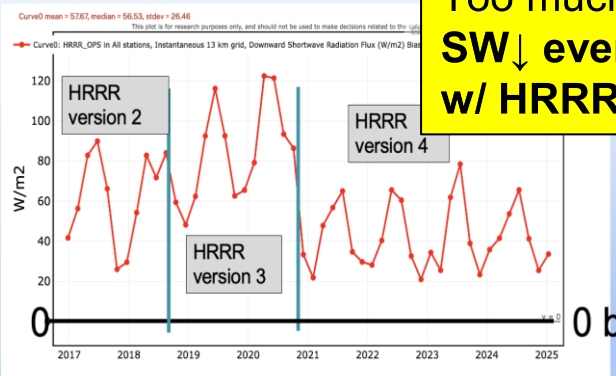
NOAA regional models (HRRR, RRFSv1, RRFSv2) status in 2025 - cloudiness issues, discovery & solutions



Too much SW↓ even w/ HRRR

Downward SW bias – 6h HRRR/RAP forecasts valid 17-20z – vs. SURFRAD obs – 2017-2025

Stan Benjamin, Dave Turner

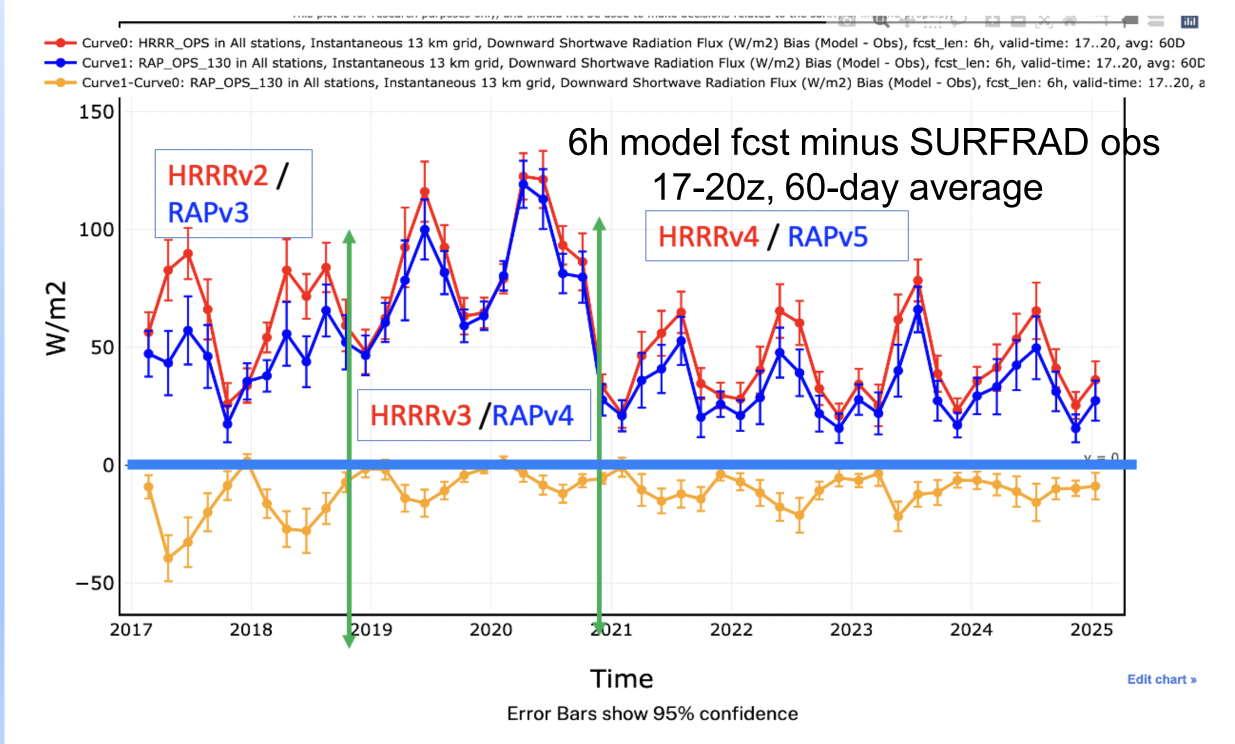
CIRES – CU Boulder,

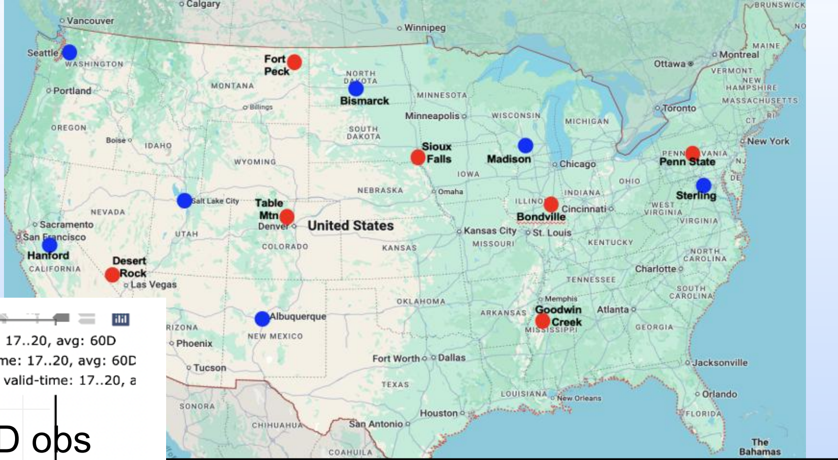
NOAA Global Systems Lab (GSL)

Excessive SW radiation in HRRR and solutions - Benjamin et al, 2025 – Mon. Wea. Rev., in review

25 June 2025 - ESIG Forecasting & Markets Workshop, Nashville

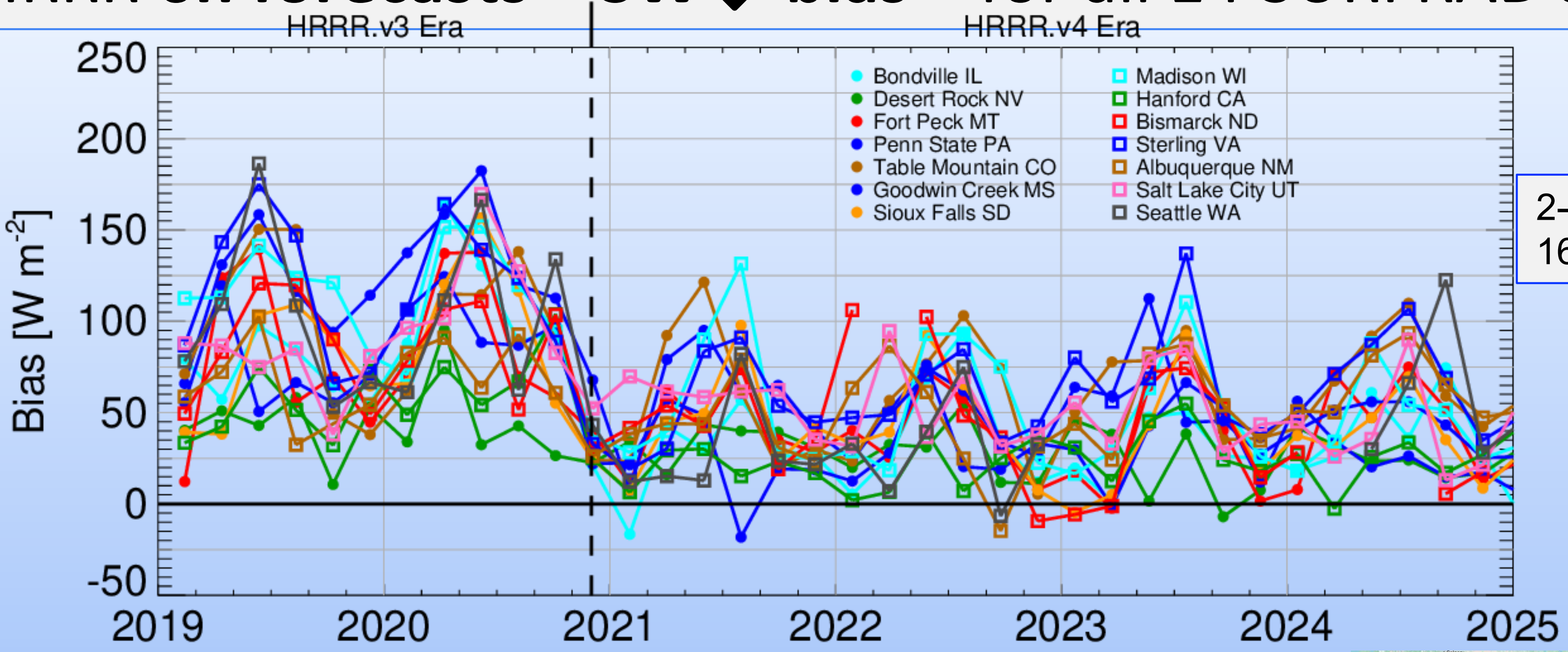
HRRR/RAP **6h forecasts – SW↓ bias** – averaged over all 14 SURFRAD stations





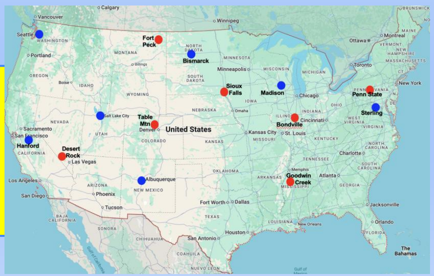
- Excessive SW↓ from both HRRR (3km) and RAP (13km)
- Improvement in 2020 with HRRRv4/RAPv5 – reduced cloud droplet size for subgrid-scale (SGS) clouds.
- **But still too much SW↓**

HRRR **6h forecasts – SW↓ bias** – for all 14 SURFRAD stations

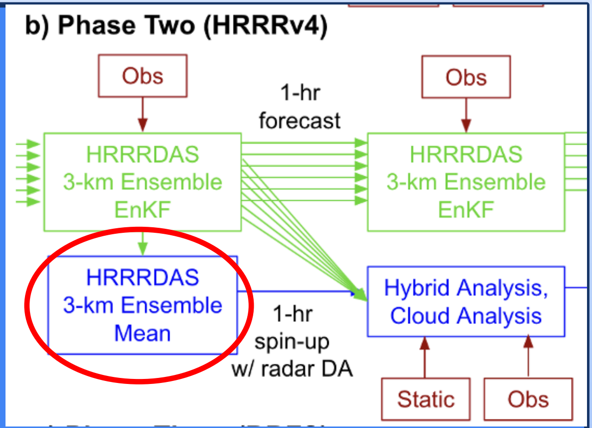


2-month average
16/17/18/19/20z

Consistent across US: Excessive **SW↓** for **<u>each of the 14 stations</u>**, even after 2020 improvement in HRRRv4

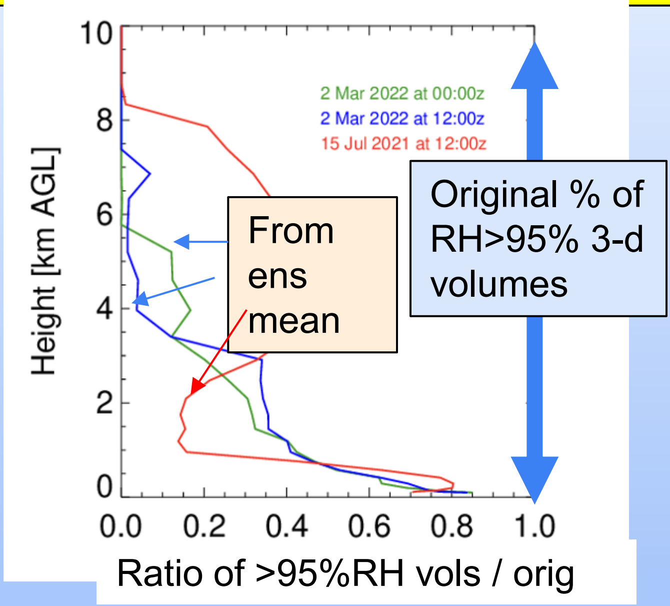


Discovery: Dry bias in HRRRv4 data assimilation - Ensemble mean removes near-saturation areas (clouds)



HRRR DA - Dowell et al 2022

Main cause for HRRRv4 dry bias



- # of near-saturated points (RH>95%) decreases by 20-100% from **ensemble mean.**
- 3 different cases shown
- Benjamin et al. 2025 (in review)

Experiment designs

Investigate these two areas:

Data assimilation comparison
- HRRRv4-oper vs. Control

Cloud optical param. comparisons
- Control vs
  - HalfRc
  - Reduced SGS
  - Combined

Experiment designs	Data assimilation	Forecast model version	Modification
HRRRv4-Operational – since Dec 2020	HRRRv4	HRRRv4	original
Control (new)	HRRRv3	HRRRv4	Data assimilation that reduces dry bias
HalfRc	HRRRv3	HRRRv4	**Explicit** cloud – droplet effective radius (Re) reduced by 50%
Reduced SGS	HRRRv3	HRRRv4	**Subgrid-scale** cloud droplet Re reduced by 33%, from 5.4 μm to 3.6 μm.
Combined	HRRRv3	HRRRv4	Explicit Re reduced 40%, SGS Re reduced 33%
HRRRv3-Operational – Aug 2018-Dec 2020	HRRRv3	HRRRv3 (larger Re, much stronger diffusion for water vapor and cloud hydrometeors) than used in HRRRv4	HRRRv3

Configuration for HRRR SW↓bias experiments-CONTROL

- Model – HRRRv4 configuration and physics – Dowell et al 2022
  - HRRRv4 – decreased excessive downSW flux due to smaller effective radius for SGS clouds (to Miles et al 2000).

→Add experiments with modified initial conditions

- Data assimilation – HRRRv3 – hybrid ens-var DA. (Benjamin et al 2016, Weygandt et al 2022 – radar refl DA)
  - Avoids dry bias from HRRRv4 DA using 3-km ensemble mean for initial conditions.

Experiment designs

Data assimilation comparison

- HRRRv4-oper vs. Control

Cloud/physics comparisons

- Control vs
  - HalfRc
  - Reduced SGS
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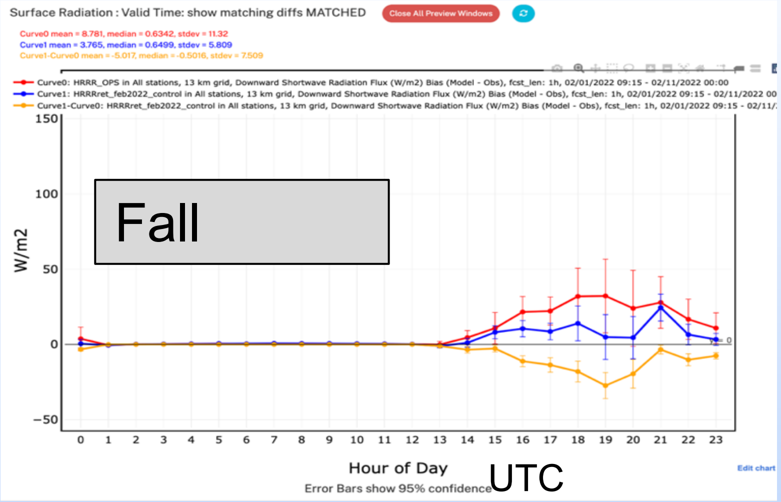
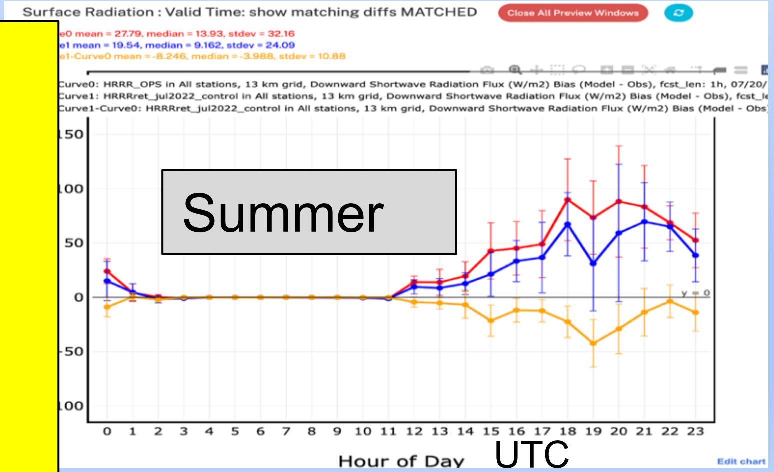
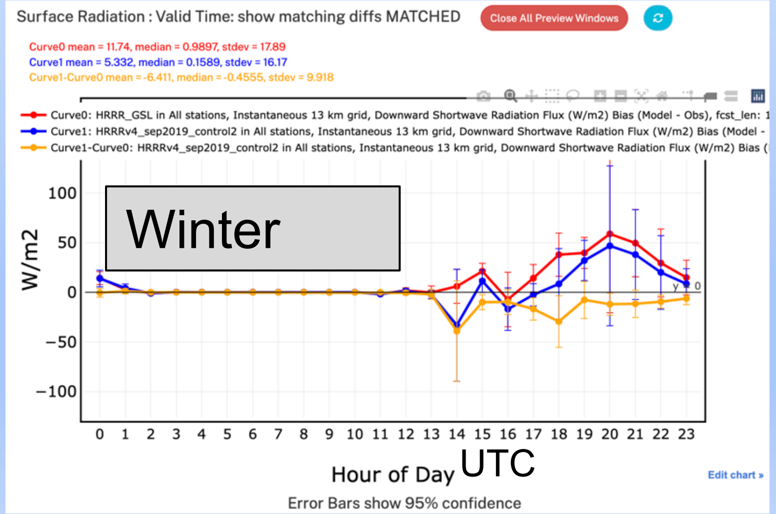
SW↓ bias –diurnal variation – **1h** forecasts

HRRRv4-oper

Control (new) – HRRRv3 DA w/ HRRRv4 model







Improved DA reduces SW↓ bias by 10-35 W m^{-2}

Experiment designs

Data assimilation comparison
- HRRRv4-oper vs. Control

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Summary of SW ↓ bias results *(Benjamin et al 2025, in review):*

- Improvements (less SW↓ bias) from both improved DA and modified cloud optical parameters

Effect of improved data assimilation alone

	HRRRv4	control	% **decrease** Control – HRRRv4	Half Rc –explicit clouds	Reduced Rc – SGS clouds	Combined	% **decrease** Combined – HRRRv4
July 2022	81	67	**17%**	62	60	52	**36%**
Sept 2019	64	39	**39%**	21	27	13	**80%**
Feb 2022	25	17	**32%**	10	9	4	**84%**

SW↓ bias (model – obs) for 6h forecasts valid 1800 UTC

Combined effect of reduced cloud droplet effective radius and improved data assimilation

2025 status - Rapid Refresh NWP Models in NOAA

- High-Resolution Rapid Refresh (HRRR)
    - *New tests identifying dryness in initial conditions – data assimilation issue (Benj et al 2025)*
- Rapid Refresh Forecast System (RRFSv1)
    - Code frozen, in final evaluation. If passes evaluation, would become operational in summer 2026
    - *Also has dry bias in initial conditions due to separate data assimilation issue.*
- RRFS version 2
    - Uses different dynamic core (MPAS – from NCAR), major NOAA development since 2024.
    - Will avoid data assimilation misdesigns in HRRRv4 and RRFSv1
- RRFS.v1 vs HRRR.v4
    - RRFSv1 generates too much and too intense convection. RRFSv1 is even drier than HRRRv4 and has poorer downward solar forecasts than HRRRv4.
    - **HRRR.v4 will remain operational until RRFS.v2 (anticipated 2028-2030)**
    - Other regional models (e.g., NAMnest) will be retired when RRFS.v1 becomes operational

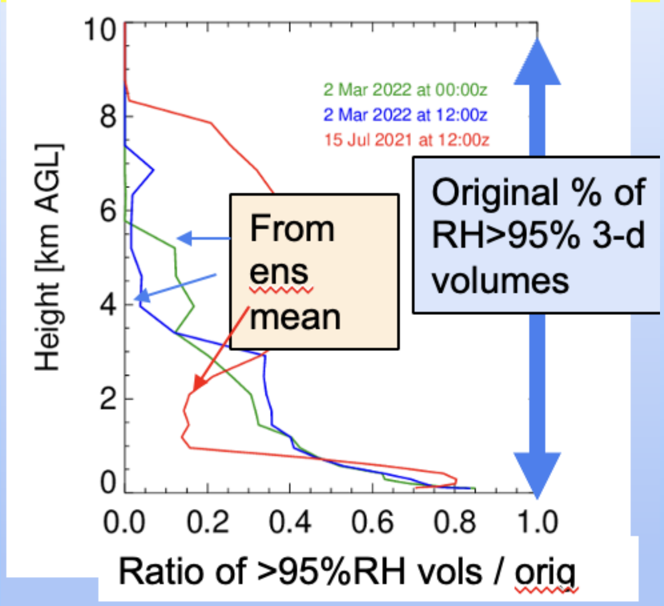
Past and future NOAA regional rapid-refresh models

Estimated - >

	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
HRRR	HRRR v3	HRRR v4									End w/ RRFS v2 imp..	
RAP	RAP v4	RAP v5									End w/ RRFS v2 impl.	
RRFS v1							In evaluat.	Implem. if approvd			End w/ RRFS v2 impl.	
RRFS v2							Testing w/o DA	Testing w/ DA			Estim. Imple.	

Data assimilation problems causing dry bias

- HRRRv4

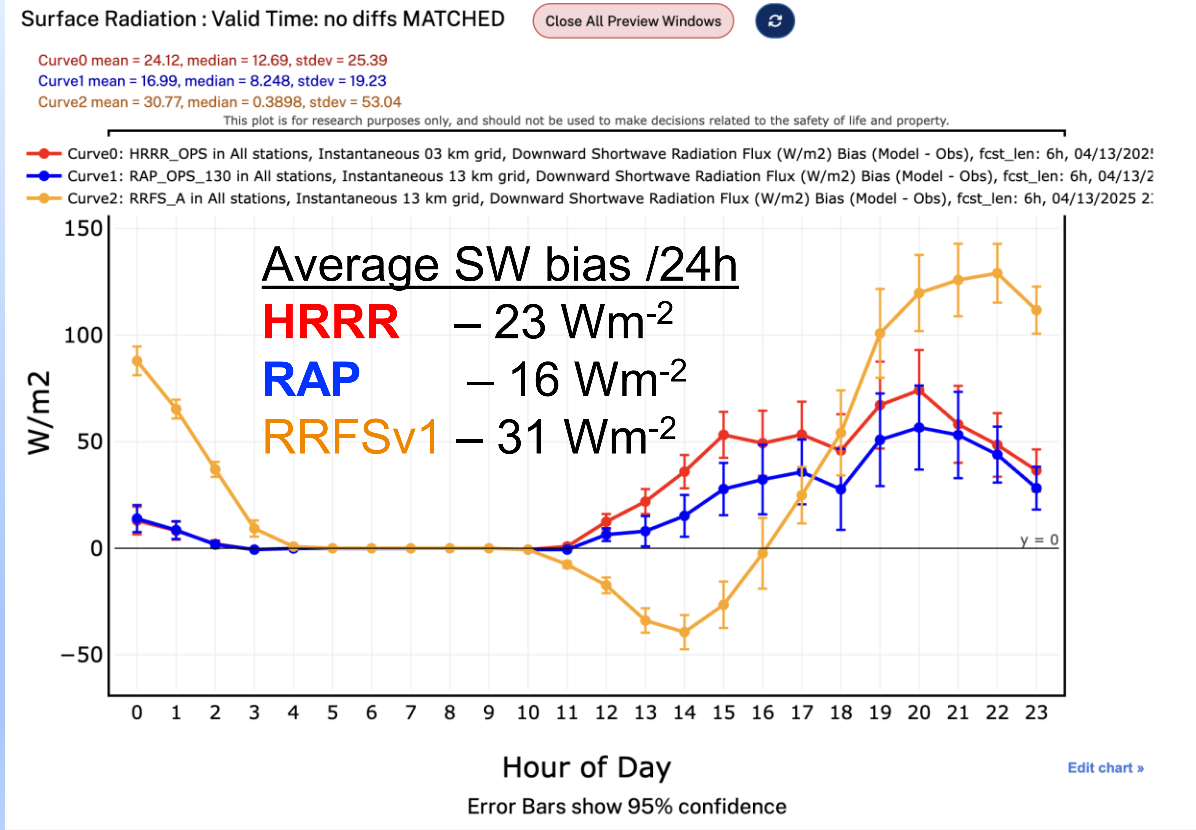


From DA using ensemble mean which eliminates most saturated 3-d volumes in HRRRv4 initial conditions Documented in journal manuscript submitted to MWR (Benjamin, James, et al., 2025)

Subsaturation introduced by use of ensemble mean for HRRRv4 initial conditions.

- RRFSv1
  - Use of different 2m dewpoint temperature diagnostic (diff from HRRR or RAP diag) which exaggerates 2m dewpoint temp.
  - Result: erroneous drying effect from the RRFSv1 data assimilation

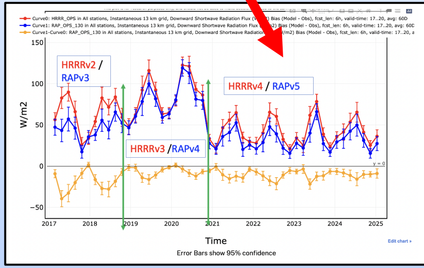
HRRR / RAP / RRFSv1 - Downward SW bias - vs. SURFRAD obs – 6h forecasts over time of day. April-May-June 2025



- HRRRv4 running 50-70 W/m^2 bias.
- RAP continues to be 10-20 W/m^2 lower bias than HRRR.
- RRFSv1 is worse than either HRRRv4 or RAPv5. It has even less cloudiness.
- RRFSv1 also has a time-lag radiation error – sun comes up 30 min late.
- All of this will be fixed in RRFSv2.

Conclusions: Excessive downward shortwave radiation (SW↓) in NOAA storm-scale NWP and strategies for reduction

- Continued evidence of excessive SW↓ even in storm-scale NWP (NOAA HRRR – 3km) across different climate regimes over the lower 48 US.
- Two strategies for reduction were formed and tested:
  - Modify data assimilation (DA) to reduce atmos dry bias
  - Modify cloud optical parameters - Reduce cloud-droplet size for explicit and subgrid-scale clouds



- Both DA and cloud optical parameter strategies contributed to lowering SW↓ bias in all 3 seasons, both strategies contributing similarly.
- Data assimilation 'misdesigns' hampered clouds in both HRRRv4, RRFSv1.
- RRFSv1 has a worse dry (i.e., cloud) bias than HRRRv4 – a separate DA problem. **RRFSv2 will have clearly improved solar forecasts (via** improved DA and cloud brightness. Keep HRRR cloud DA and soil DA.)

Benjamin, James, Turner et al, 2025 – Mon. Wea. Rev., in review

Recent Advancements in Wind, Solar and (Load) Forecasting

Lars Rohwer
06/24/2025

Three companies, one goal: 100% renewable energy!

- Headquarters in Oldenburg, Germany
- Approx. 250 employees
- Operations on all continents
- Over 20 years of experience

emsys grid services

- Grid Operation
- Network Platform

energy & meteo systems

- Wind & Solar Forecasts
- Consulting

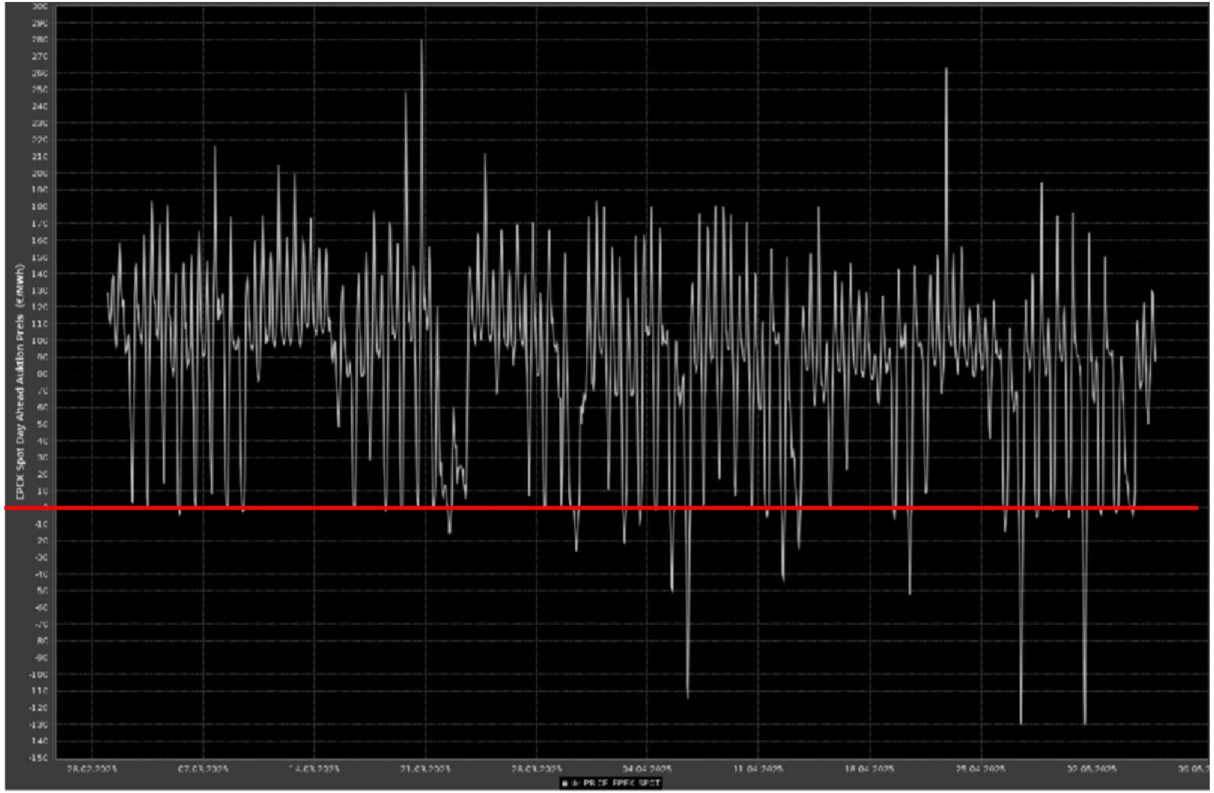
emsys vpp

- Virtual Power Plant
- Balancing Power Services

AI / Machine Learning

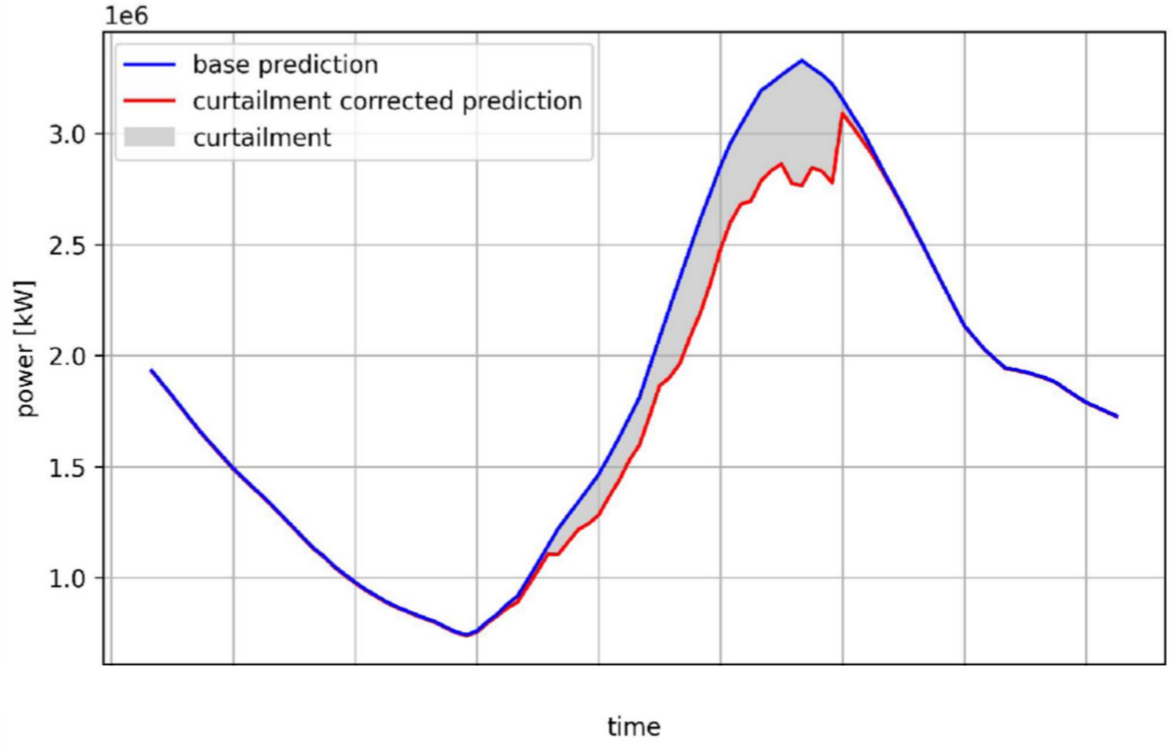
- AI weather models are well on their way, but have disadvantages
  - Parameters for energy forecasts often unavailable
  - Smearing / smoothing effects
- Machine learning can help to improve NWP-based forecasts
  - extensive training opportunities
- A wide range of data and data sources can be used – new forecasting options
  - self-consumption
  - curtailment forecasts

AI / Machine Learning - Example



- DA market prices in Germany have very frequently been in negative territory this spring
- Up to 25 GW curtailments (market-driven)
- -> Grid operators need forecasts for curtailment volumes

AI / Machine Learning - Example



- A wide variety of input data, e.g. on
  - *consumption*
  - *production*
  - *prices*
- enables a more accurate estimation of curtailment quantities

Comparison between Europe and the USA

- US-ISOs (grid operators in general) are clearly leading the way in dealing with (extreme) weather and uncertainty forecasts
- European grid operators have promoted smarter use of grids

Dynamic Line Rating
(similar to FERC Order No. 881) is an established process

Grid Congestion Management
Including distributed producers from 100 kW into the Redispatch process

Vertical Grid Load
Prediction of the vertical grid load at network nodes of different voltage levels

Grid platform combines all necessary information

Base data

Master data
Entity master data management incl. Consolidation

Grid model
grid modeling, including import of all common network models and switching requests

Determine congestions

Flexibilities
Entity power forecasts incl. (Quality-) Reports

Grid nodes
Vertical grid load forecasts on transformer level and measured value import

Grid analysis
Calculation of own bottlenecks in HV-grid and processing of sensitivities

Curing congestions

Dimensioning of measures
Entity measures incl. optimization for cluster call-offs and own bottlenecks; exports for common control rooms

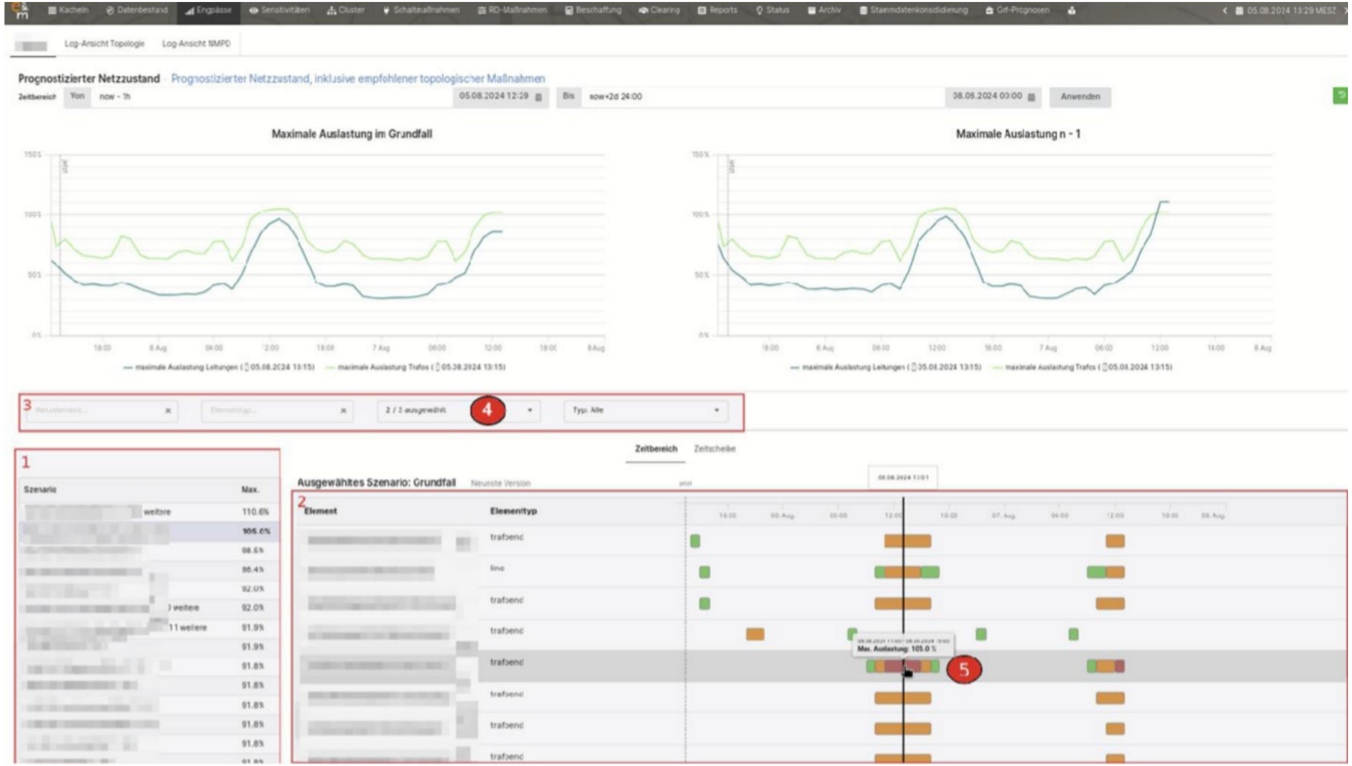
Ex-Post-Processes
Reports

Non-functional building blocks

- Alerting
- API-Access

Grid platform
UI-Platform, Data Exchange Service

Grid platform combines all necessary information



Thanks for your attention!

emsys-renewables.de