 11 November 2023



Cycled RRFS snow water equivalent (left) and IMS snow analysis (right), 11 November 2023

The video below demonstrates the snow depth evolution in the 18-h RRFS forecast initialized at 15 UTC,11 Nov 2023.

[VIDEO] https://res.cloudinary.com/amuze-interactive/video/upload/q_auto/v1700256477/agu23/10-74-FB-EF-FE-59-A7-89-1D-43-CD-C8-AB-92-7B-A9/Video/Tata_2023_01_k26ha8.mp4

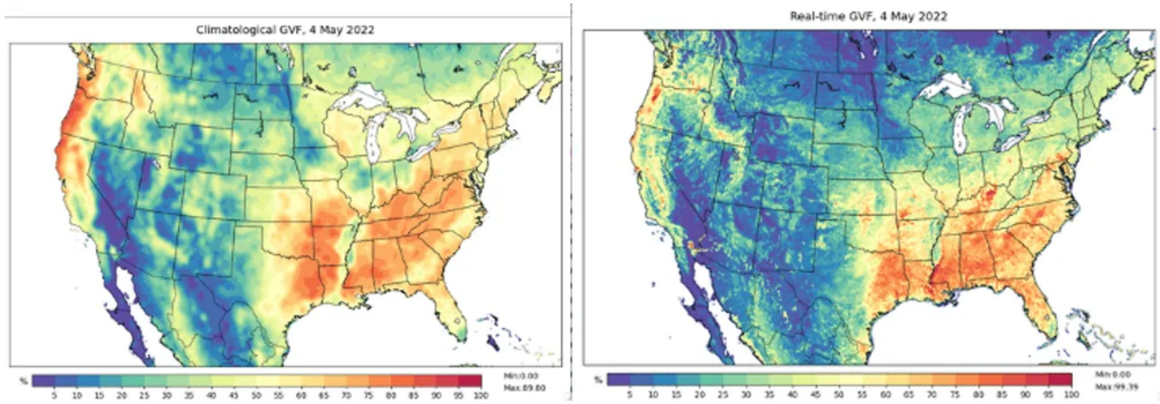
[VIDEO] https://res.cloudinary.com/amuze-interactive/video/upload/q_auto/v1700592015/agu23/10-74-FB-EF-FE-59-A7-89-1D-43-CD-C8-AB-92-7B-A9/Video/Tata_2023_03_ukokxt.mp4

Forecast loops for other surface variables (soil temperature, soil moisture, skin temperature, snow water equivalent, 2-m temperature, 2-m dewpoint, etc.) could be viewed in real time from the RRFS web site: RAP and RRFS graphics (https://rapidrefresh.noaa.gov/RAP/) (use drop-down menu to switch between the models).

IMPROVED REPRESENTATION OF SURFACE PROPERTIES

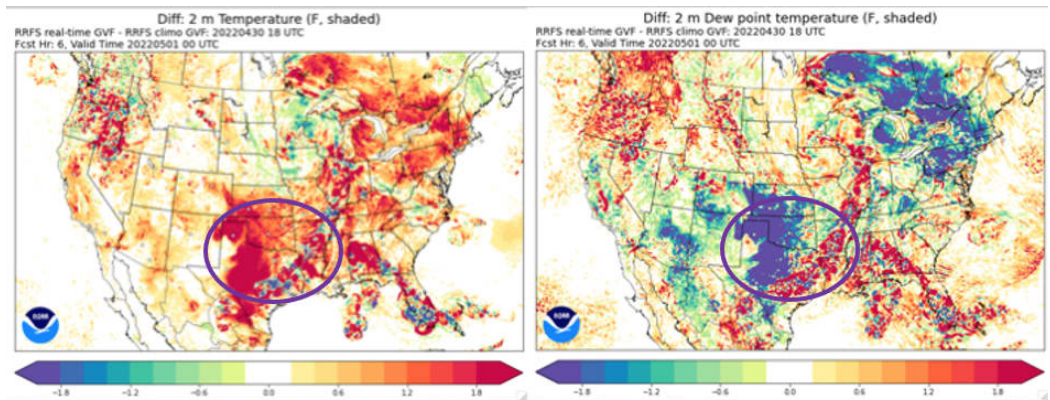
1. Use of real-time VIIRS greenness fraction (GVF)

Real-time information about the vegetation is important for accurate simulation of evapotranspiration processes, especially for the years with substantial deviation from the climatology and for the periods following severe weather events, like tornados, hurricanes and flooding that modify the greenness properties of the surface.



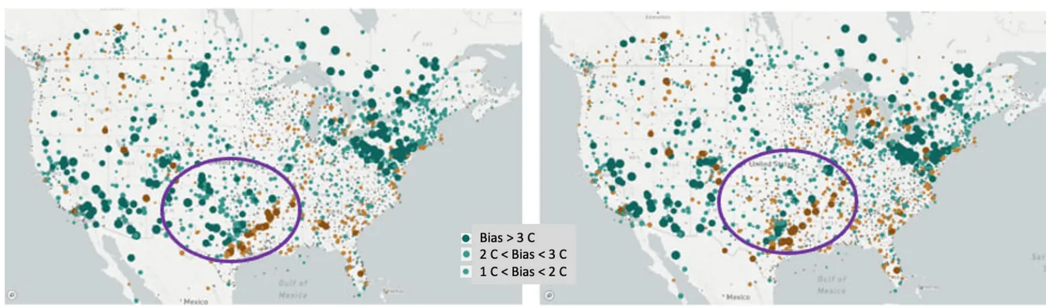
The impact from real-time GVF was evaluated in the retrospective RRFS experiment for 29 April - 8 May 2022 (Smirnova et al. 2024). The snapshots of the climatological GVF for 4 May 2022 is shown on the left and the real-time VIIRS GVF is on the right. The real-time GVF has more detailed information compared to climatology with lower values in the Midwest and Northeastern US.

More accurate information about vegetation greenness is important for more realistic partitioning of evapotranspiration between its components: direct evaporation from the non-vegetated portion of the grid cell, transpiration and canopy evaporation from the vegetated portion. The potential improvements from more accurate evapotranspiration fluxes can happen during the day in the areas with strong coupling between land and atmosphere.



Differences in 2-m temperature (left) and 2-m dewpoint (right): real-time GVF minus climatological GVF, 6-h forecast, valid at 00 UTC, 1 May 2022

The above figure shows that inside the circled areas the differences between 6-h forecast valid at 00 UTC on 1 May 2022 of 2-m temperatures and 2-m dewpoints with the use of the real-time GVF instead of climatology are substantial.



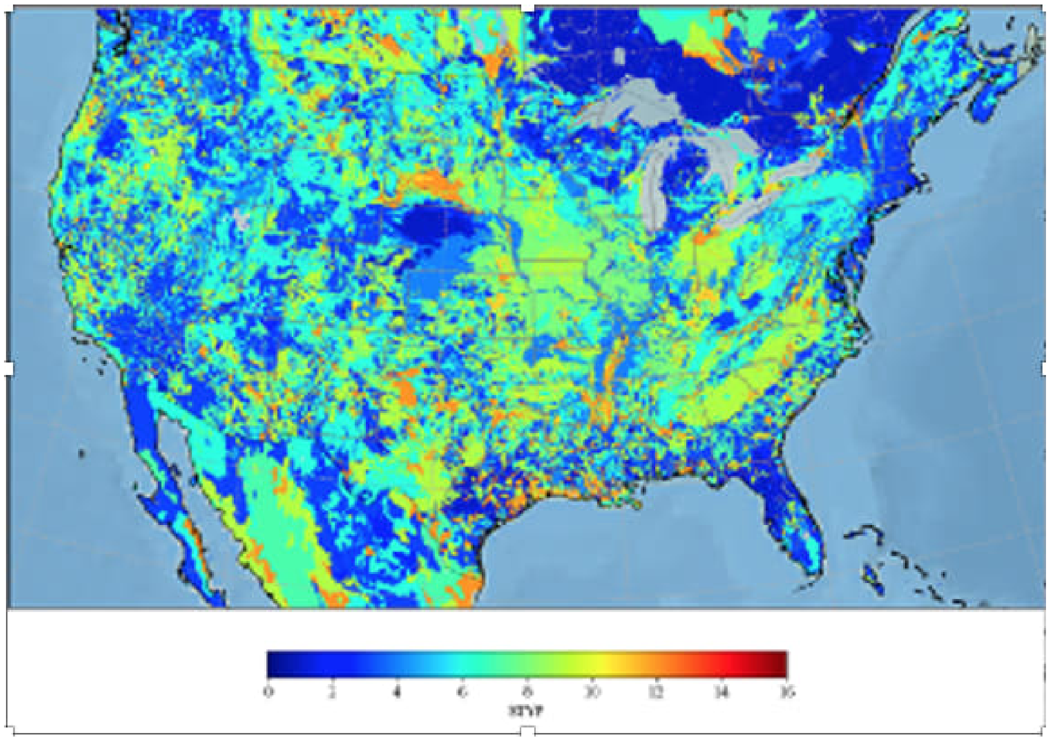
2-m dewpoint biases with climatological GVF (left) and real-time GVF (right), 6-h forecast, valid at 00 UTC, 1 May 2022

The above figure shows spatial distribution of 2-m dewpoint biases for the same time at 00 UTC, 1 May 2022. The moist biases inside the circled area with climatological GVF (left) have improved with the use of real-time GVF (right).

The real-time VIIRS greenness vegetation fraction is utilized in the operational RAP, HRRR and recently has been implemented in the experimental RRFS.

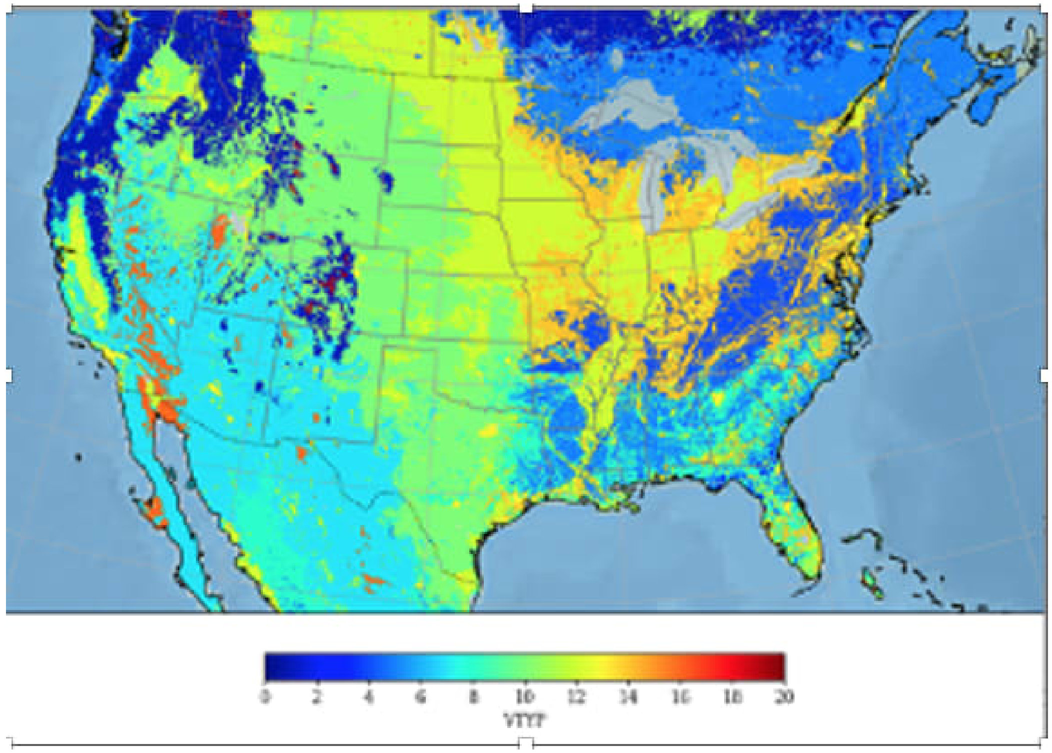
2. High-resolution information about soil and vegetation types

Advances in soil research allowed to produce a more accurate, high-resolution global soil data at Beijing Normal University (BNU) (Shangguan et al. 2014). Sixteen USGS soil categories are based on the percentages of sand, silt, and clay on a horizontal resolution of 30 arc sec. It was demonstrated that the BNU soil data can improve prediction of both 2 m temperature and 2 m relative humidity (Dy and Fung, 2016). This global BNU data (WPS (https://www2.mmm.ucar.edu/wrf/users/download/get_sources_wps_geog.html)) was used to produce dominant categories on the RRFS domain, as well as fractional information for each soil category in the grid cell.



RRFS dominant soil categories based on the BNU 30 arc-sec global soil data

For vegetation information, RRFS uses a 15 arc-sec MODIS global dataset (WPS (https://www2.mmm.ucar.edu/wrf/users/download/get_sources_wps_geog.html)). This high-resolution dataset was critical for accurate representation of ocean coast lines and also for the initialization of lakes (Benjamin et al, 2022b). It also has advantages over complex terrain (Golzio et al. 2021).



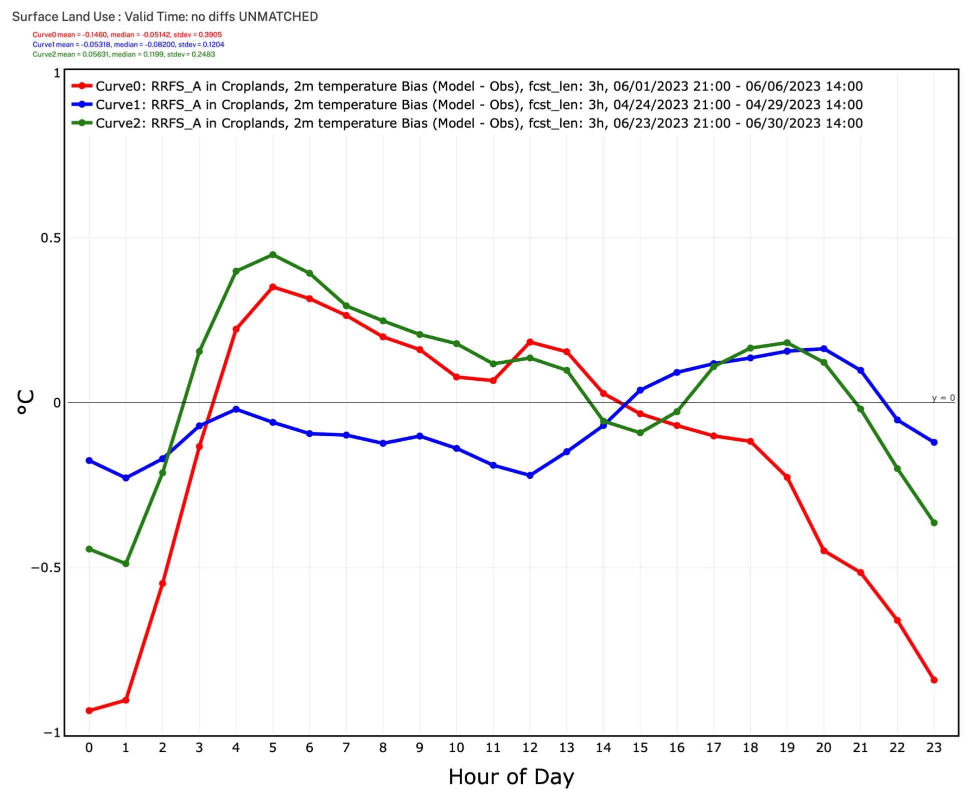
RRFS dominant vegetation categories based on 15 arc-sec MODIS global land use data

IMPROVEMENTS IN LAND SURFACE PHYSICS PARAMETERIZATIONS

1. Modifications to RUC LSM irrigation algorithm.

Modifications to the irrigation parameterization was required for fixing the problem in RRFS with cold/moist biases in the areas with croplands. When crops are close to their maturity, the irrigation algorithm should be activated if soil moisture is deficient. The original algorithm was using the look-up table values of Leaf Area Index (LAI) to evaluate the growing phase of the crops. This method does not account for specific conditions at different cropland regions and was triggering the irrigation too early, causing cold and moist biases in cropland areas of central Texas. The method was modified to use real-time VIIRS greenness fraction to capture the deviations from the climatological greenness and to provide more accurate information on the growing phase of the crops.

The modified method was implemented in RRFS two weeks after the system upgrade which introduced the problem.



RRFS, bias of 2-m temperature for croplands, 3-h forecast.

Red - 1-6 June 2023, Blue - 24-29 April 2023, Green - 24-30 June 2023 (after fixing the problem)

The red curve on the above figure shows diurnal variation of 2-m temperature bias before the problem was fixed, and the green curve is for the period after the fix. The green curve shows that daytime cold bias has been significantly reduced.

2. Modifications to the RUC snow model.

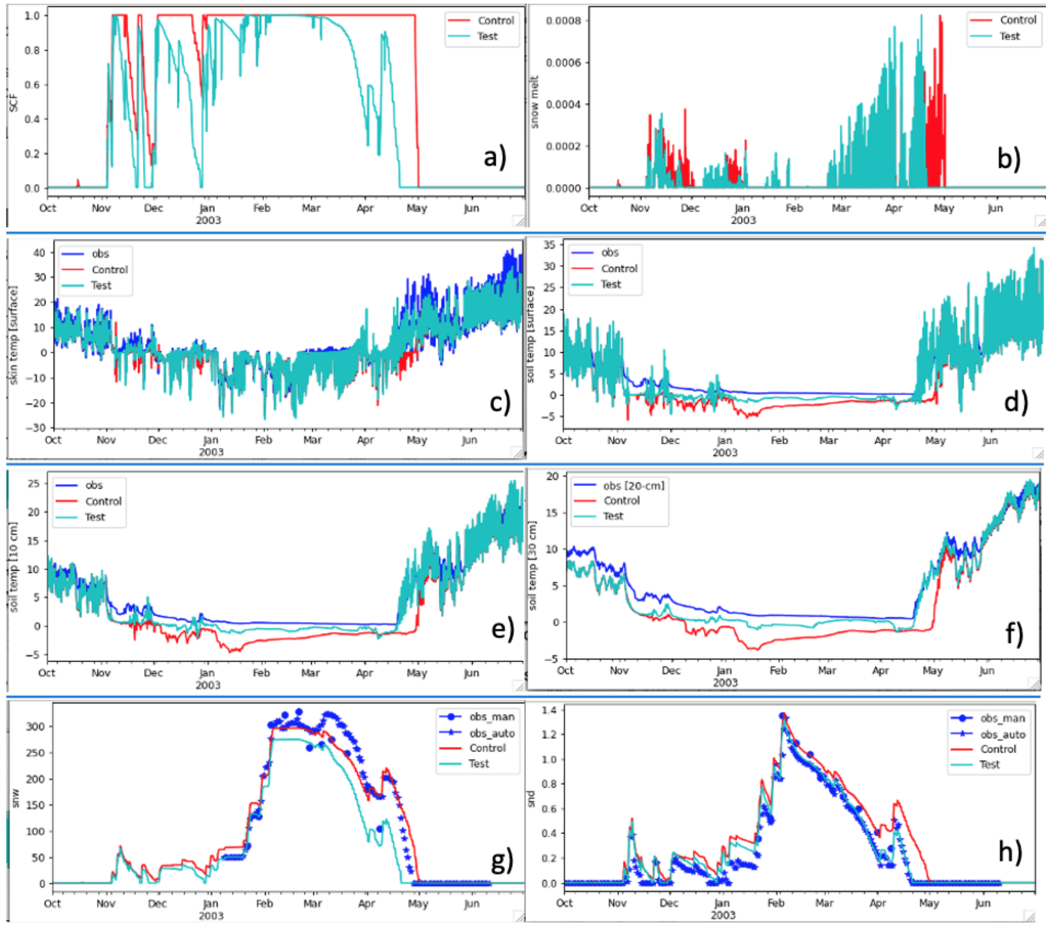
Several modifications to RUC LSM's snow module have been made to improve the RRFS performance during the cold season. These modifications include:

- Dependence on snow density and vegetation type in the computation of snow cover fraction (SCF). new formulation is based on the Niu, G.-Y., and Yang, Z.-L. (2007) with some modifications for 3-km horizontal scale. New formulation led to reduction of SCF during snow accumulation and snow melting seasons and to the improvements of cold biases for areas with partial snow cover.
- Estimation of snow thermal conductivity depending on the density of snow accumulated on the ground (Sturm et al. 1997). This modification allowed to represent more accurately the insolation properties of snow when its density is low.

The details of these modifications are described in Smirnova et al. 2024 (work in progress).

The snow model enhancements have been tested first in the one-dimensional framework with the use of observed atmospheric forcing from ESM-SnowMIP experiment (Krinner et al., 2019). The 10 ESM-SnowMIP sites ar

e located in different climatological zones of the world and present a great asset for testing of snow model changes.



Col de Porte, France, winter 2003-2004. a) snow cover fraction, b) snow melt (mm/s), c) skin temperature (C), d) temperature at snow-soil interface (C), e) soil temperature at 10-cm depth (C), f) soil temperature at 30-cm depth (C), g) snow water equivalent (mm), h) snow depth (m)

The Col de Porte (CDP) site, France, is located in the French Alps on the grassy meadow surrounded by spruce forests. The CDP site represents a humid continental climate with substantial snowfall in winter. The results for 2003-2004 winter season are shown on the above figure. Control (red) uses original formulations for SCF and thermal conductivity, and Test (turquois) uses new formulations for SCF and snow thermal conductivity. The Test run captures more accurately the date when snow on the ground is completely melted, and has improvements in snow and soil temperature during snow accumulation and snow melting seasons when SCF is below one.

CONCLUSIONS

1. Improvements in the operational surface prediction require understanding the reasons for model biases in 2-m temperature and dewpoint. Different MATS verification evaluations have been used to identify times of the day, regions and vegetation types with the largest biases in the experimental RRFS.

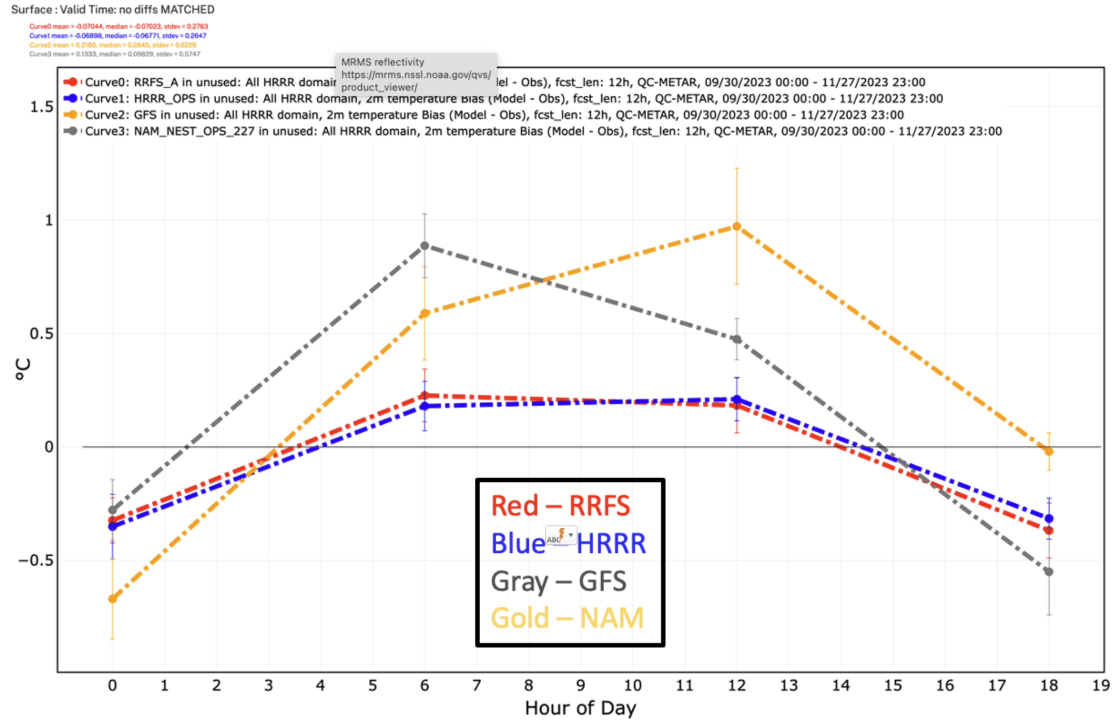
2. Enhanced MCLDA used in RRFS for soil moisture reduced cold and moist biases in summer 2021 for the US Midwest.

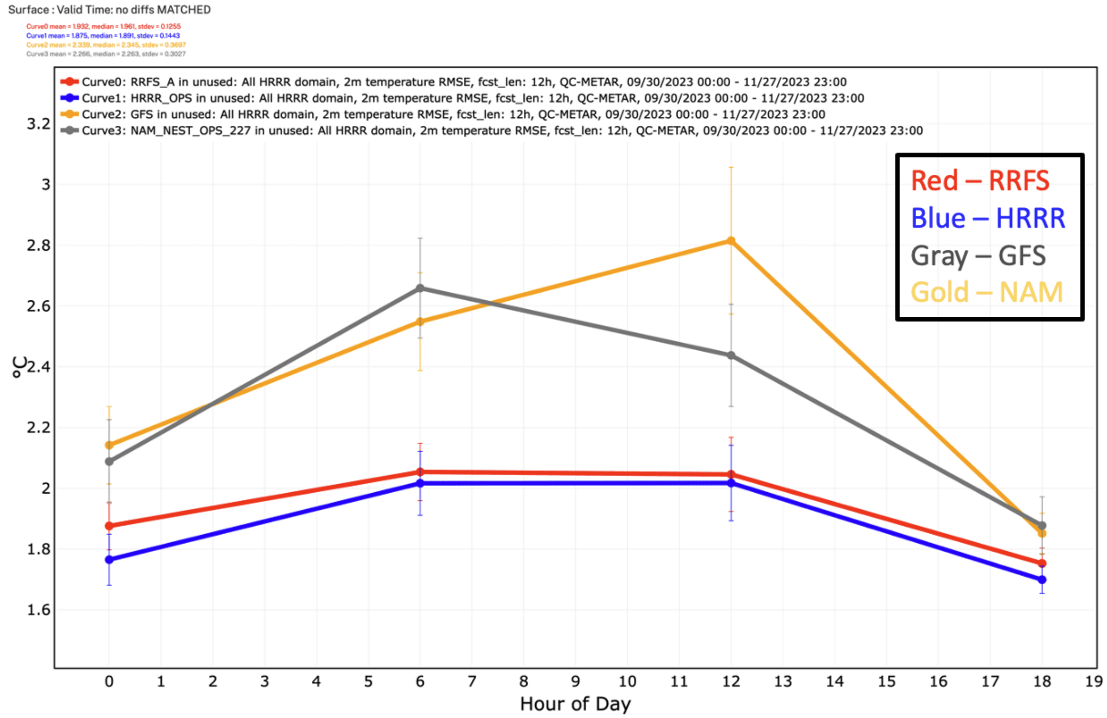
3. Snow trimming/building in RRFS using the IMS 4-km snow cover analysis mitigates a spin-up in precipitation forecast (snow building) and corrects the misplaced snowfall in 1-h precipitation forecast (snow trimming).

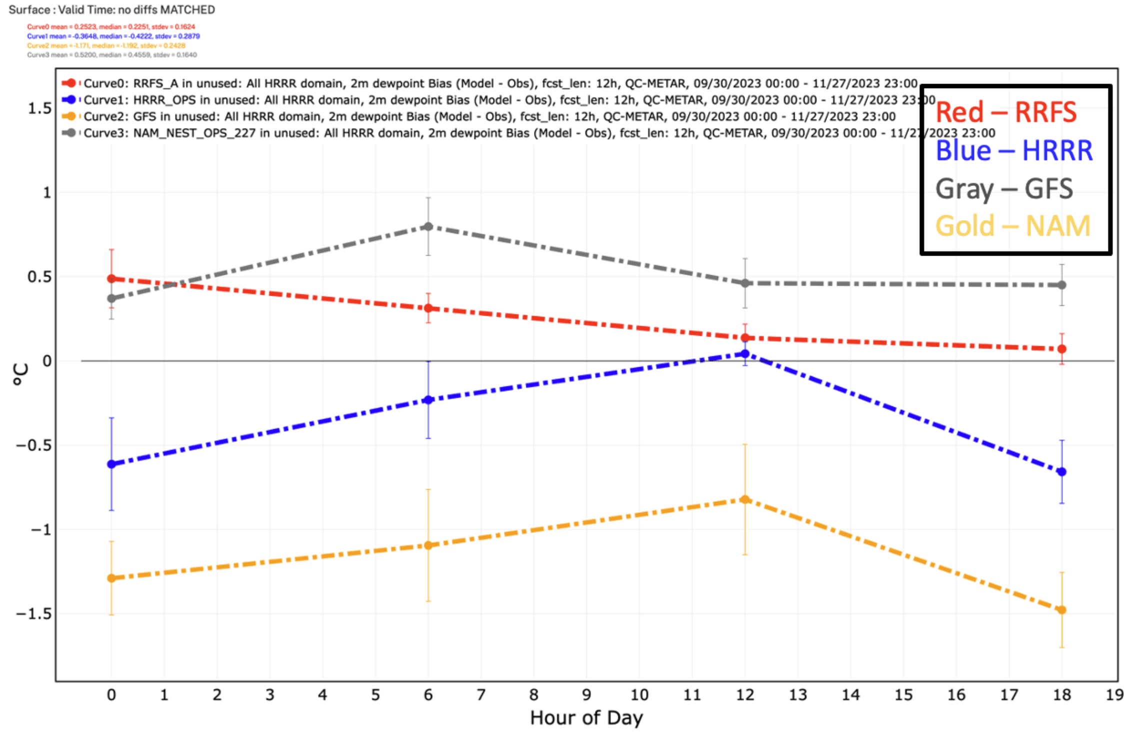
4. State-of-the-art high-resolution information for soil, land use and real-time vegetation greenness are used in RRFS for more accurate representation of surface characteristics. Surface characteristics take into account subgrid-scale heterogeneity.

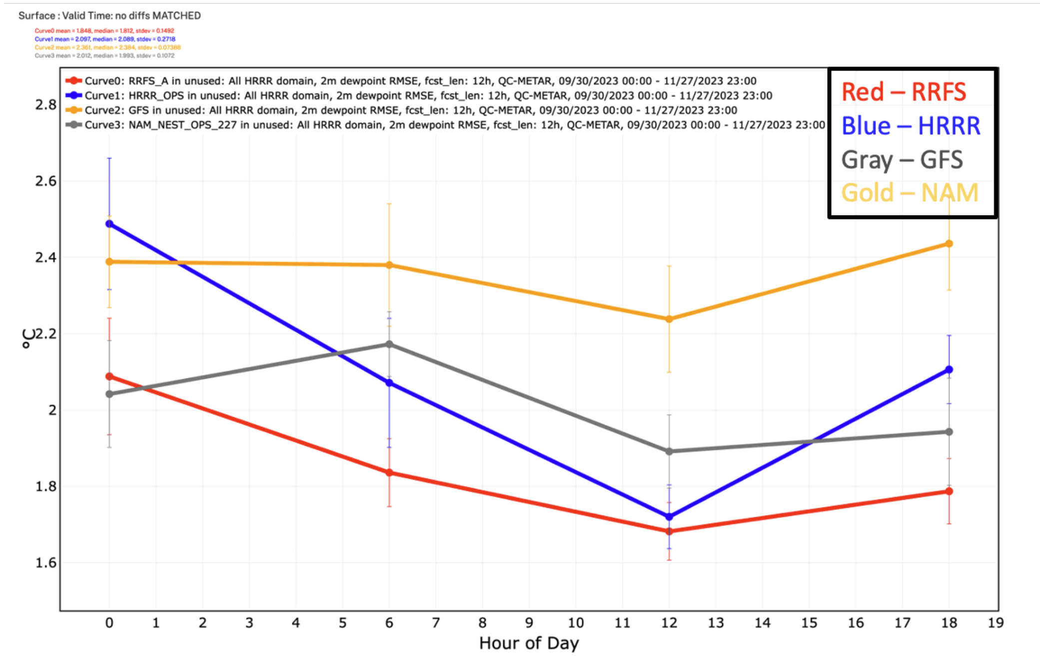
5. Advances in RUC LSM fixed the identified problems and improved surface predicitons in RRFS.

6. Following the strategies described in this poster led to substantial improvements in surface predictions during the development of next-generation operational RRFS model. As of now, surface verification of the experimental RRFS (red) is competitive with HRRR (blue) and improves over GFS (gray) and NAM (gold).


Surface : Valid Time: no diffs MATCHED
Curve0 mean = -0.07044, median = -0.07023, stdev = 0.2763
Curve1 mean = -0.06898, median = -0.06771, stdev = 0.2647
Curve2 mean = 0.2180, median = 0.2845, stdev = 0.6226
Curve3 mean = 0.1333, median = 0.09829, stdev = 0.5747
MRMS reflectivity
https://mrms.nssl.noaa.gov/qvs/product_viewer/
Curve0: RRFS_A in unused: All HRRR domain ... el - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve1: HRRR_OPS in unused: All HRRR domain, 2m temperature Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve2: GFS in unused: All HRRR domain, 2m temperature Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve3: NAM_NEST_OPS_227 in unused: All HRRR domain, 2m temperature Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
°C
1.5
1
0.5
0
−0.5
Red – RRFS
Blue – HRRR
Gray – GFS
Gold – NAM
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
Hour of Day


Surface : Valid Time: no diffs MATCHED
Curve0 mean = 1.932, median = 1.961, stdev = 0.1255
Curve1 mean = 1.875, median = 1.891, stdev = 0.1443
Curve2 mean = 2.339, median = 2.345, stdev = 0.3697
Curve3 mean = 2.266, median = 2.263, stdev = 0.3027
Curve0: RRFS_A in unused: All HRRR domain, 2m temperature RMSE, fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve1: HRRR_OPS in unused: All HRRR domain, 2m temperature RMSE, fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve2: GFS in unused: All HRRR domain, 2m temperature RMSE, fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve3: NAM_NEST_OPS_227 in unused: All HRRR domain, 2m temperature RMSE, fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Red – RRFS
Blue – HRRR
Gray – GFS
Gold – NAM
°C
Hour of Day


Surface : Valid Time: no diffs MATCHED
Curve0 mean = 0.2523, median = 0.2251, stdev = 0.1624
Curve1 mean = -0.3648, median = -0.4222, stdev = 0.2879
Curve2 mean = -1.171, median = -1.192, stdev = 0.2428
Curve3 mean = 0.5200, median = 0.4559, stdev = 0.1640
Curve0: RRFS_A in unused: All HRRR domain, 2m dewpoint Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve1: HRRR_OPS in unused: All HRRR domain, 2m dewpoint Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve2: GFS in unused: All HRRR domain, 2m dewpoint Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Curve3: NAM_NEST_OPS_227 in unused: All HRRR domain, 2m dewpoint Bias (Model - Obs), fcst_len: 12h, QC-METAR, 09/30/2023 00:00 - 11/27/2023 23:00
Red – RRFS
Blue – HRRR
Gray – GFS
Gold – NAM
°C
Hour of Day



Comparison of diurnal cycles of RRFS (red) RMS errors (solid) and biases (dashed) for 2-m temperature (top) and 2-m dewpoint (bottom) against HRRR (blue), GFS(gray), and NAM (gold). 12-h forecasts over CONUS, 30 Sept - 27 Nov 2023.

AUTHOR INFO

Tatiana G. Smirnova, senior scientist at the Cooperative Institute for Research in Environmental Sciences (CIRES (https://cires.colorado.edu/)), University of Colorado Boulder / NOAA Global Systems Laboratory (GSL (https://gsl.noaa.gov/)), Boulder, Colorado.

Tatiana's main expertise is in the land surface modeling for operational weather predictions. She developed Rapid Update Cycle (RUC) land surface model which has been utilized in several generations of NOAA operational weather prediction models since1998 up to present.

Stanley G. Benjamin, Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, Colorado / NOAA Global Systems Laboratory, Boulder, Colorado.

Ming Hu, NOAA Global Systems Laboratory, Boulder, Colorado.

Ruifang Li, Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, Colorado / NOAA Global Systems Laboratory, Boulder, Colorado.

TRANSCRIPT

ABSTRACT

The main purpose of land surface schemes in the weather prediction models is to provide more accurate lower boundary conditions for the atmosphere, especially important for improved predictions of severe weather having critical impact on aviation operations, ground transportation, and other areas of human activities. The required input to most boundary layer schemes are sensible and latent heat fluxes computed within the land surface models. These fluxes to a large extent depend on accurate initialization of initial land surface state, including soil moisture, soil temperature, vegetation greenness and snow in the cold season. Several functionalities within a coupled land data assimilation system have been developed for the High-Resolution Rapid Refresh (HRRR) model, operational at the National Center for Environment prediction (NCEP). These functionalities have been transferred to the next generation UFS-based regional Rapid Refresh FV3 Standalone (RRFS, under development at present time). Other strategies for improved surface predictions include identifying model biases in 2-m temperature and moisture, revealing the sources of errors and providing methods to alleviate these biases. Errors in surface fluxes could be caused by biases in clouds, precipitation and incoming solar radiation computed in the atmospheric components of the forecasting system. Land-surface-related factors would most likely include soil moisture affecting the Bowen ratio. Another important factor is the vegetation fraction that affects splitting evapotranspiration between direct soil evaporation, canopy evaporation and transpiration. Use of real-time greenness fraction rather than climatology should provide more realistic information about the state of the vegetation and thus provide more realistic evapotranspiration flux. For cold seasons snow cover depth and fraction can play a critical role in 2-m temperature over snow-covered areas. Experiments performed within the RRFS model in terms of described strategies for improved surface predictions will be presented at the meeting.

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