Probabilistic Forecasts for *S*olar *U*ncertainty *M*anagement and *M*itigation for *E*xceptional *R*eliability in *G*rid *O*perations (SUMMER-GO)

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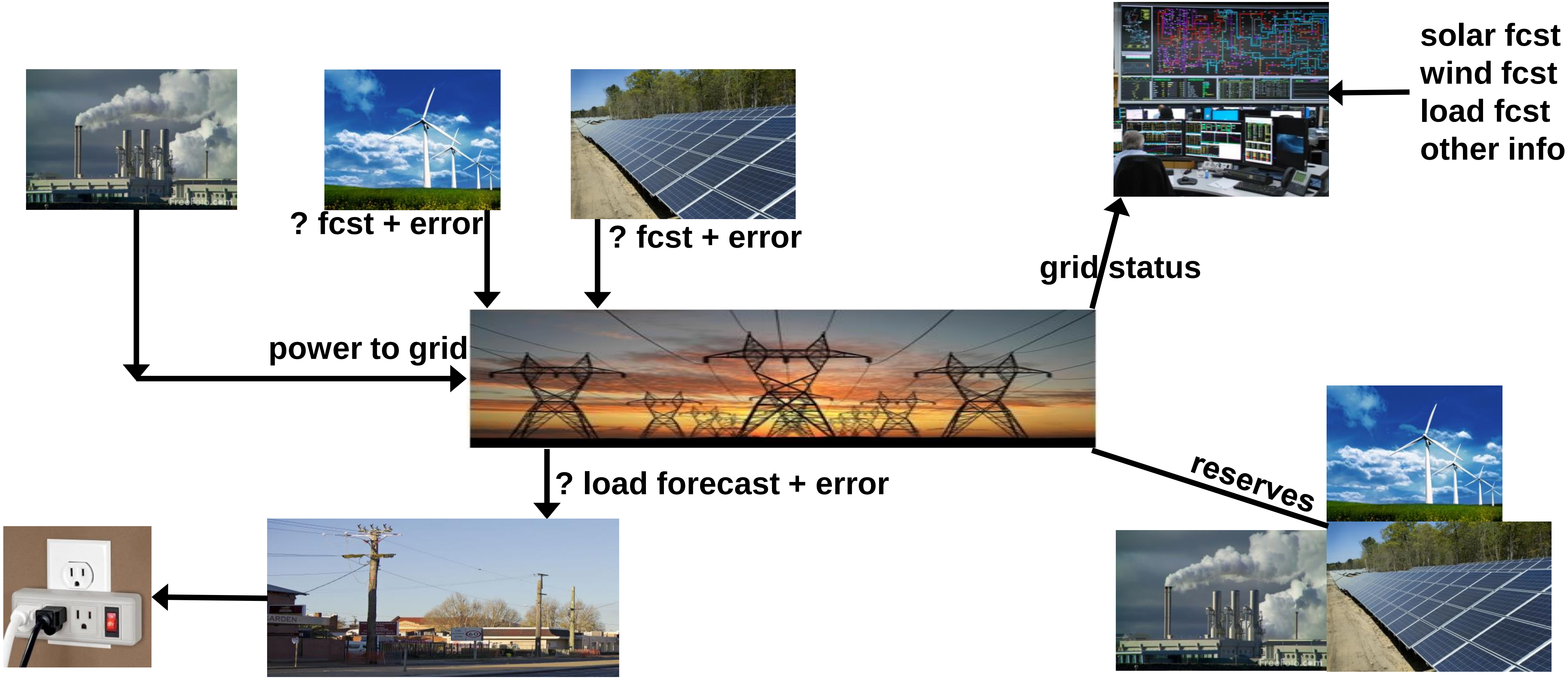
and Chris Cassidy, Eric Wertz, and Travis Hartman
and many others who contributed to the programming, data gathering, and more
and the project partner teams at NREL, ERCOT, and University of Texas at Dallas

Outline

1. What is SUMMER-GO?
2. Probabilistic Forecasting (configuration, large ensemble)
3. Bayesian Model Averaging (overview and results from 21-member multi-model ensemble)
4. Case examples from large ensemble:
   Clear day
   Cloudy morning, mostly sunny afternoon with cumulus
5. Summary/conclusion

What is SUMMER-GO?



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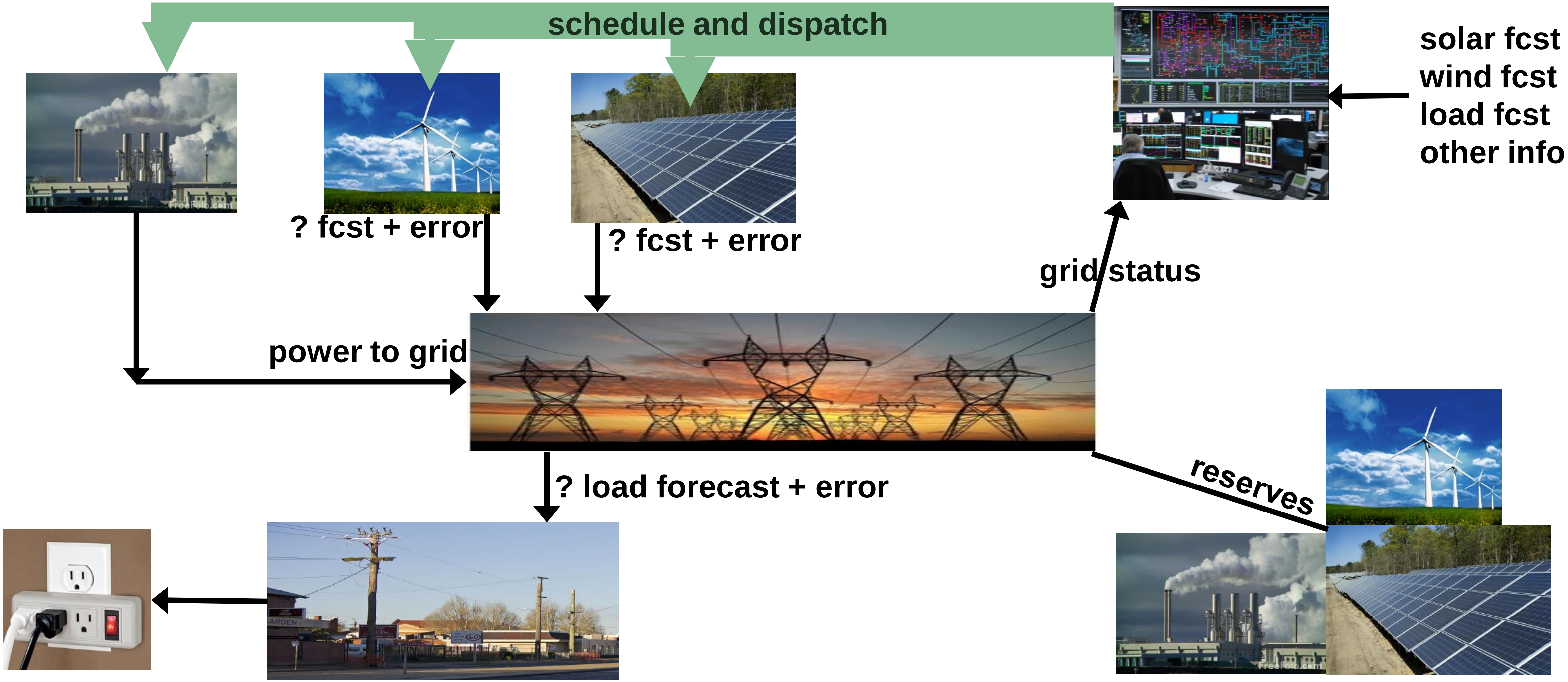
What is SUMMER-GO?



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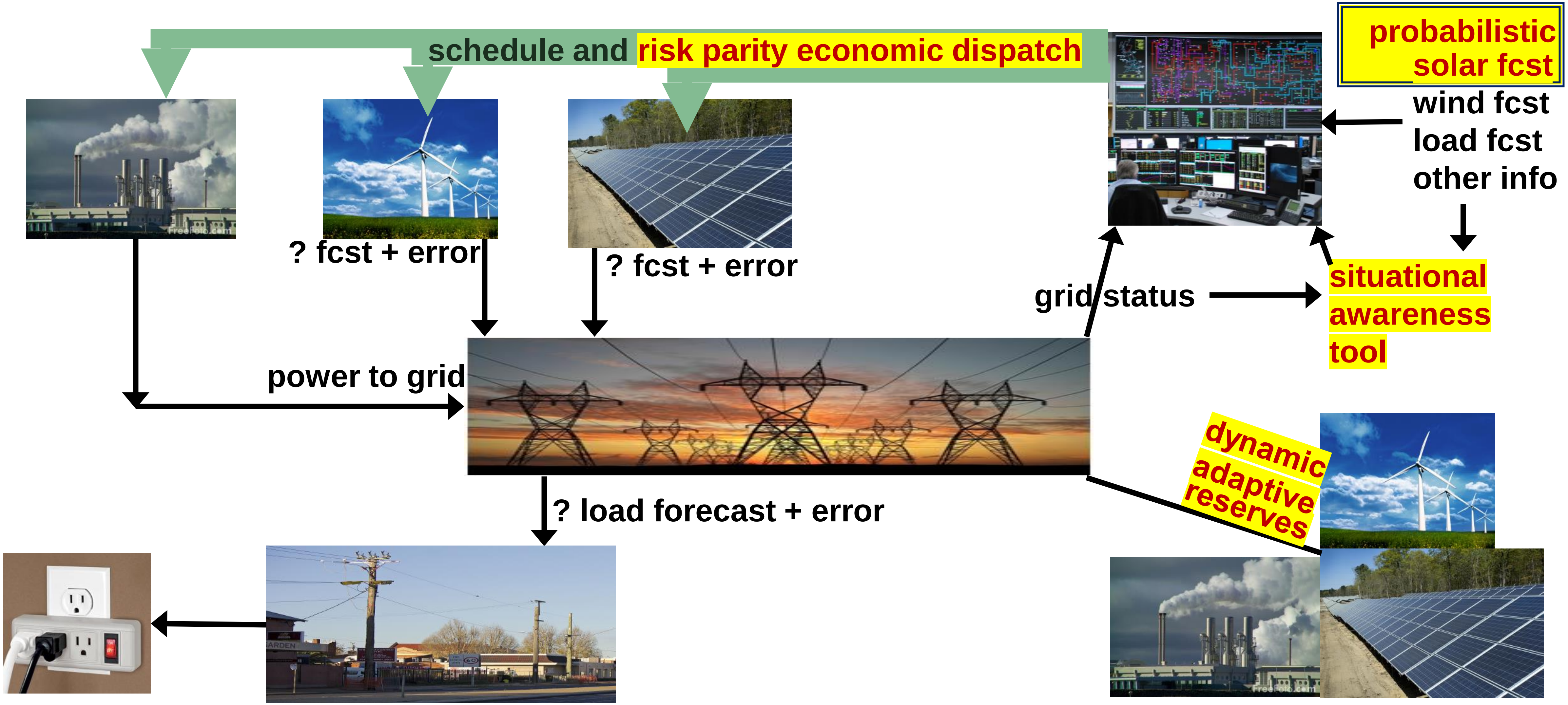


What is SUMMER-GO?

Solar **U**ncertainty **M**anagement and **M**itigation for **E**xceptional **R**eliability in **G**rid **O**perations

probabilistic solar power forecasts in **operational** decision systems in ERCOT

→ Risk parity economic dispatch **(5-min)** → reduce operating costs
2-year simulation: build-out to 39 GW utility-scale solar capacity
(supplies ~30% of annual total ERCOT power in this scenario)

→ **Dynamic adaptive** reserves **(hourly)** → increase reliability
→ reduce cost and reduce pollution

→ Open source solar power forecasting visualization tool and situational awareness tools

3-year project funded by DOE Solar Energy Technologies Office

Project team

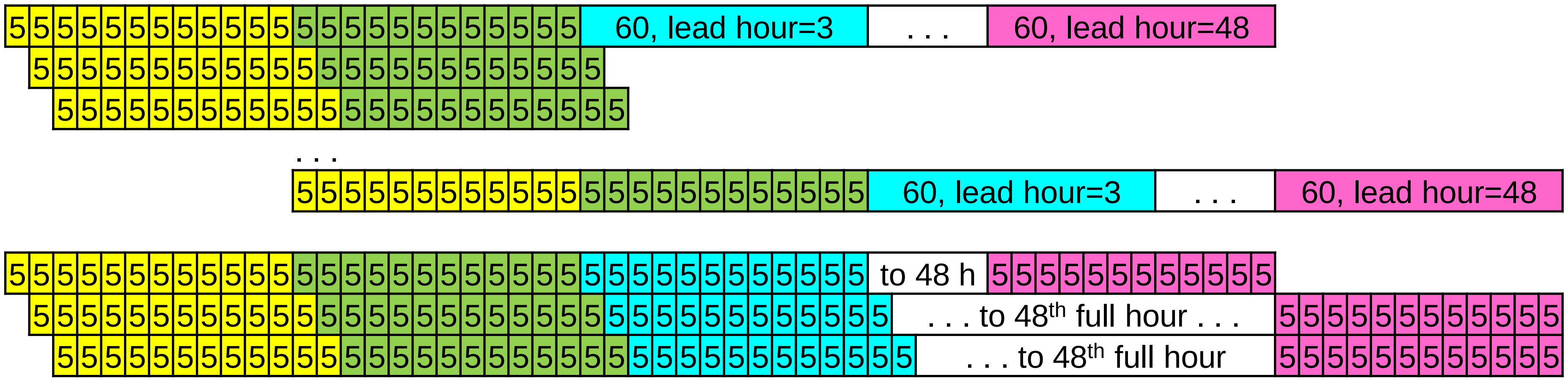
Probabilistic Forecasting in SUMMER-GO

Running now for all operating ERCOT utility-scale solar plants modeled by ERCOT (soon #plants=30)

Time averages, intervals, updates:

Original plan

Running now



NWP inputs parsed into direct, diffuse, reflected, then transposed to POA, converted to power

Ensemble set of inputs (NWP ***and others***) → algorithm → probabilistic forecast

Algorithm now: weighted blend=50th %ile, ensemble distribution and error stats → other %iles

Algorithm to implement: Bayesian Model Averaging (Doubleday et al. in review)

Probabilistic Forecasting: NWP Inputs

Model	Updates per day	Running now: # members in set	Running now: # time lags	Coming soon: # members in set	Coming soon: # time lags	total NWP sources/day
ECMWF	4	1	3	1	3	4
ECMWF ensembles	4	mean only	3	51	1	204
High Res Rapid Refresh	24	1	3	1	15	24
Rapid Refresh	24	1	3	1	15	24
GFS	4	1	3	1	3	4
GFS ensembles	4	mean only	3	20	1	80
SREF – NMMB	4	mean only	3	13	1	52
NAM	4	1	3	1	3	4
Canadian Global	2	1	3	1	2	2
Canadian Global Ens	2	mean only	3	20	1	40
Canadian Regional	4	1	3	1	3	4
Canadian Regional Ens	4	mean only	3	20	1	80
Total NWP		**36 x 2 power curves=72**		**168 x 2 power curves =336**		**522**

Bayesian Model Averaging: What is it

Doubleday et al. “Probabilistic Solar Power Forecasting using Bayesian Model Averaging” in *IEEE Transactions on Sustainable Energy* (in review)

Deterministic forecast + training set → full probability distribution

Sum of 2 parts:
1. Discrete probability of clipping=$P_{clipping}$

2. $(1-P_{clipping})$*(beta kernel for debiased forecast)

Collection of forecasts (superensemble):
Probability distribution = weighted sum of individual distributions

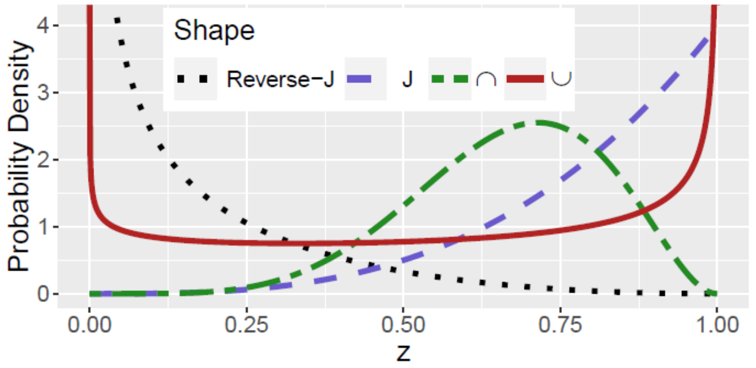
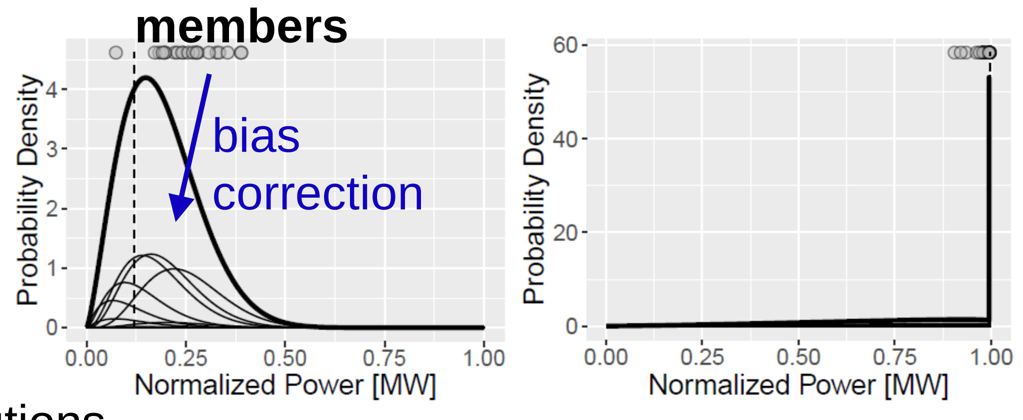


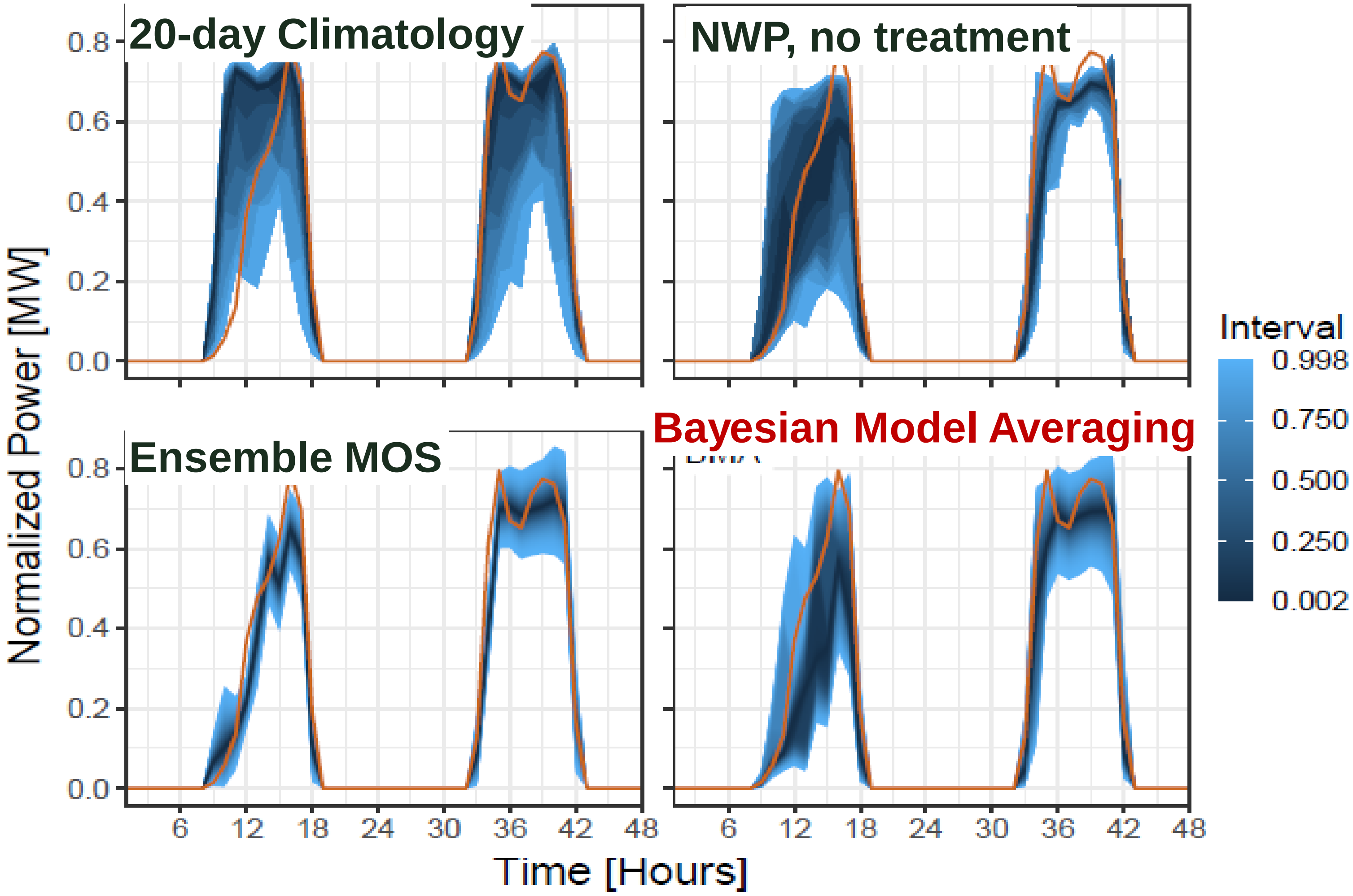
Fig. 3. Some typical beta distribution shapes.



(a) (b)

Fig. 4. Example BMA forecasts, (a) without and (b) with a high likelihood of clipping. The shaded circles show the NWP member forecasts, the thick

Bayesian Model Averaging: Example 2 days



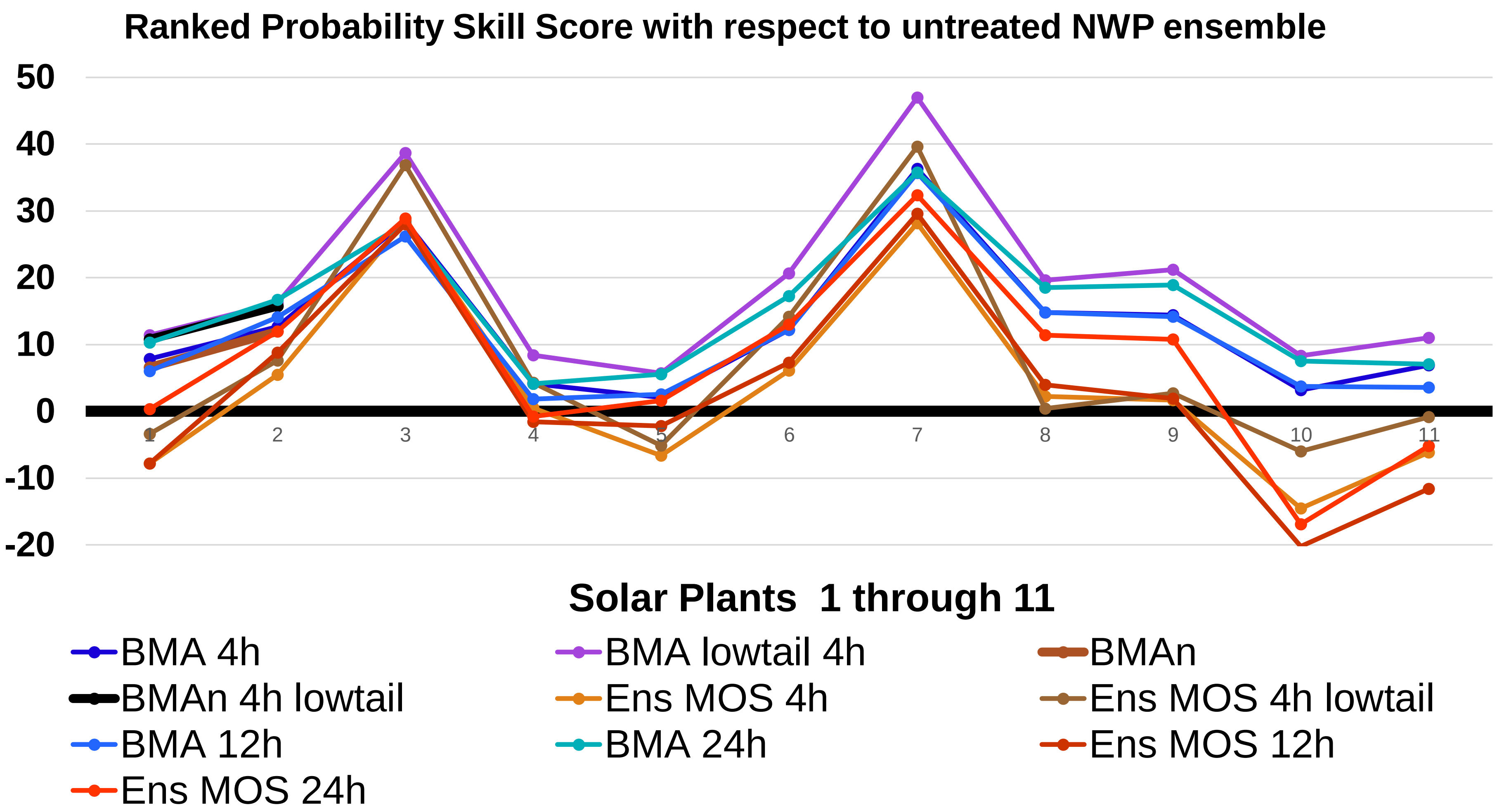
Forecasts for **hour average** power/capacity

Lead=4 hours,
new forecast every 1 hour

Input=**21 NWP members**
no non-NWP members

Ensemble MOS uses normal kernel, minimizes ranked probability score for a weighted sum of members and ensemble variance

Bayesian Model Averaging: Skill



Validation period=1 year

Skill score =
100% * (1 – RPS1/RPS2)
RPS1=treated forecast
RPS2=untreated NWP
100=perfect
<0 = worse than untreated

lowtail: RPS weighted
to accentuate low tail

BMA=
Bayesian Model Averaging

BMAn=
uses normal kernel
instead of beta kernel

Ens MOS=
Ensemble MOS

Bayesian Model Averaging: Reliability Diagram

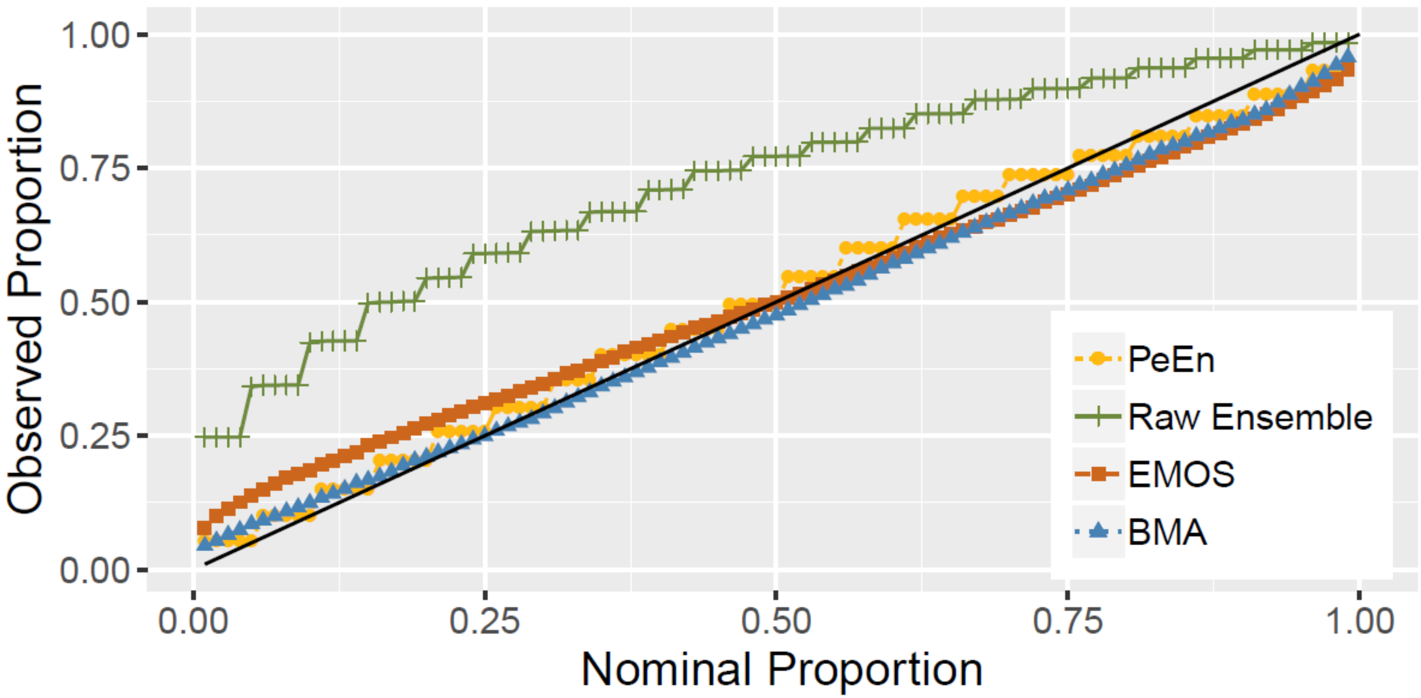


Fig. 9. Reliability diagram of the 1st to 99th forecast percentiles for site C. The black line shows ideal calibration.

Case Examples

“Running Now” version: 5-minute time averages and 5-minute updates

Site	Located adjacent	Tracking	case 1: Jan 4, 2020	case 2: Jan 3, 2020
9	no	single axis N-S	clear	stratiform cloud, then clearing
13	yes to 10	single axis N-S	clear	stratiform cloud, clearing, moderate cumulus
10	yes to 13	dual axis	clear	stratiform cloud, clearing, moderate cumulus

Plots: (single lead time, range of initial, valid times except day ahead=all from initial time 2pm CST)

Cumulative Distribution Function

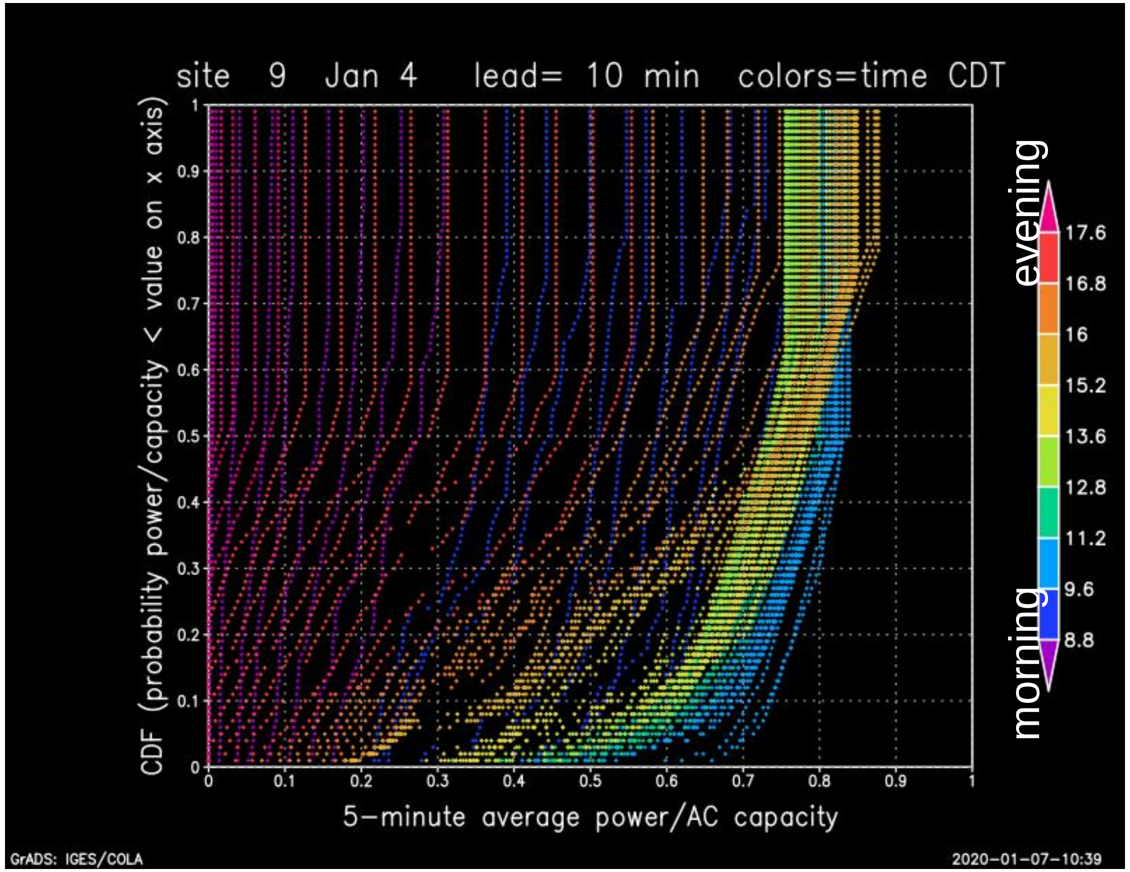
Colors=valid time every 5 min

Time series (diurnal curve, every 5 min)

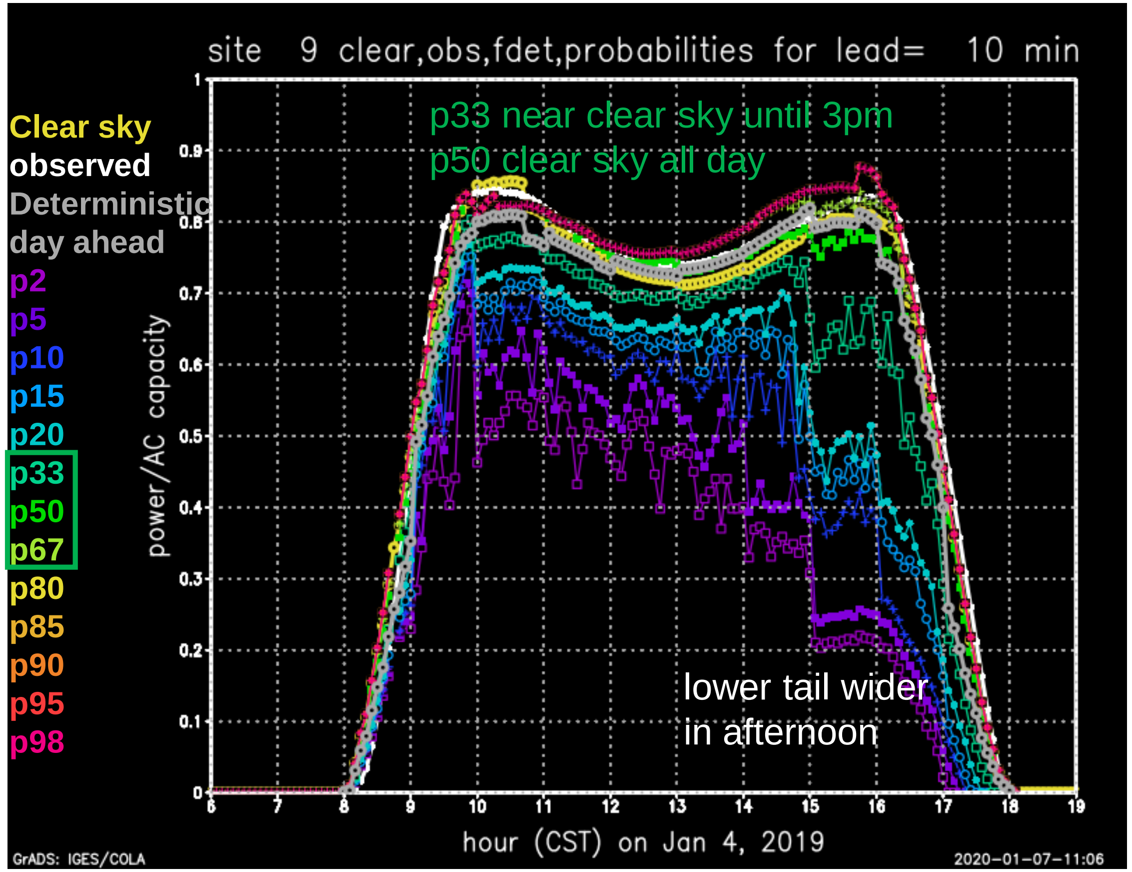
Colors=percentiles

Case 1: Clear day, site 9, lead=10 min

CDF steep all day, steepest in morning, shows high probability of high power, low probability of low power



winter, single axis
→ double hump, max ~80% of AC capacity



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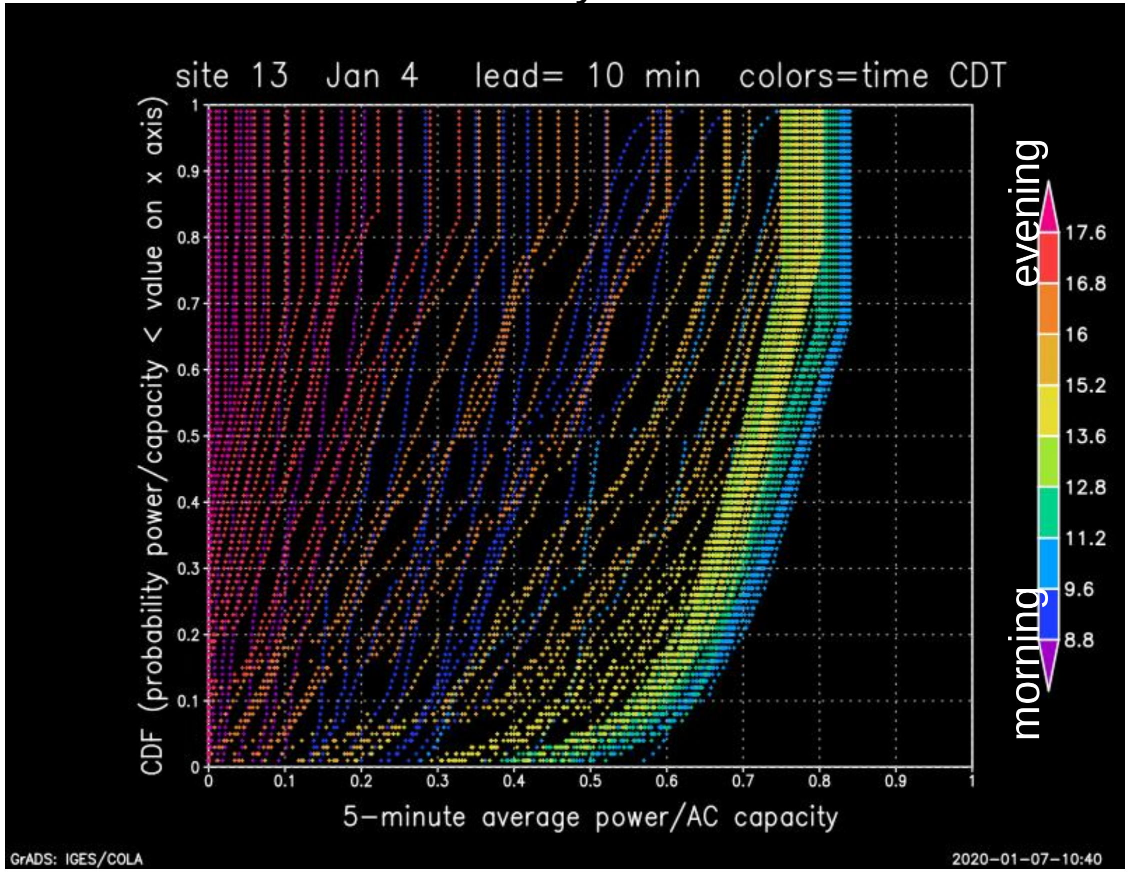
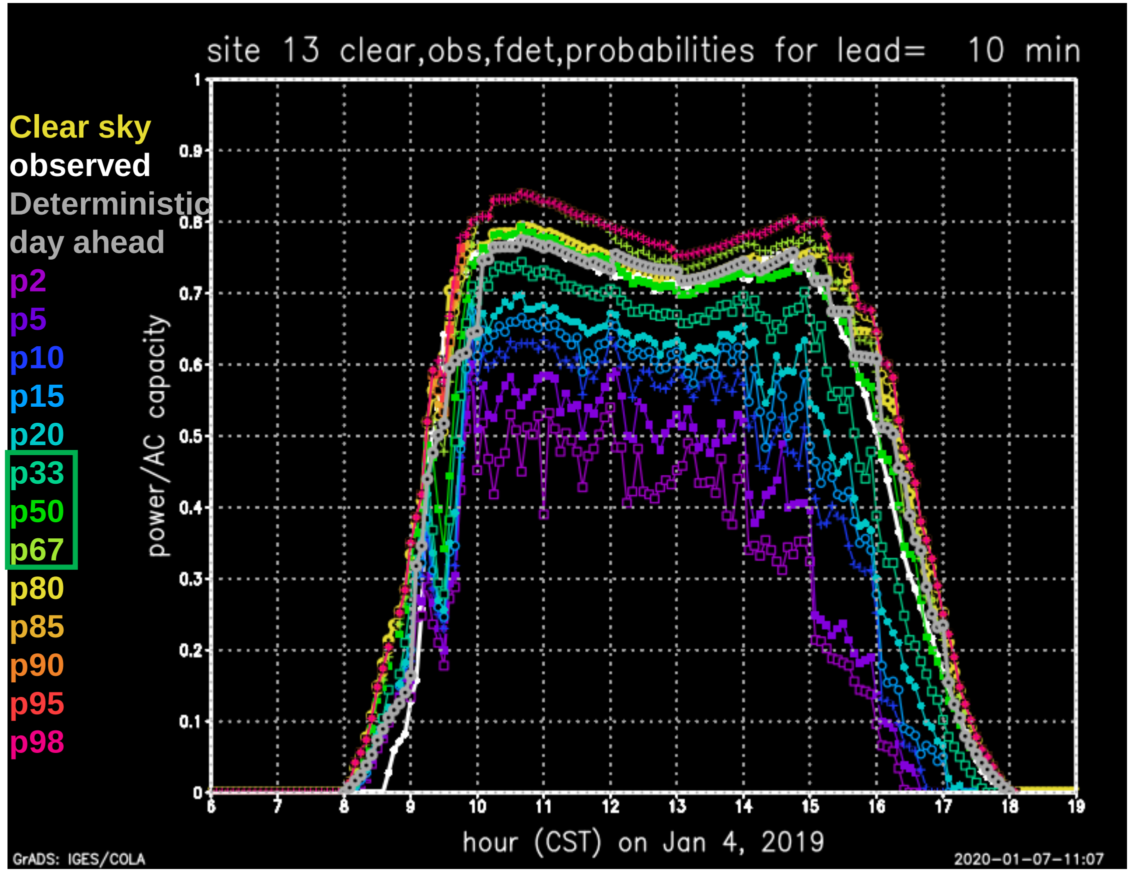
Case 1: Clear day, site 13, lead=10 min

Same story as for site 9





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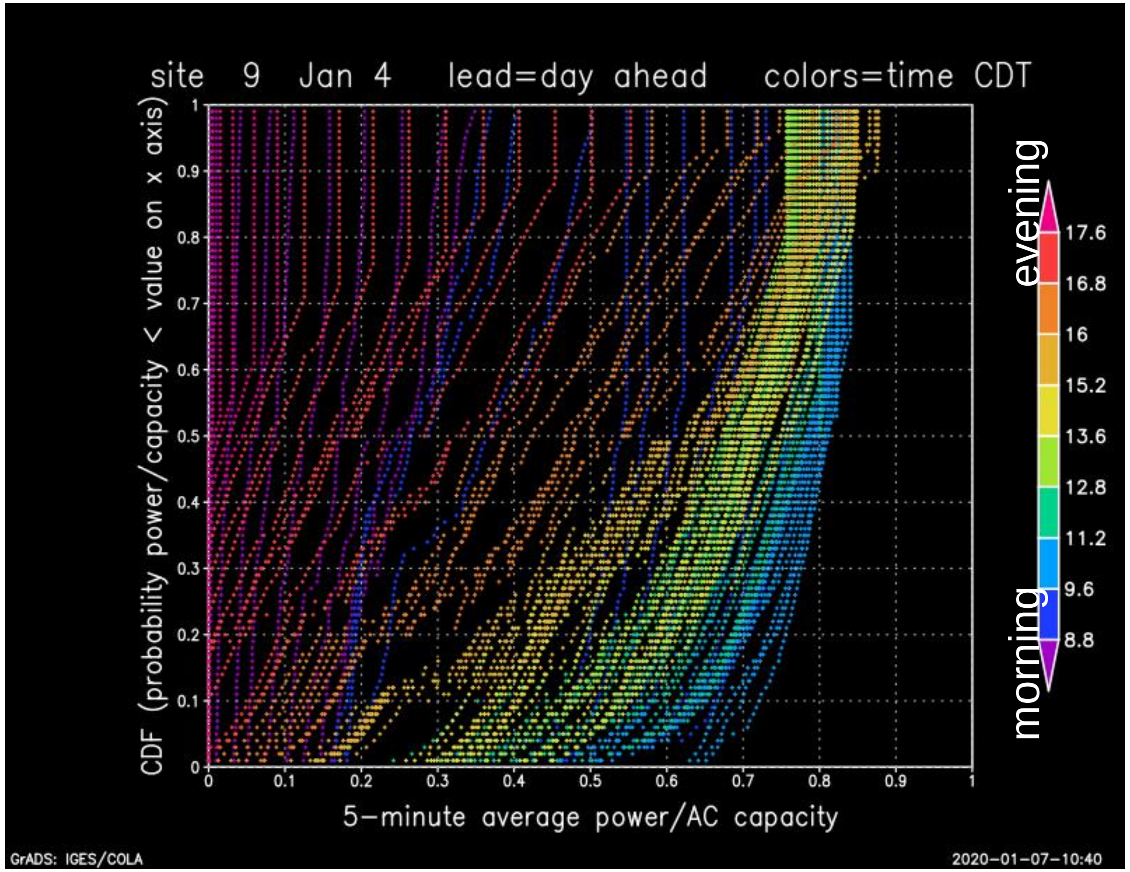
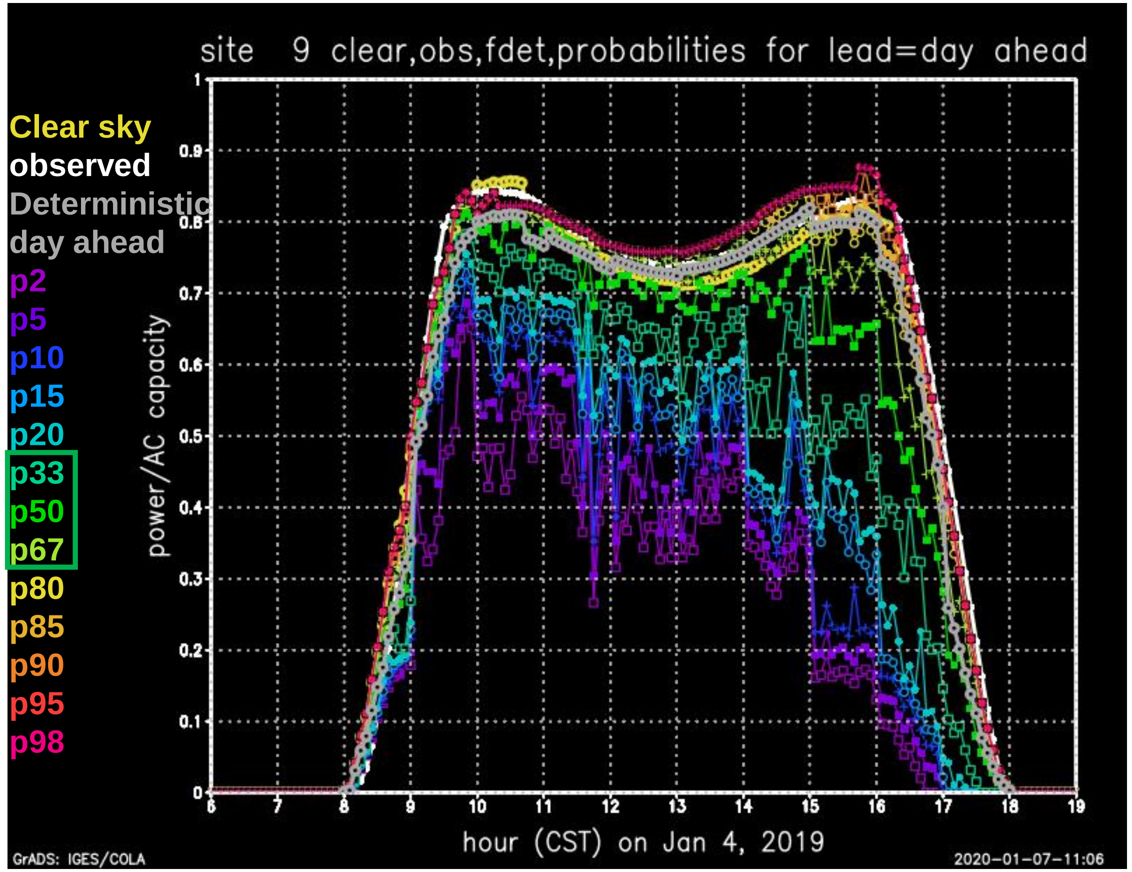
Case 1: Clear day, site 9, day ahead

CDF not as steep at longer lead time



low tail wider at longer lead time



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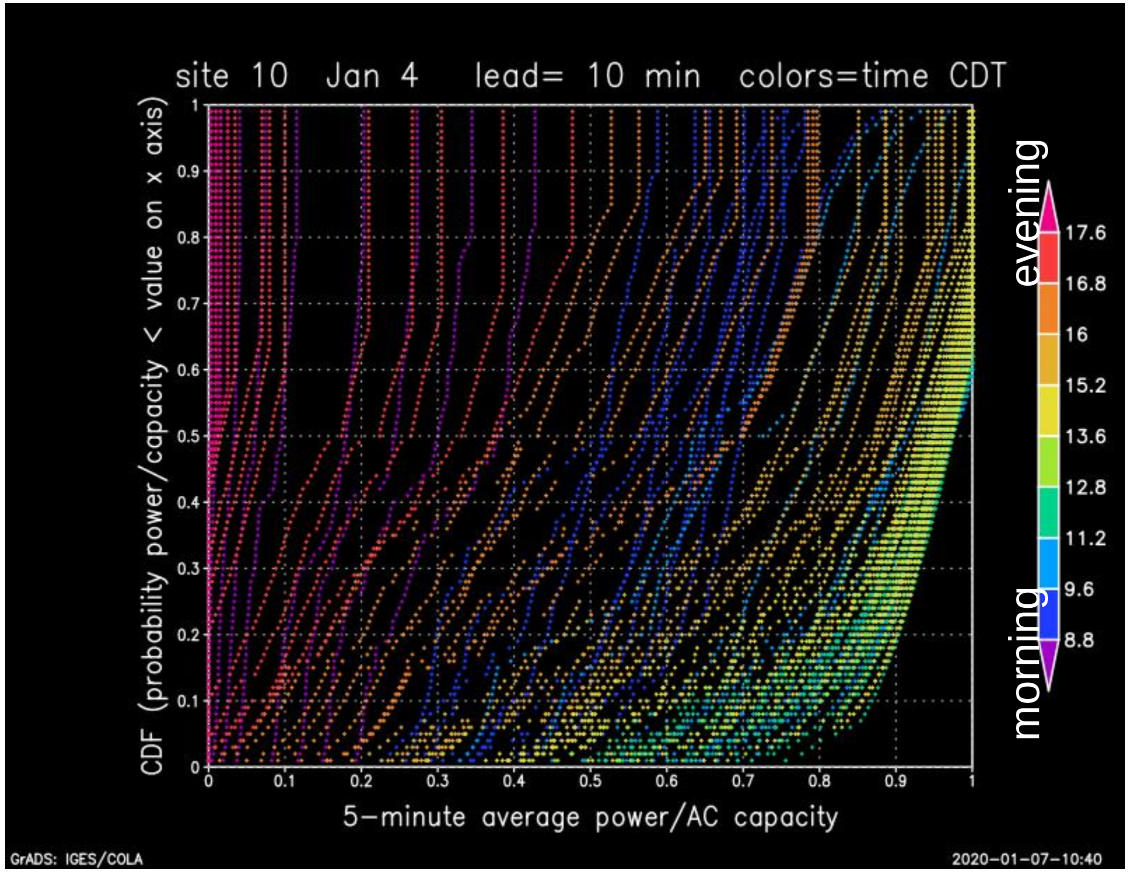
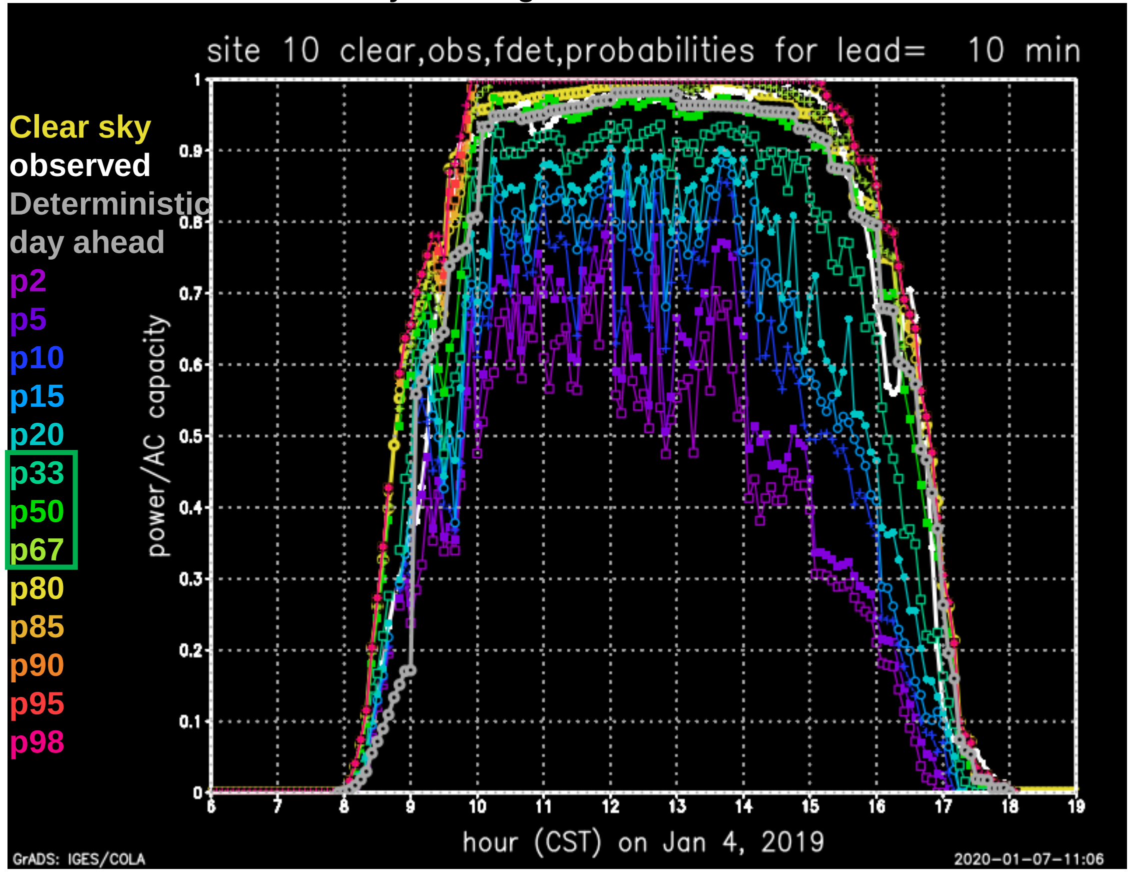
Case 1: Clear day, site 10, lead=10 min

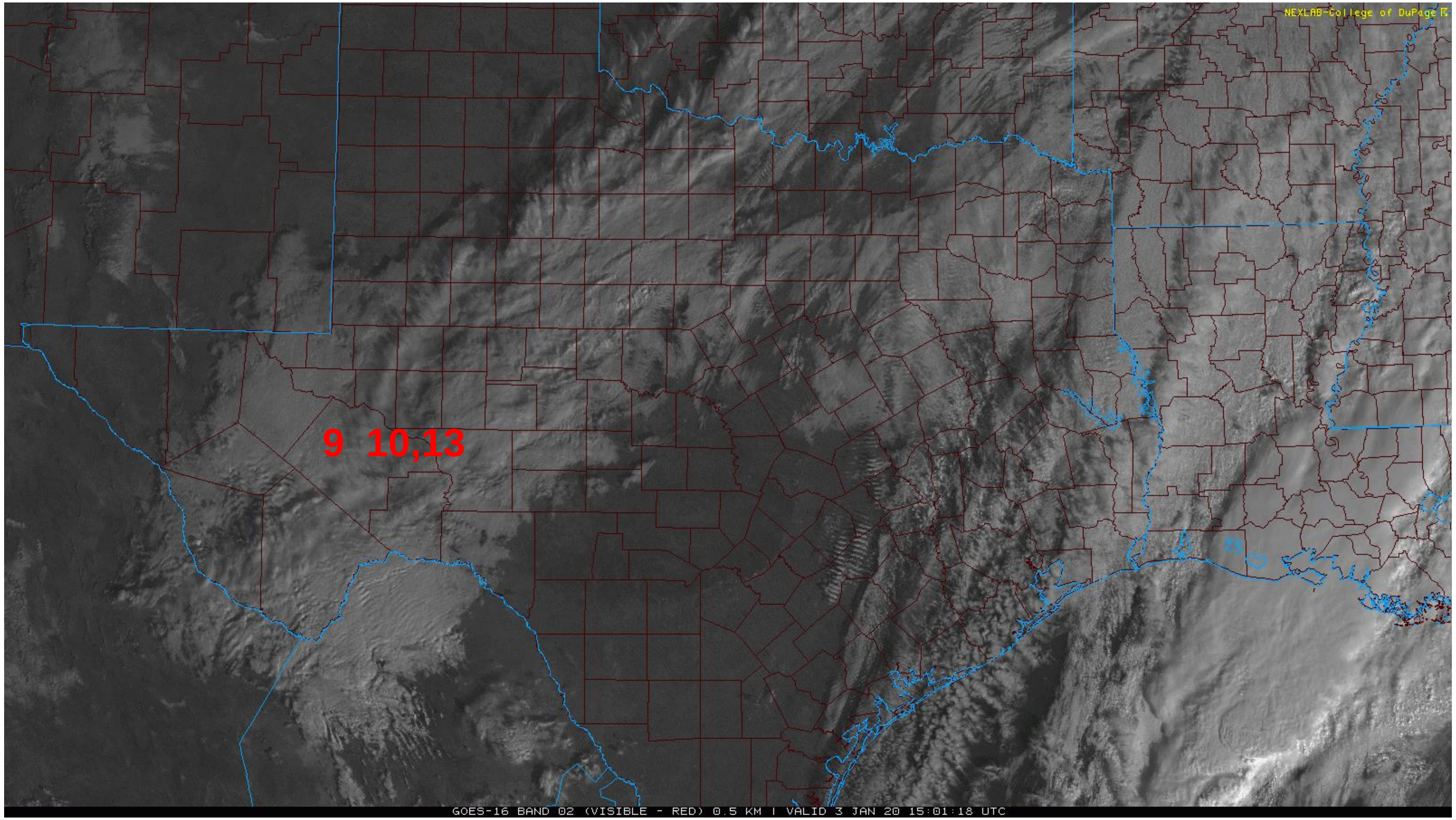
clilpping probability > 40% in late morning



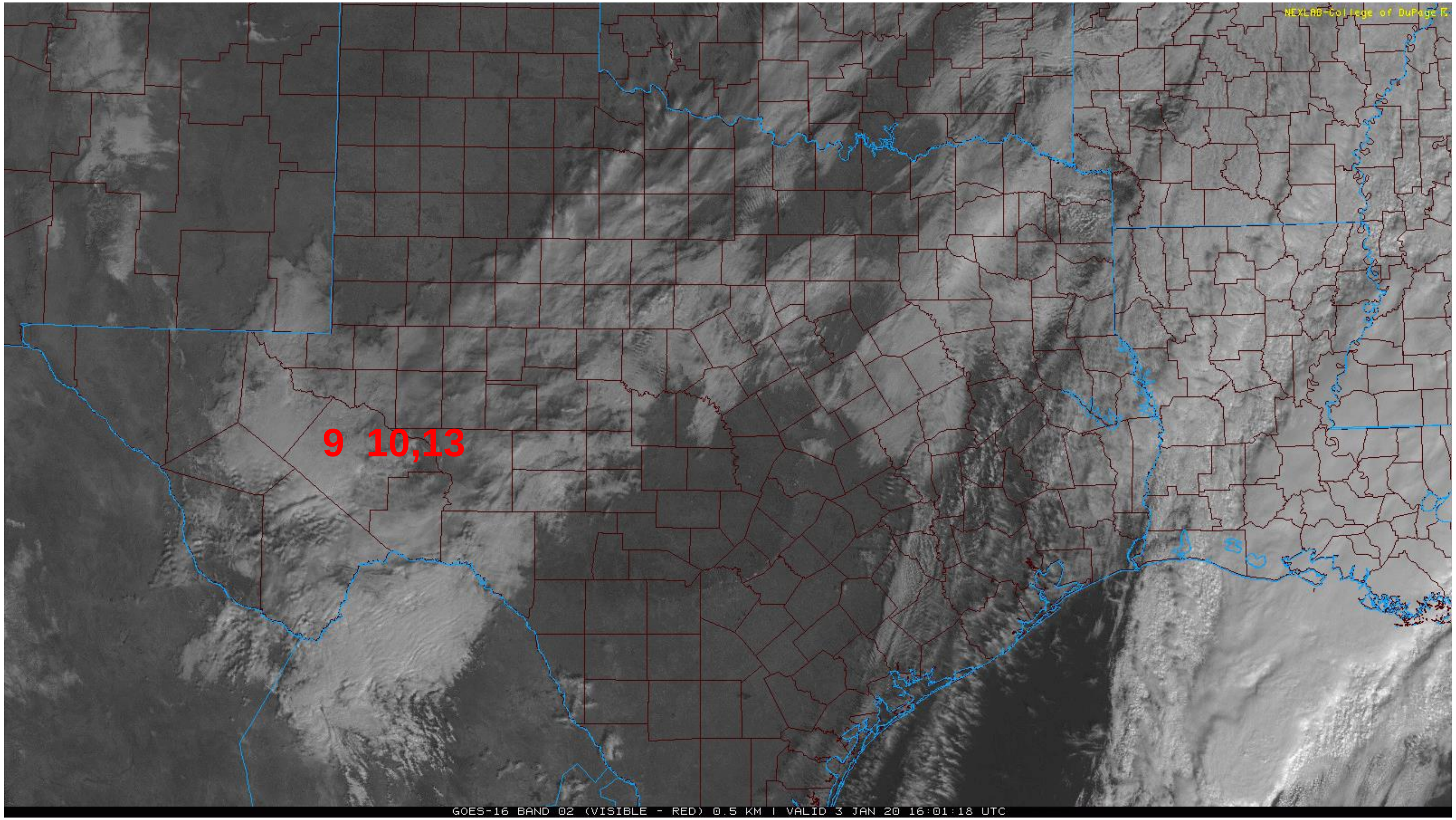
Dual axis → near 100% of capacity for 5 hours.
Otherwise same story as single axis



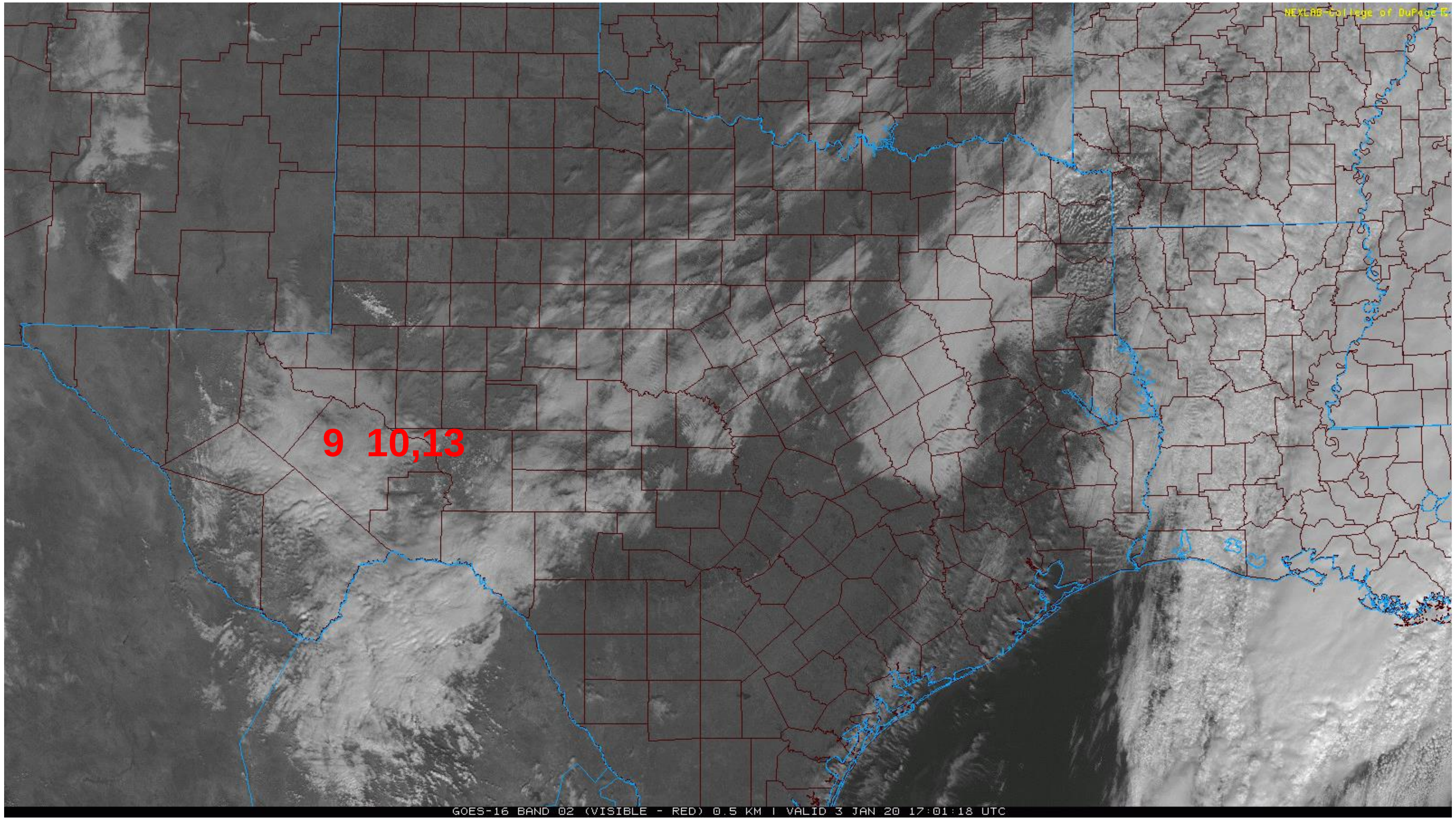
Jan 3 case: 9am



Jan 3 case: 10am



Jan 3 case: 11am



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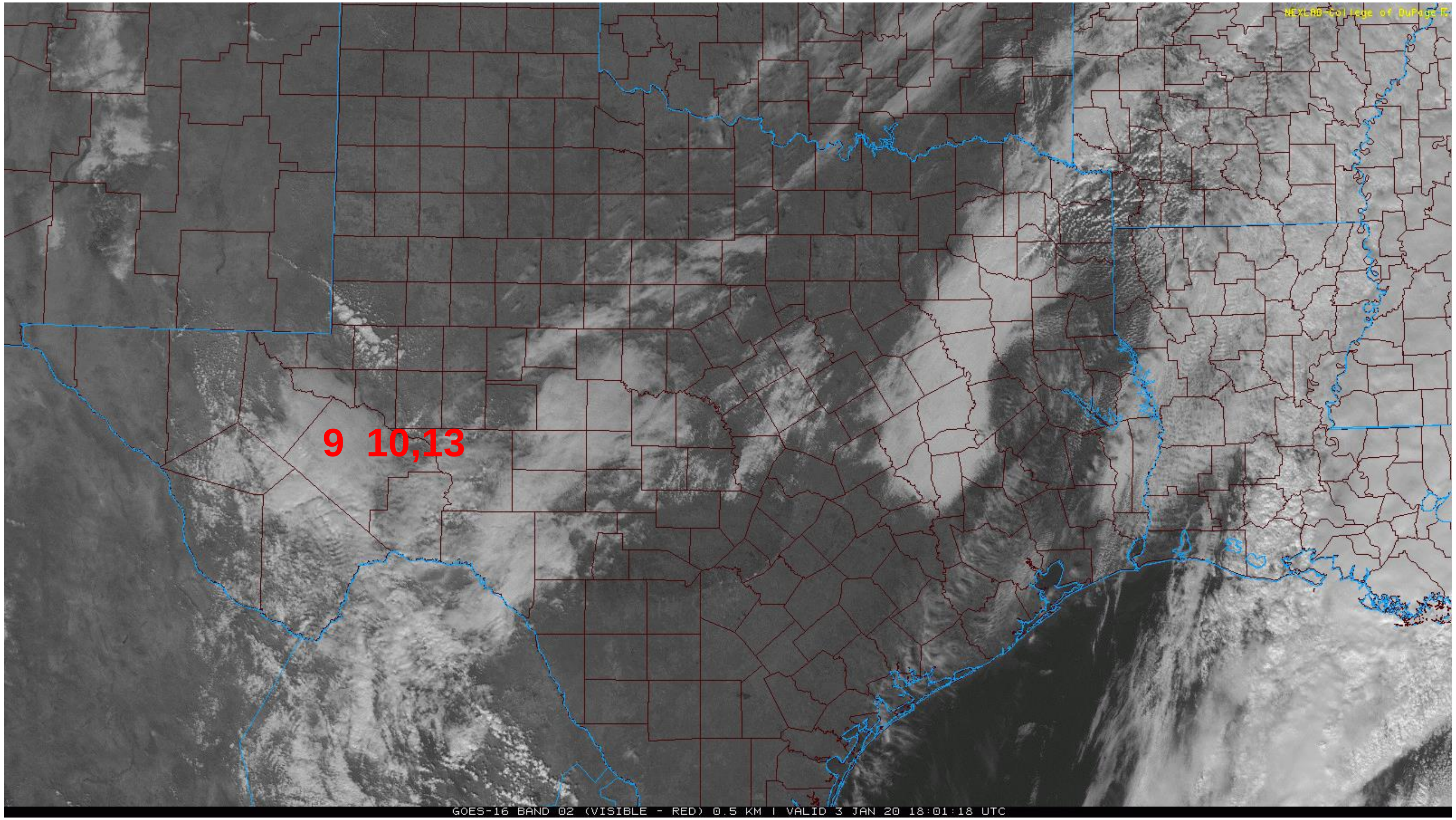
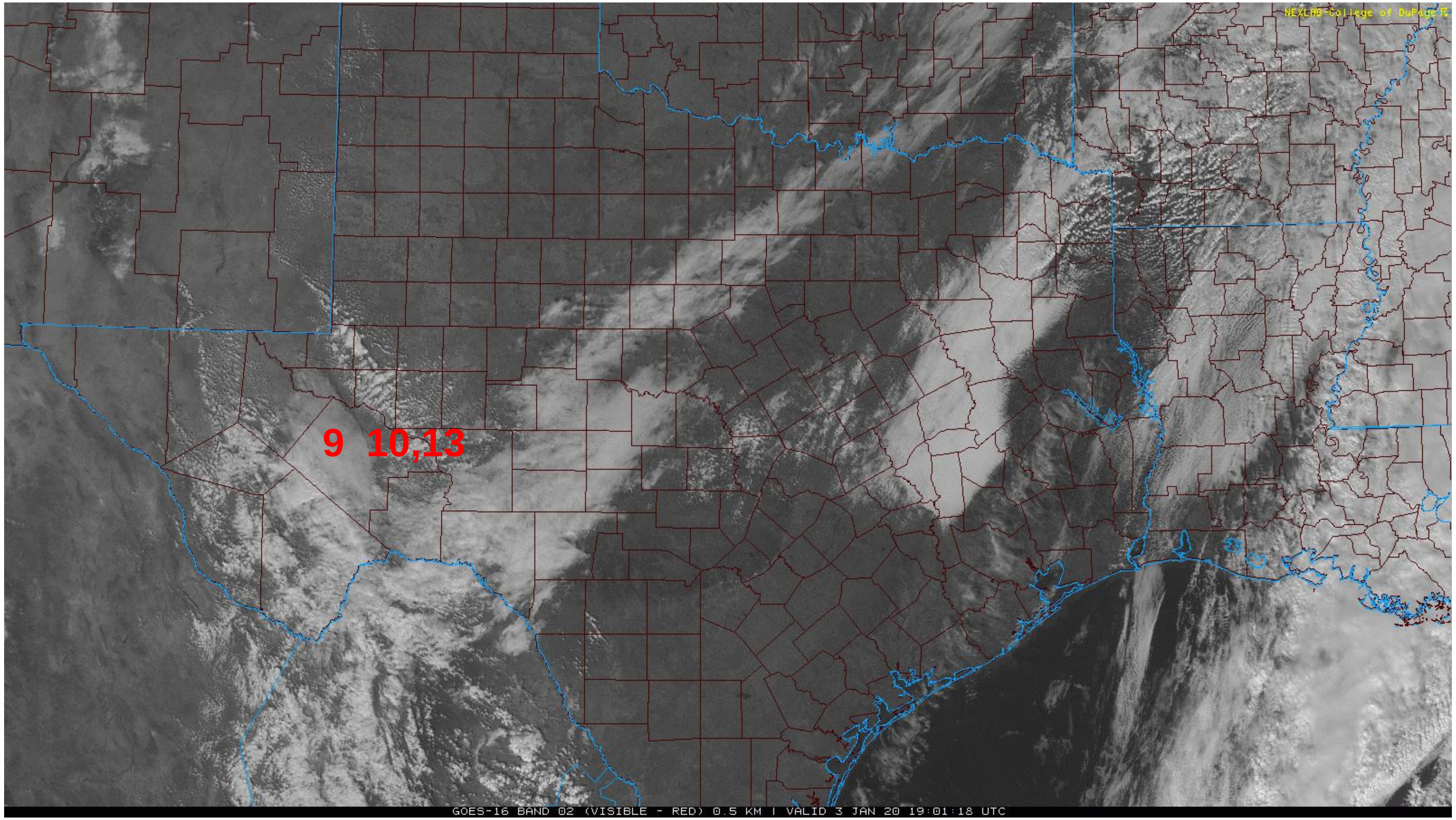
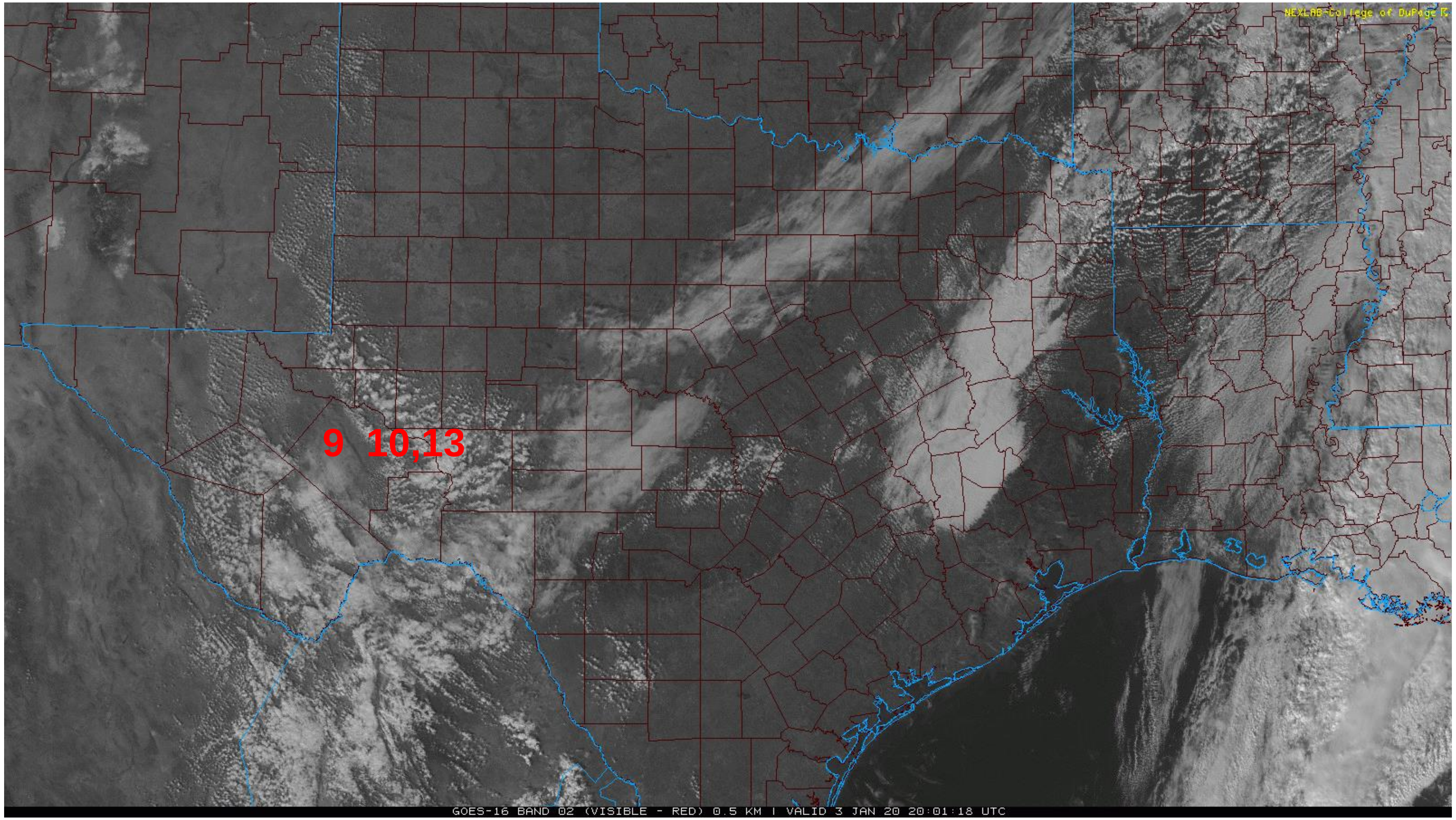
Jan 3 case: 12pm



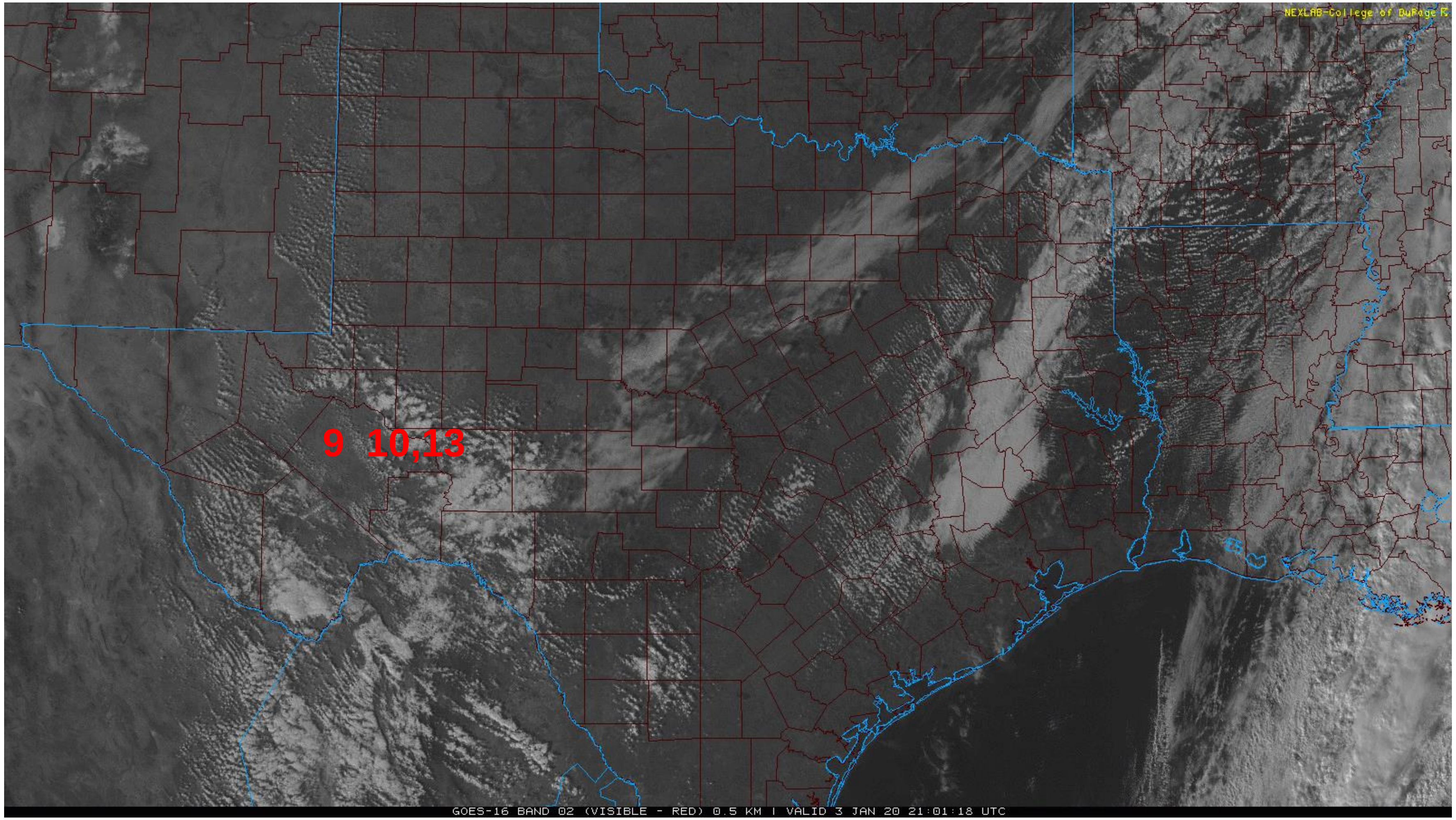
Jan 3 case: 1pm



Jan 3 case: 2pm



Jan 3 case: 3pm



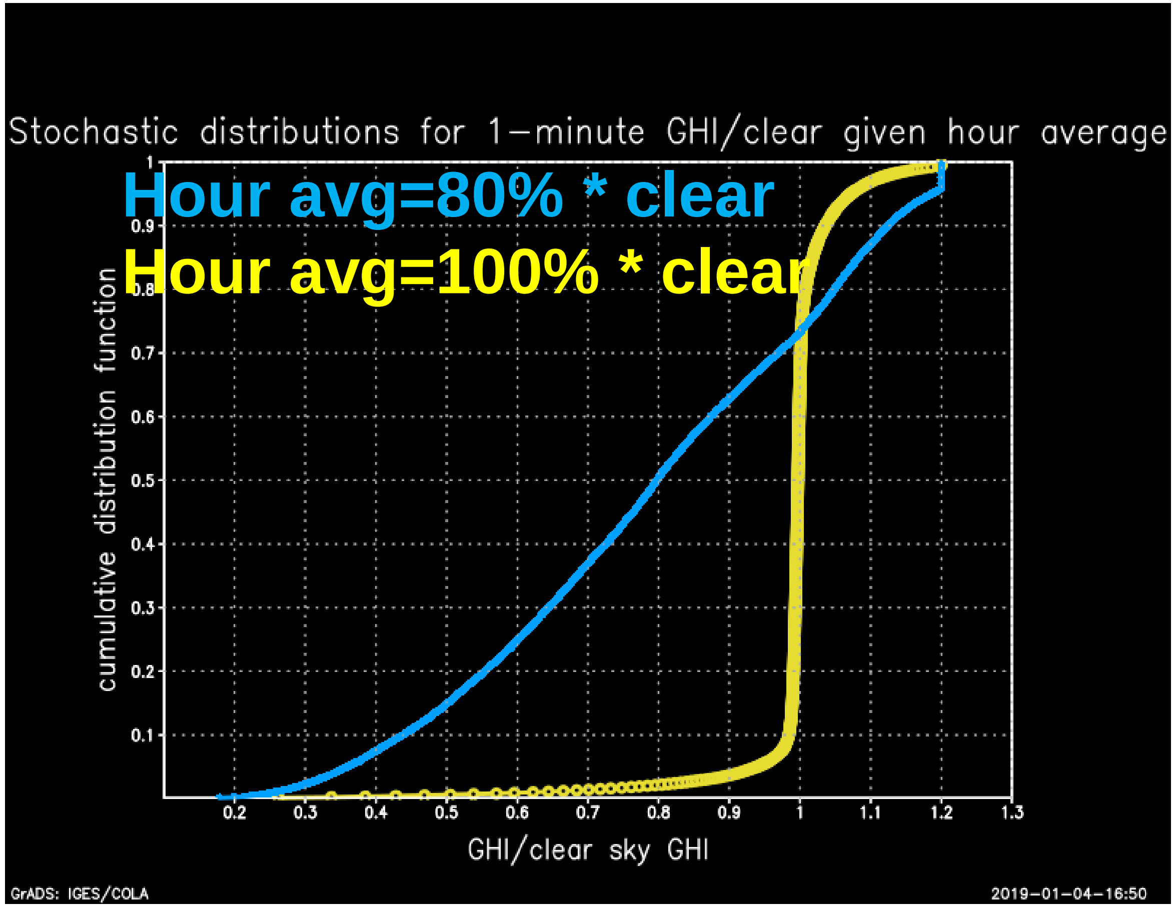
Case 2: Cloudy morning with clearing

Cumulative Distribution Functions used for temporal downscaling (plot)

→ much broader on mostly-sunny day than on clear day

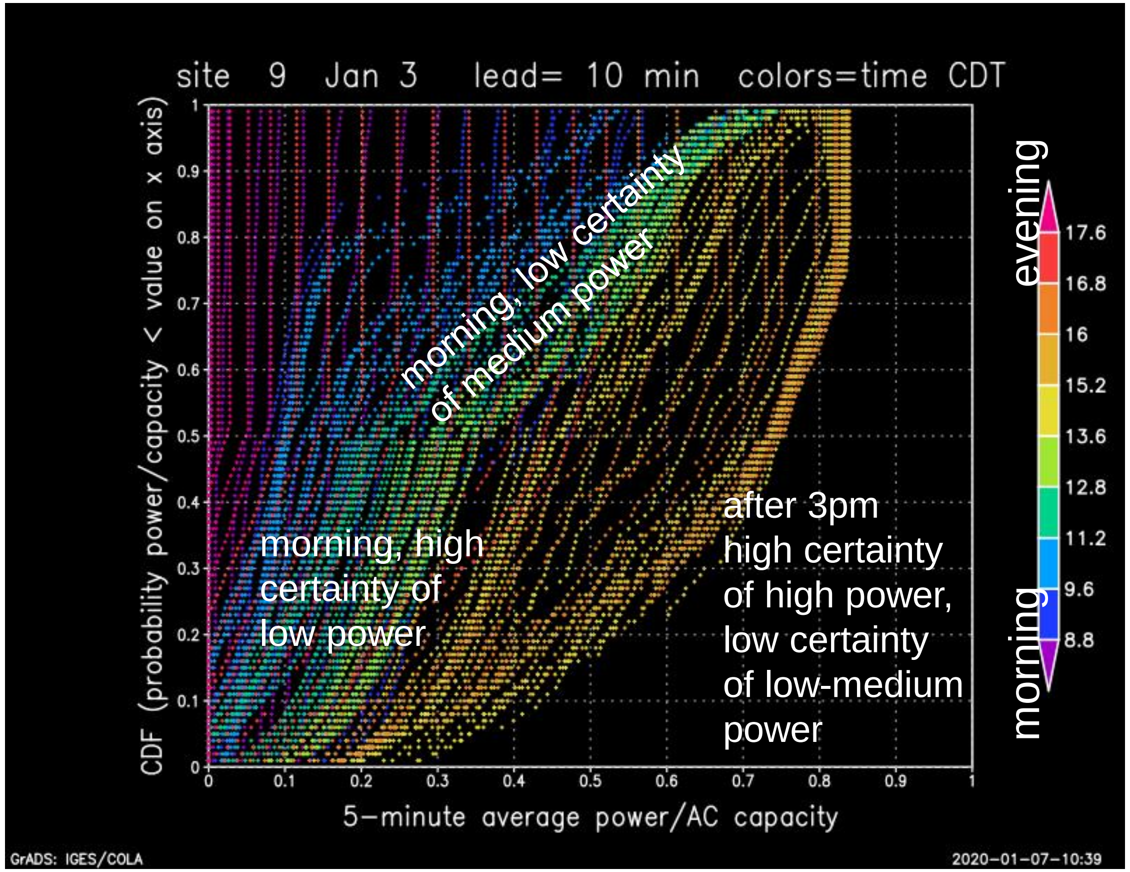
Forecast CDF influenced by

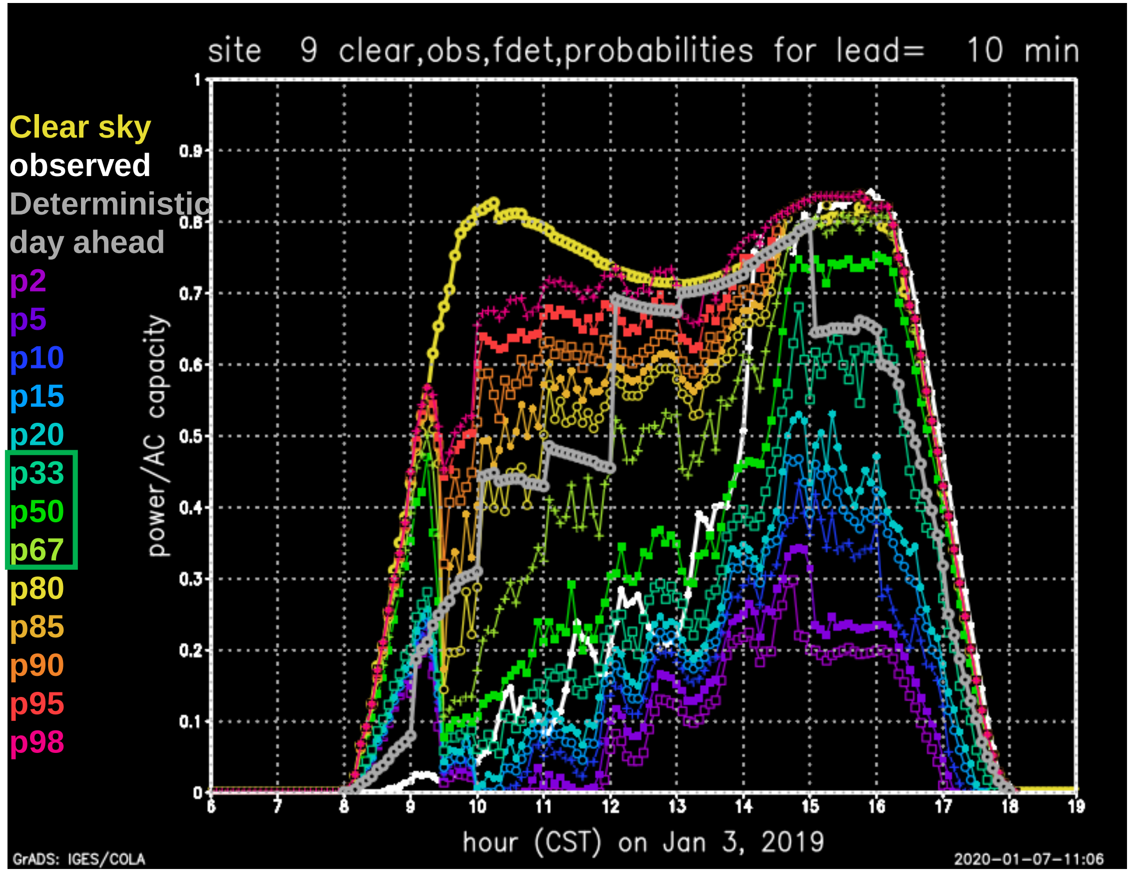
1. ensemble set diversity
2. stochastic perturbations added for temporal downscaling
3. statistical adjustment to correct for ensemble underdispersion



Case 2: Cloudy morning with clearing, site 9, lead=10 min

obs: low in morning, increase ~ steady to 2pm, then clear
50th %ile tracks obs well all day
middle tercile has wider range than on clear day





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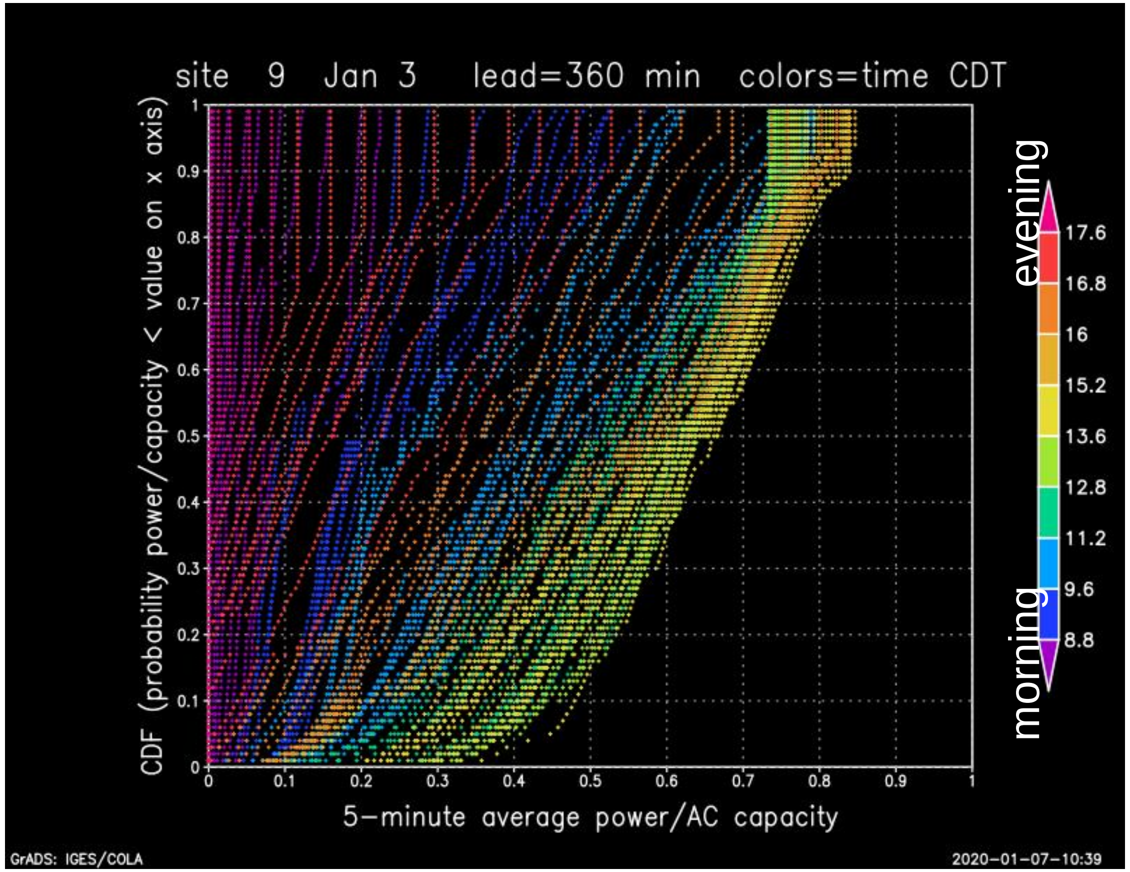
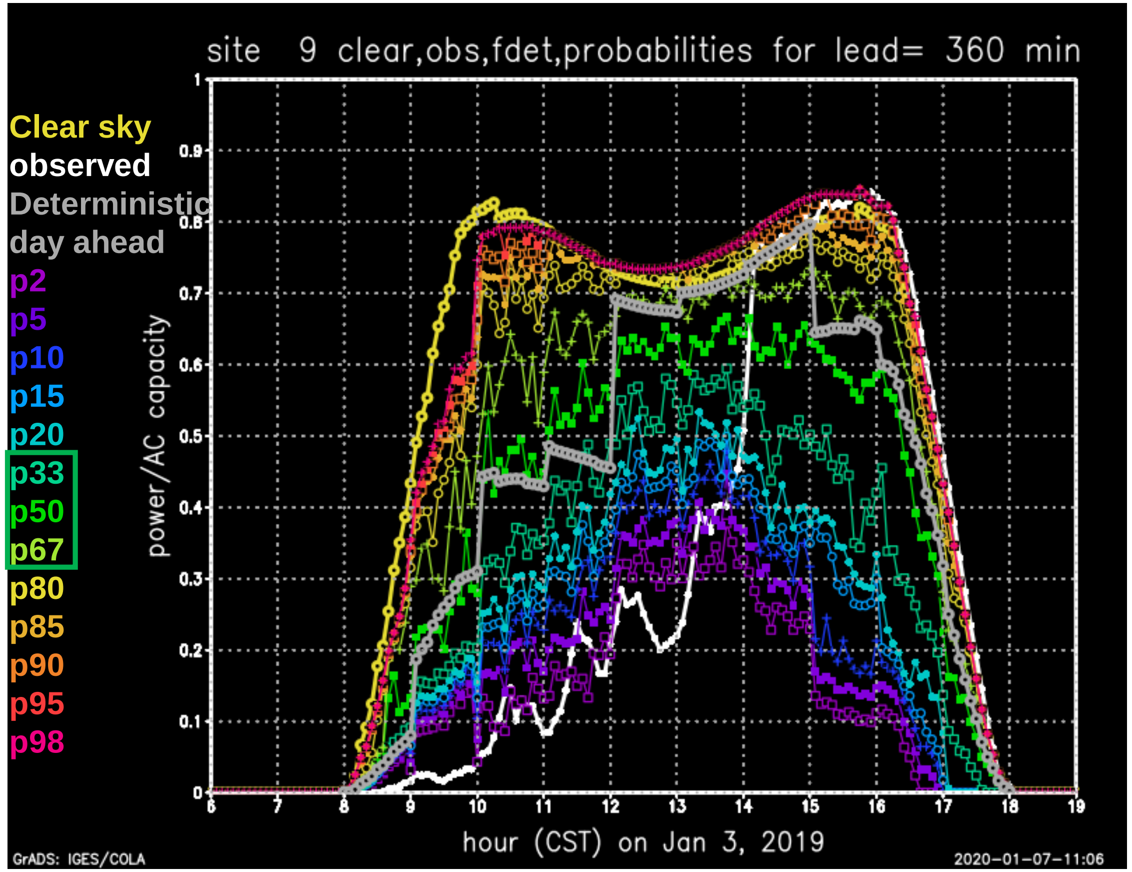
Case 2: Cloudy morning with clearing, site 9, lead=6 hours

Fundamental improvement in cloud forecast needed, postprocessing will not help obs < low tail!

CDF shifted higher than for lead=10 min
Similar all day, trending only a little toward higher power in afternoon



50th %ile does not track obs well
Obs in far low tail through morning, distribution poor match vs obs



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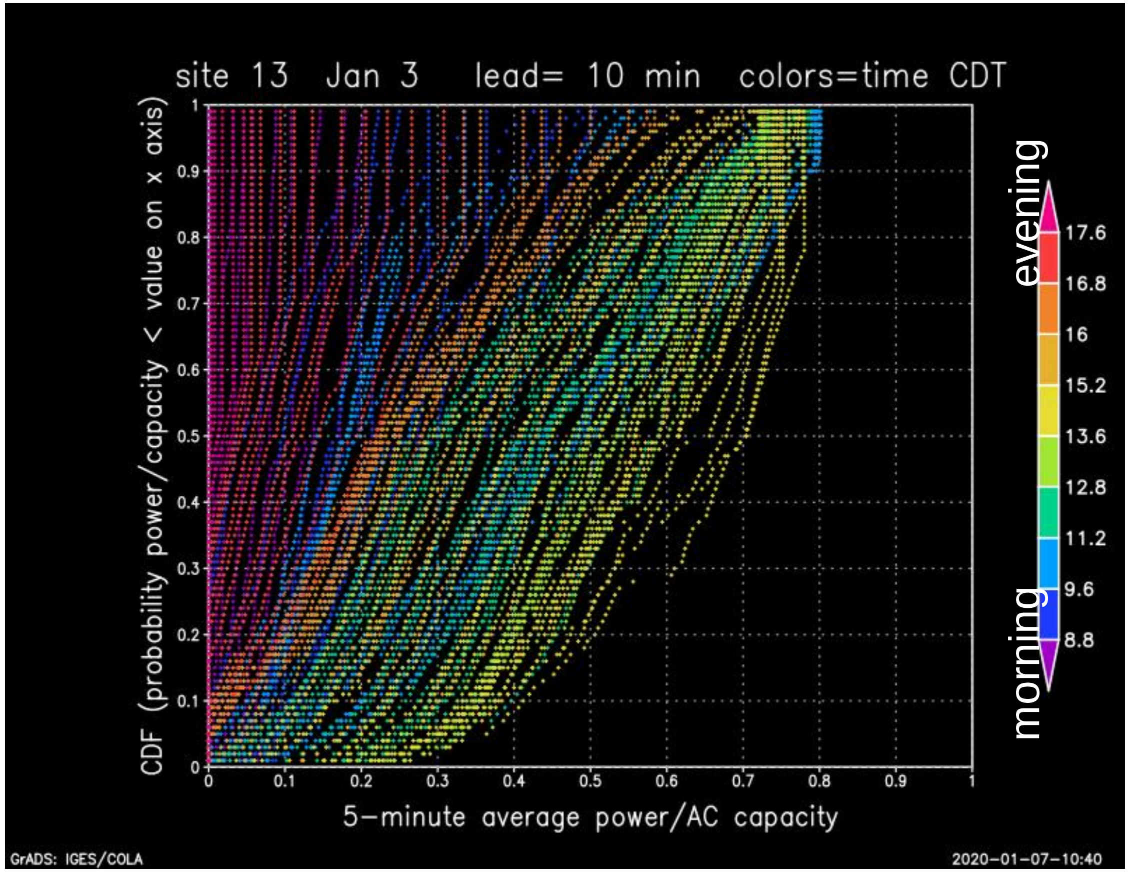
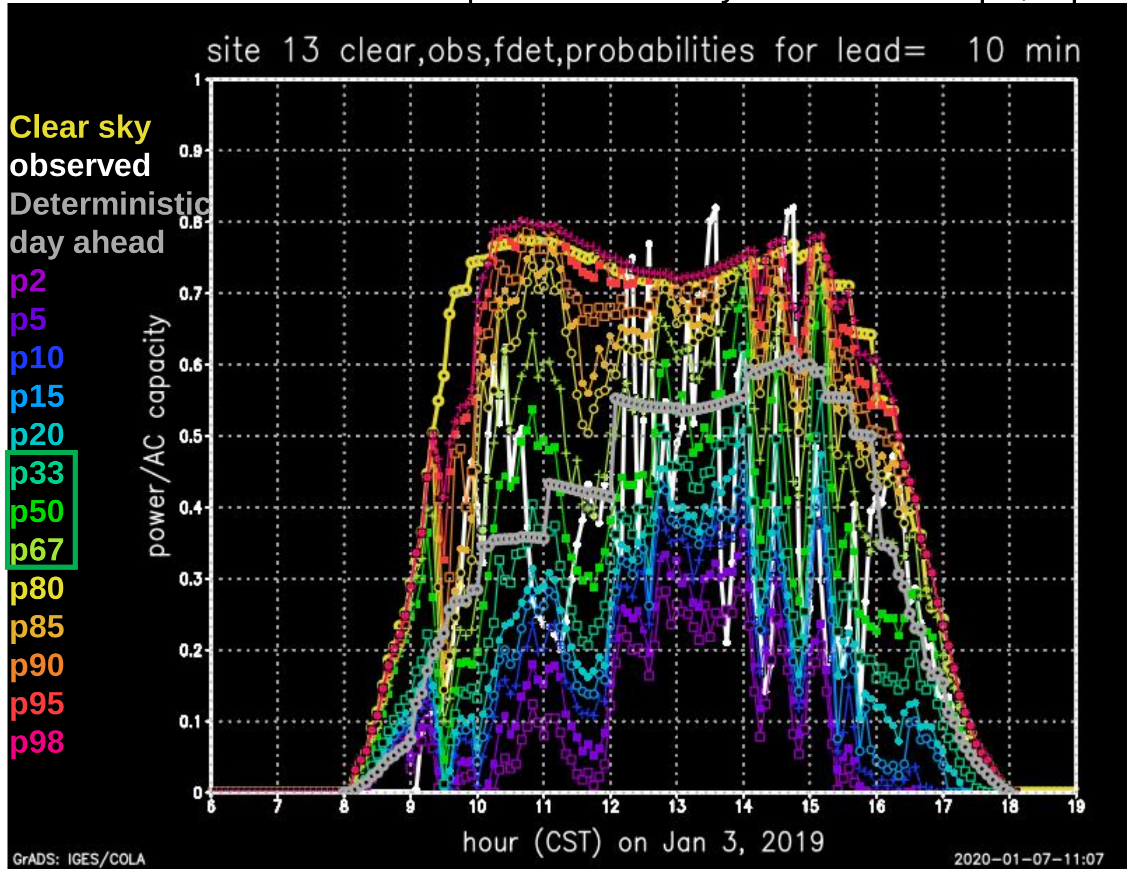
Case 2: Cloudy morning with clearing, site 13, lead=10 min

CDF less steep than for site 9, notably shallow for 10-min lead
Shallow CDF good match for wild oscillations

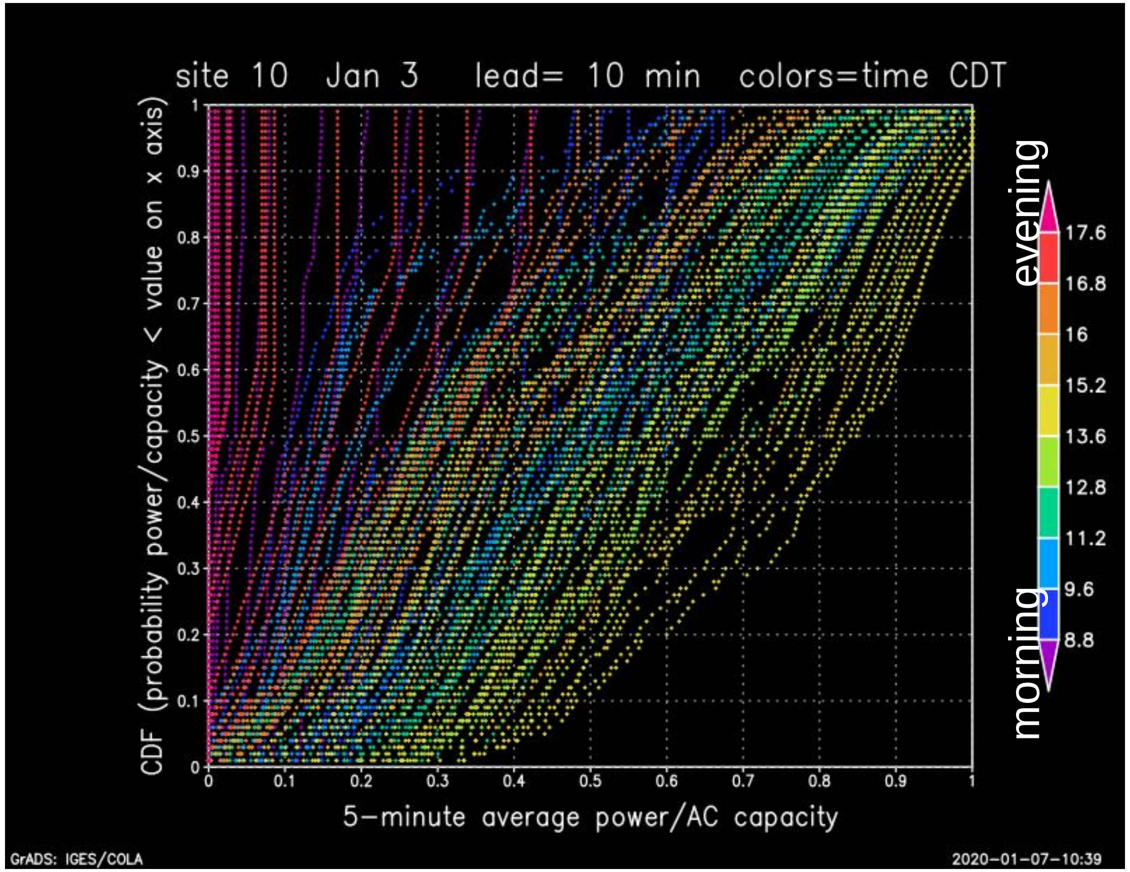


Obs spikes above clear sky from sun btwn cld and reflecting off sides
Obs has deep oscillations
Probabilities indicate wide spread and nicely fits the envelope, dips

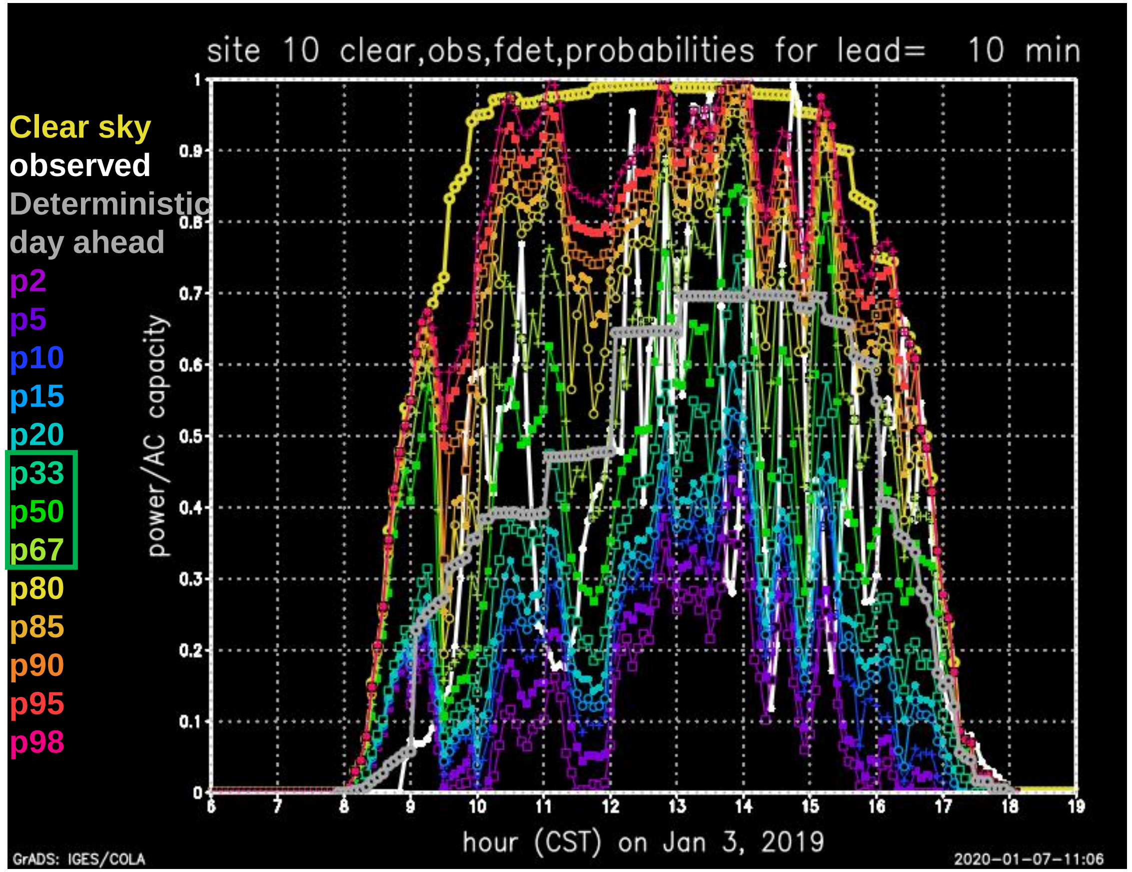


Case 2: Cloudy morning with clearing, site 10, lead=10 min

CDF looks like for a cumlus field



Obs similar to site 13 but without spikes > clear sky (no headroom)
Central probabilities rise and dip with some of the obs rises and dips



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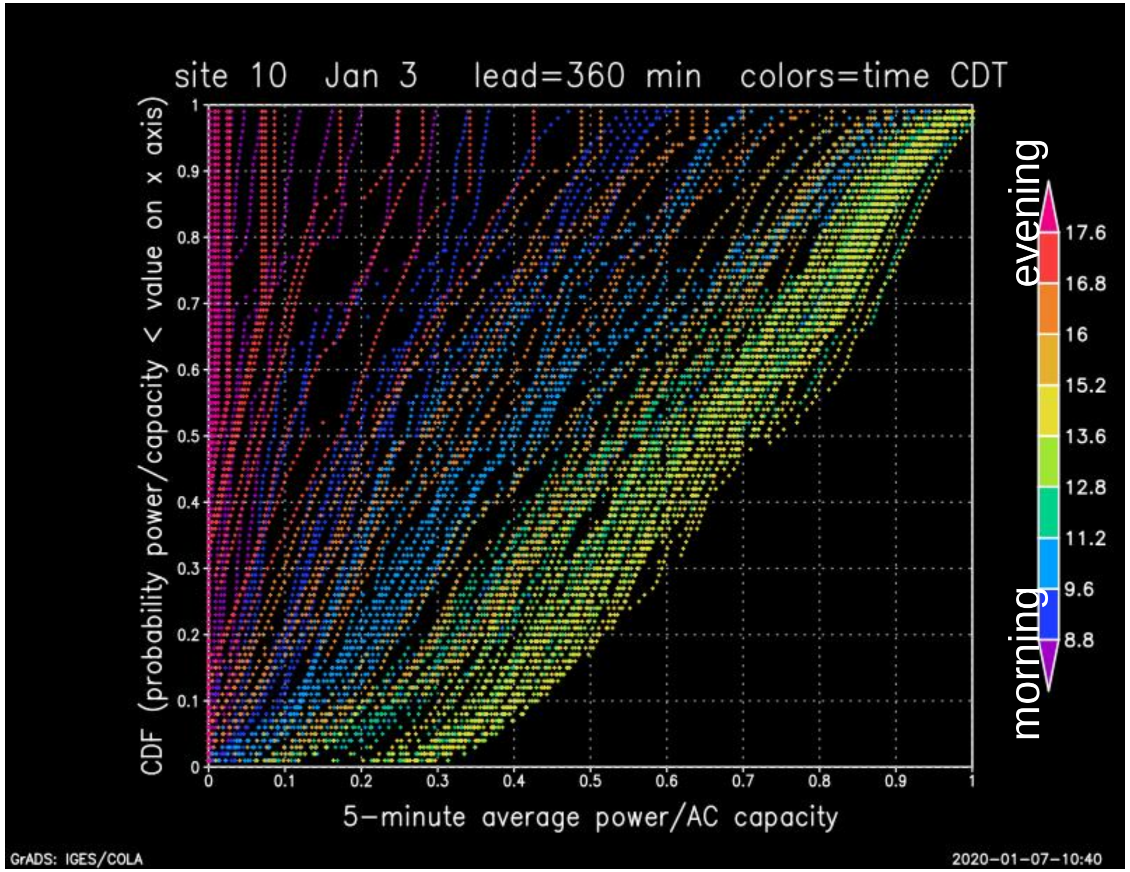
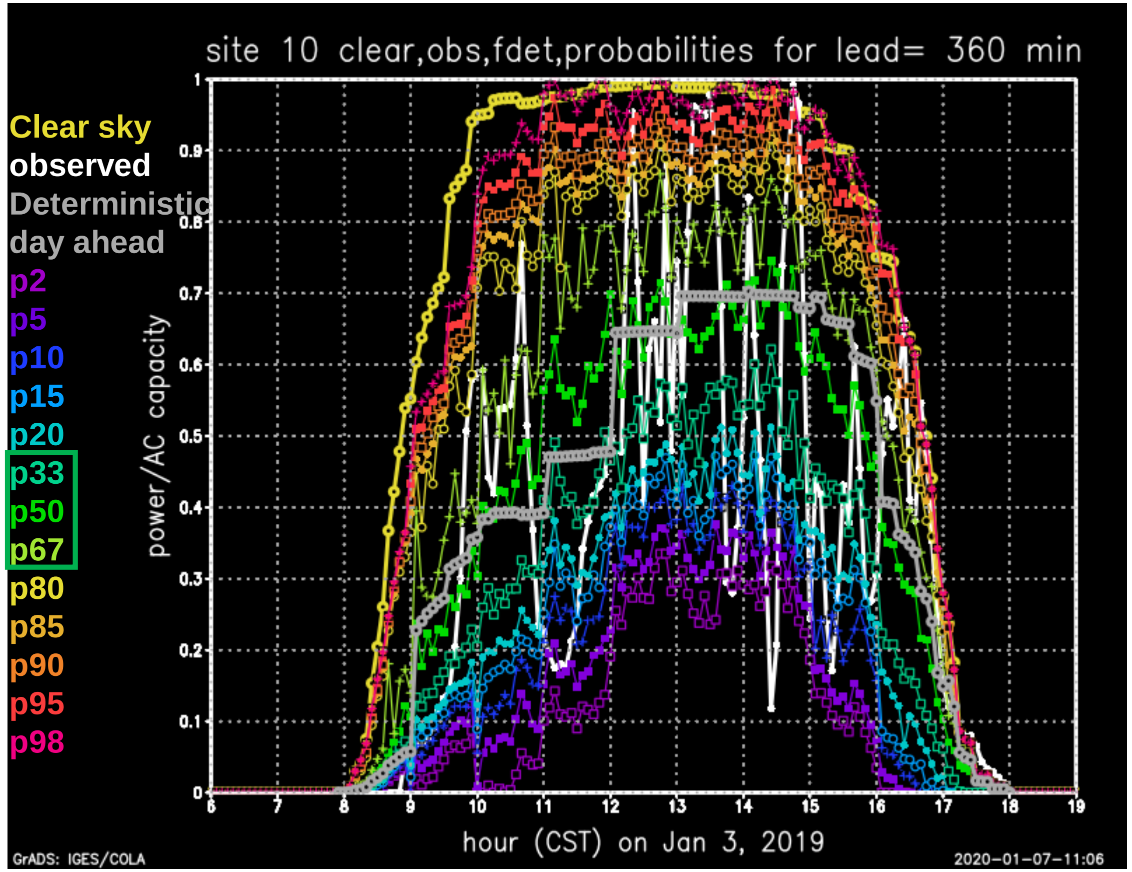
Case 2: Cloudy morning with clearing, site 10, lead=6 hours

Wild excursions not predictable at 6 hours lead time
Probabilistic forecast nicely brackets excursion envelope while indicating high uncertainty





Summary/Conclusion

SUMMER-GO is going!

- **Probabilistic forecasts** are being issued **in real time with 5-min intervals and 5-min updates**
- Probabilistic forecasts already issued appear to contain useful and realistic information
- Improvements in ensemble handling and algorithm to make probabilities underway
  → anticipate large improvements in quality of probabilistic forecasts
- Risk parity economic dispatch, dynamic adaptive reserves, and situational awareness visualization tools are being developed to **leverage the operational use of probabilistic forecasts**

Thank you

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