Naval Postgraduate School

Fog Prediction Errors Evaluated for Multiple Physical Parameterization Schemes in the AFWA Mesoscale Ensemble

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AFWA Mesoscale Ensemble (MEPS)

- 10-member ARW-WRF ensemble with 3 nests; inner-most has 4-km horizontal resolution, 42 Eta levels, no cumulus parameterization
- Each member gets ICs, BCs from different member of NCEP's Global Ensemble Forecast System (GEFS)
- Water vapor field is initialized, other water phases are not
- 20-h runs initialized at 00Z every 3-4 days from Nov 2008 to Feb 2009 ➔ 29 total runs
- Configuration based on work by Hacker et al (2011) to obtain "most skillful ensemble with least degree of complexity"

Verification sites (elevation in m)

AFWA Mesoscale Ensemble (MEPS)

- **Model perturbations obtained via unique physics suite, in addition to unique lower boundary properties**

Member	Microphysics	PBL	Shortwave	Longwave	Land Surface	Cumulus (none on inner-most nest)
1	Kessler	YSU	Dudhia	RRTM	Thermal	KF
5	WSM6	MYJ	CAM	RRTM	Thermal	KF
7	Kessler	MYJ	Dudhia	CAM	Noah	BM
8	Lin	MYJ	CAM	CAM	Noah	Grell
10	WSM5	YSU	Dudhia	RRTM	Noah	KF
11	WSM5	MYJ	Dudhia	RRTM	Noah	Grell
15	Lin	YSU	Dudhia	CAM	RUC	BM
16	Eta	MYJ	Dudhia	RRTM	RUC	KF
17	Eta	YSU	CAM	RRTM	RUC	BM
19	Thompson	MYJ	CAM	CAM	RUC	Grell

Physics suite used by each member

Extracting visibility from WRF

- **Relationship between model output (q_c, RH, etc.) and visibility cannot be explicitly modeled ➔ need a visibility parameterization**
- **Desirable to use only critical variables (as determined by first principles) rather than a customized, highly-statistical approach**
  - **Stoelinga and Warner, 1999**

$$\beta_e = 144.7(q_c)^{0.88}$$

  - **Gultepe, 2006**

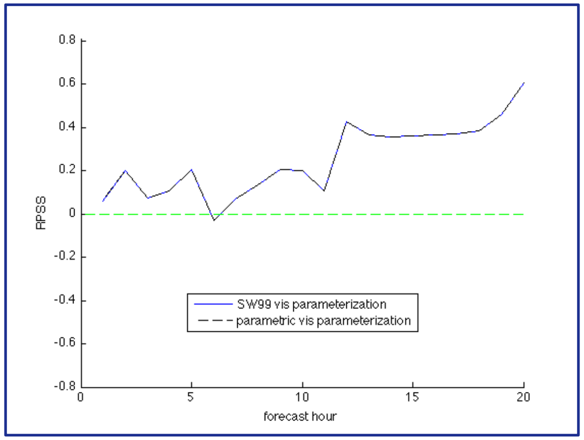
$$\beta_e = 178.6(q_c)^{0.96} \qquad \cancel{\beta_e = 3.904(q_c \cdot N)^{0.6473}}$$

(Vis$_{day}$ related to extinction coef (β_e) as $Vis_{day} = \dfrac{3.0}{\beta_e}$

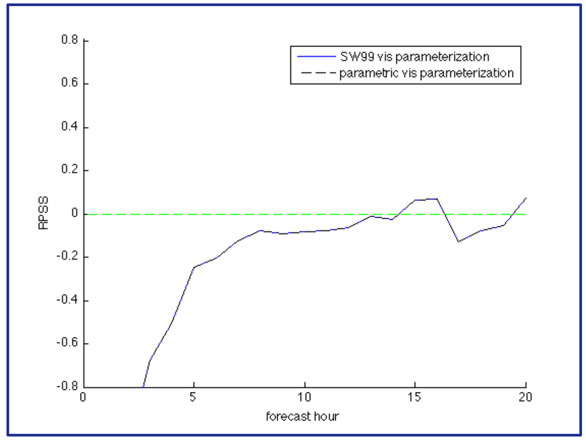
Vis$_{night}$ typically 2-3 times higher)

Droplet number concentration (*N*) not predicted by microphysics schemes

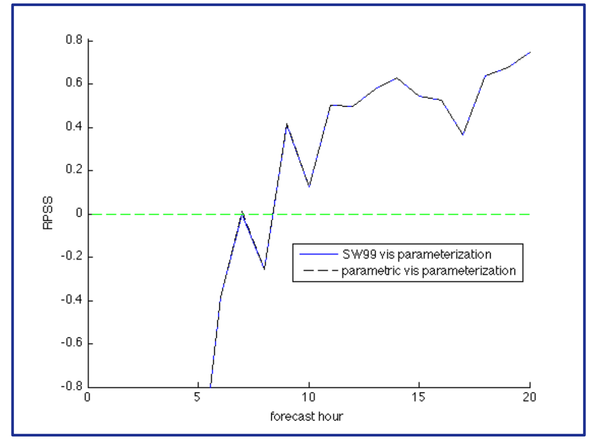
Layer 1 cloud water RPSS (thresholds of 7, 5, 3, 1 mi)



Coastal



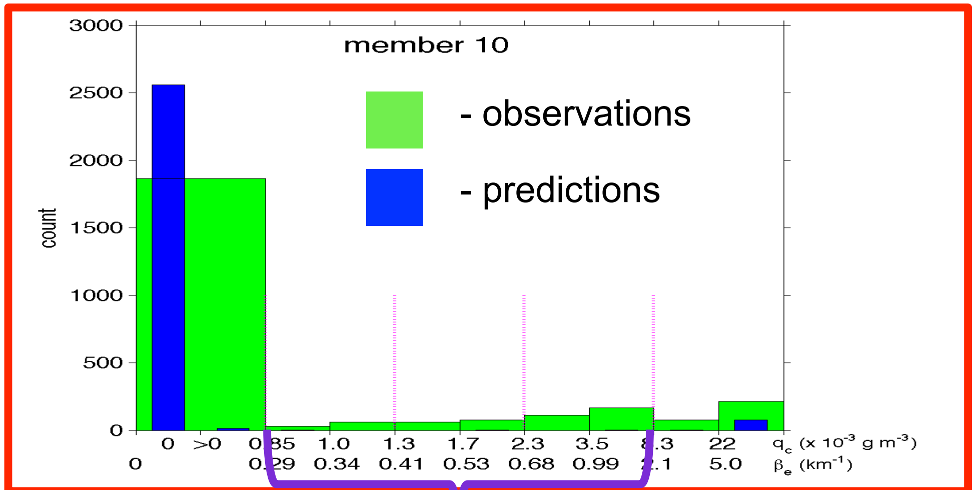
Valley



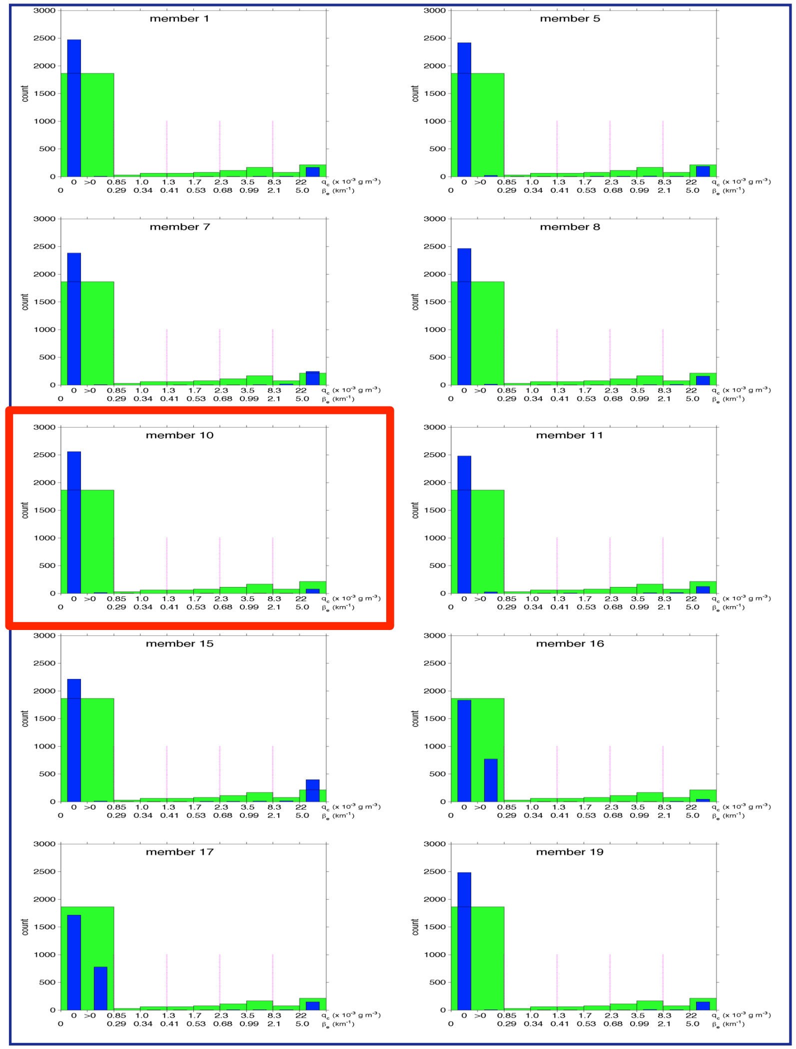
Mountain

- **After period of spin up, predictions in coastal and mountain regions demonstrate skill relative to persistence**
- **Valley region predictions generally not skillful, temporarily drop after sunrise (17-19 h)**
- **Skill generally increases with forecast hour**
- **Parametric visibility parameterization adds no skill ➔ primary source of error is from NWP predictions**

Member climatologies of layer 1 cloud water



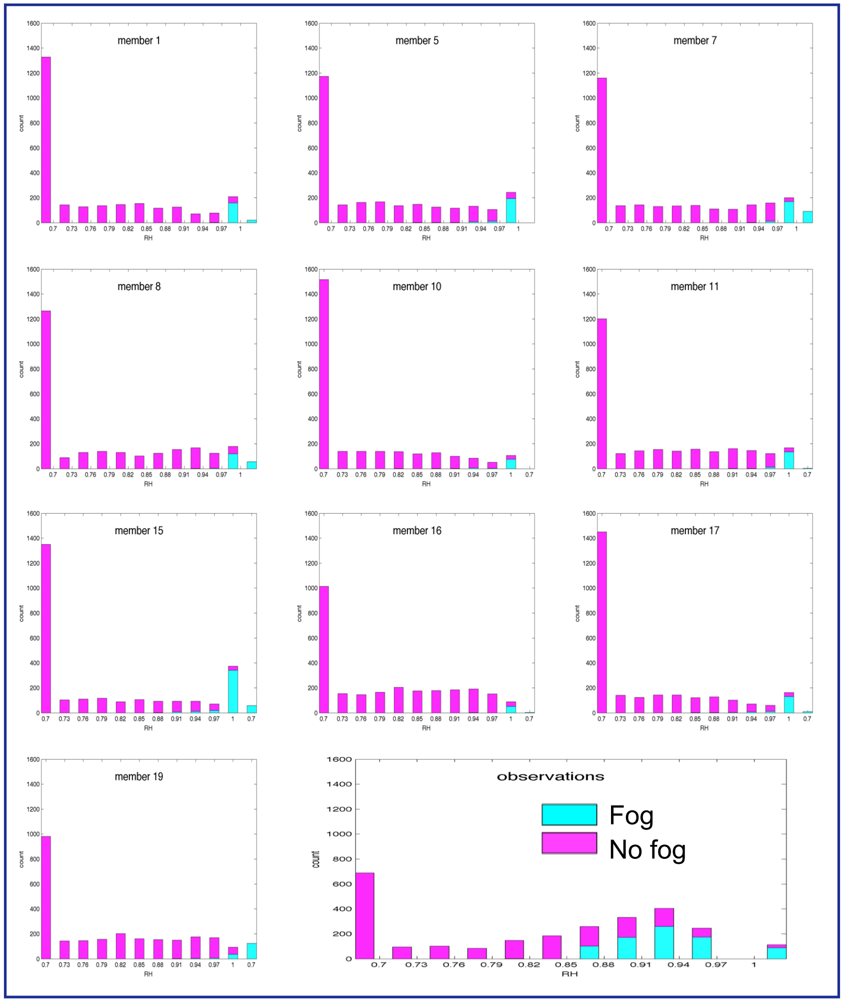
"light fog" (1~7 mi)



- **Predictions highly bimodal in every member**
  - **Excessive zero-q_c predictions, deficit in light fog predictions**

Incidence of light fog		
	Observations:	0.196
	Predictions:	0.005

Member climatologies of layer 1 RH



Distribution of Predictions and Observations

- **Large negative bias in layer 1 RH in every member**

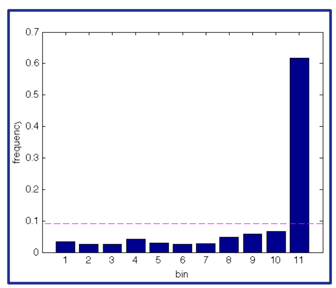
  average member bias

coastal:	-0.182
valley:	-0.069
mountain:	-0.014

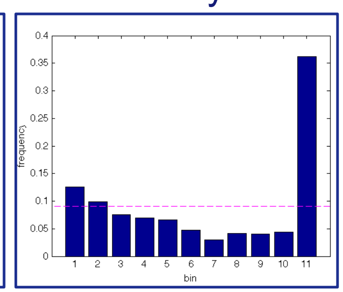
- **Additional q_c error from members restricting fog to very high RH range compared to obs**

- **Stochastic predictions negatively biased and underdispersive**

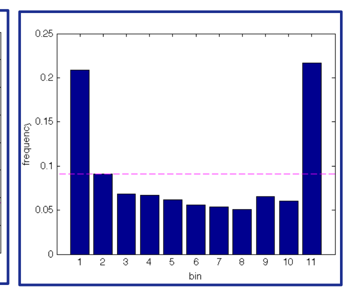
Coastal



Valley

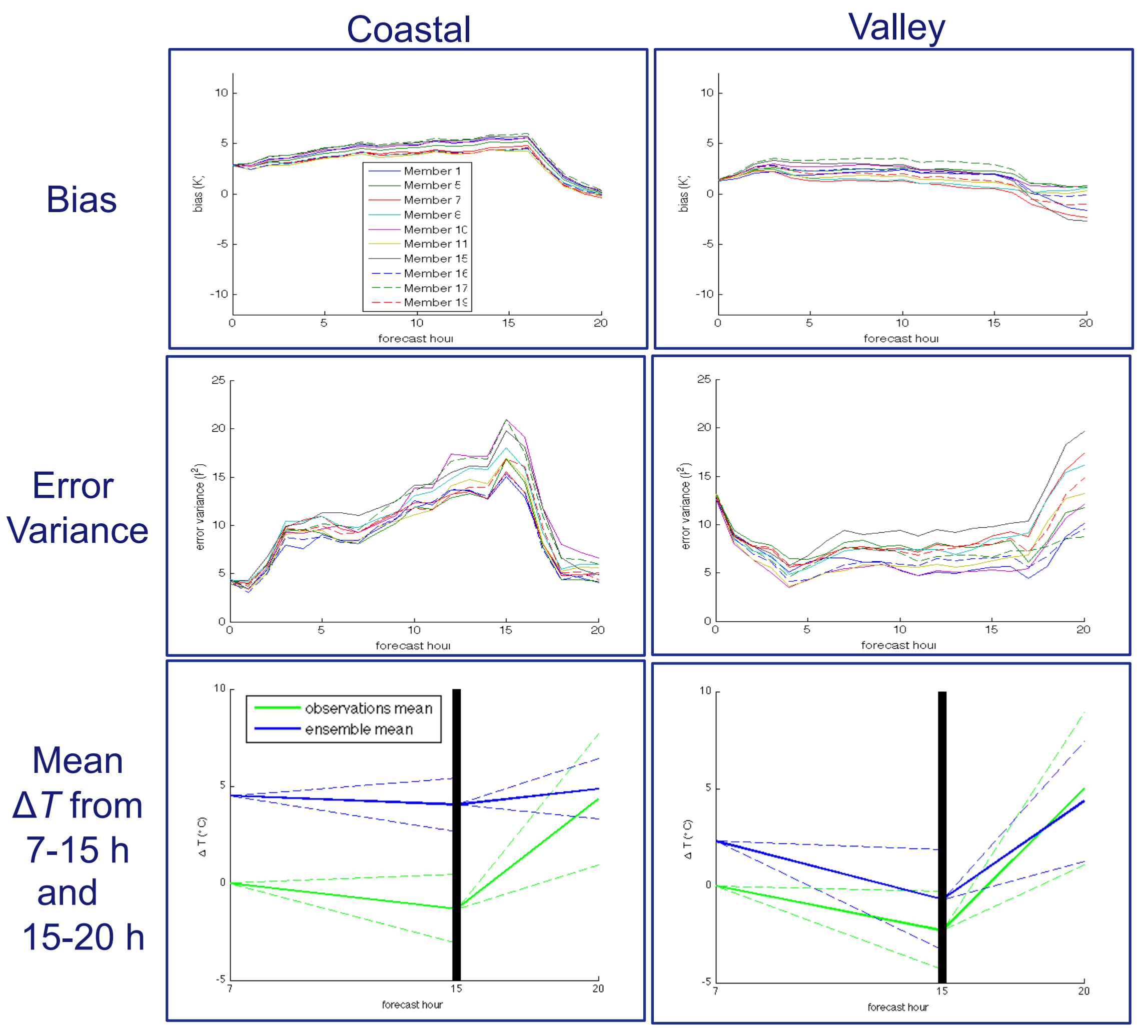


Mountain



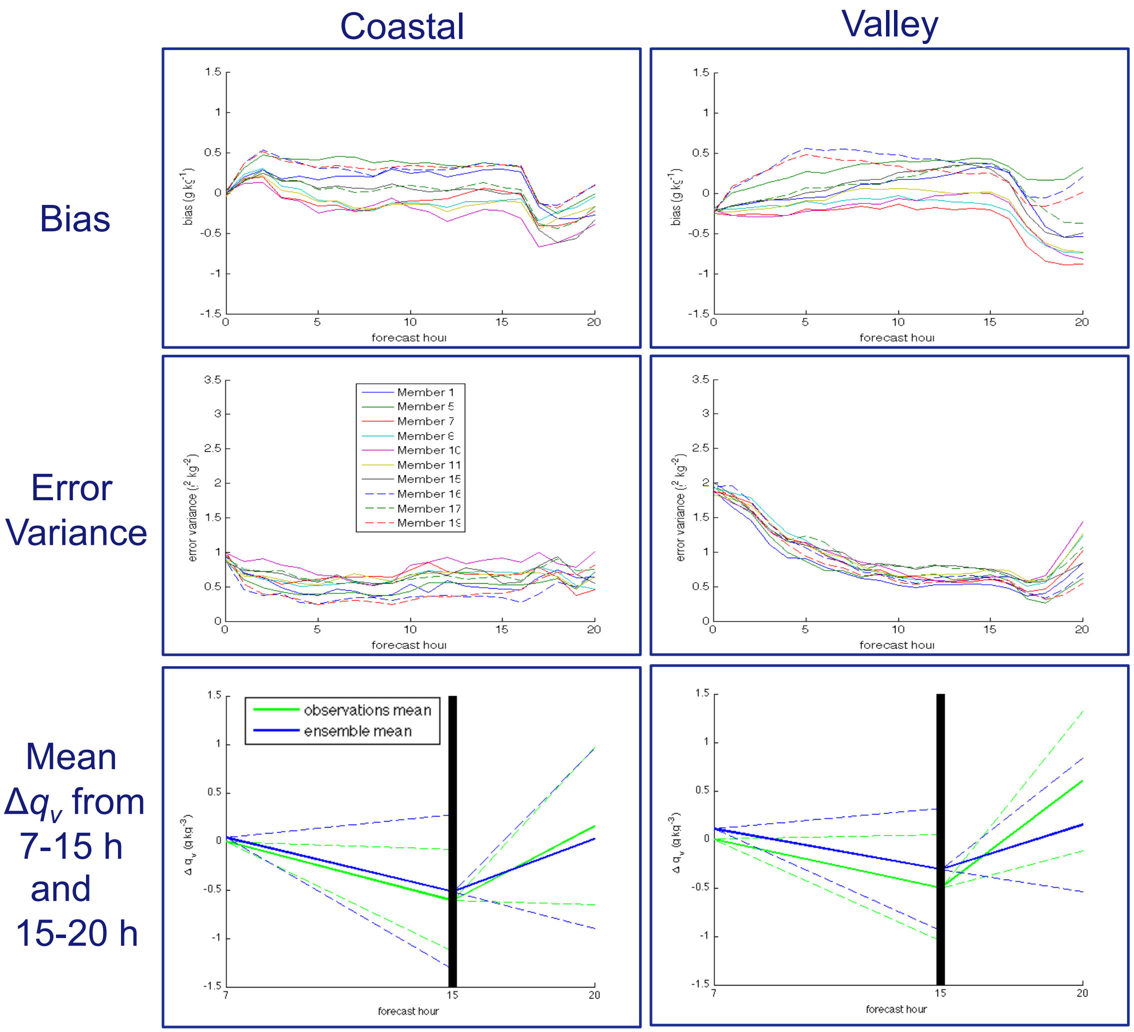
Verification Rank Histograms

Layer 1 temperature



- **Warm biases highest overnight, and in coastal region**
- **Coastal predictions have little diurnal variation, high error variances overnight ➔ seemingly lower predictability**
- **Post-sunrise warming inadequate in both regions, with larger error variances in valley (observed warming is less consistent)**

Layer 1 water vapor



- **Near-neutral overnight biases**
- **q_v error variances lower than temperature error variances in coastal region, comparable in valley region**
- **Diurnal changes well-predicted**
  - **Insufficient post-sunrise moistening has minor impact on RH compared to temperature biases**

Layer 1 and 2-m temperature

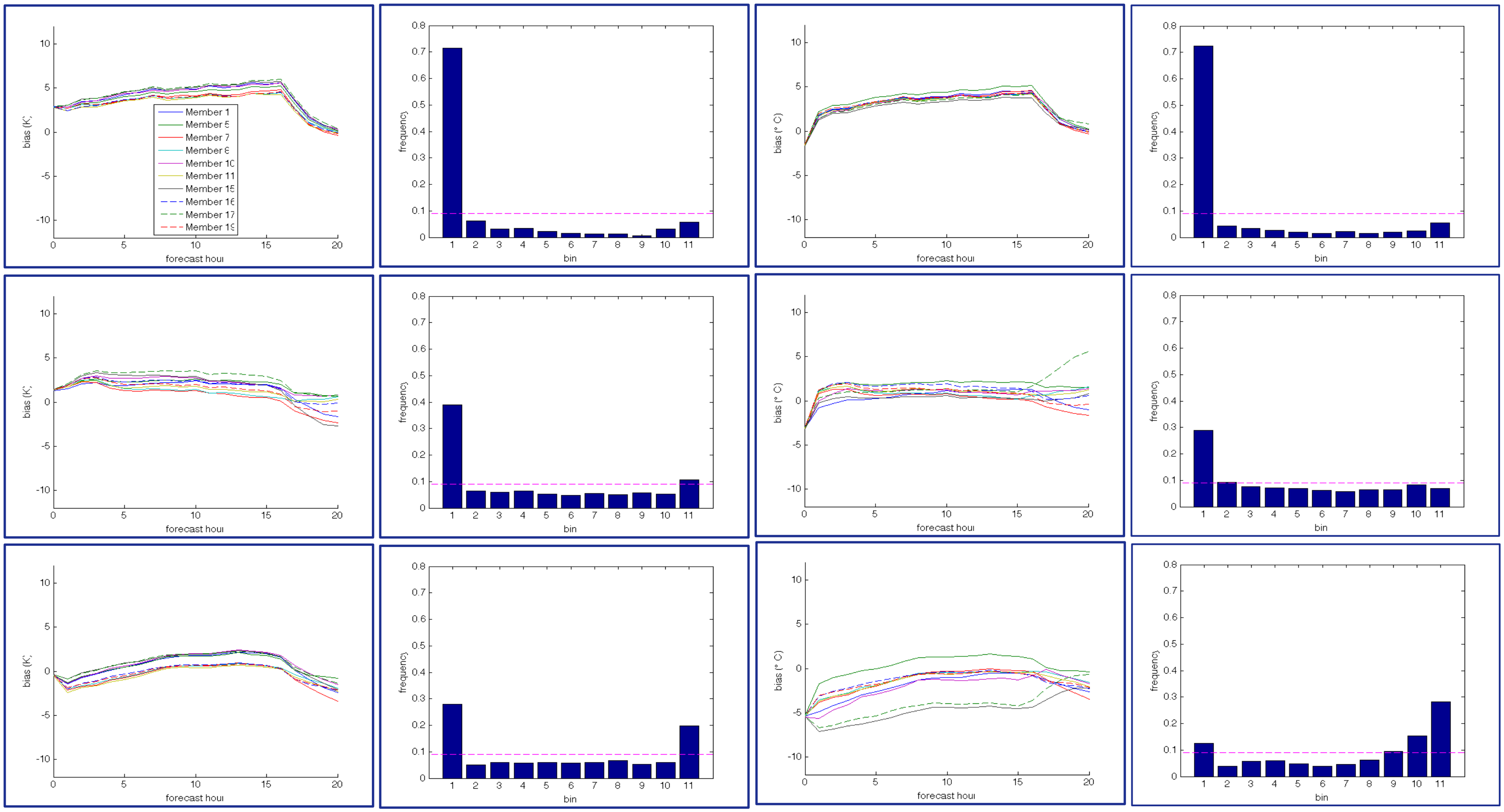
Layer 1 | **2 Meters**

Bias | Rank Histogram | Bias | Rank Histogram

Coastal

Valley

Mountain



Layer 1 and 2-m water vapor

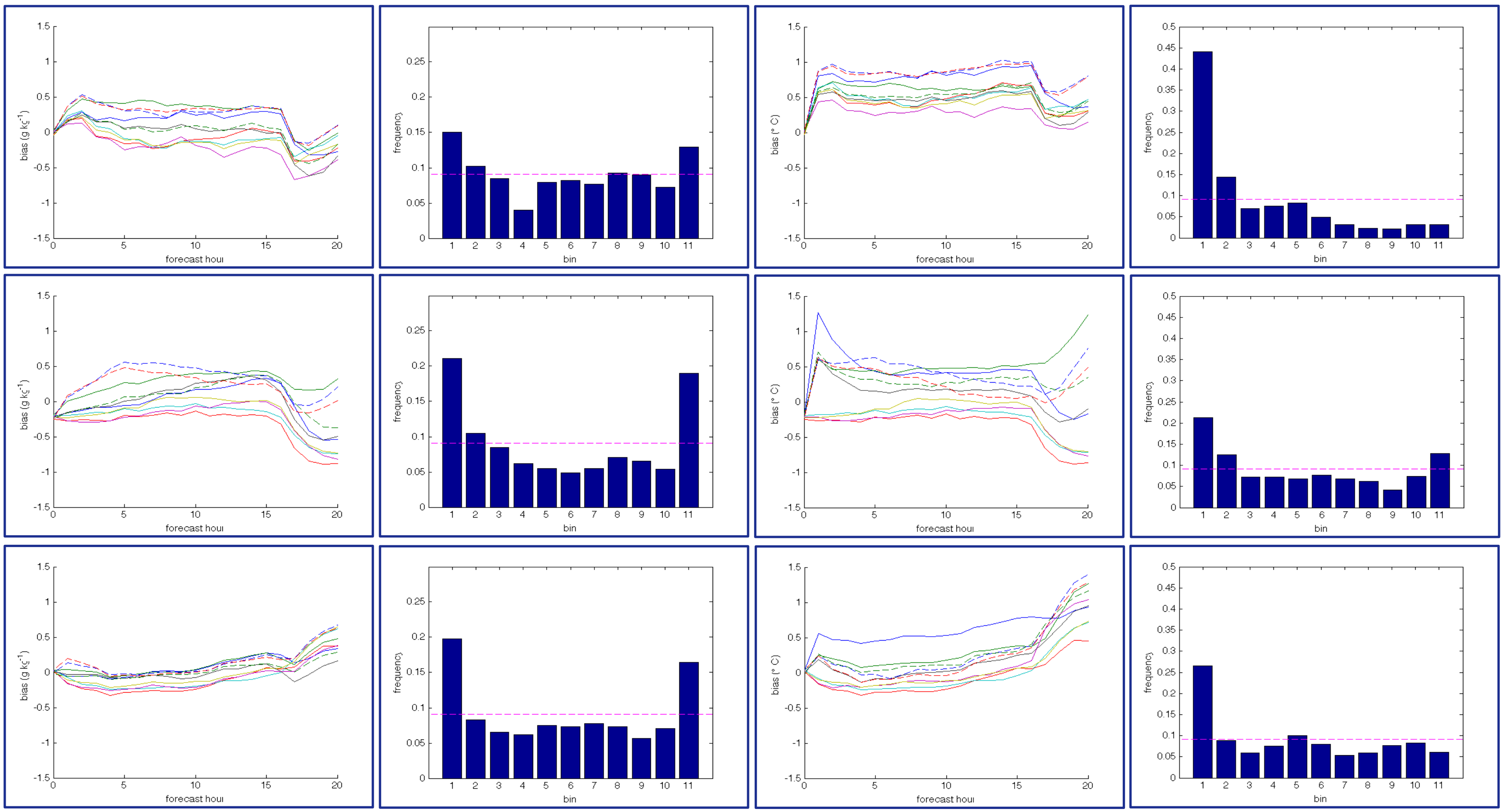
Layer 1 | **2 Meters**

Bias | Rank Histogram | Bias | Rank Histogram

Coastal

Valley

Mountain



Layer 1 and 2-m RH

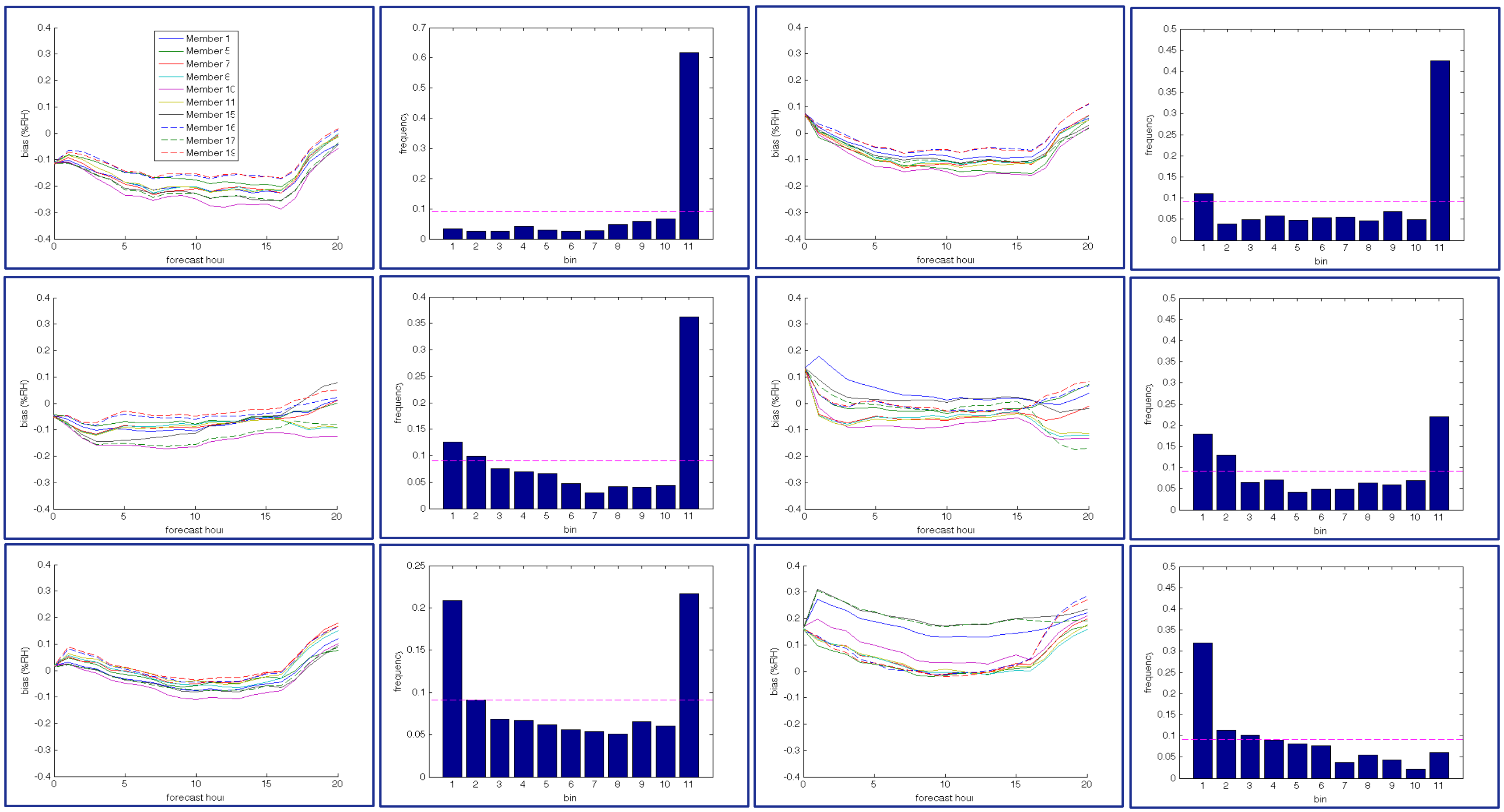
Layer 1 | 2 Meters

Bias | Rank Histogram | Bias | Rank Histogram

Coastal

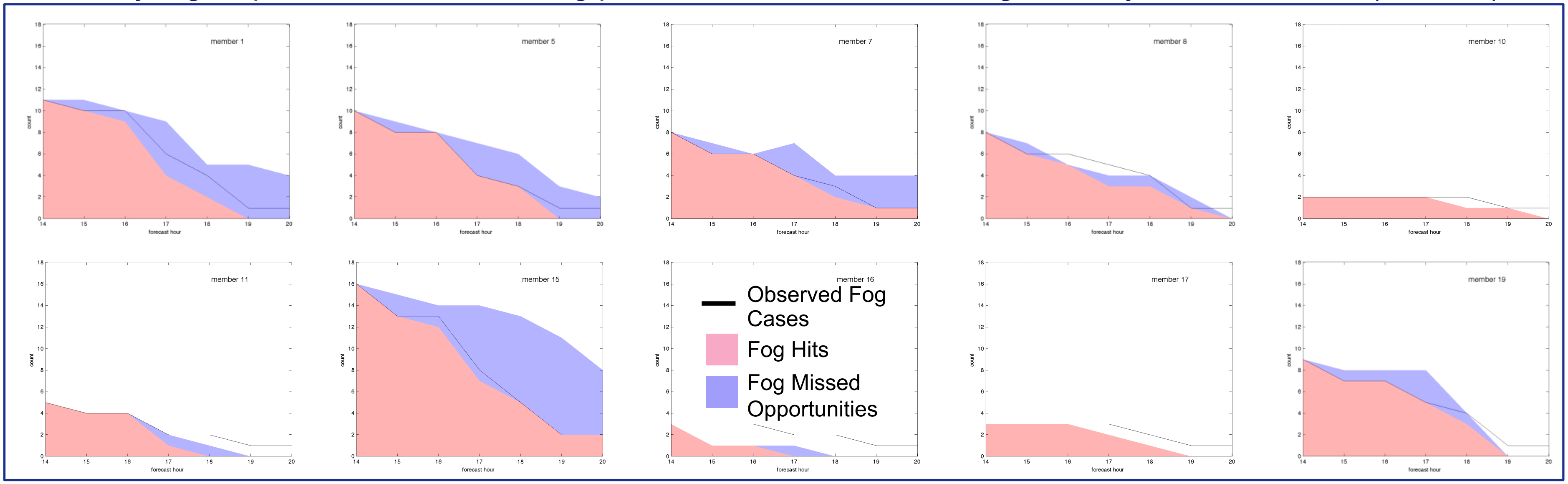
Valley

Mountain



Valley fog dissipation timing

Valley region post-sunrise count of fog predictions for cases when fog correctly forecast at 14 h (0600 LT)



- Number of cases in verification ranges from 2 (mbr 10) to 16 (mbr 15)
- Individual members exhibit biases in dissipation rate, but no clear systematic bias in this conditional sample
- Poor post-sunrise skill due to cases not shown: high false alarm rate (all members >0.75), low probabilities of detection (<0.30), and improving skill of persistence forecast

Summary and discussion

- Layer 1, q_c predictions are highly bimodal, with virtually no values corresponding to light fog
  - Except in mountains, warm biases minimize q_c production
  - Visibility parameterization error is inconsequential unless incidence of light fog predictions is increased
  - Due to positive resolution, ensemble fog predictions still outperform persistence in coastal and mountain regions after 9 h
  - Post-sunrise skill generally worse, but conditional results in valley region suggest promise
- At 2 meters, less RH bias in coastal and Central Valley regions, but large dry bias in mountains due to cold bias of up to 6 K
  - Error variances at least as good as layer 1 predictions, with better ensemble dispersion

Member-specific behavior

Member	Microphysics	PBL	Shortwave	Longwave	Land Surface	Cumulus (none on inner-most nest)
1	Kessler	YSU	Dudhia	RRTM	Thermal	KF
5	WSM6	MYJ	CAM	RRTM	Thermal	KF
7	Kessler	MYJ	Dudhia	CAM	Noah	BM
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16	Eta	MYJ	Dudhia	RRTM	RUC	KF
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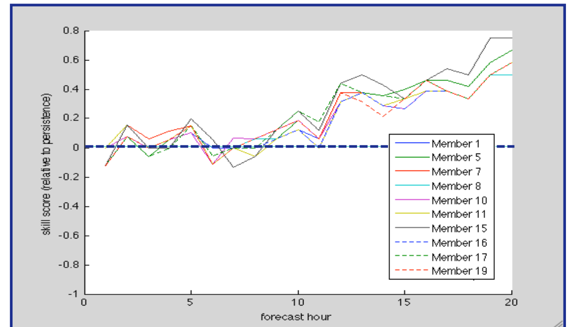
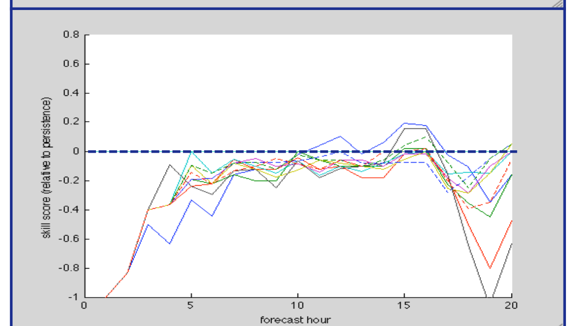
19	Thompson	MYJ	CAM	CAM	RUC	Grell

Accuracy
Skill Score

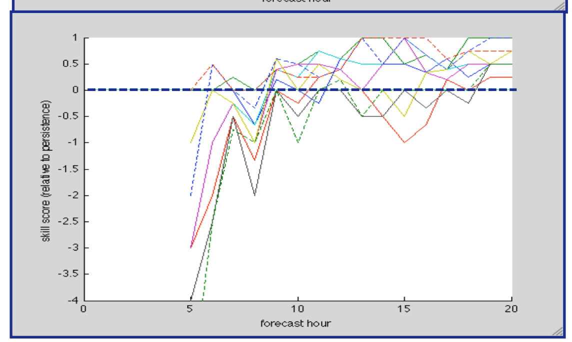
Coastal



Valley



Mountain



Way forward

- Introduce *gentle* statistical element to make upward adjustments to zero and near-zero q_c predictions
    - Layer 1 virtual temperature predictions in valley/mountain region
    - Layer 1 absolute moisture and d/dt virtual temperature predictions in coastal region

NPS

PRAESTANTIA PER SCIENTIAM

1909

Backup Slides

Statistical vs physical techniques in fog prediction

- Statistical approaches to visibility-in-fog (VIF) prediction include formation of predictors based on observations, NWP output (statistically calibrated), or combination of both
  - \+ Inherently calibrated, often outperform NWP data alone
  - − Require long observational record
  - − Require stable inputs (i.e., sensitive to NWP platform changes)
- Purely physical techniques place full confidence in NWP output, and convert to desired parameter using only first principles
  - \+ No reliance on observations (only needs model data)
  - \+ First principles valid everywhere
  - − No calibration; at mercy of model error
  - − First principles can be complex, entail many unknown quantities

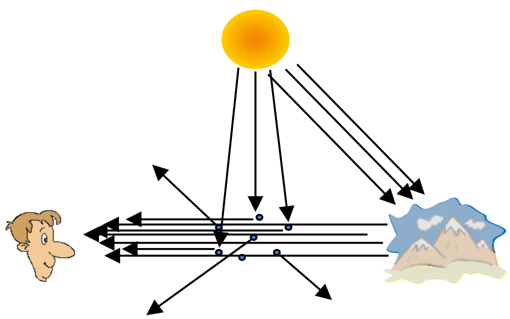
Statistical vs physical techniques in fog prediction

- **Many military operations are conducted far away from nearest airfield, where statistical calibration or climatological tools don't exist (targeting, reconnaissance, search and rescue, etc.)**

- **Aim of this research is to strike appropriate balance between statistical and physical approaches for VIF prediction suitable for remote locations:**
  - **Use physical approach as baseline, introduce statistical components judiciously only where necessary**
  - **Gain insight into error characteristics, physical processes, future research needs**

Defining visibility

- **True visibility determined by complex process involving contrast between object and its background, contrast threshold of observer, and (during day) scattering of ambient sunlight**



- **With automated instrumentation, visibility estimated using measured scattering coefficient (σ_s) within 1.5 ft^3 sample**
  - **During day, based on distance at which brightness difference between object and its background is 5% of the background brightness:**

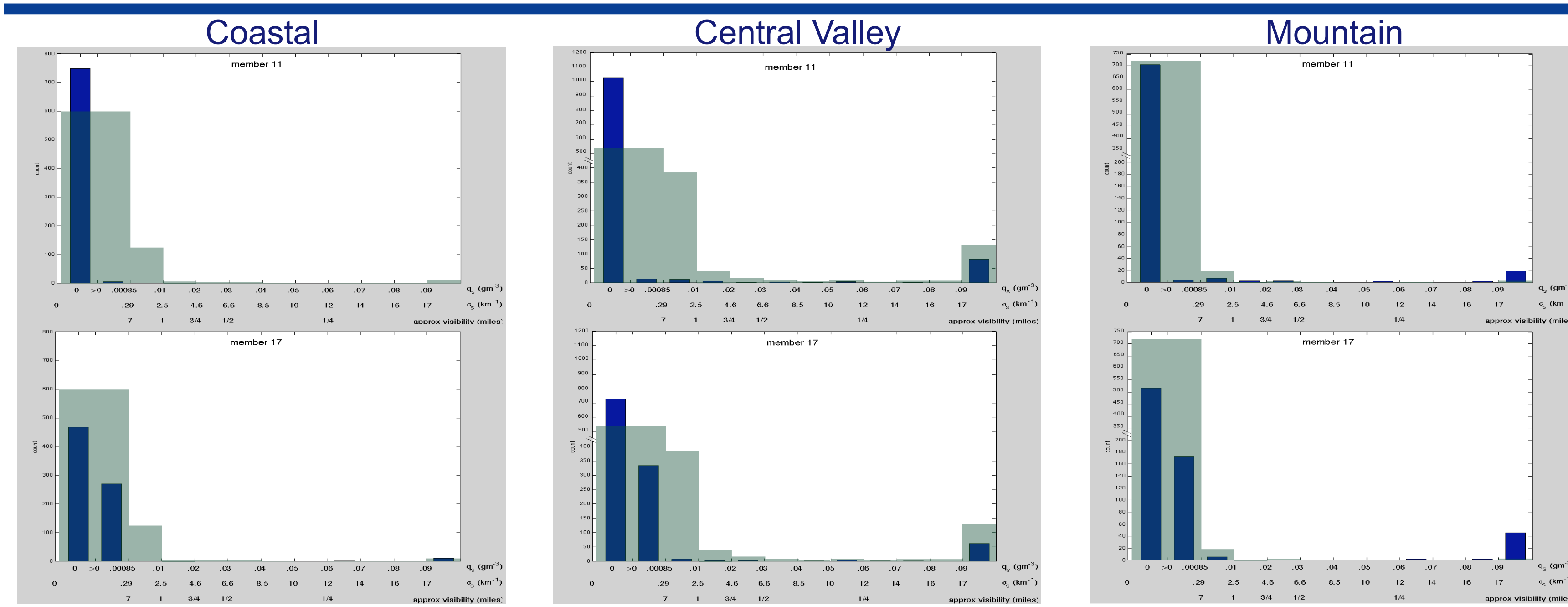
$$\left|\frac{B_o' - B_b'}{B_b}\right| = 0.05 = \exp\left[-\int_0^{x_{vis}} \sigma_s(x)\,dx\right]$$

…and if we assume homogeneity within the observing area:

$$x_{vis} = Vis_{day} = \frac{-\ln(0.05)}{\sigma_s}$$

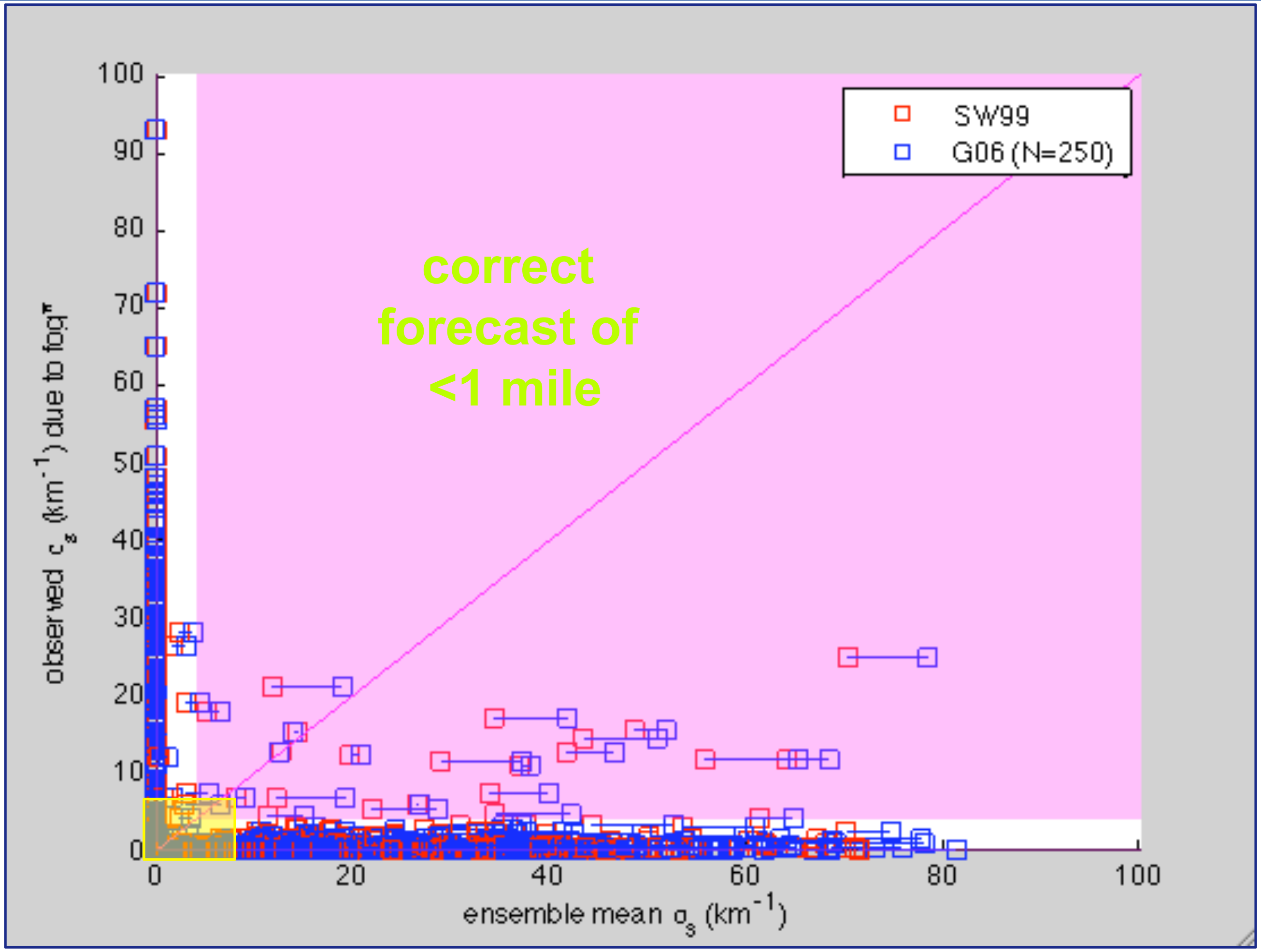
- **Different algorithm used for nighttime visibility**
  - **Verification performed against σ_s since it is the measured parameter**

Individual member climatologies of q_c



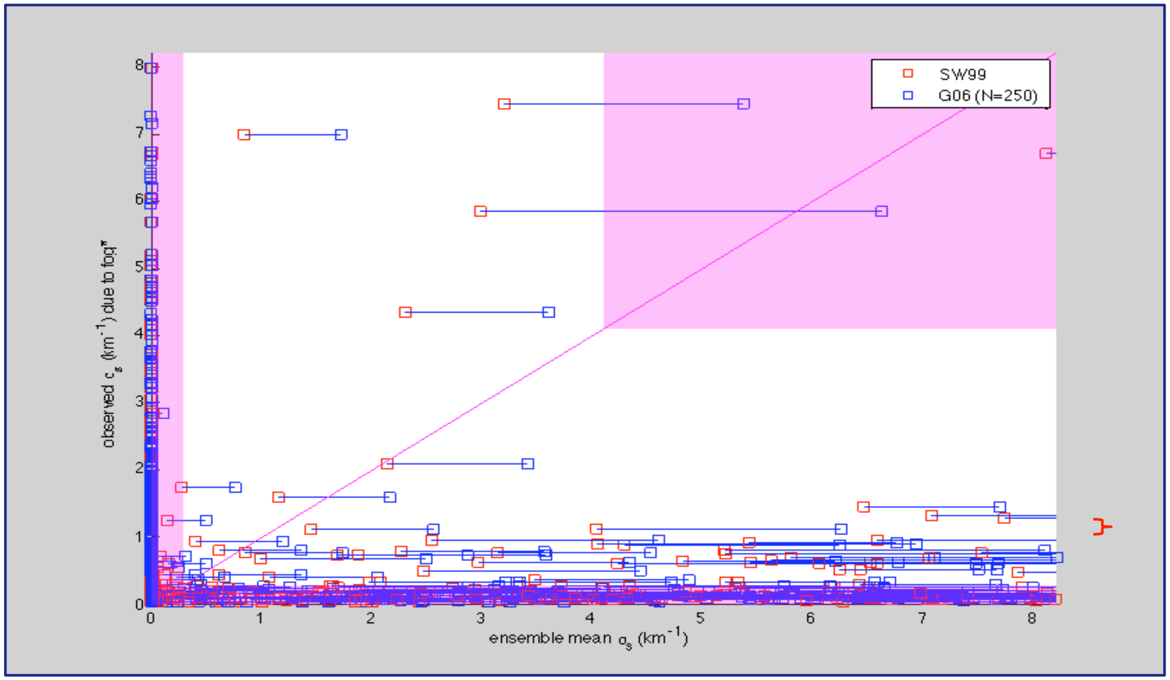
- **In general, NWP correctly models bimodal nature of VIF**
- **All members have excess zero or near-zero q_c forecasts at expense of intermediate q_c forecasts (less so in mountain region)**
- **Error suggestive of deficiency in NWP model, not initial conditions**
  - **Climatology of NWP members avoids intermediate values, despite them being common in observed climatology**

NWP forecast error vs visibility parameterization error



Scatter plot of observed σ_s vs ensemble mean σ_s using SW99 and G06 visibility parameterizations

NWP forecast error vs visibility parameterization error



- Many false alarms are close to verifying in intermediate range, whereas missed opportunities are not

Scatter plot of observed σ_s vs ensemble mean σ_s using SW99 and G06 visibility parameterizations

- **False alarms likely to benefit from ensemble spread, whereas most missed opportunities have $\overline{q_c} \approx 0$, meaning ensemble spread is small**
- **When all members forecast $\overline{q_c} \approx 0$, there can be virtually no visibility parameterization dispersion**

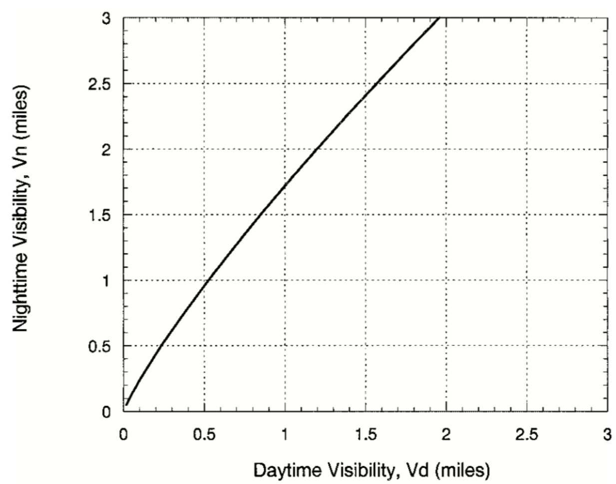


Figure 1. Nighttime visibility versus daytime visibility for the same extinction coefficient using standard assumptions used by ASOS regarding contrast of an object against its background (during day), luminous intensity (during night), and visual contrast threshold (Rasmussen et al, 1999).

Day	$visibility = \frac{1.8615}{\sigma_s}$
Night	$\frac{-5.7 + \ln(visibility)}{(1.609 \cdot visibility)} = \sigma_s$

Table 1. Algorithms used for conversion of σ_s (in km^{-1}) to visibility (in miles) in all FAA ASOS systems. Given σ_s, the nighttime algorithm requires an iterative process to solve for visibility (Belfort Instrument, 2005).

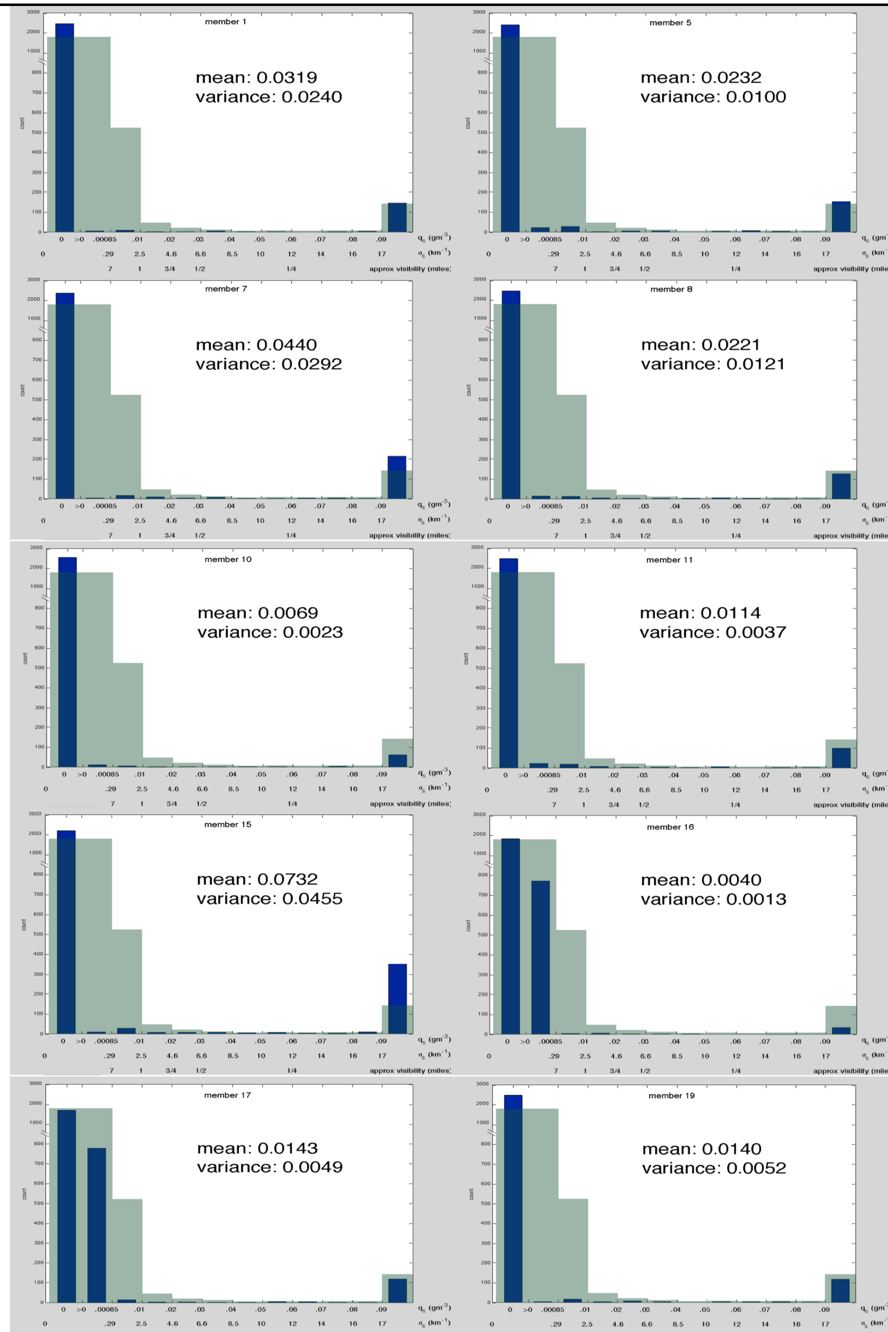


Figure 4. Distribution of q_c forecasts (dark blue bars, top x-axis labels) for each member, and the distribution of observed σ_s (light green bars, middle x-axis labels). The first six hours of each case are excluded. The mean and variance of the q_c distribution is indicated (in gm^{-3}).

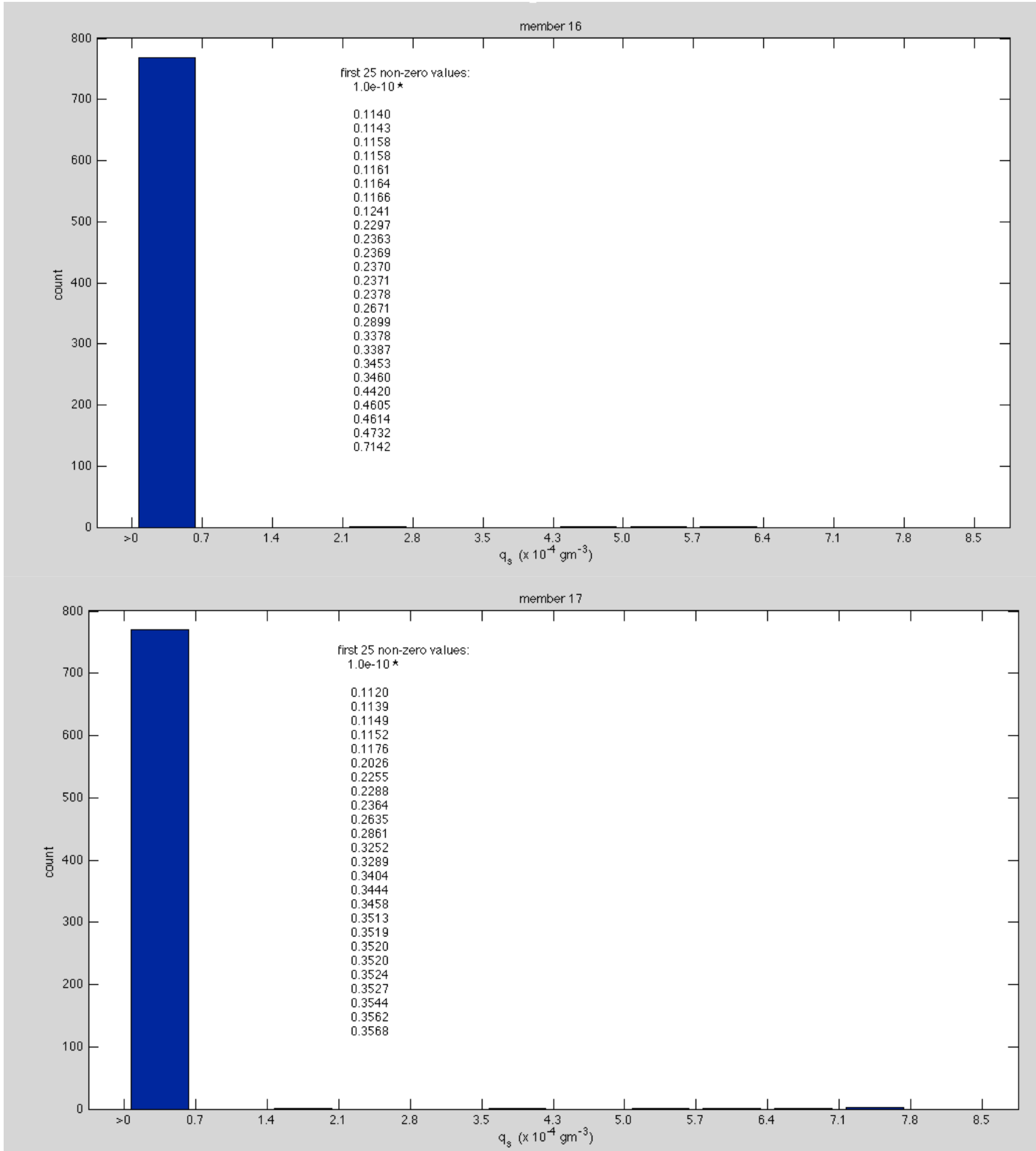


Figure 5. Histogram of q_s forecasts from members 16 (top) and 17 (bottom) for very small but non-zero values. The domain for this plot was created by partitioning bin 2 from Figure 4 into 12 equal sub-bins to allow closer examination. The first 25 non-zero values are also listed for each member.

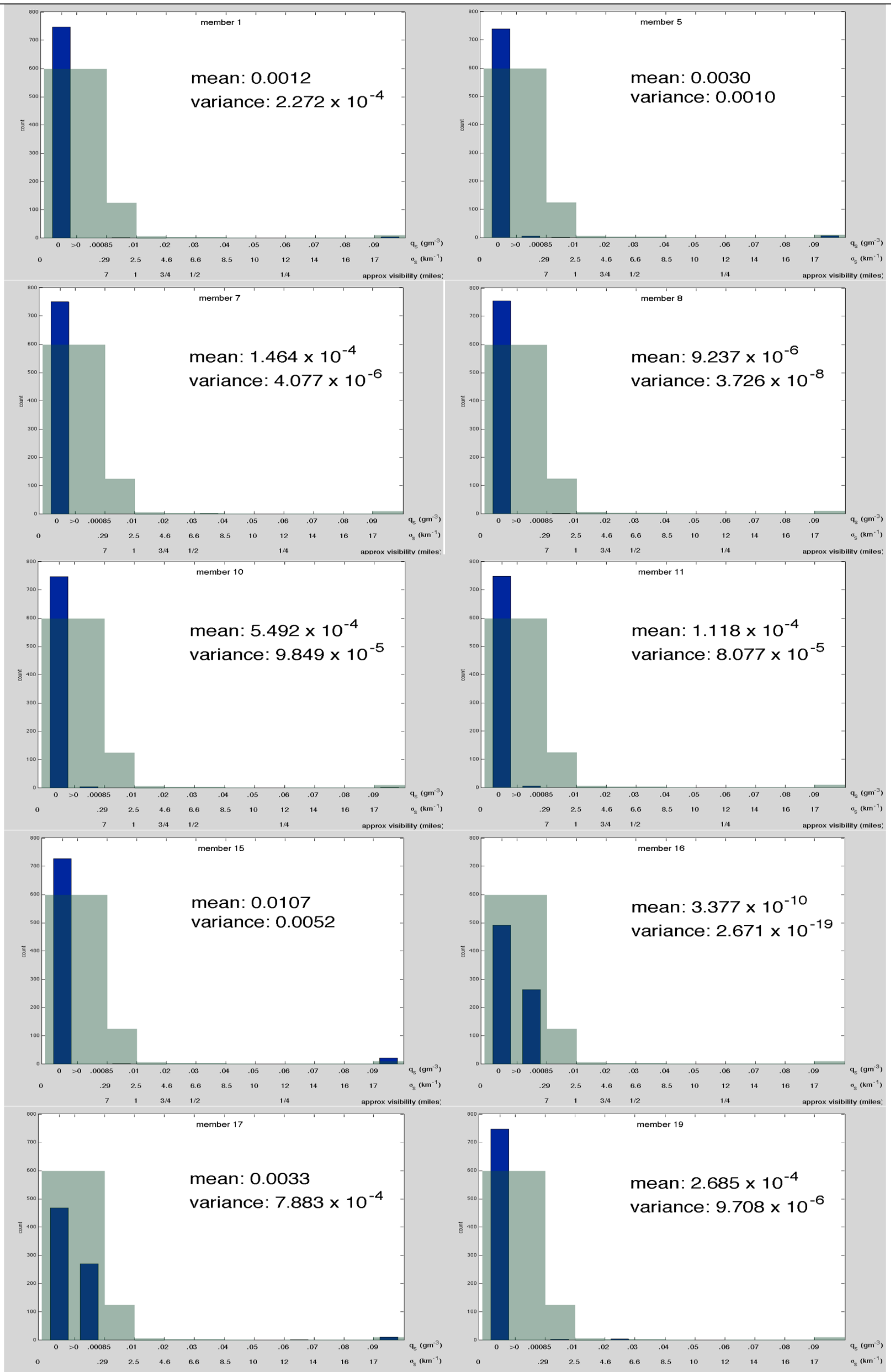


Figure 6. Same as in Figure 4, but for coastal sites only. Note there is no discontinuity in the y-axis.

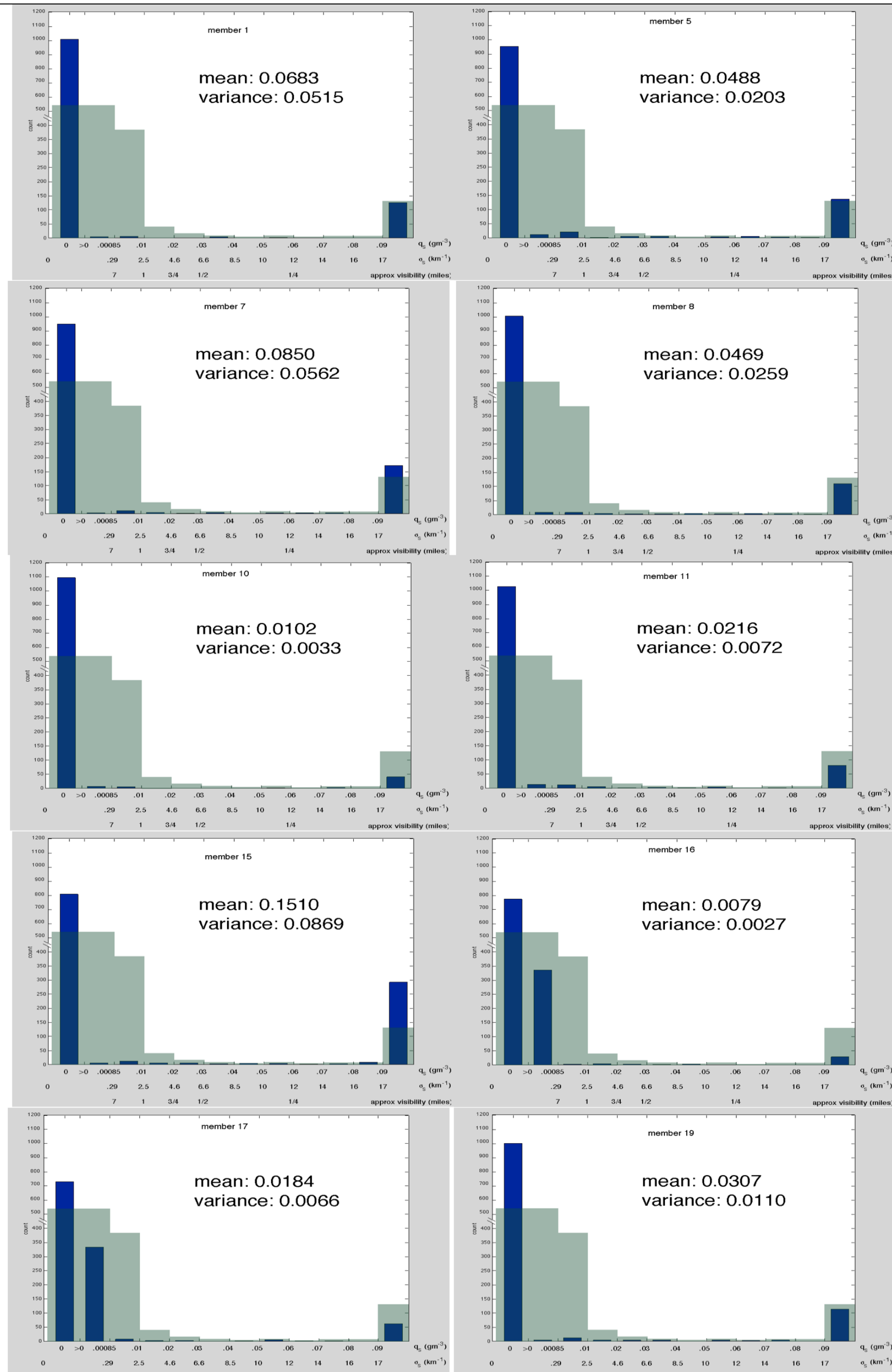


Figure 7. Same as in Figure 4, but for Central Valley sites only.

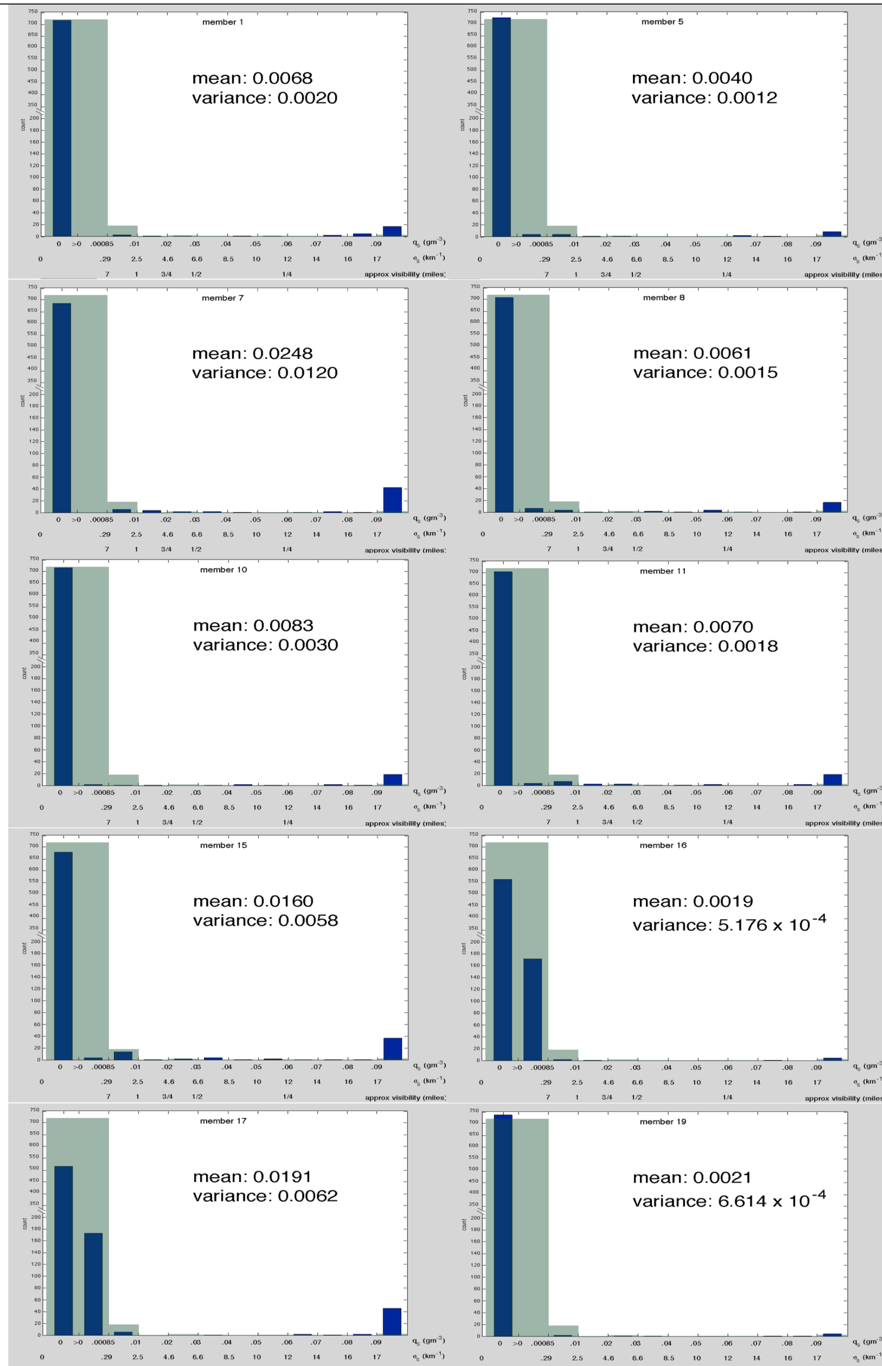


Figure 8. Same as in Figure 4, but for mountain sites only.

Metric	Formula	Description	Best Score	Worst Score
Percent Correct	$\frac{(correct\ forecasts)}{(total\ forecasts)}$	Summarizes overall performance with no bias or skill information.	1	0
Skill Score (relative to persistence)	$\frac{(correct\ forecasts)-(persistencecorrect\ forecasts)}{(total\ forecasts)-(persistencecorrect\ forecasts)}$	Measures overall skill. Value of 0 indicates forecast is no better or worse than persistence forecast.	1	$-\infty$
Bias	$\frac{(total\text{"}\ yes\text{"}\ forecasts)}{(total\text{"}\ yes\text{"}observations)}$	Reveals whether predictions, on average, are too ambitious or too conservative in forecasting event.	1	Overforecast: $+\infty$ Underforecast: 0
False Alarm Ratio	$\frac{(incorrect\text{"}\ yes\text{"}\ forecasts)}{(total\text{"}\ yes\text{"}\ forecasts)}$	Answers question "when event is forecast, at what rate does is occur?"	0	1
Probability of Detection (each member)	$\frac{(correct\text{"}\ yes\text{"}\ forecasts)}{(total\text{"}\ yes\text{"}\ fobservations)}$	Answers question "when event occurs, at what rate was it forecast?"	1	0

Table 2. Description of metrics used for binary verification of each member. An "event" refers to an observed $\sigma_s > 0.29$ km^{-1} due to fog. A "yes" forecast refers to a NWP forecast of $q_c \geq .00085$ gm^{-3} in the lowest NWP model layer.

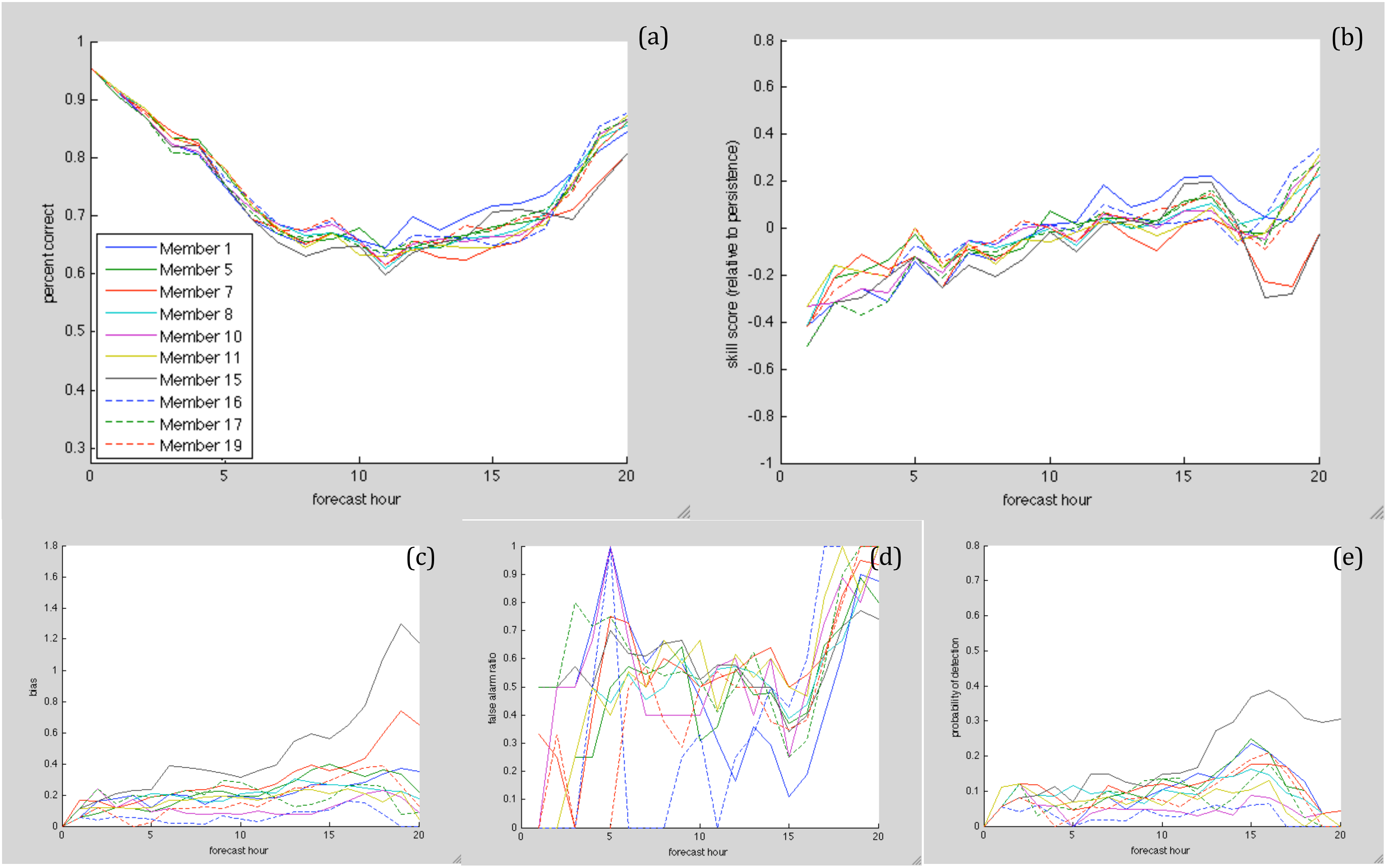


Figure 9. Binary verification of inferred presence of cloud water for all sites: a) percent correct, b) skill score relative to persistence, c) bias, d) false alarm ratio, e) probability of detection.

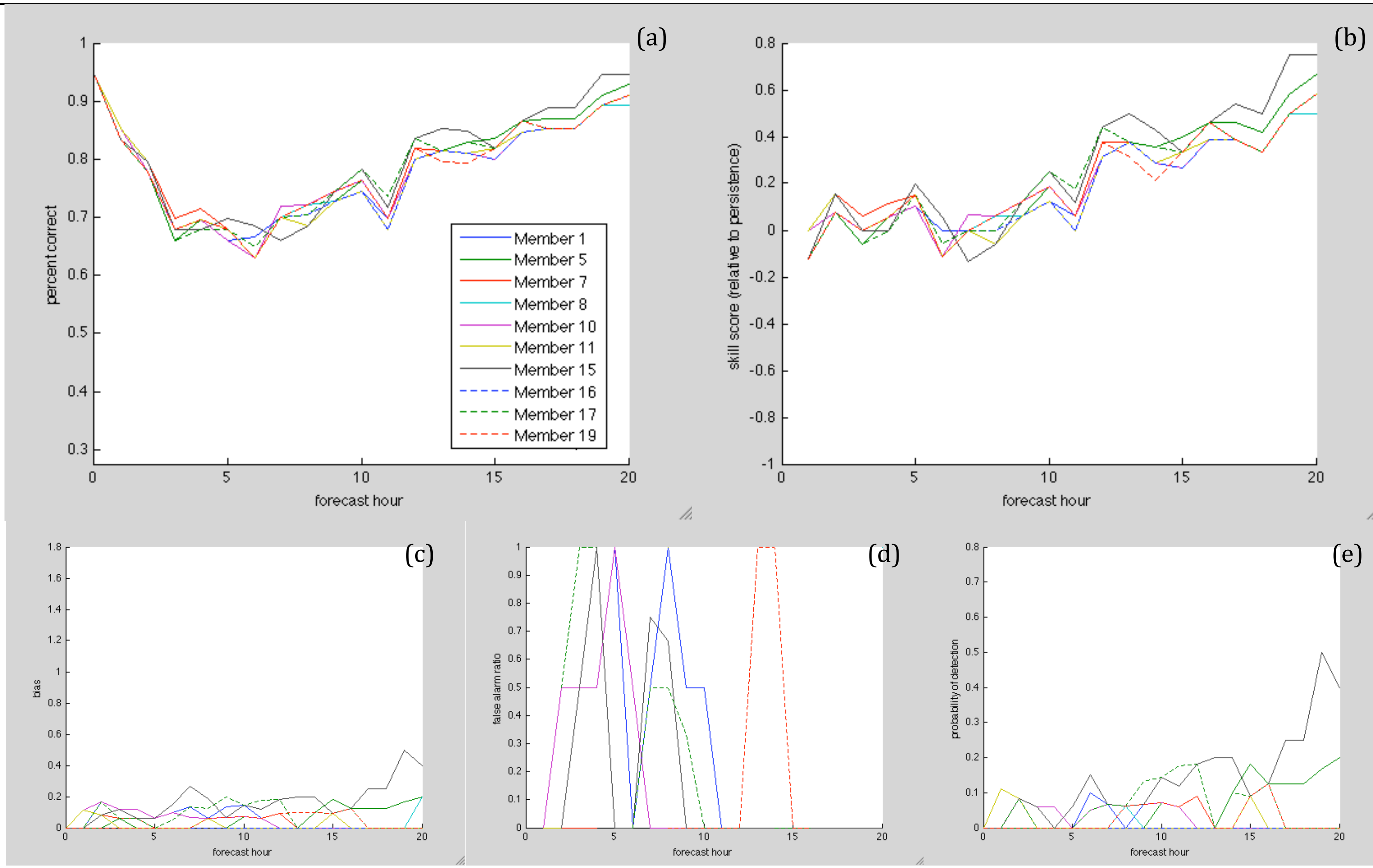


Figure 10. Same as in Figure 9, but for coastal sites only.

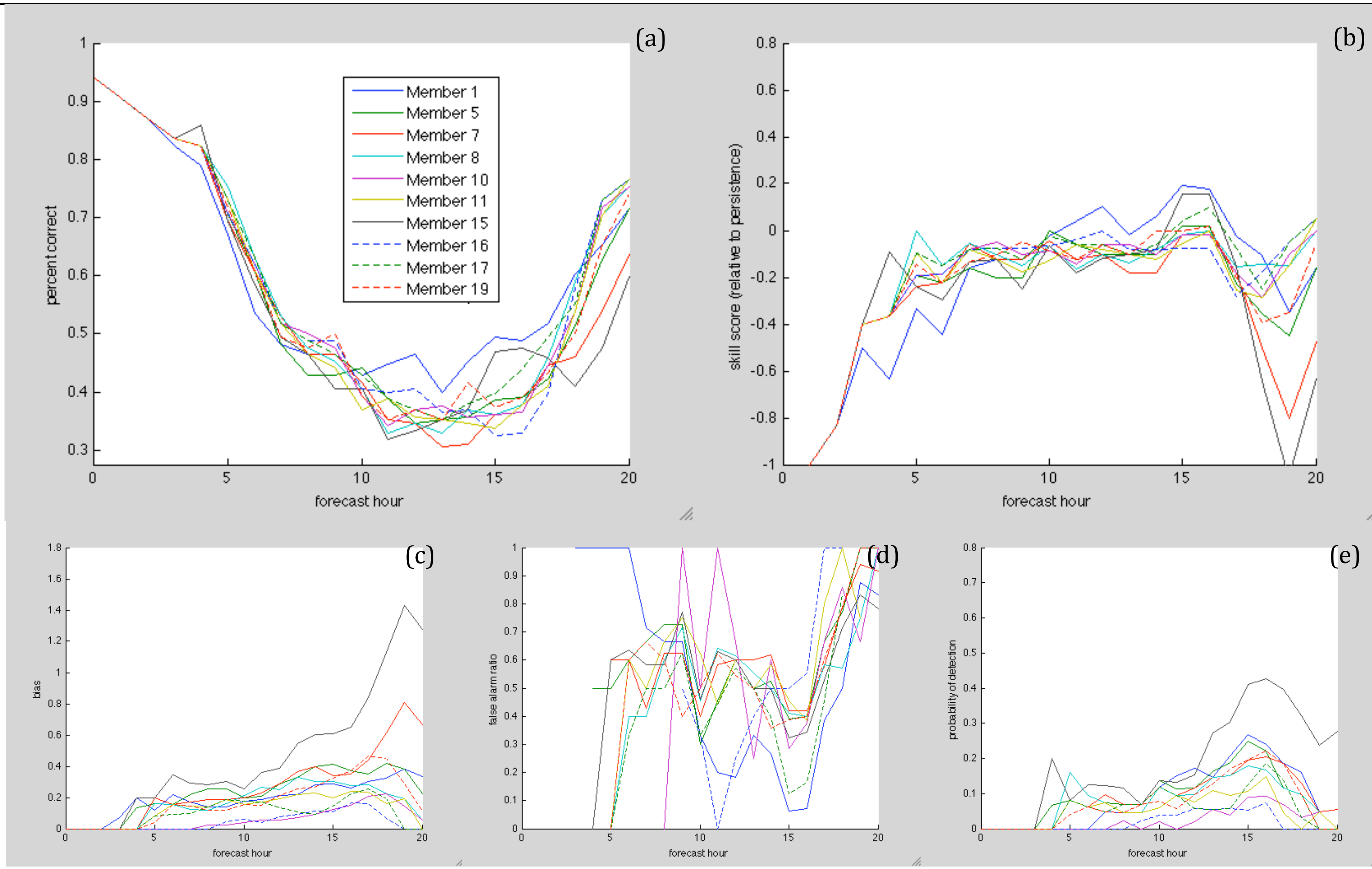


Figure 11. Same as in Figure 9, but for Central Valley sites only.

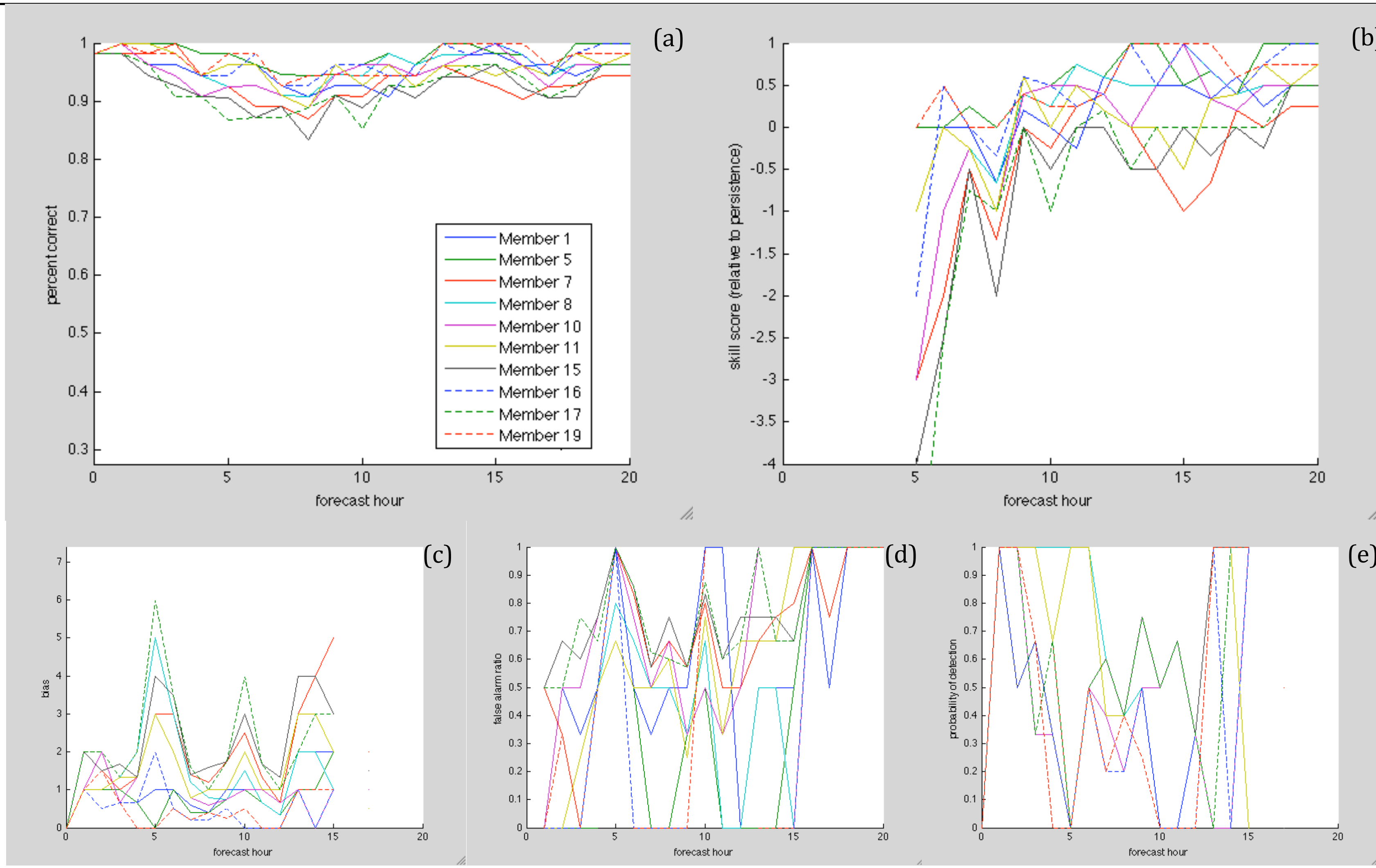


Figure 12. Same as in Figure 9, but for mountain sites only.

Metric	Formula	Description	Best Score	Worst Score
Reliability (ensemble suite)	$\frac{1}{M}\sum_{i=1}^{I} N_i\left(\left(p_e'\right)_i - \bar{o}_i\right)^2$	Measures how well a given forecast probability matches the observed frequency of occurrence	0	1
Resolution	$\frac{1}{M}\sum_{i=1}^{I} N_i\left(\bar{o}_i - \bar{o}\right)^2$	Measures degree to which ensemble, through its probability forecasts, can parse data into subsamples having frequency of occurrence different from overall climatological frequency	Uncertainty score	0 (frequency of occurrence in every subsample = overall climatological frequency)
Uncertainty	$\bar{o}\left(1-\bar{o}\right)$	Does not depend on forecast, only on climatological frequency; indicates level of difficulty in obtaining resolution	N/A – but scores may range from 0 (event occurs 0% or 100% of time, so no resolution possible) to 0.25 (event occurs 50% of time, maximizing potential resolution score)	
Brier Score	reliability – resolution + uncertainty	Combines reliability and resolution to summarize overall ensemble accuracy	0	1
Brier Skill Score (relative to persistence)	$1-\frac{BrierScore}{BrierScore_{persistence}}$	Measures overall stochastic skill of ensemble. Value of 0 indicates forecast is no better or worse than persistence forecast.	1	$-\infty$

M = number of forecast/observation pairs

I = number of probability bins (11)

N = number of data pairs in bin i

p_e' = binned forecast probability (0.0, 0.1, …1.0) for bin i

$\bar{o}_i$ = observed relative frequency for bin i

$\bar{o}$ = climatological frequency (total occurrences / total forecasts)

Table 3. Description of metrics used for binary verification of stochastic forecast from ensemble suite.

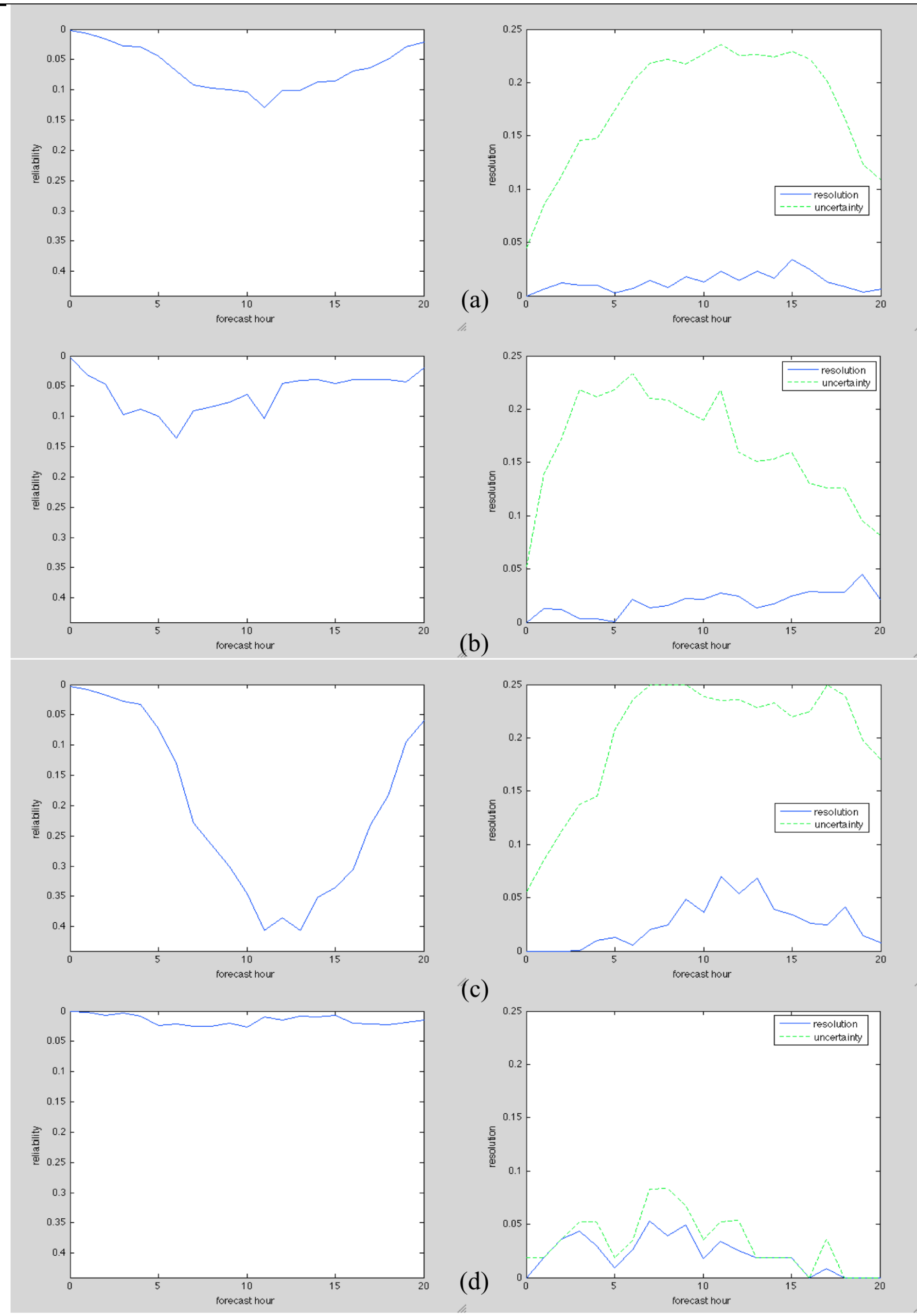


Figure 13. Binary verification of ensemble suite for inferred presence of cloud water. The left column shows reliability, and the right column shows the resolution and uncertainty for a) all sites, b) coastal sites, c) Central Valley sites, and d) mountainous sites.

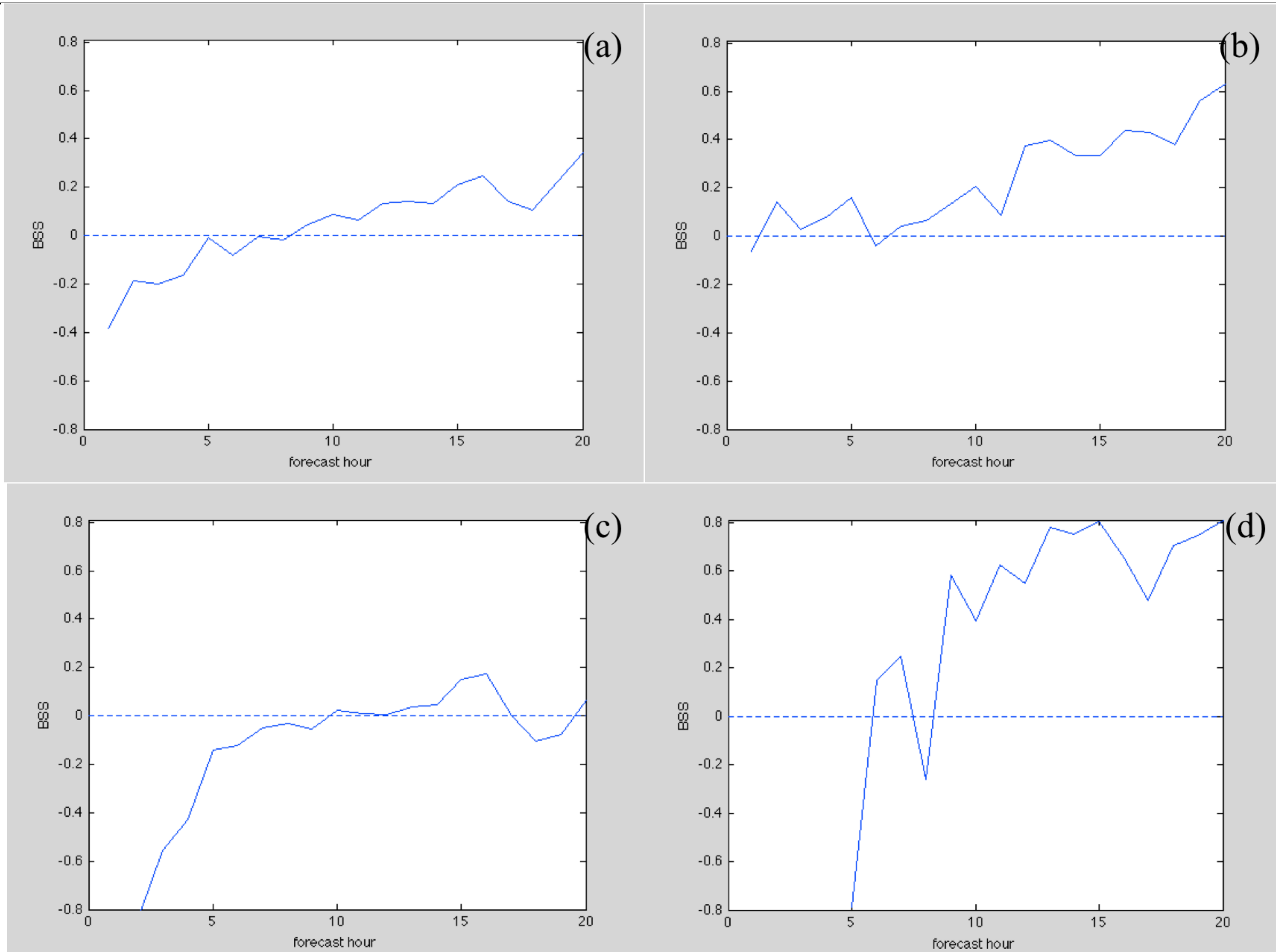
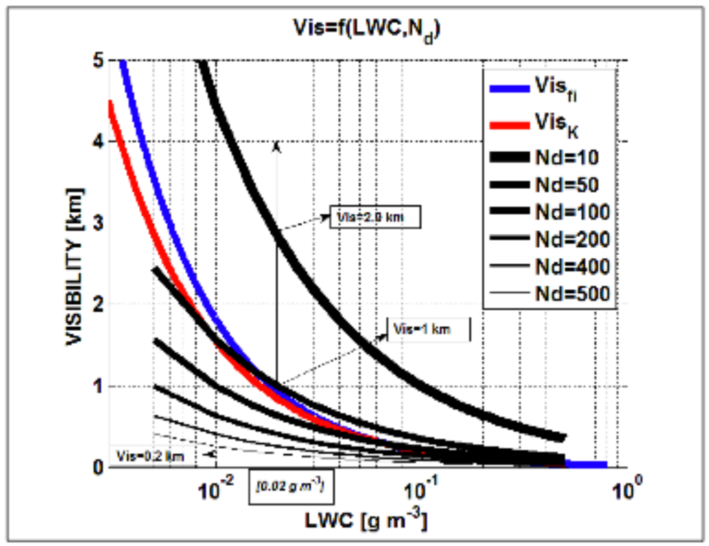


Figure 14. Brier Skill Score for the inferred presence of cloud water, using persistence as the reference forecast: a) all sites, b) coastal sites, c) Central Valley sites, and d) mountainous sites.



Visibility vs LWC for various droplet number concentrations (from Gultepe et al 2006)