

Verification of BC Hydro's short- and long-range inflow forecasts

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Adam Gobena & Frank Weber
Hydrology & Technical Services Group
Generation Resource Management

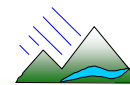
BC hydro 
FOR GENERATIONS



hydrology & technical services

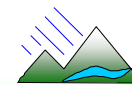
Outline

- Motivation & Objectives
- Data, methods, assumptions and limitations
- Highlights of results
- Summary and recommendations



Objective & Motivation

- ✓ Verification of BC Hydro's operational reservoir inflow forecasts
- ✓ As part of the project, an inflow forecast verification toolbox was designed.
 - *Hydrologic Forecast Verification System (HFVS)*: Short- & long-range; deterministic & probabilistic; statistical & process-oriented model forecast verification capabilities
- ✓ ***Why do we verify forecasts?***
 - User awareness
 - How good (or bad) are our forecasts?
 - How good (or bad) are competing models?
 - Understand sources of skill and uncertainty in forecasts
 - Identify targets when forecasts are skilful or not
 - Track evolution of forecast skill over time (*not performed here*)
 - Provide direction for future R&D



Operational Inflow Forecast Archive

- ✓ Operational short-range forecasts for 20 projects (UBCWM)
 - Jan 1, 2003 – Dec 31, 2010
- ✓ Long-range forecasts for Mica and Williston projects
 - ESP (UBCWM-based volume forecasts)
 - ✓ Mica: 1980 – 2010 (operational)
 - ✓ Williston: 1986 – 2010 (operational)
 - VoDCa (Statistical volume forecasts)
 - ✓ Mica: 1966 to 2002 (hindcasts) & 2007 to 2010 (operational)
 - ✓ Williston: 1973 to 2003 (hindcasts) & 2007 to 2010 (operational)
- ✓ Verifying “observations” are calculated inflows; QC’d to WY2007 and raw to end of 2010



Assumptions & Limitations

- ✓ Observations and forecasts were assumed to be homogeneous in time.
- *Short-range forecast verification*
 - ☒ Impact of any changes in weather forecasting process on inflow forecasts was not taken into account.
- *Long-range forecast verification*
 - ☒ *ESP*: Impact of changes in forecast model versions, input & output processing techniques and forecasters was not accounted for.
 - ☒ *VoDCa*: impact of hindcasts (generated with high quality data but with no forecaster updating) vs. operational forecasts (produced with non-QC'd data but with possible forecaster updating) was not accounted for.
 - ☒ Uncertainty in verification statistics due to sample size not analyzed
- ✓ Process-based model forecasts are based on old to very old model versions

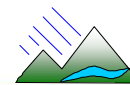
Analysis details

Short-range verification statistics were computed for each lead time &:

- Entire forecast
- Hydrologic seasons (Winter: Jan-Mar; Spring: Apr-Jun; Summer: Jul-Sep; Fall: Oct-Dec)
- High flows (observed flows > 90th percentile of 1971-2000 climatology)
- Rising / receding flows (for observed flows > 50th percentile of 1971-2000 climatology)

Long-range verification statistics were computed for:

- Entire forecast for each forecast issue date (Jan – Aug), for monthly & residual Feb-Sep targets



BCH Hydrologic Forecast Verification System

File Output Help

Data Specification

Project Folder Browse

Observed Data File Browse

Forecast Data File Browse

Forecast Source Info

Forecast Issue Date Info

Observations Forecasts

Time Step Daily Daily

Unit of Measurement cms - Cubic meter per second cms - Cubic meter per second

Verification Data Preparation

Verification Start Date YYYY MM DD Info

Verification End Date Info

Extract Verification Data

Verification Specifications

Verification Horizon

Target Period

Unit of Measurement

Refine Verification Dates

Select Years Info

Select Months

Select Days

Select Weeks

Rising Limb of Hydrograph

Verification Metrics

Deterministic

Sample Size

Bias

Relative Bias (%)

Minimum Error

Relative Minimum Error (%)

Maximum Error

Relative Maximum Error (%)

Mean Absolute Error

Relative MAE (%)

Root Mean Square Error

Relative RMSE (%)

Standard Error

Clim MAE Skill Score (%)

Pers MAE Skill Score (%)

Clim RMSE Skill Score (%)

Pers RMSE Skill Score (%)

Correlation Coefficient

Modify Parameters

Ensemble

Continuous Ranked Probability Score

CRPS Skill Score (%)

Relative Operating Characteristic

Reliability Diagram

Forecast Error Diagram

Mean Capture Rate Diagram

Probability Integral Transform

Spread-Error Diagram

Relative Economic Value

Modify Parameters

Evaluate Metrics

metrics used

Metrics selected for this work emphasize forecast bias, accuracy, skill, discrimination, and reliability.

Deterministic forecast verification

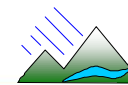
Overall performance: Bias, Mean absolute error, MAE Skill score

High flows: Hit rate, False alarm ratio

Probabilistic forecast verification

Overall performance: CRPS skill score, ensemble spread-error relationships,

Diagnostics: PIT (*not discussed here*)



Some of the verification metrics used

Metrics selected for this work emphasize forecast bias, accuracy, skill, discrimination, and reliability.

Bias (or Mean error) – a measure of correspondence between the average observation and the average forecast; is zero for unbiased forecasts.

$$Bias = \bar{y} - \bar{o}$$

Mean absolute error (MAE) – a measure of correspondence between individual forecasts and observations; **measure of accuracy**; is zero for a perfect forecast.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - o_i|$$

Hit rate - proportion of high flow events for which a forewarning was correctly issued.

False alarm ratio - proportion of predicted high flow warnings that turned out to be wrong.

Ranked probability score – analogous to MAE but is computed in probability space; **measure of accuracy for probabilistic forecasts**; is zero for a perfect forecast.

Skill score – relative accuracy measure evaluated against a control forecast; is zero or negative for a naïve forecast

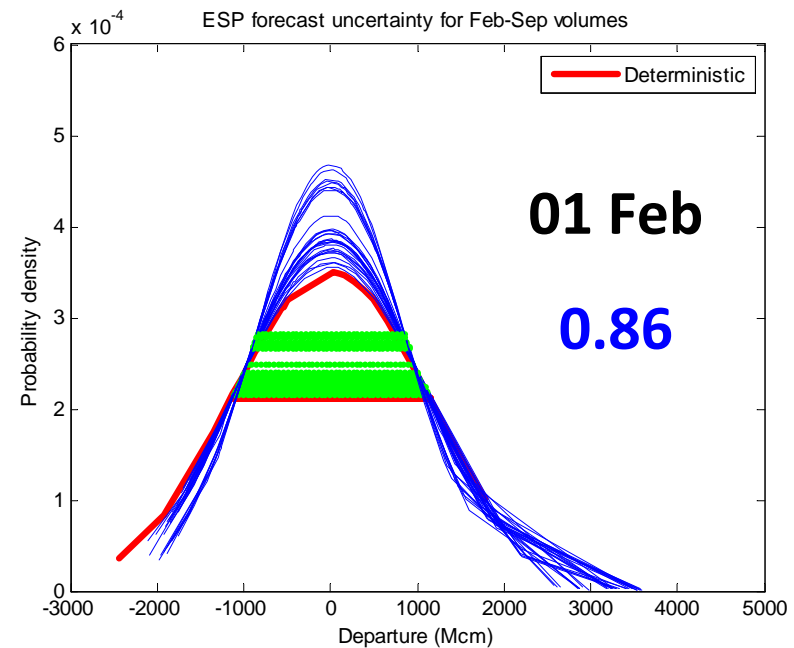
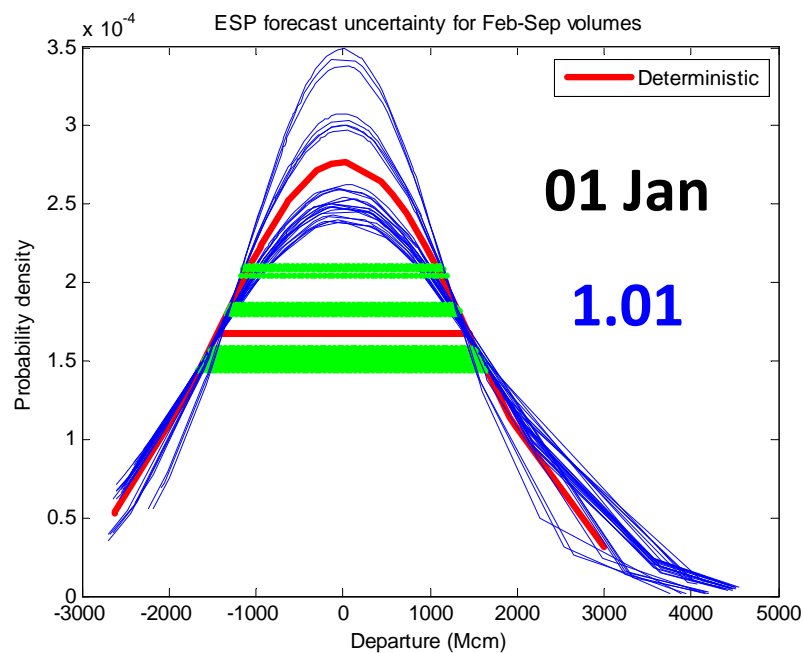
$$MAE_{SS} = 1 - MAE_{fcst} / MAE_{reference}$$



Forecast Spread to Error comparison

SD/RMSE ratio as a measure of the reliability of predictive intervals

Small ensemble spread (e.g., small SD) \leftrightarrow more confidence in ensemble mean (e.g., small RMSE) & the forecast in general.



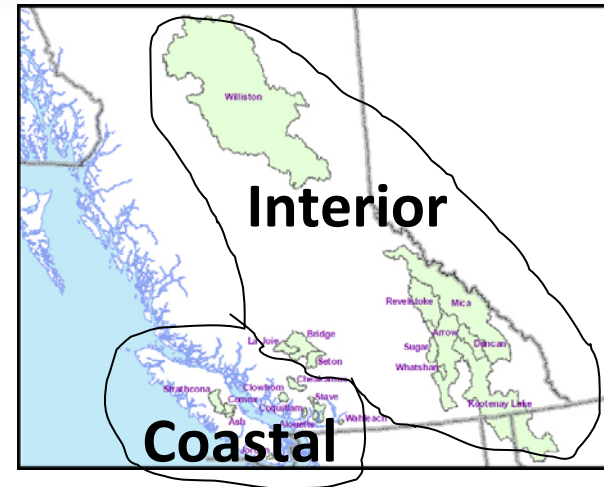
Short-range forecast verification highlights

For the purpose of this presentation, verification results were aggregated into coastal (Vancouver Island, Lower Mainland & South Coast) and interior (Bridge, Columbia/Kootenay and Williston) separately.

Something to note when interpreting regional statistics: Hydrologic characteristics for the two regions are vastly different!

Coastal basins: typically small; are characterized by primarily rainfall-driven, flashy response

Interior basins: typically large; are characterized by primarily snowmelt-driven response

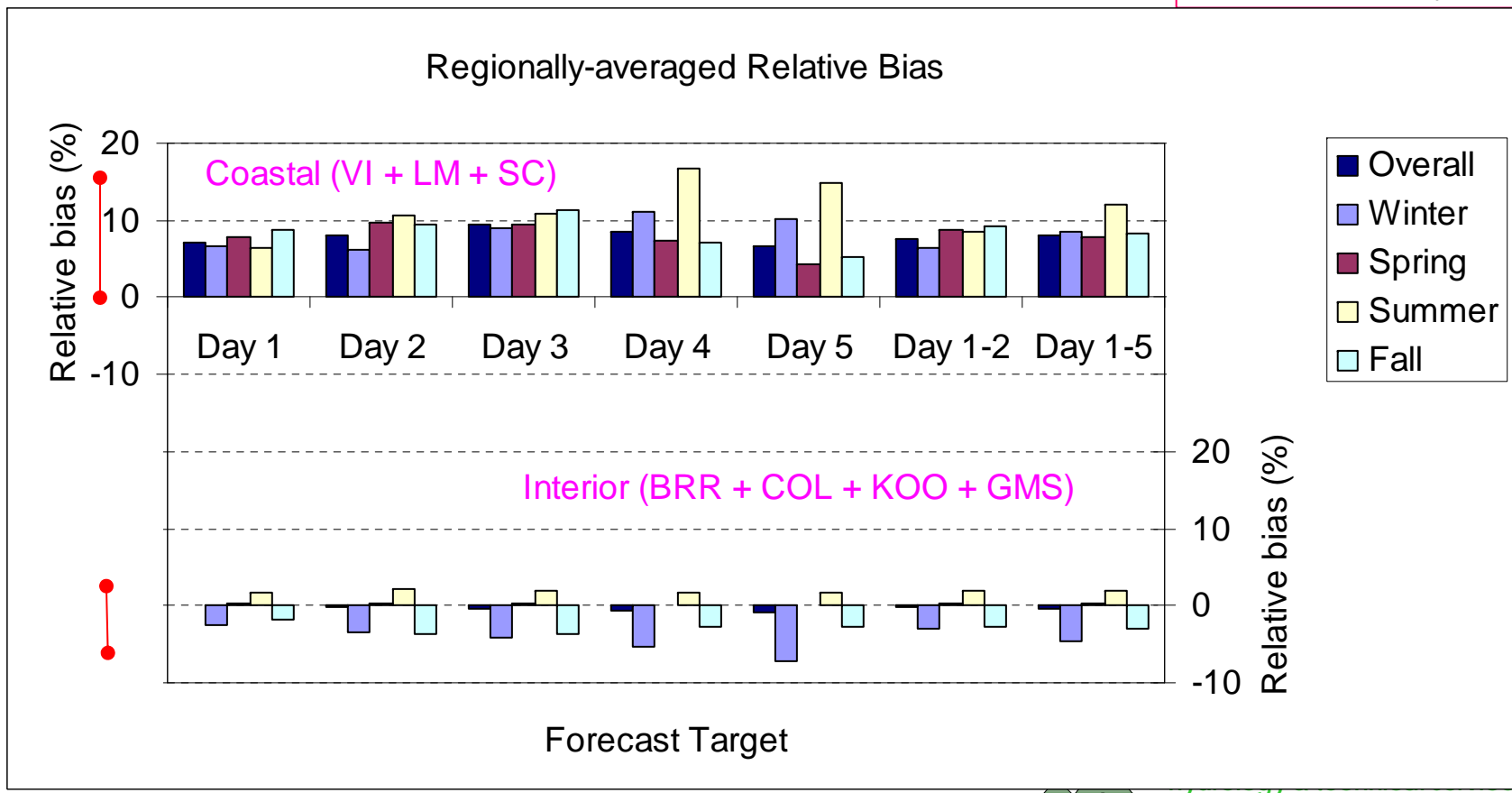


Short-range: Forecast bias relative to observed mean

Unbiased forecasts have bias of zero.

- (1) Coastal basins are typically over-forecasted all year round
- (2) Basins that stand out: Jordan, Alouette, Stave, Coquitlam

$$rBias(\%) = 100 \frac{Bias(cms)}{\overline{Q}_o(cms)}$$

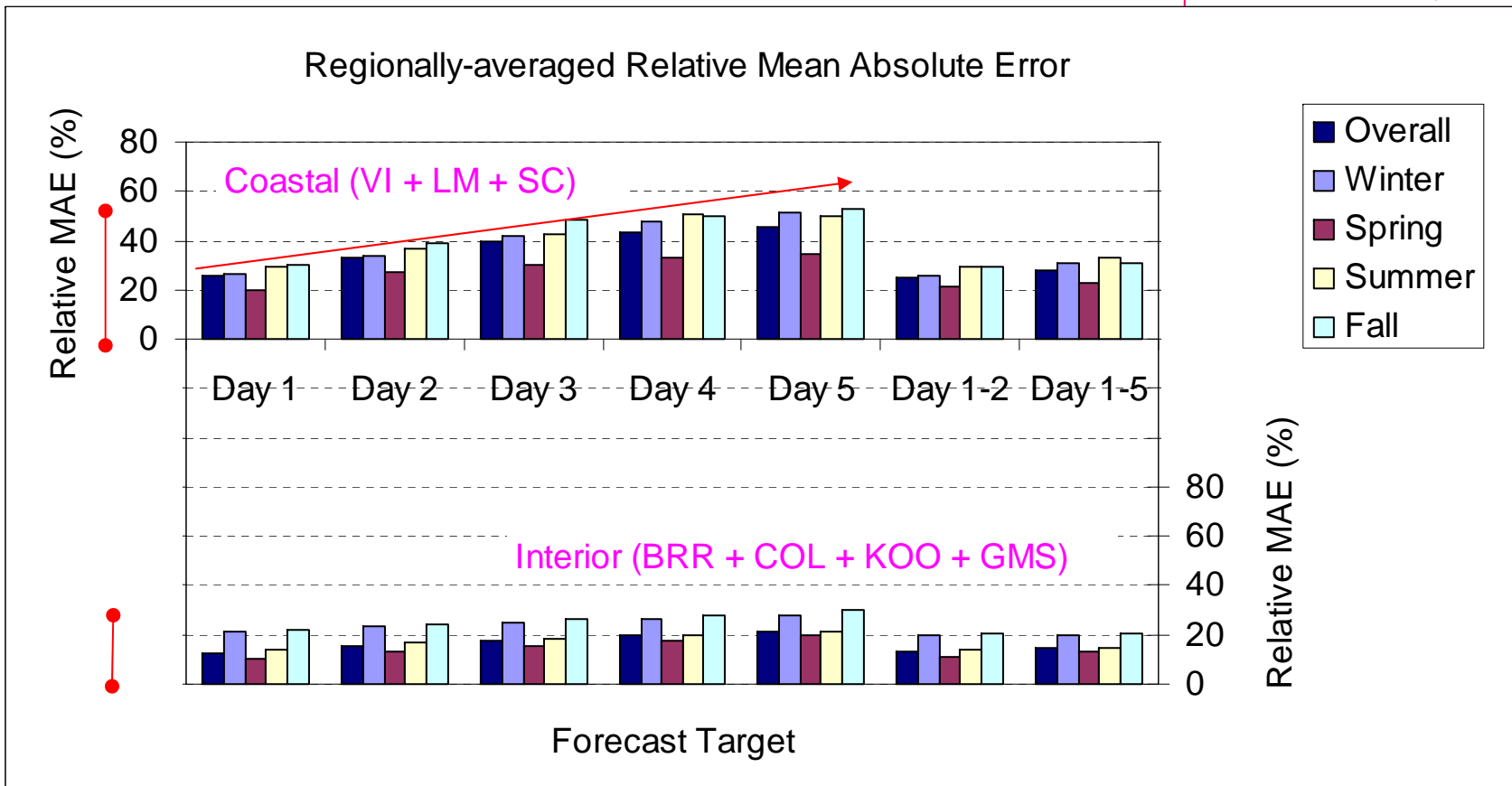


Short-range: Forecast accuracy relative to observed mean

Accurate forecasts have MAE of zero

- Interior projects forecasts are more accurate for all seasons
- Forecast accuracy deteriorates with lead time

$$rMAE(\%) = 100 \frac{MAE(cms)}{\bar{Q}_o(cms)}$$

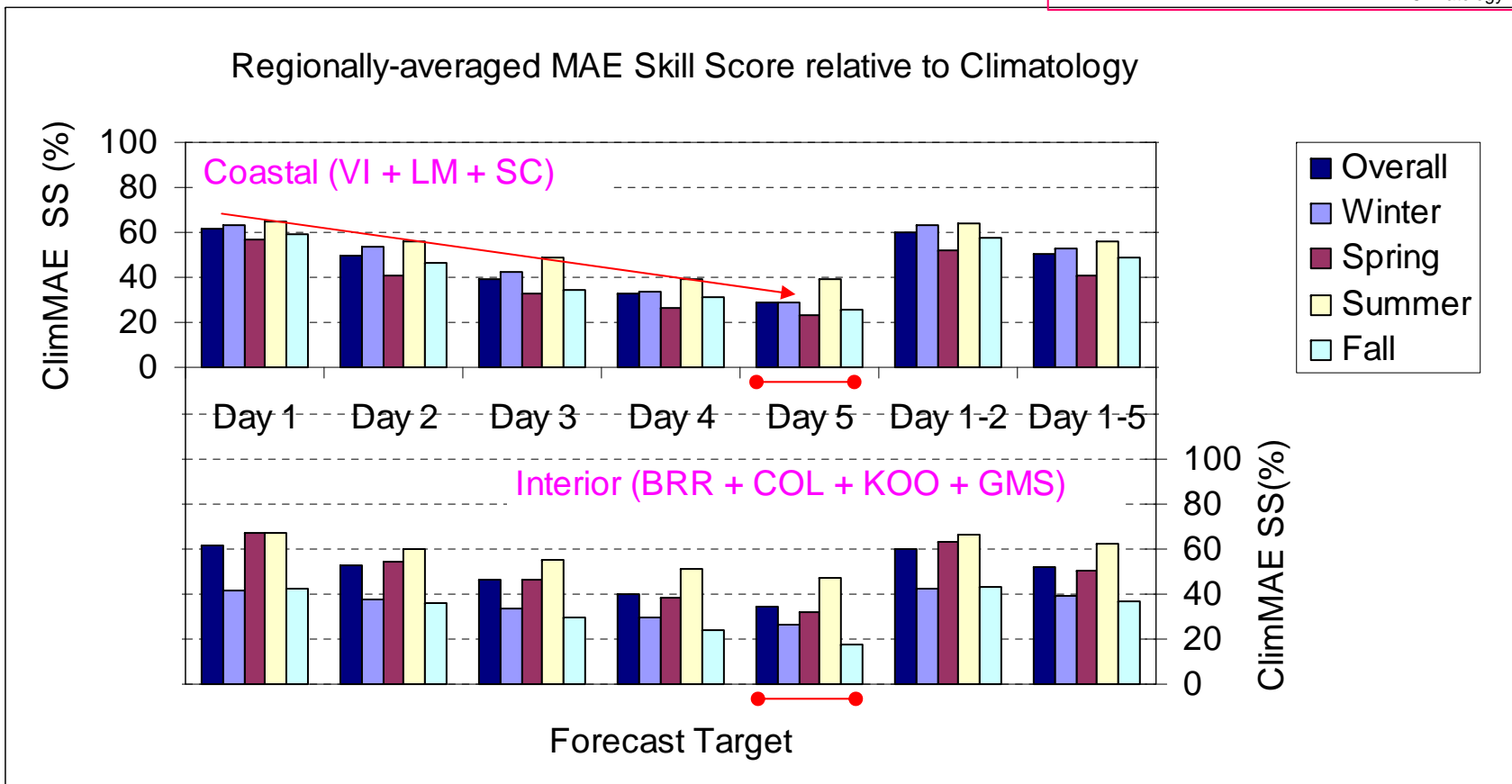


Short-range: Forecast MAE skill score relative to climatology

Perfect forecasts have skill of 100%; -ve skill if climatology is better

- Forecasts for both regions are better than climatology for all lead times & seasons

$$MAESS(\%) = 100(1 - \frac{MAE_{Forecast}}{MAE_{Climatology}})$$

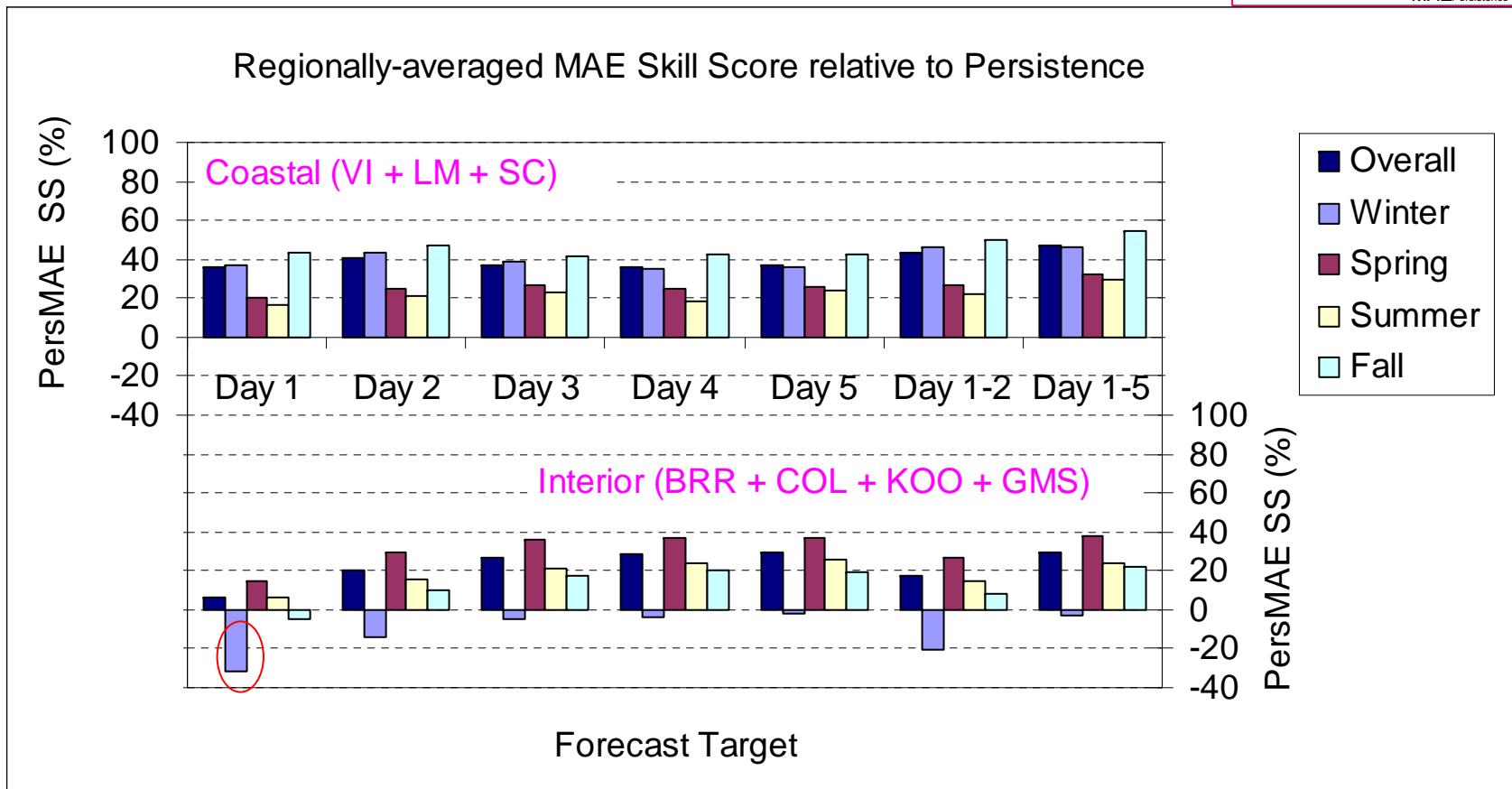


Short-range: Forecast MAE skill score relative to persistence

Perfect forecasts have skill of 100%; -ve skill if persistence is better

- Forecasts are skillful for most lead times & seasons
- Forecast skill for interior basins is affected by uncertainty in observed inflows

$$MAESS(\%) = 100(1 - \frac{MAE_{Forecast}}{MAE_{Persistence}})$$

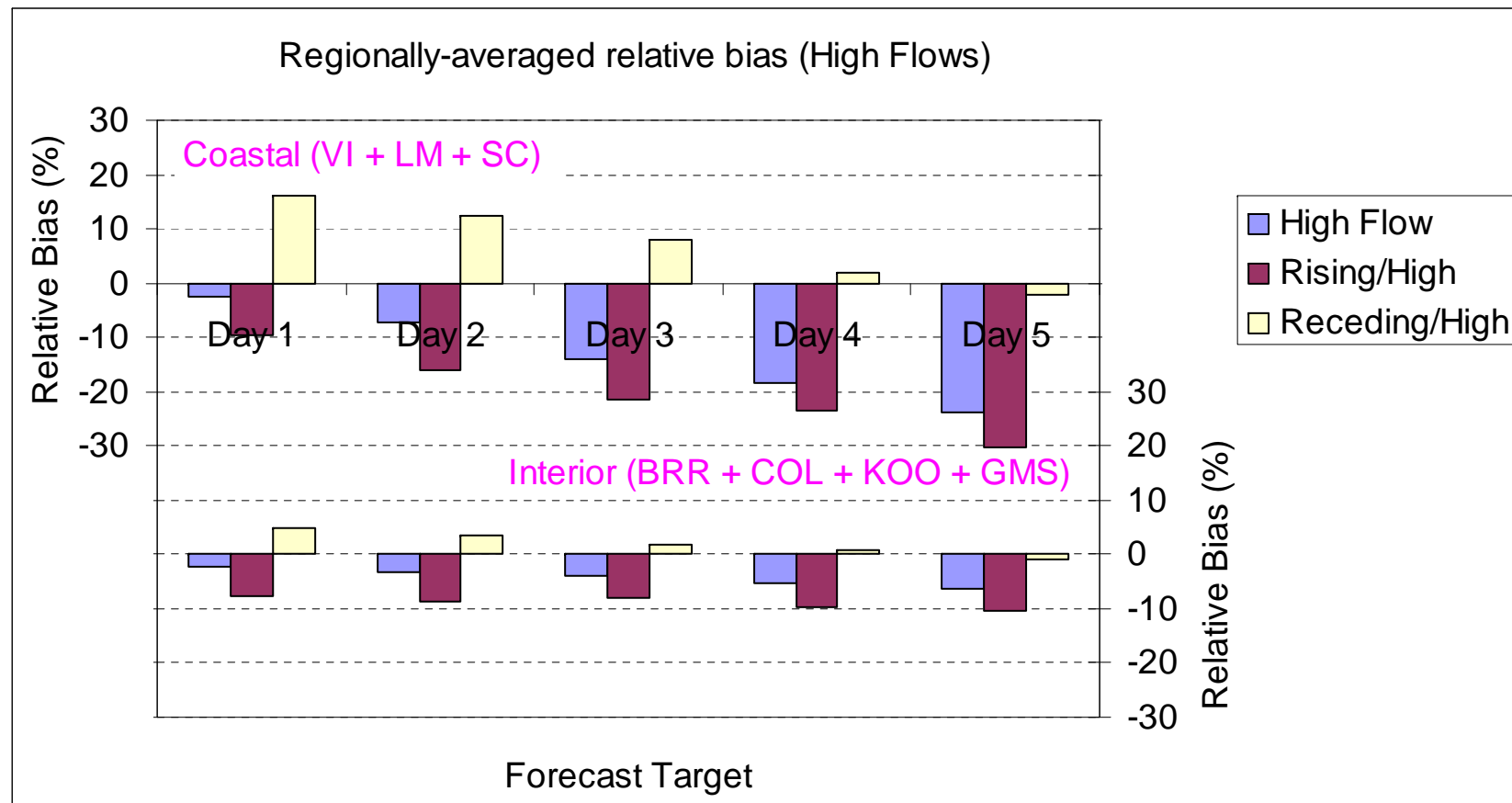


Short-range: High Flow forecast bias relative to observed mean

Unbiased forecasts have bias of zero

- High flows are generally under-forecasted
- Rising high flows are the worst offenders

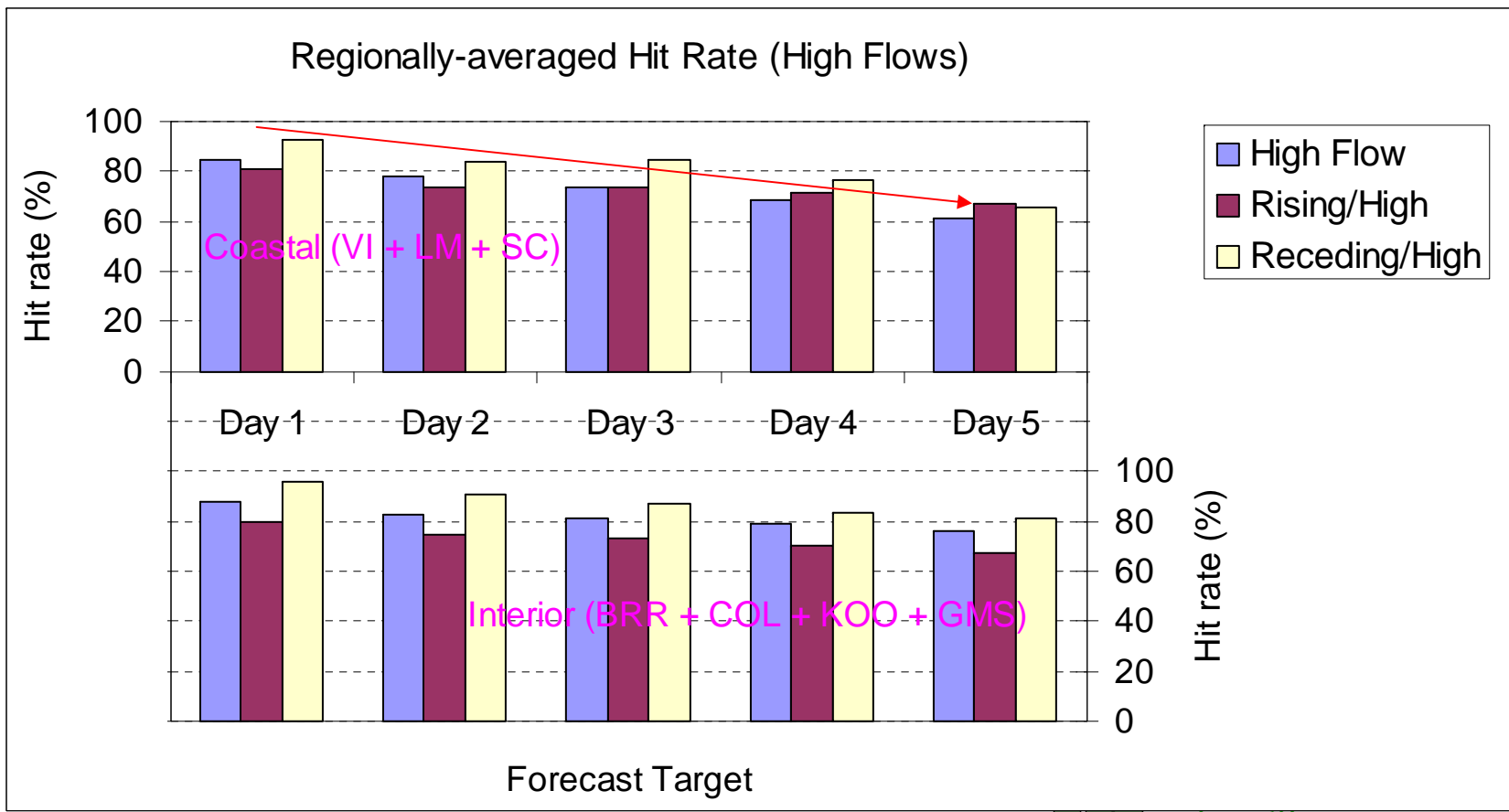
$$rBias(\%) = 100 \frac{Bias(cms)}{\overline{Q_o}(cms)}$$



Short-range: categorical High Flow forecasts – hit rate

Forecasts have relatively high ability to forewarn high flow event occurrences out to day 5.

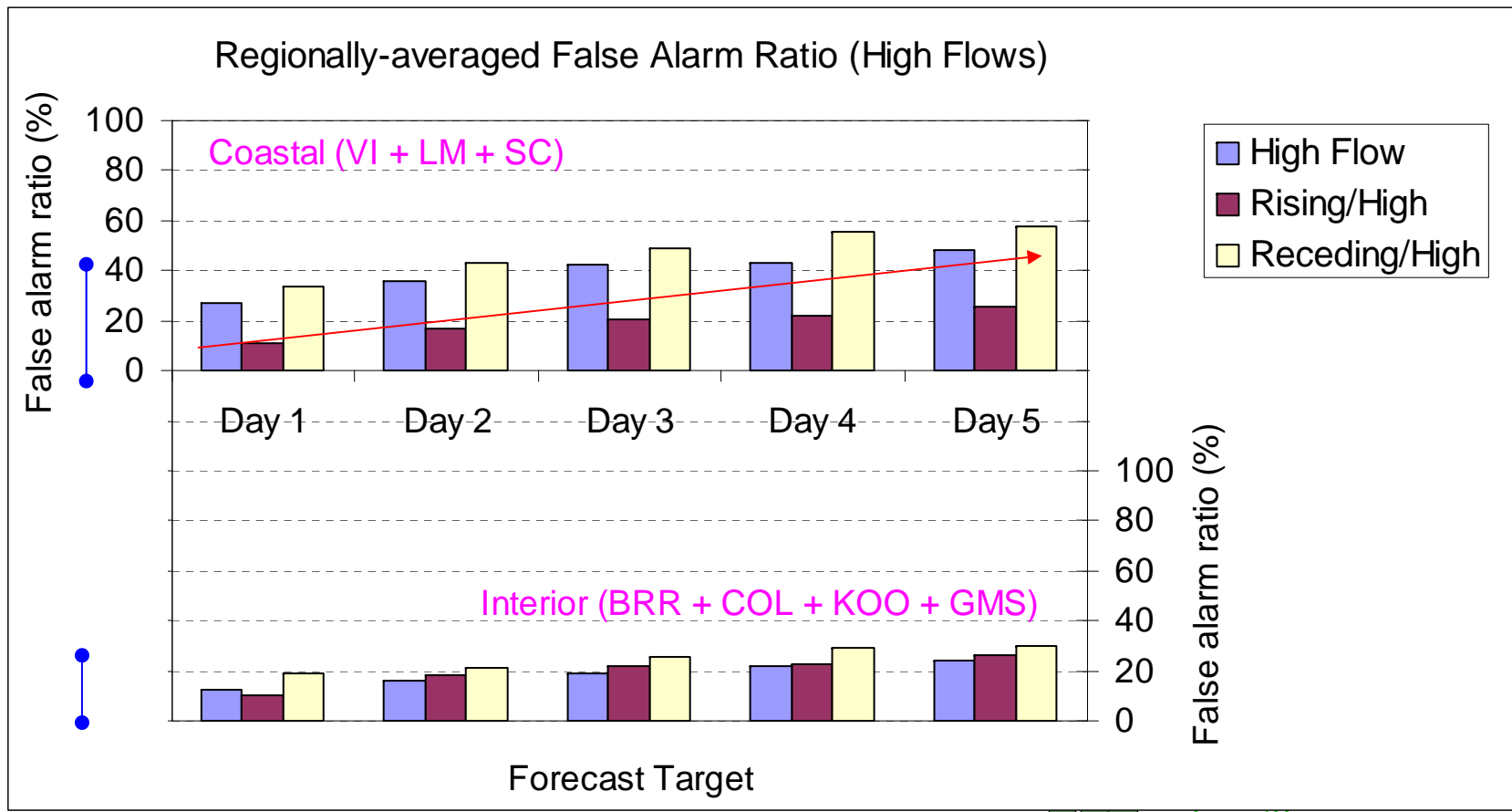
$$\text{HitRate}(\%) = 100 \frac{\# \text{ hits}}{\# \text{ hits} + \# \text{ misses}}$$



Short-range: categorical High Flow forecasts – false alarm ratio

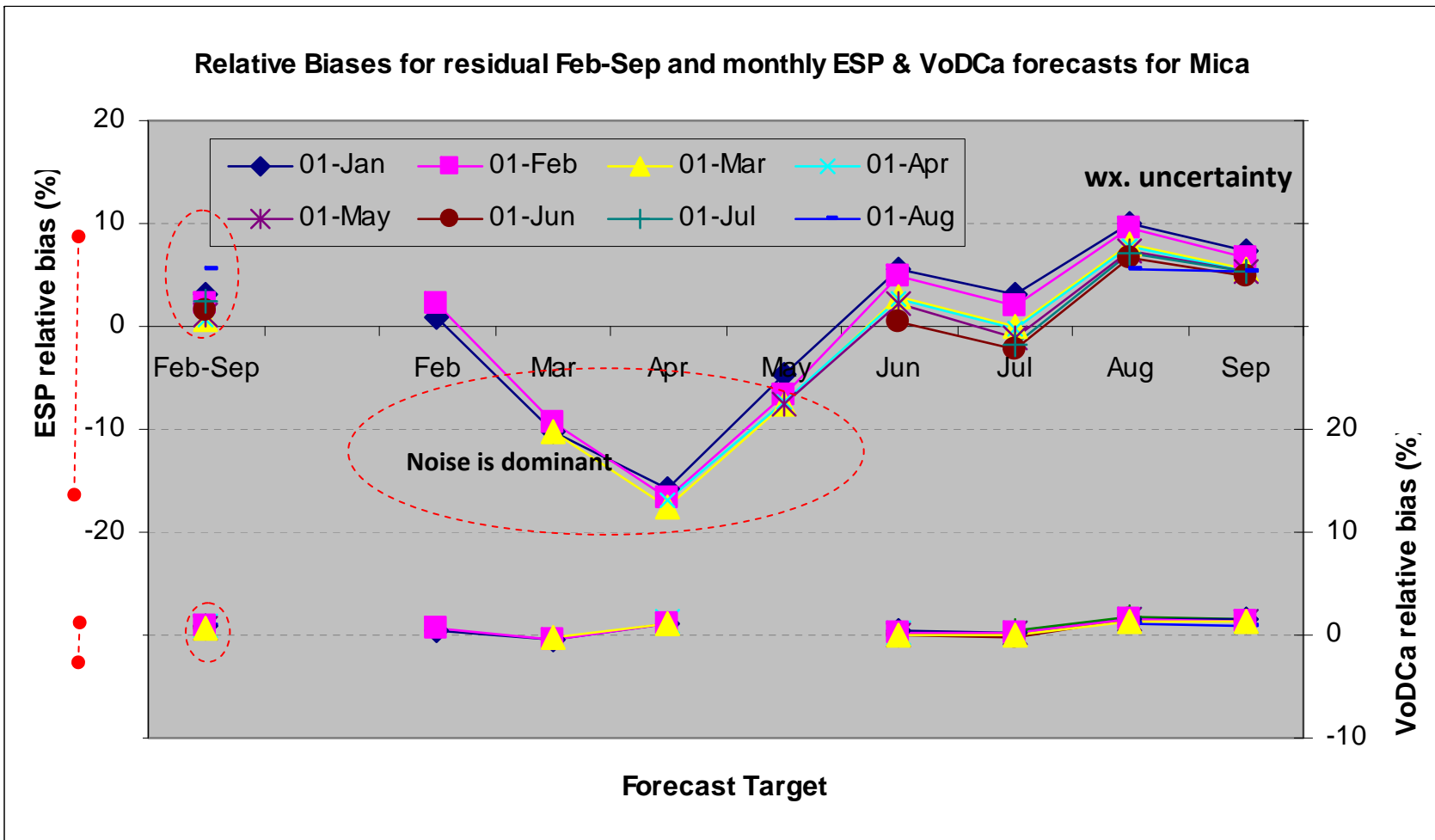
Perfectly reliable: 100% hit rate; 0% false alarm ratio
 For coastal basins, high hit rates come at the expense of relatively high false warnings

$$FAR(\%) = 100 \frac{\# \text{ false alarms}}{\# \text{ hits} + \# \text{ false alarms}}$$



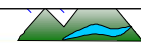
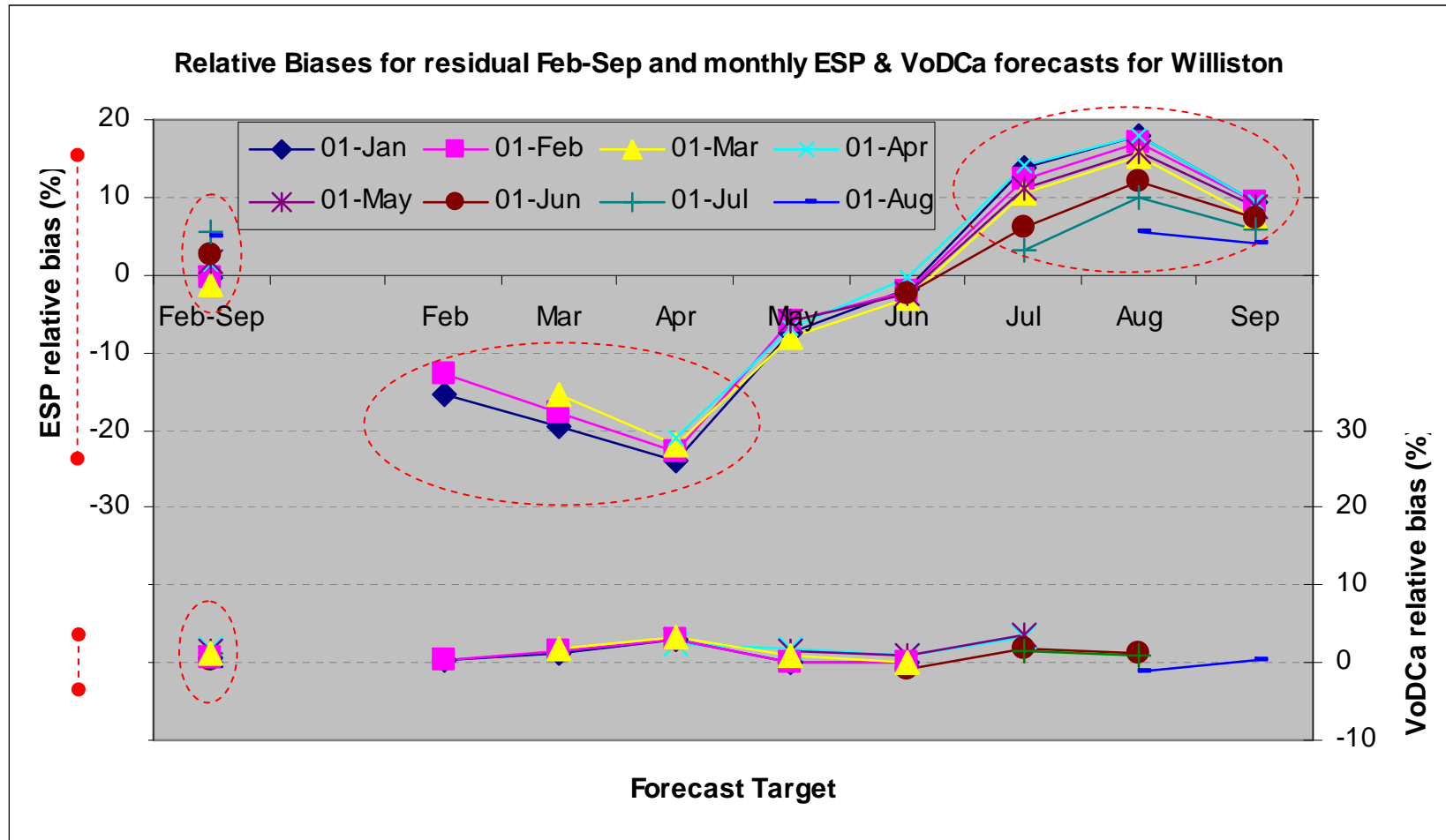
Long-range: Forecast biases for Mica

For ESP forecasts, Feb-Sep biases are small but biases in monthly forecast can be substantial; VoDCa forecasts are essentially unbiased.



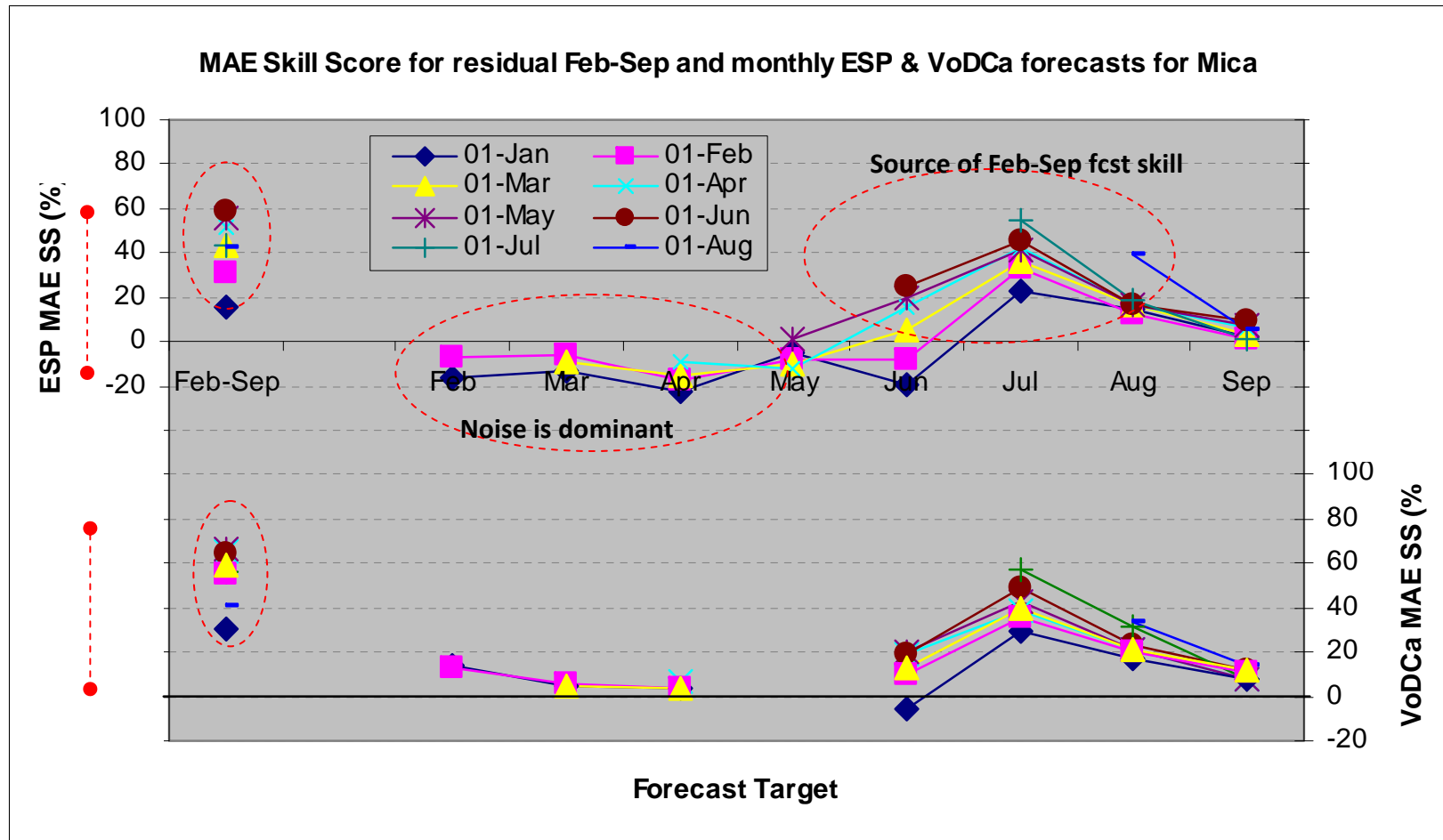
Long-range: Forecast biases for Williston

For ESP forecasts, Feb-Sep biases are small but biases in monthly forecast can be substantial; VoDCa forecasts are essentially unbiased.



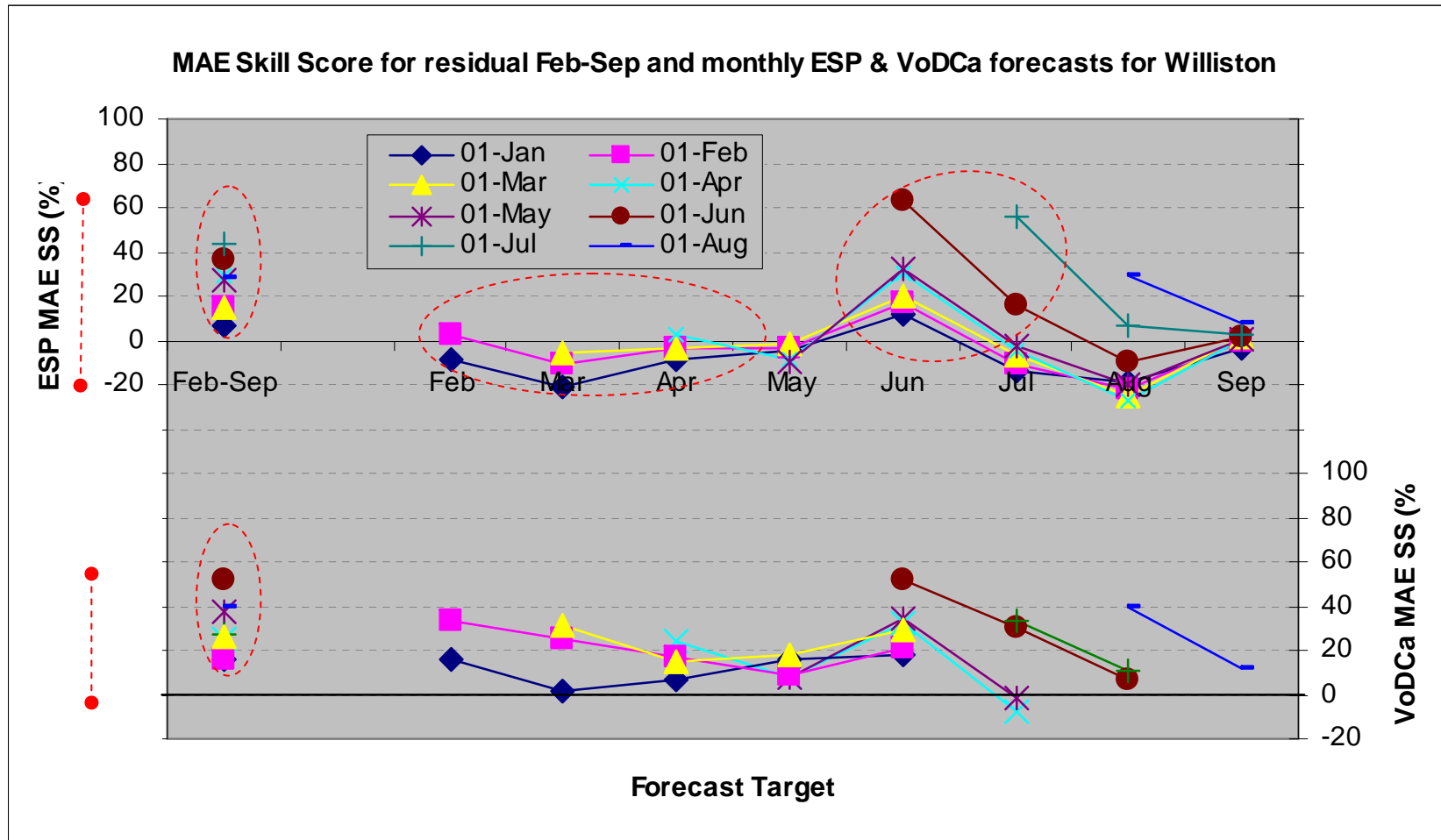
Long-range: Forecast skill relative to climatology for Mica

VoDCa forecast skill is marginally better than ESP. Feb-Sep forecasts from both models draw skill from forecasts for the freshet period.



Long-range: Forecast skill relative to climatology for Williston

VoDCa forecast skill is marginally better than ESP. Feb-Sep forecasts from both models draw skill from forecasts for the freshet period.

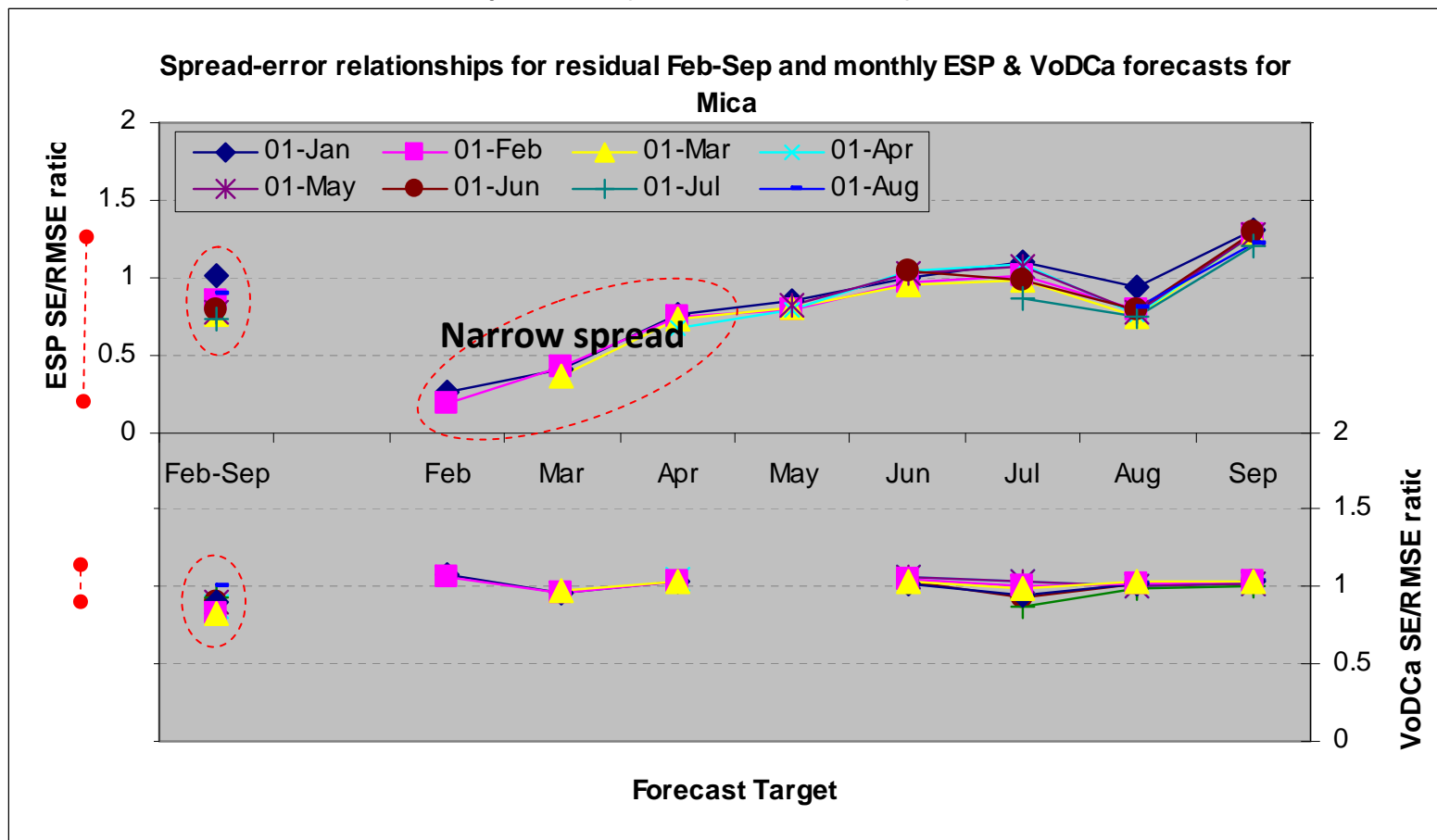


Long-range: Forecast spread-error relationships for Mica

SE/RMSE ratio $\sim 1 \rightarrow$ predictive uncertainty is reliable.

SE/RMSE $> 1 \rightarrow$ over-dispersed (under-confident) forecast

SE/RMSE $< 1 \rightarrow$ under-dispersed (over-confident) forecast

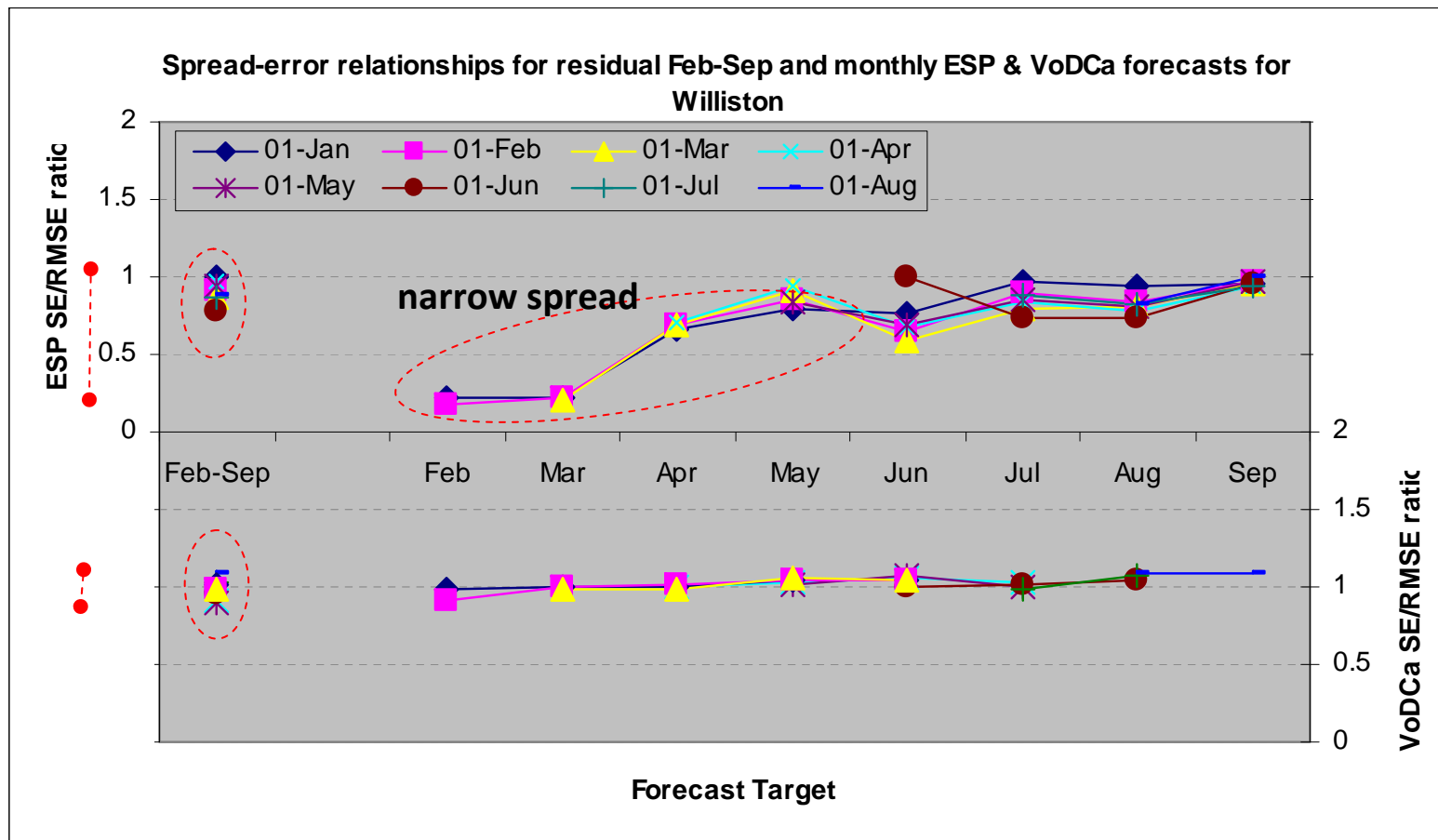


Long-range: Forecast spread-error relationships for Williston

SE/RMSE ratio $\sim 1 \rightarrow$ predictive uncertainty is reliable.

SE/RMSE > 1 : over-dispersed (under-confident) forecast

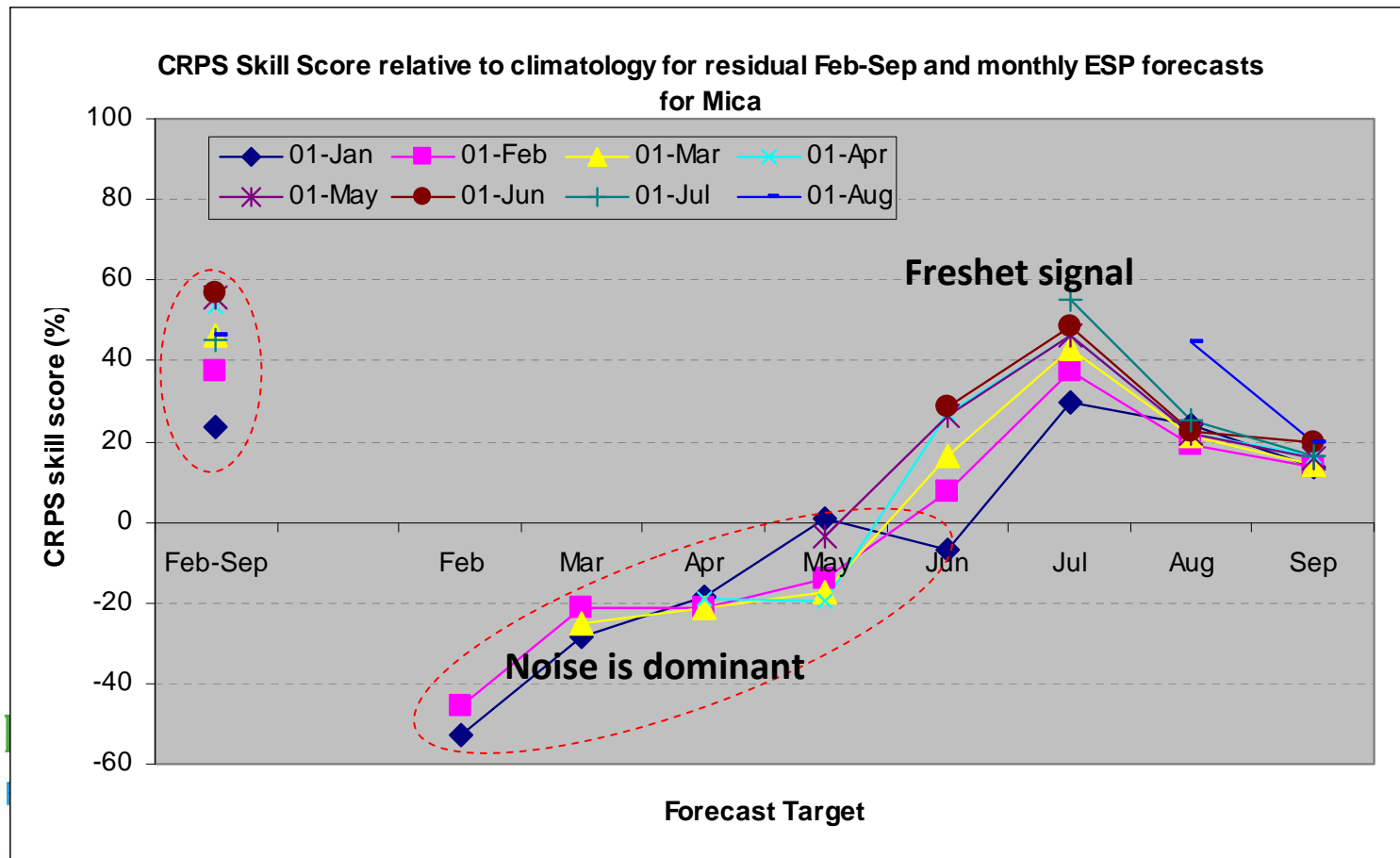
SE/RMSE < 1 : under-dispersed (over-confident) forecast



Long-range: CRPS skill score for Mica

CRPS > 0 → improvement over climatological forecast
 In spite of reliability issues, ESP forecasts for Feb-Sep volume forecasts are better than climatology; monthly forecasts for the freshet period are also skillful.

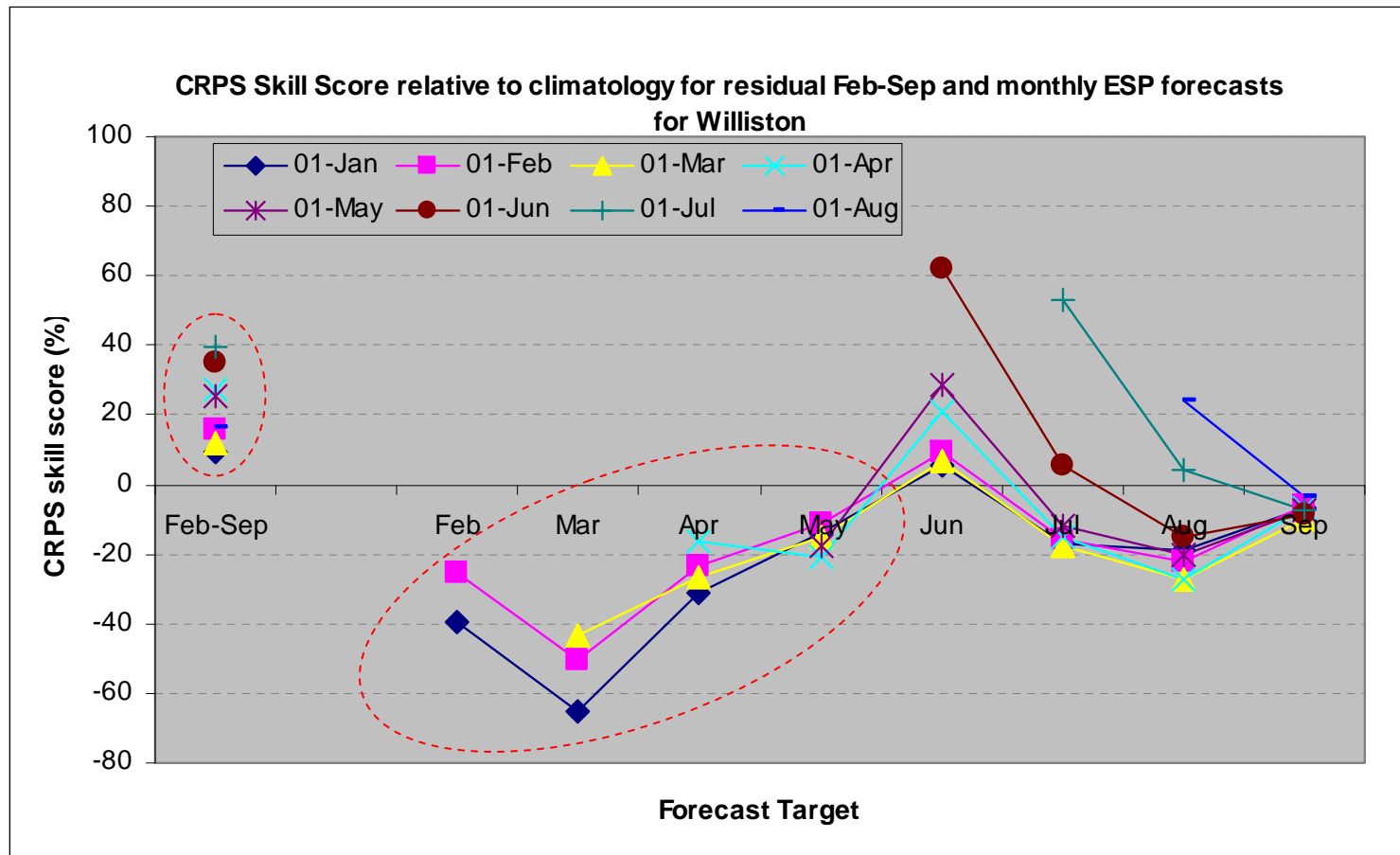
$$CRPS = \int_{-\infty}^{\infty} [F(y) - F_o(y)]^2 dx$$



Long-range: CRPS skill score for Williston

CRPS SS > 0 → improvement over climatological forecast

$$CRPS = \int_{-\infty}^{\infty} [F(y) - F_o(y)]^2 dx$$



Summary

The Positives

Short-range

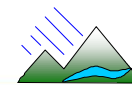
- overall forecast quality is good
- forecasts are skilful out to day 5
- good discrimination of high flow occurrences

Long-range

- VoDCa forecasts are unbiased
- VoDCa predictive uncertainty is good
- ESP residual Feb-Sep forecasts have small biases
- skill is good for peak flow months

The Negatives

- forecast biases for some coastal basins are of concern
- low flow forecasts are less skilful
- large bias in high flow forecasts, esp. for coastal basins
- high false alarm ratio of high flow forecasts for coastal basins
- ESP monthly forecast biases
- ESP predictive uncertainty
- low skill for winter and late summer



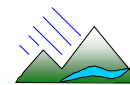
Work to date/ wish list for further work

- **Just completed:**

- UBCWMM recalibration aimed at reducing forecast biases
- Super-ensemble framework in place (can incorporate uncertainty due to wx fcst and/or observational sample size)

- **Wish List**

- Analyze performance of new calibrations for forecast bias
- Analyze the ESP super-ensemble framework for predictive uncertainty
- Analyze viability of ESP forecasting for hybrid watersheds
- Track operational ESP forecast performance with new model calibrations & new processing tools (bias correction, SWE adjustment)
- Attribute forecast errors to weather & hydrologic modeling
- Implement near real-time inflow quality procedures
- Evaluate the \$\$\$\$\$\$ value of forecasts**



Thank You!

