Week 3 Temperature Probabilistic Forecasts using Bayesian Processor of Ensemble

貝氏系集處理器應用於第三周溫度機率預報

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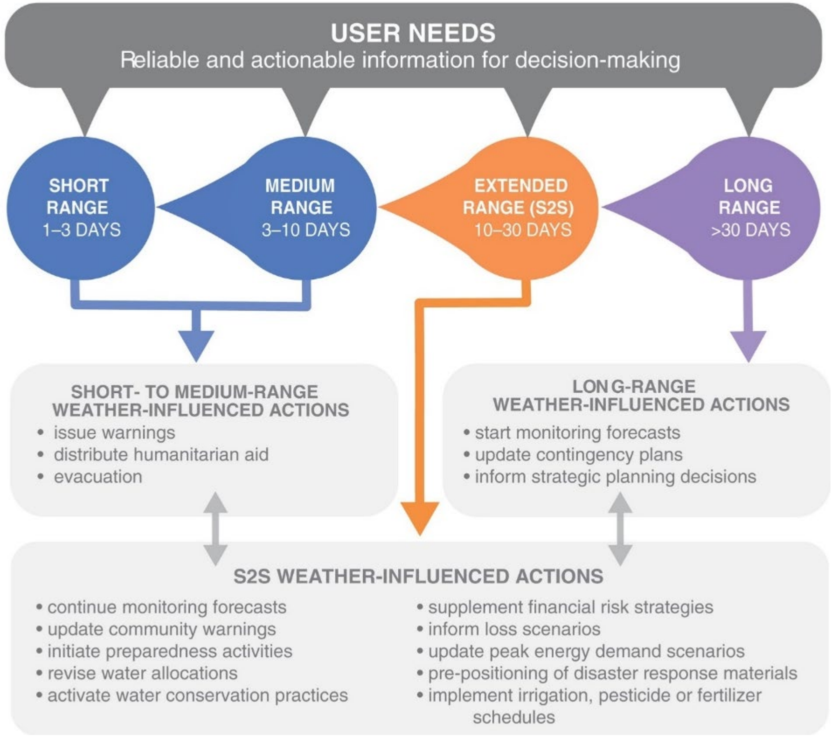
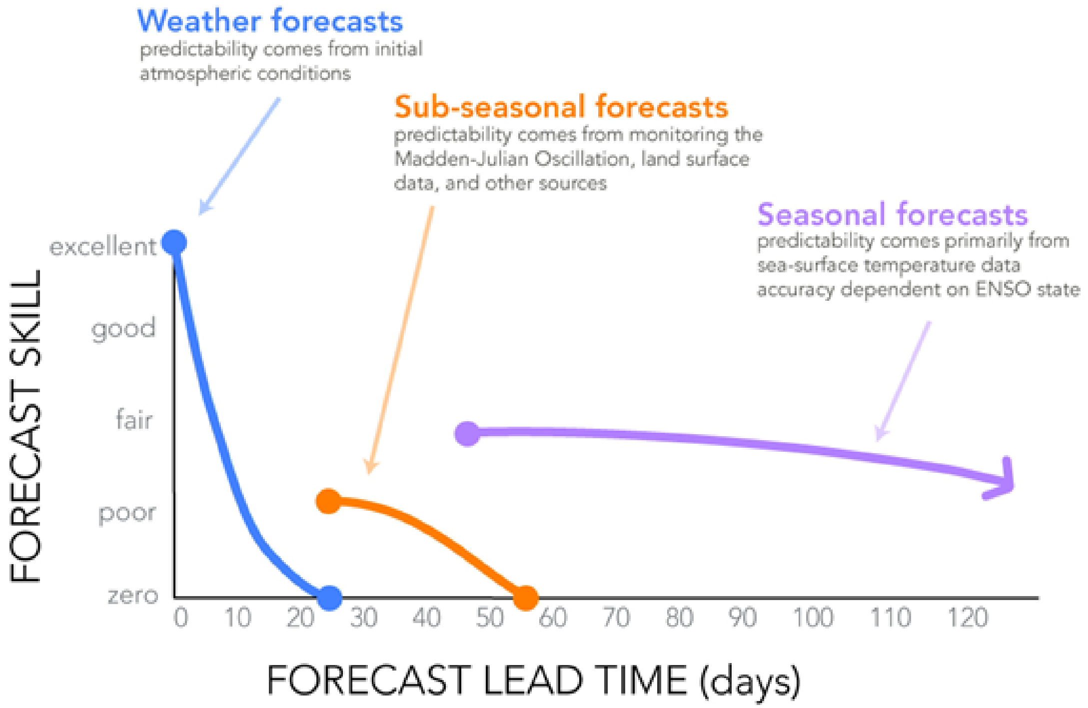
Outline

- Introduction
- Methodology
- Data and Results
- Conclusion and Future Work

Motivation





(White et al., (2017), Potential applications of subseasonal-to-seasonal (S2S) predictions)

<Potential Applications>

- Resource management on energy, agri/aqua culture and hydrological sectors.
- Early outlooks of climate-related public health incidents(e.g. Malaria, Dengue Fever).

<Challenges>

- “Desert Zone” of predictability
- Requirement of large hindcast sets of coupled ensemble model → Computational resource

Motivation

- Reforecasts (Hindcasts) are usually shorter than observation records, data fusion between a shorter model dataset and longer climatological dataset using rigorous Bayesian formulations may improve the performance of forecast after post-processing

  → **Saves computational power and storage.**

  → **Maximizes** the usefulness of limited data points.

- Various benchmarks indicates that the skill of numerical models **asymptotically closes to the skill of climatological distribution** as leadtime reaches the current predictability limit.

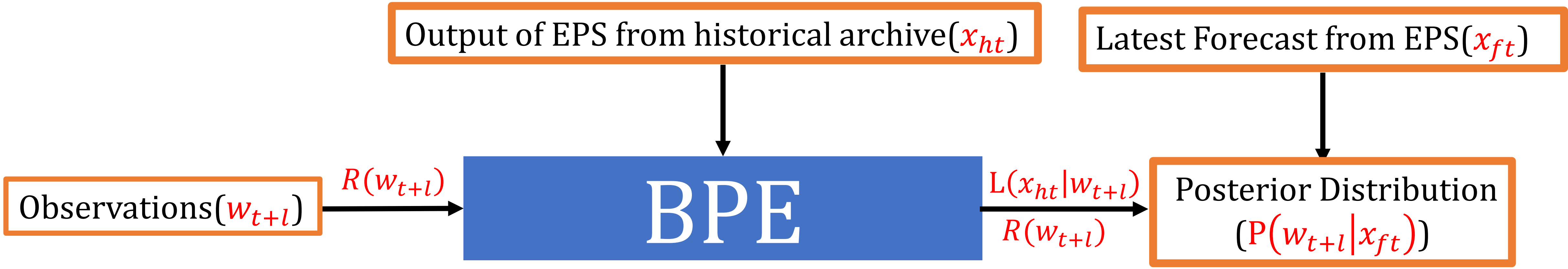
  → Fusing the climatological distribution can act as a **powerful constraint to the posterior to prevent overfitting** when the output of the numerical model is no longer informative as a predictor.

Introduction to Bayes Theorem

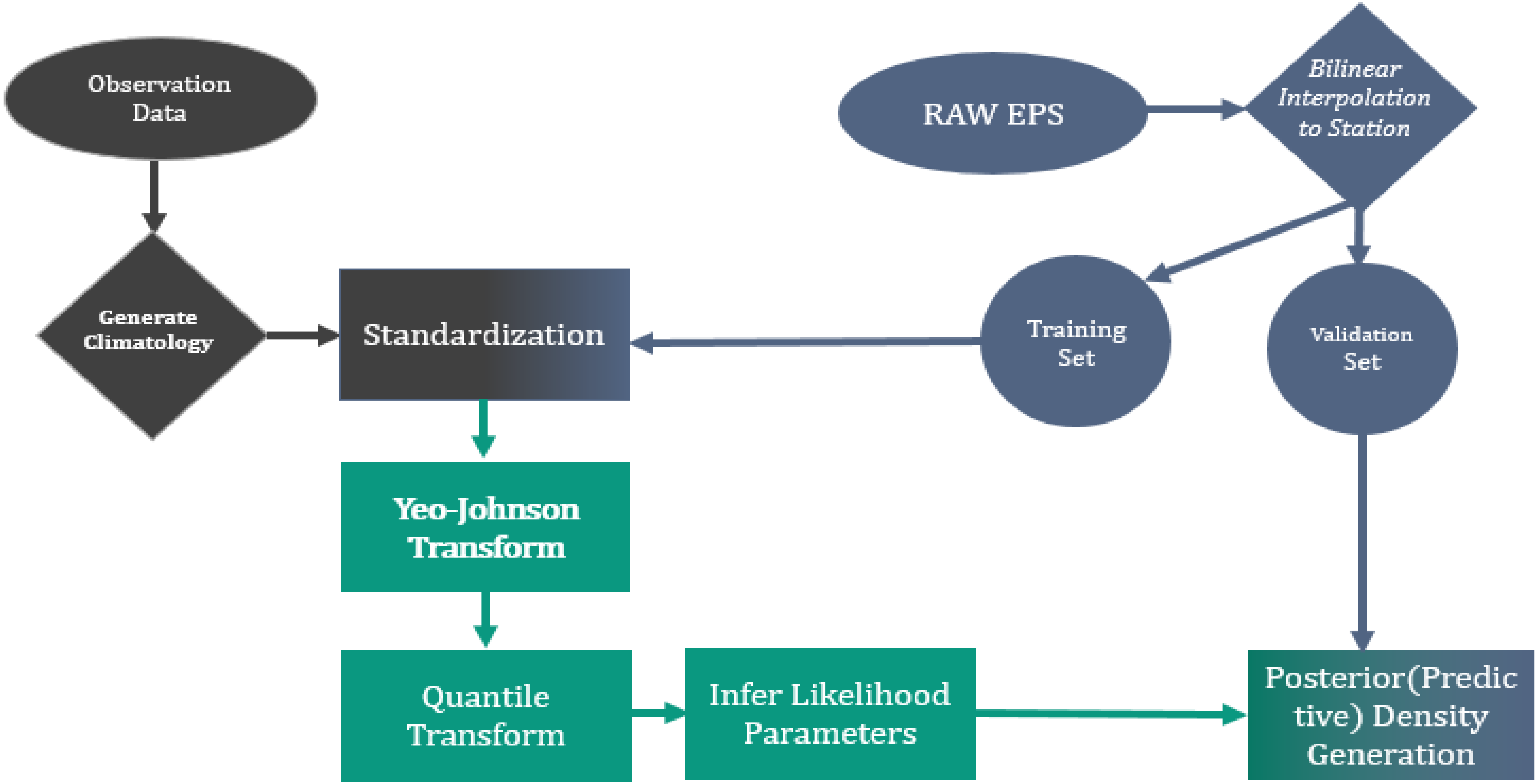
$$\boxed{\mathrm{P}\left(w_{t+l} \middle| x_{ft}\right) = \frac{\mathrm{L}(x_{ht}|w_{t+l})R(w_{t+l})}{H(x_{ht})}}$$

(Krzysztofowicz & Evans, 2008)

$x_{ht} \equiv$ vector of predictors
$w_{t+l} \equiv$ realization of predictand at time $t + l$
$\mathrm{L}(x_{ht}|w_{t+l}) \equiv$ Likelihood
$R(w_{t+l}) \equiv$ Prior (Climatology)
$\mathrm{P}\left(w_{t+l} \middle| x_{ft}\right) \equiv$ Posterior

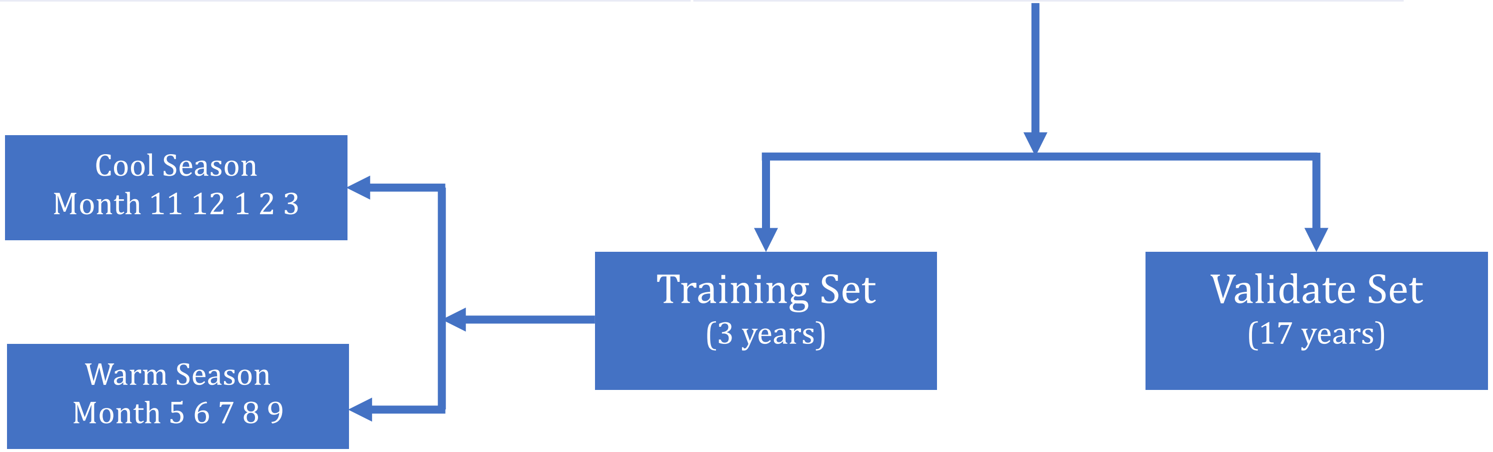


BPE Structure Overview



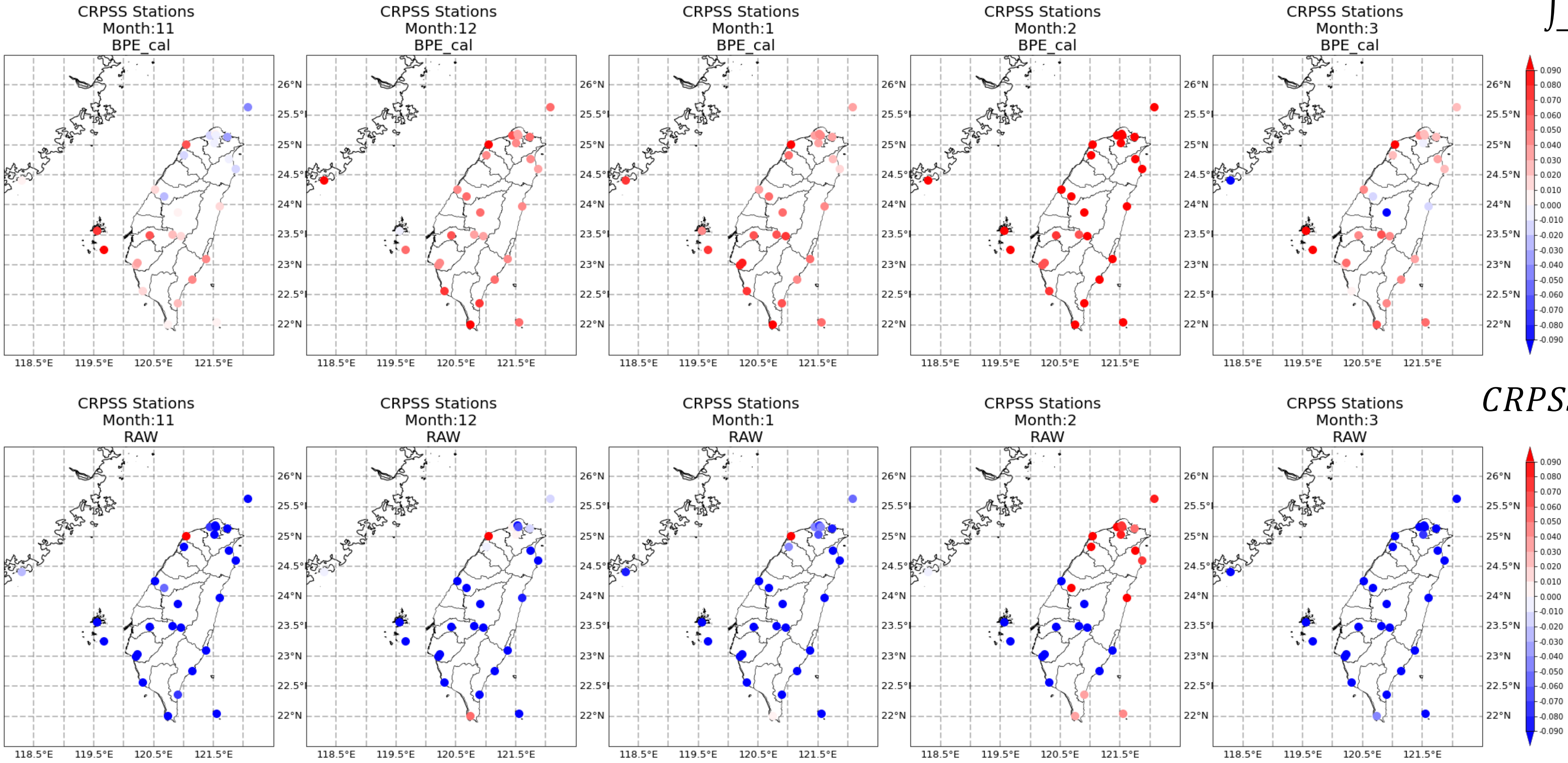
Data

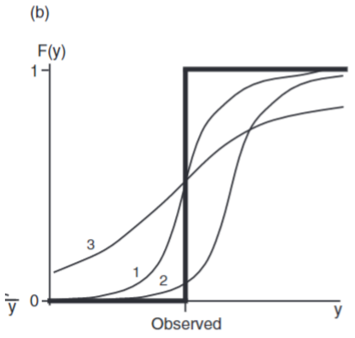
	Observation/Climatology	Model
Name	Station	NCEP_SubX Bilinear-Interpolated & Height corrected to station
Time Length	1989-2020/05	Forecast : 2017-07~2020/05 Hindcast: 1999-01~2016/12
Time Resolution	24 hours	24 hours
Member	1	10
Spatial Resolution	x	1°x1°
Variable	Tx (Predictand)	T2M (Predictor)



CRPSS – Cool Season

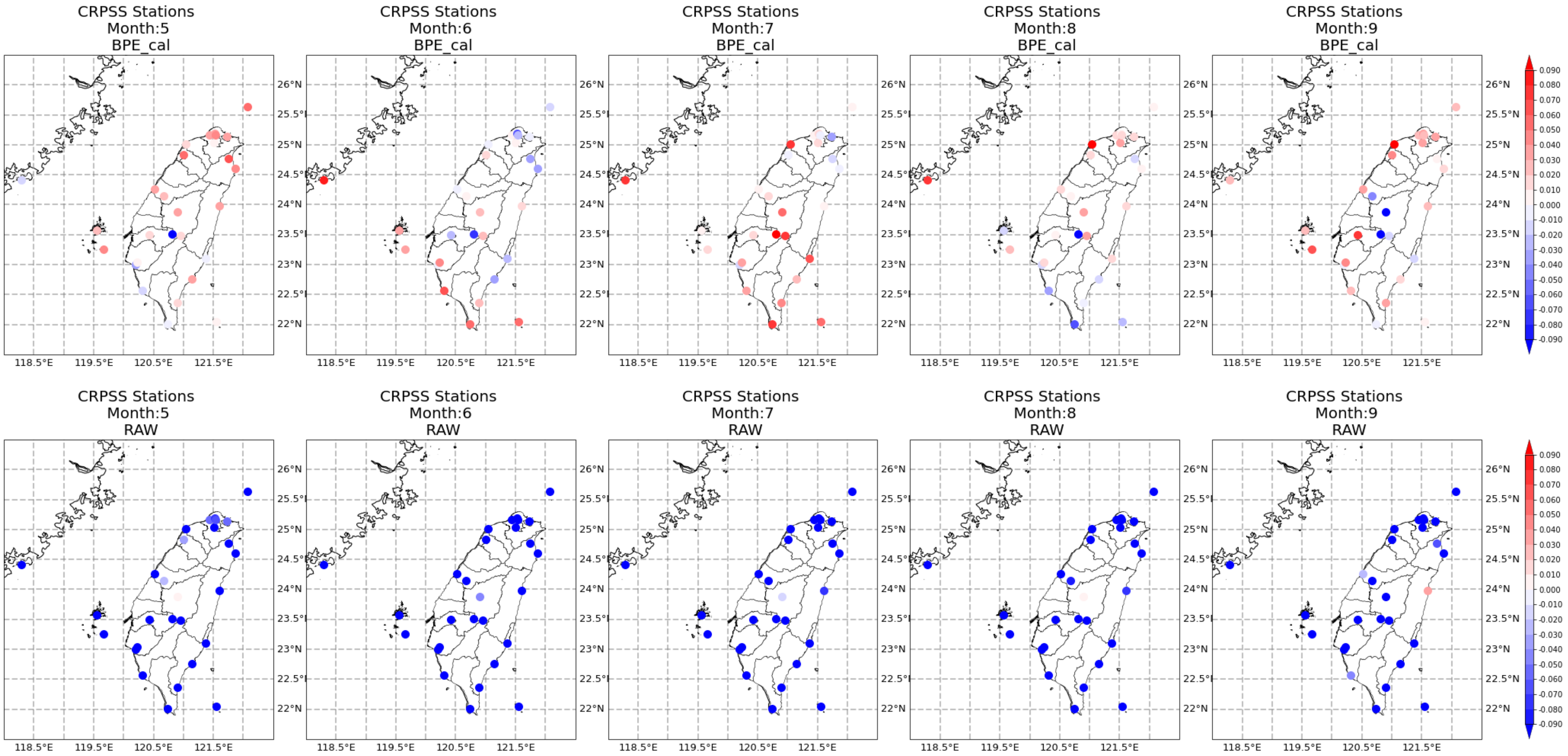
$$CRPS \equiv \int_{-\infty}^{\infty} [F(y) - H(y - o)]^2 dy$$



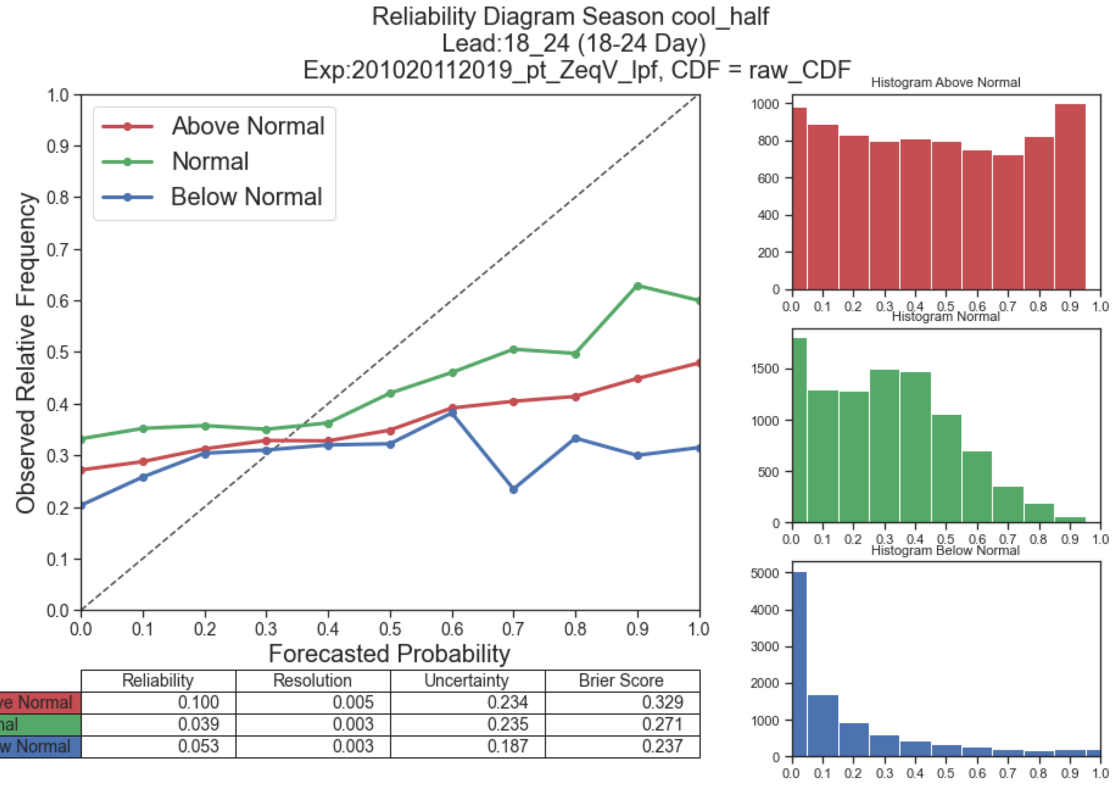


$$CRPSS = 1 - \frac{CRPS_{BPE}}{CRPS_{CLIM}}$$

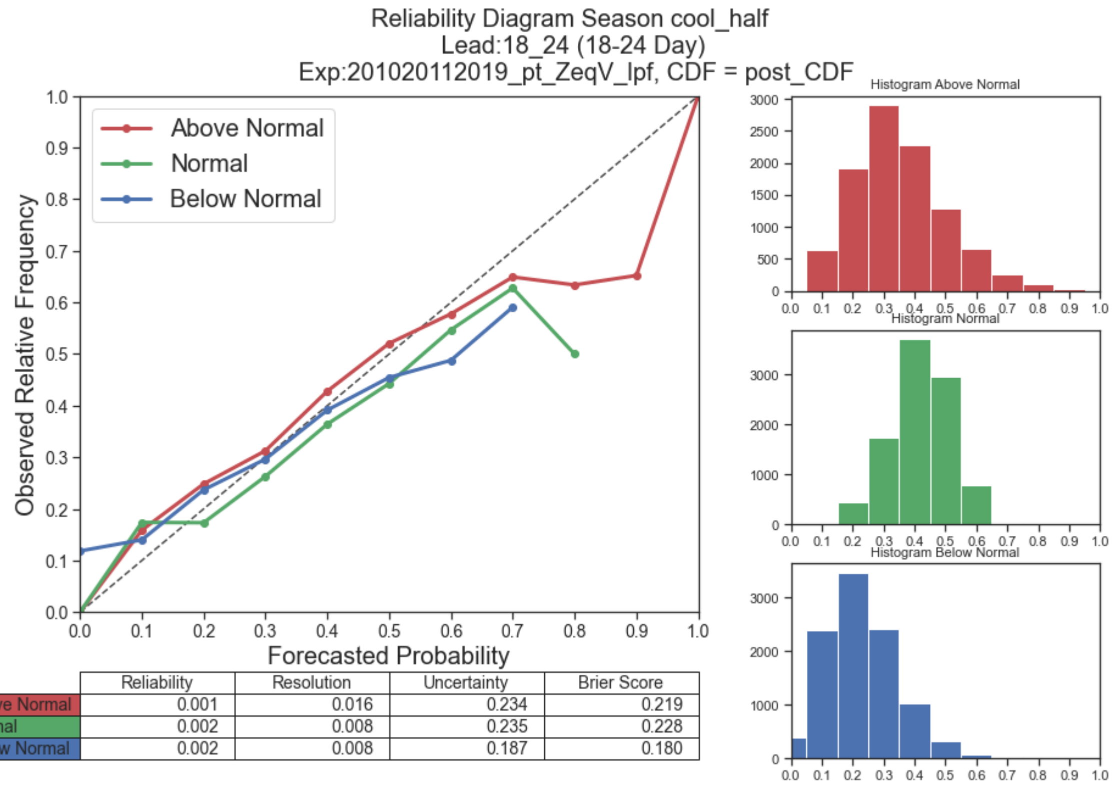
CRPSS – Warm Season



Reliability Diagram



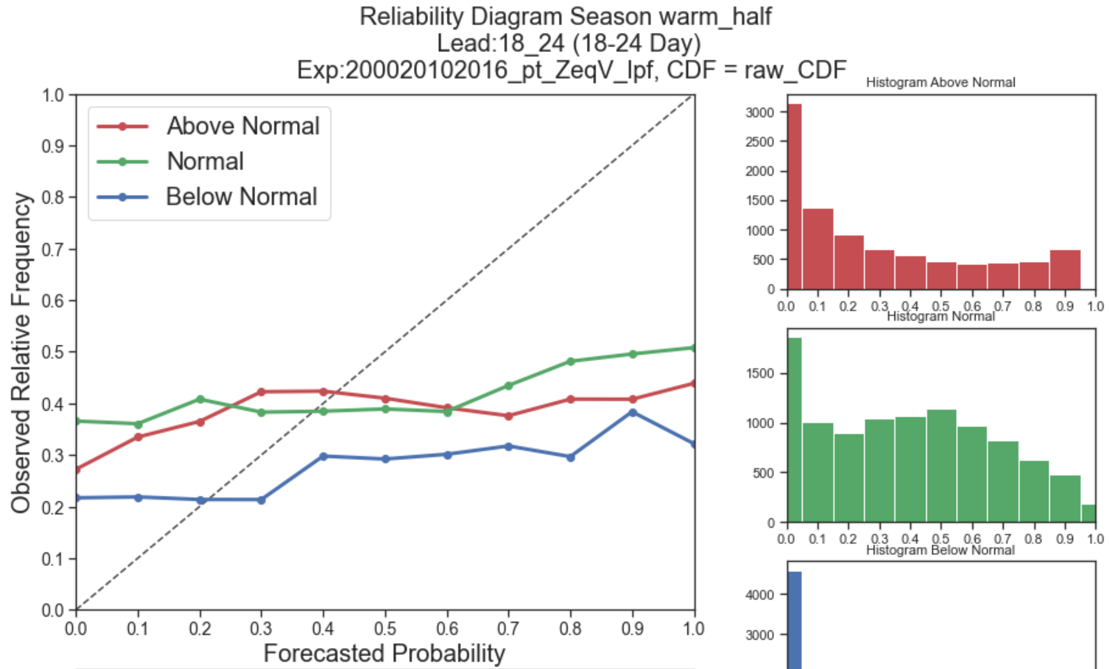
	Reliability	Resolution	Uncertainty	Brier Score
Above Normal	0.100	0.005	0.234	0.329
Normal	0.039	0.003	0.235	0.271
Below Normal	0.053	0.003	0.187	0.237



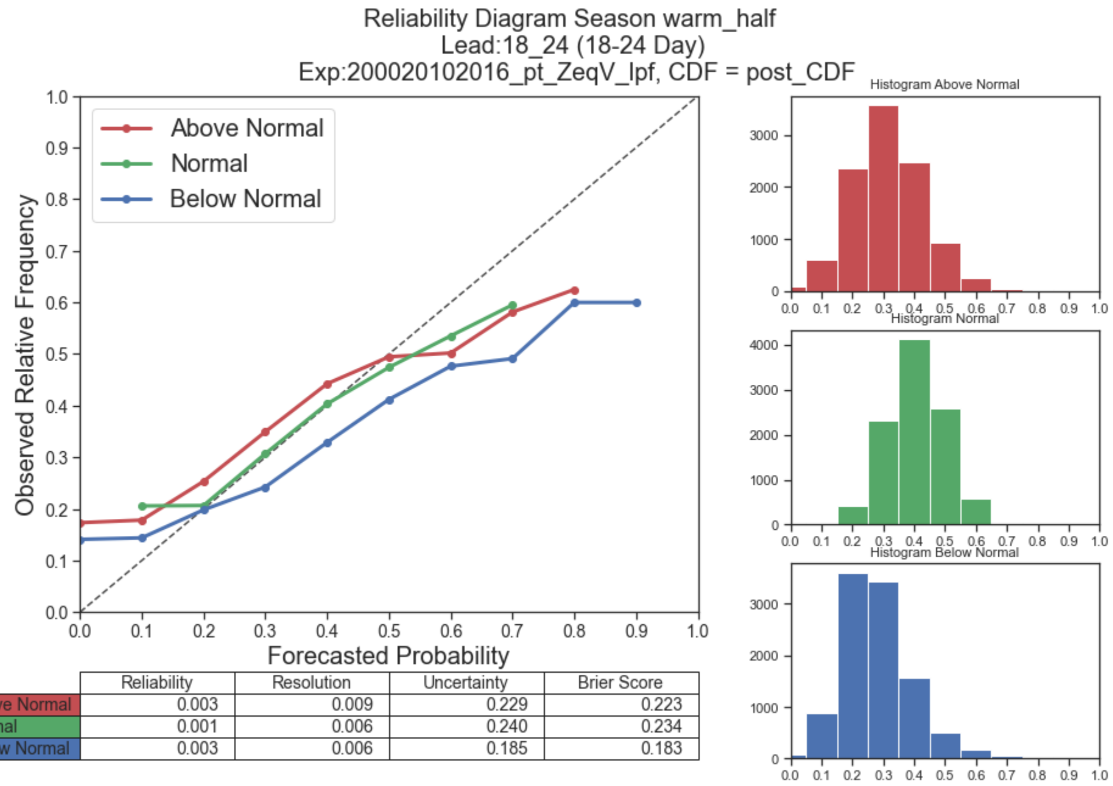
	Reliability	Resolution	Uncertainty	Brier Score
Above Normal	0.001	0.016	0.234	0.219
Normal	0.002	0.008	0.235	0.228
Below Normal	0.002	0.008	0.187	0.180

$$\mathrm{BS} = \frac{1}{n}\left[\underbrace{\sum_{i=1}^{I} N_i (y_i - \bar{o}_i)^2}_{\text{(a) Reliability}} - \underbrace{\sum_{i=1}^{I} N_i (\bar{o}_i - \bar{o})^2}_{\text{(b) Resolution}}\right] + \underbrace{\bar{o}(1-\bar{o})}_{\text{(c) Uncertainty}}$$

Reliability Diagram



	Reliability	Resolution	Uncertainty	Brier Score
Above Normal	0.099	0.004	0.229	0.324
Normal	0.066	0.002	0.240	0.304
Below Normal	0.081	0.002	0.185	0.264



	Reliability	Resolution	Uncertainty	Brier Score
Above Normal	0.003	0.009	0.229	0.223
Normal	0.001	0.006	0.240	0.234
Below Normal	0.003	0.006	0.185	0.183

→ BPE improves both the **resolution and reliability** components of the Brier Score, but overall calibration is better in cool season opposed to warm season.

Informativeness Score and Calibration Score

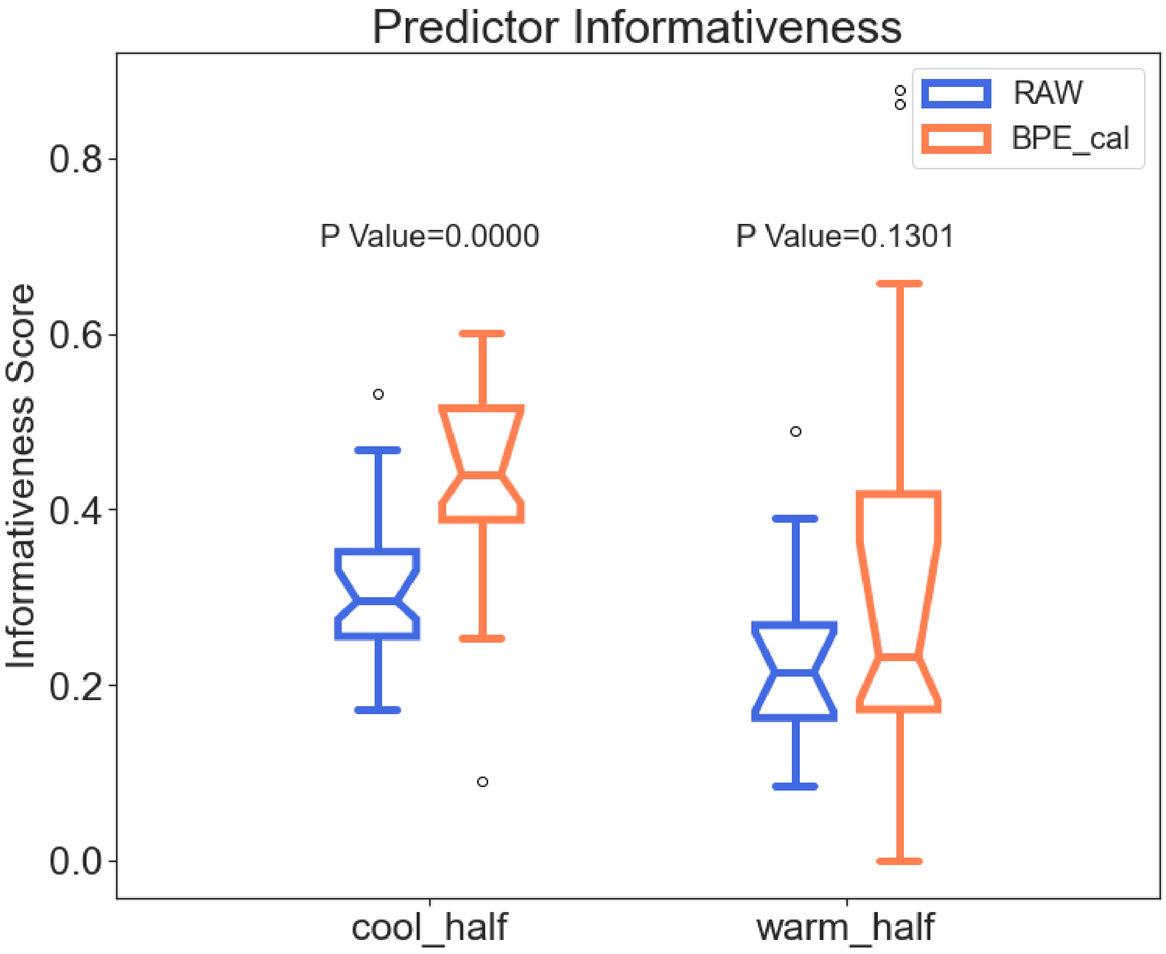
$$\text{Informativeness Score} = \left(1 + \left(\frac{\sigma}{aS}\right)^2\right)^{-\frac{1}{2}}$$

→ If $IS(\omega_i, x_i) > IS(\omega_j, x_j)$:

- Predictand-forecast pair (ω_i, x_i) has the ex-ante economic value *at least as high as* the pair (ω_j, x_j).

(Krzysztofowicz, 1992)

→ BPE improves predictor informativeness significantly in cool season, but inconclusive results in the warm one.



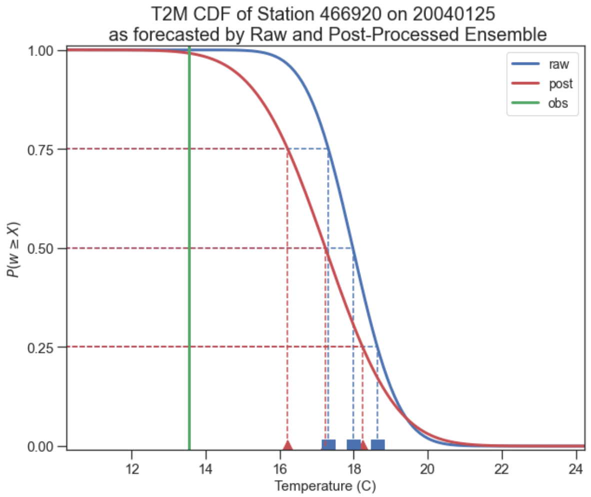
Informativeness Score and Calibration Score

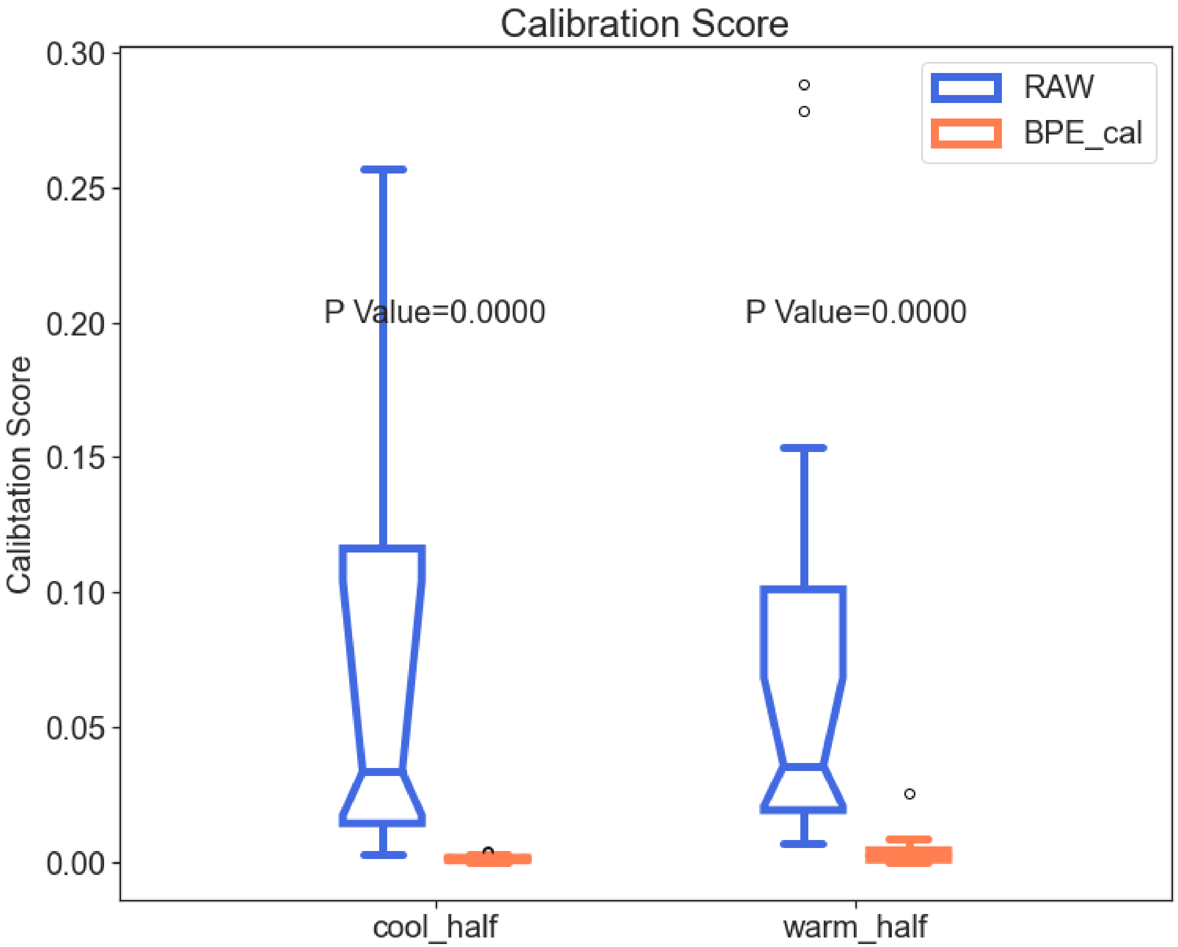
$$\text{Calibration Score} = \left\{\frac{1}{3}\left[(r_{75} - 0.75)^2 + (r_{50} - 0.5)^2 + (r_{25} - 0.25)^2\right]\right\}$$

- Exceedence fractiles are well calibrated if and only if :

$$P(W > x_{75} \mid \mathbf{X} = \mathbf{x}) = 0.75,$$
$$P(W > x_{50} \mid \mathbf{X} = \mathbf{x}) = 0.50,$$
$$P(W > x_{25} \mid \mathbf{X} = \mathbf{x}) = 0.25,$$

(Krzysztofowicz, 1992)





Conclusion and Future work

- BPE improves accuracy, reliability, resolution and probably potential economic value over the raw EPS.
- Works better in cool season than warm season
- BPE achieves reasonably robust results with only 3 years of training data using NCEP_GEFS
- Future work:

(1) Test BPE in post-processing CWB-GEPS, the prominent EPS developed by CWB.
(2) Extend the structure of BPE to allow two or more predictors.
(3) Use wave-filters to select predictable wavebands, filtering unpredictable noise from the raw EPS.
(4) Adjust climatic prior to long-term climate drifting, using trend-detection technique

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Thanks for your attention!

Q&A