

# Decaying Average BMA

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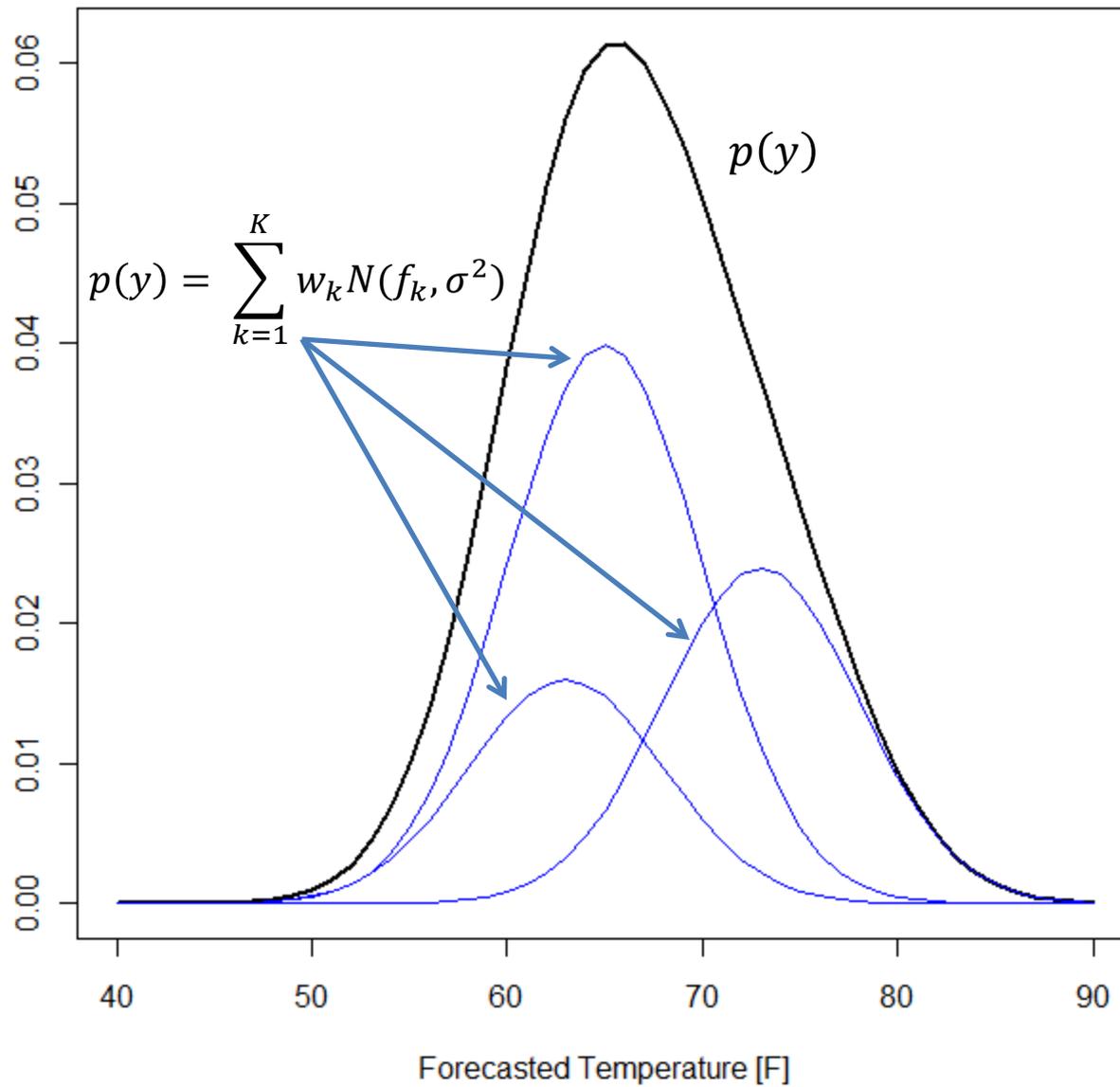
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# Introduction

- Raftery et al. (2005) proposed applying Bayesian Model Averaging (BMA) to ensembles
- Basic Idea
  - Weight ensemble members based on past performance
  - Calibrate ensemble spread
  - Do this by fitting a Normal Mixture statistical model to ensemble member forecasts

# Normal Mixture Model



# Fitting the Statistical Model

- Challenge is to estimate statistical model parameters

$$p(\mathbf{y}) = \sum_{k=1}^K w_k N(\mathbf{f}_k, \sigma^2)$$

Where

$w_k$  are weights  $\rightarrow p(M_k | \mathbf{y}^T)$

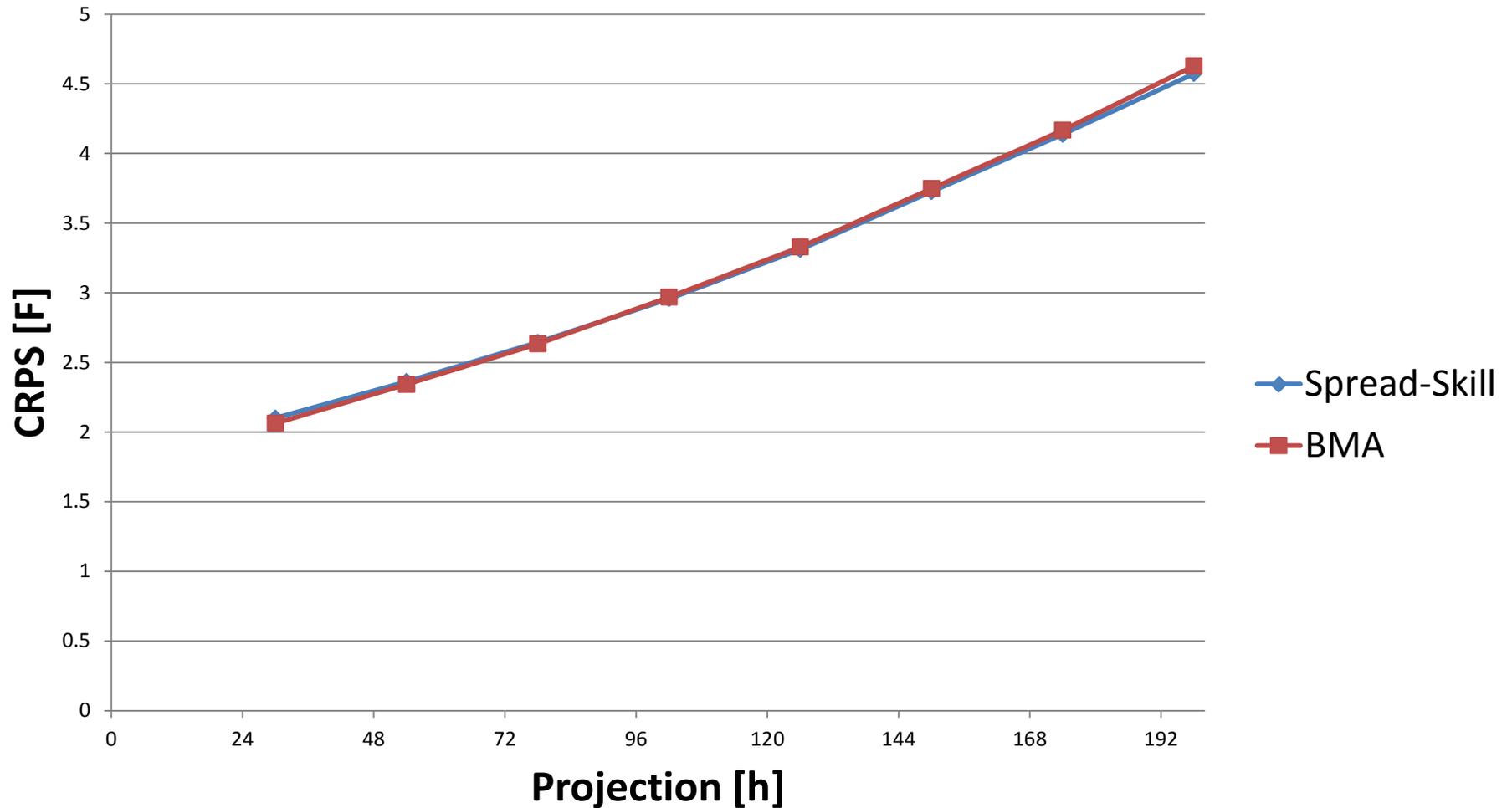
$f_k$  is the ensemble-member forecast

$\sigma$  is the predictive variance

- Raftery et al. (2005) estimated parameters with the Expectation Maximization Algorithm (Dempster et al., 1977).

# Example NAEFS Application

Max T, CRPS, Cool Season, 4 Years Cross Validated



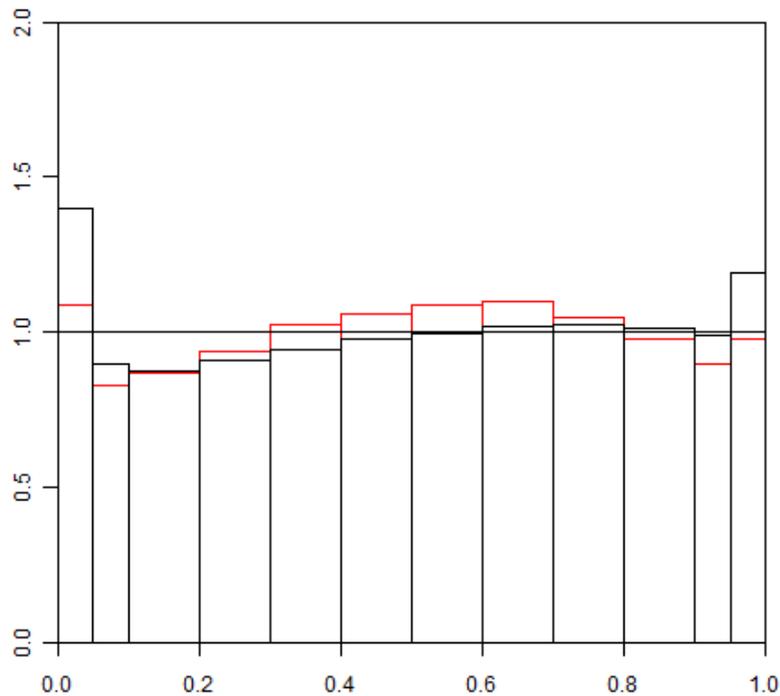
# Example NAEFS Application

## Spread-Skill

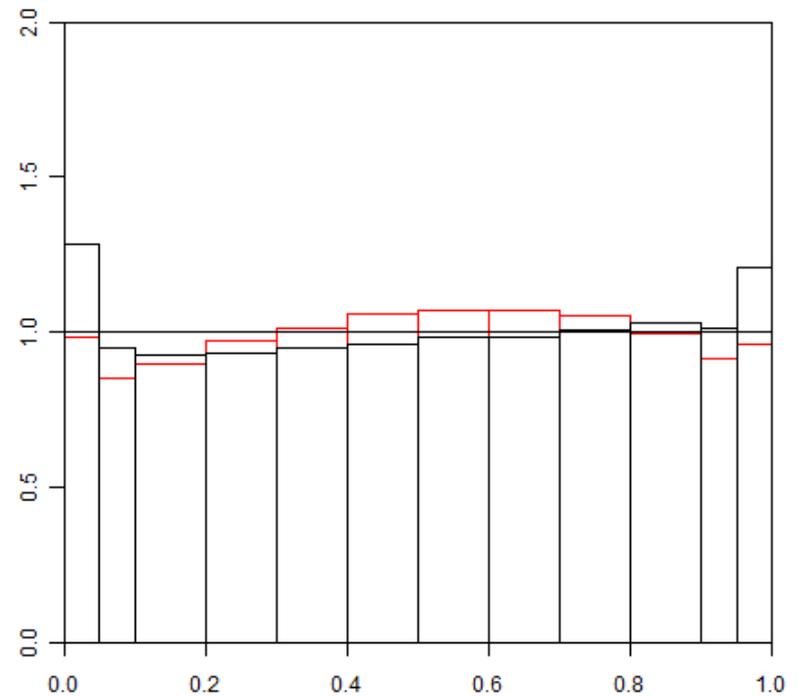
**BMA**

Max T, Cool Season, 4 Years,  
Cross Validated

78-hr Projection Cool Season



126-hr Projection Cool Season





# Fitting the Statistical Model

- EM Algorithm
  - Iterative
  - Must keep entire training sample on hand
  - Prone to overfitting with small samples (Hamill 2007)
- Propose Decaying Average BMA
  - Estimate parameters with decaying averages rather than EM algorithm
  - Stable estimates
  - Less data storage
  - Results comparable to EM algorithm
  - Similar to NCEP's bias correction

# Decaying Average BMA

- Use similar formulation to Raftery et al. (2005)
- Continuously update estimate of weights and predictive standard deviation as past forecasts verify
- Update is via a decaying average

$$\text{New Estimate} = (0.95 \times \text{Old Estimate}) + (0.05 \times \text{Latest Estimate})$$

# Decaying Average BMA

- Issue a forecasts
  - For example, the 42 hour 2-m temperature forecast
- Wait for forecast to verify
  - Different projections verify at different times
- Pair forecast with its verifying observation
- Begin update process

# Decaying Average BMA

- Two-step procedure
  - First update weights
  - Then update predictive standard error
- Going to demonstrate procedure for updating weights
  - Update for predictive error is similar

For one case, take member forecasts and observation, and compute...

$$z_k^j = \frac{w_k^{j-1} g(y^j | f_k^j, \sigma^{j-1})}{\sum_{i=1}^K w_i^{j-1} g(y^j | f_i^j, \sigma^{j-1})}$$

$w_k^{j-1}$  Previous weight estimate for member  $k$

$g(y_t | f_{kt}, \sigma^{j-1})$   $N(f_k^j, \sigma^{j-1})$  evaluated at observation  $y_t$ .

$k$  Ensemble Member

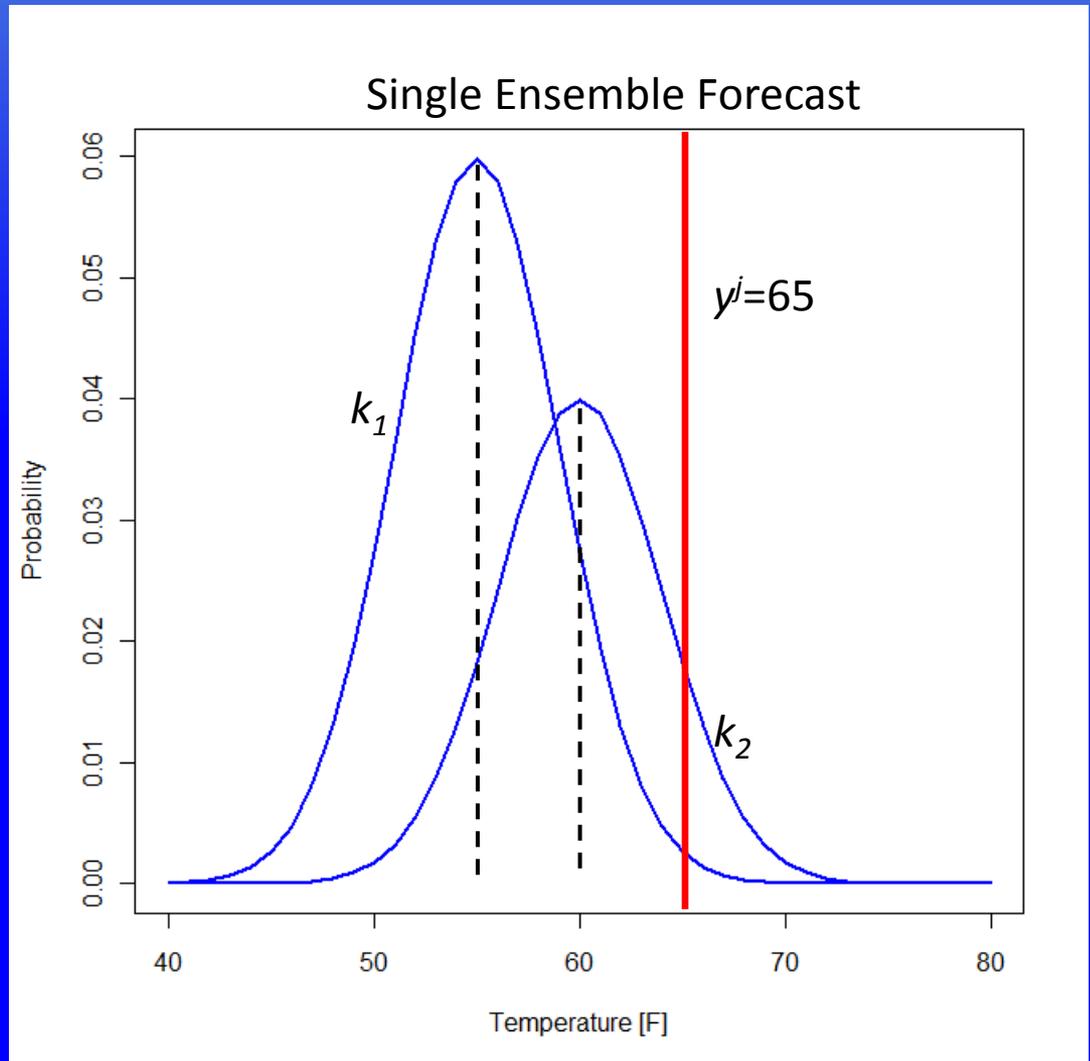
$j$  Current day being verified

$y_j$  Observation

# Example Z calculation

$$z_k^j = \frac{w_k^{j-1} g(y^j | f_k^j, \sigma^{j-1})}{\sum_{i=1}^K w_i^{j-1} g(y^j | f_i^j, \sigma^{j-1})}$$

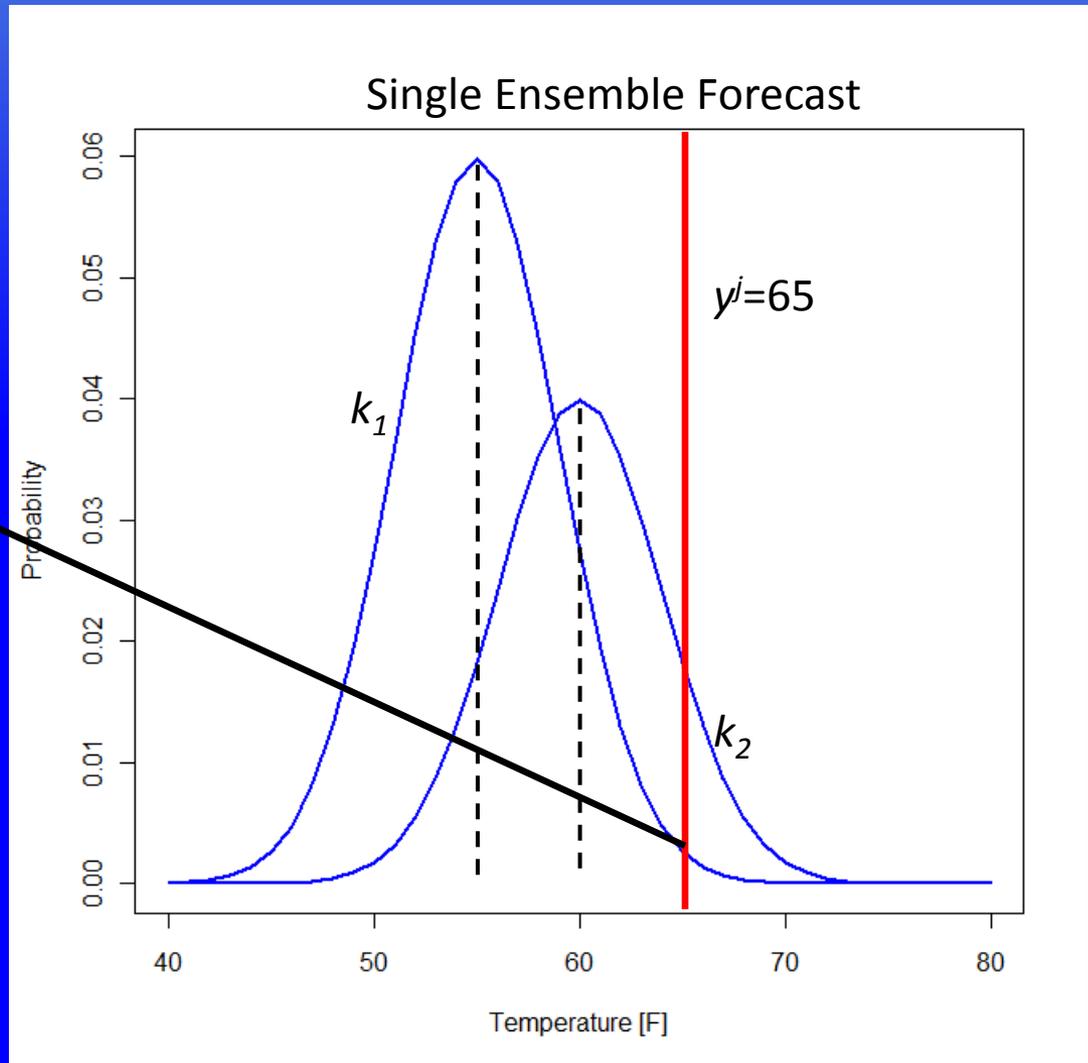
$$z_1^j = \frac{0.005}{0.005 + 0.020}$$



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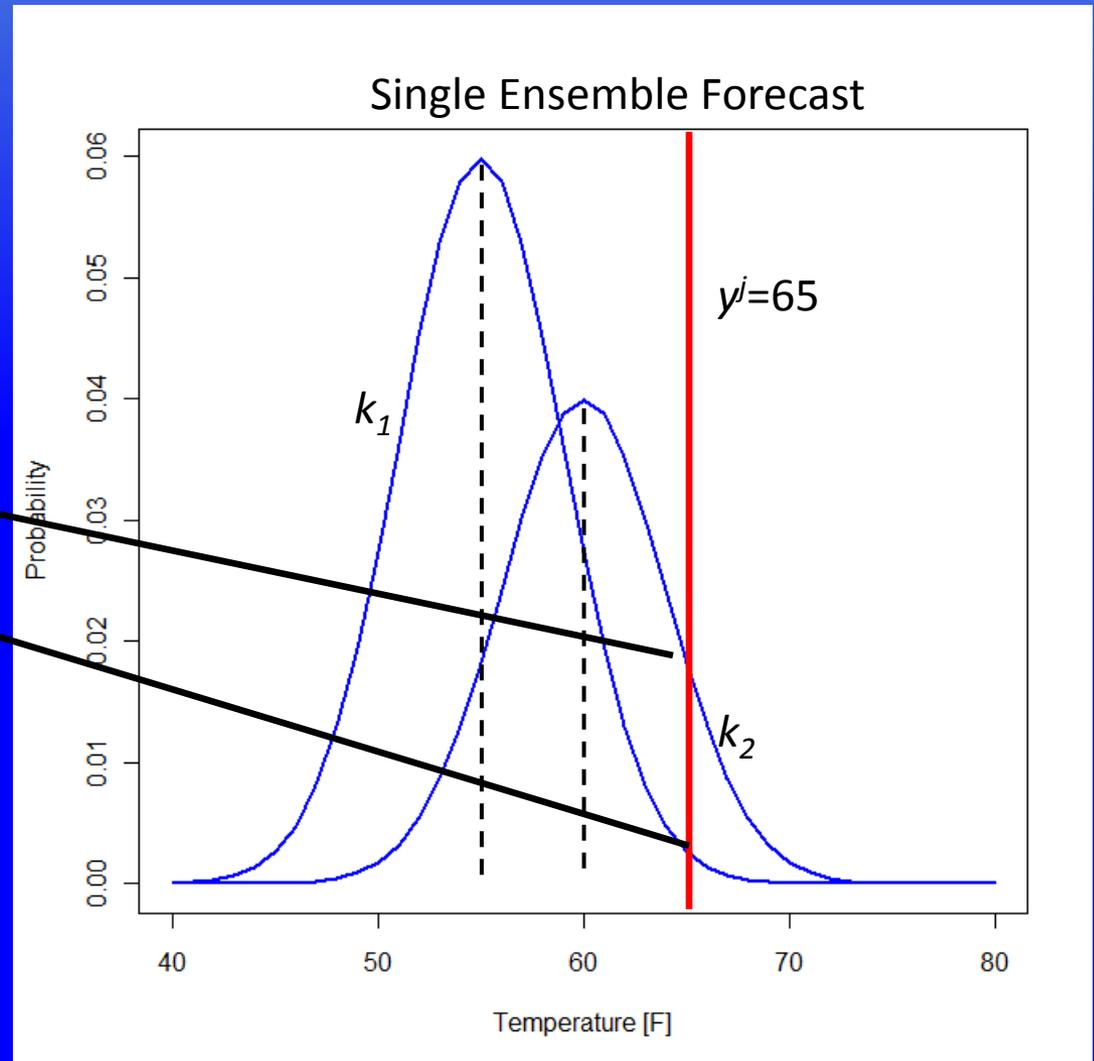


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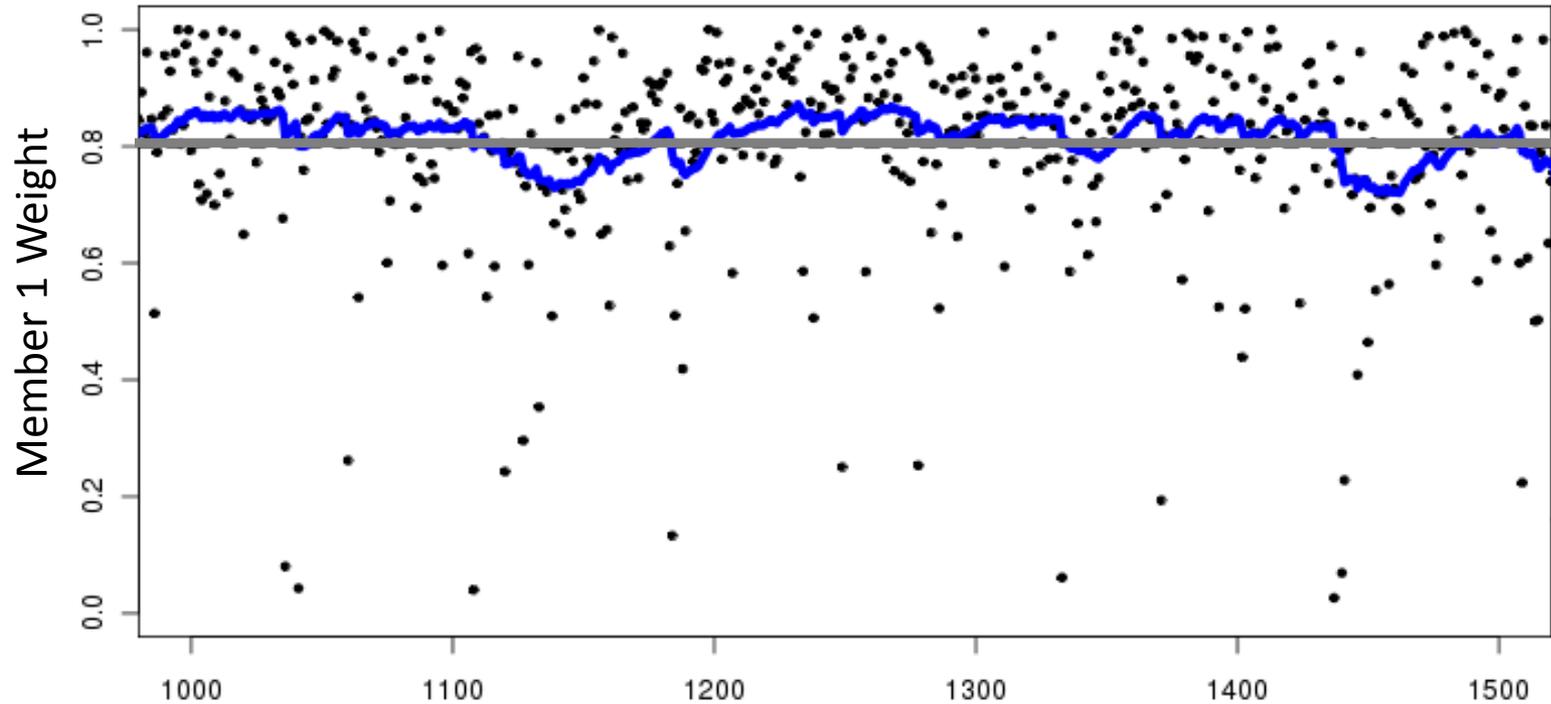
$$z_1^j = 0.2$$





# Decaying Average BMA Example

Hypothetical 2 member ensemble



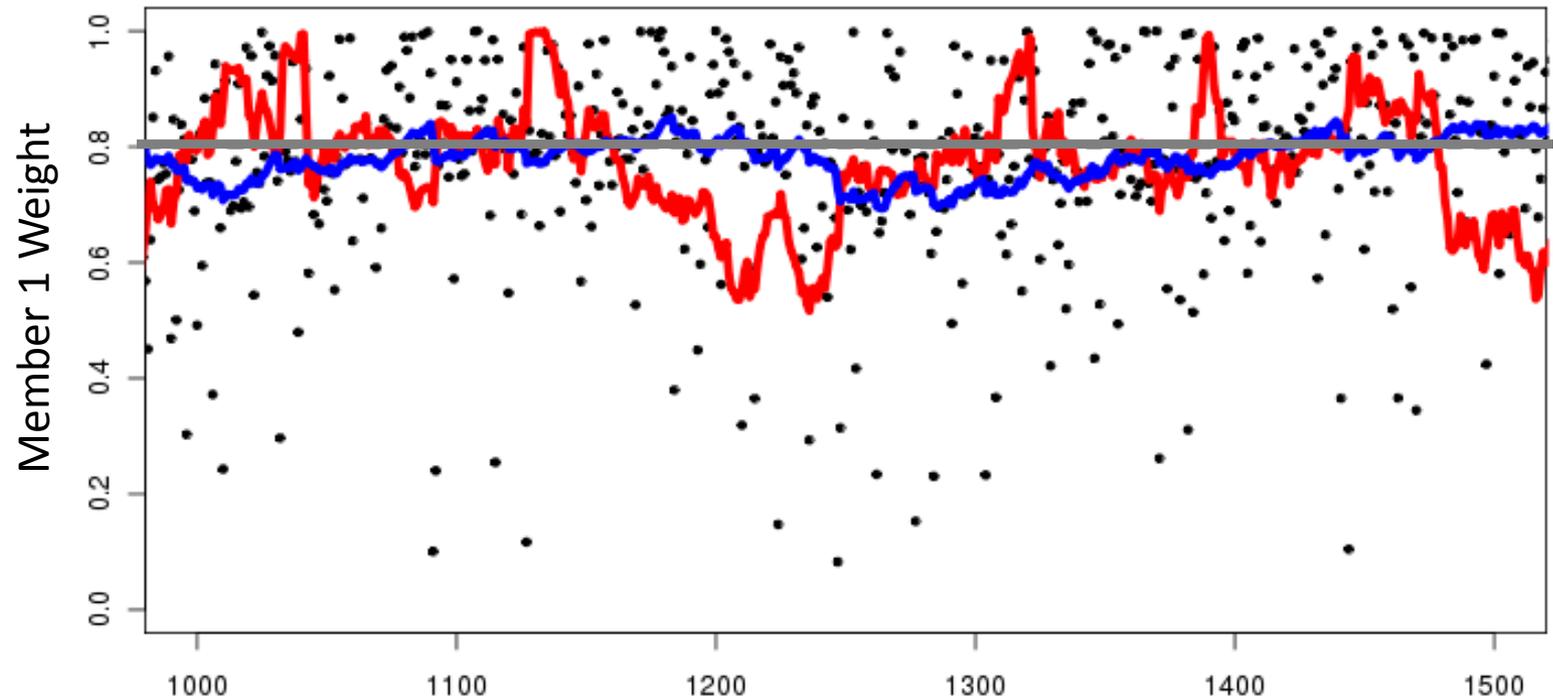
• Single z Value

Day in Sample

— Decaying Average ( $\alpha = 0.05$ )

# Comparison with Raftery's BMA

## Hypothetical 2 member ensemble



- Single z Value
- Decaying Average ( $\alpha = 0.05$ )
- EM Algorithm (50 days)

# Decaying Average BMA Spread

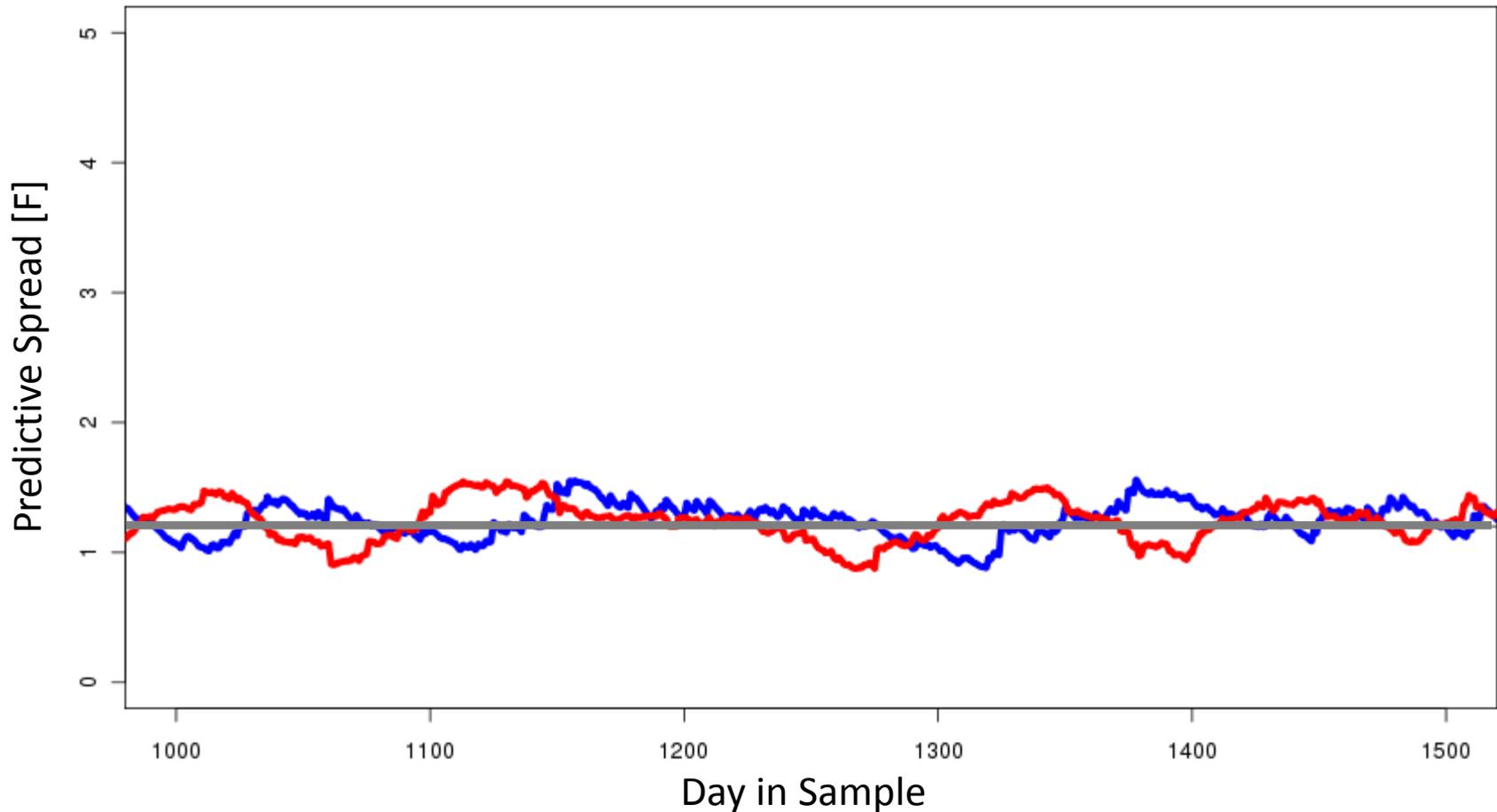
- With today's  $z_k^j$  values compute

$$s^{2(j)} = \sum_{k=1}^K z_k^j (y^i - f_k^j)^2$$

$k$	Ensemble Member
$j$	Current day being verified
$y_j$	Observation
$f_j$	Ensemble Member Forecast $k$



# Comparison with Raftery's BMA



- Decaying Average ( $\alpha = 0.05$ )
- EM Algorithm (50 days)

# Conclusions

- Propose to use Decaying Average BMA
  - Stable parameter estimates
  - Less data storage (~3 days)
  - Avoids iterative algorithm
  - Results asymptotically similar to EM algorithm
- SREF
  - 21 members – 3 distinct models
  - 7 member sub-ensembles -> 3 weights, 1 standard deviation