Probabilistic Weather Forecasting via Bayesian Model Averaging and EMOS

Adrian E. Raftery
University of Washington
raftery@u.washington.edu
www.stat.washington.edu/raftery

Joint work with Tilmann Gneiting
with contributions by Veronica Berrocal, Chris Fraley, Yulia Gel and McLean Sloughter
In collaboration with Cliff Mass, Susan Joslyn, and Jeff Baars
Supported by NSF and the ONR MURI Program

National Workshop on Mesoscale Probabilistic Prediction, NCAR
September 23, 2009

Basic Idea

Basic Idea

- Forecast ensembles:

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters
  - for entire weather fields and multiple parameters simultaneously (desirable for aviation)

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters
  - for entire weather fields and multiple parameters simultaneously (desirable for aviation)
- BMA is the basis for `Probcast`, the first operational PDF-based calibrated probabilistic forecasting website

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters
  - for entire weather fields and multiple parameters simultaneously (desirable for aviation)
- BMA is the basis for `Probcast`, the first operational PDF-based calibrated probabilistic forecasting website
  - up since June 25, 2004

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters
  - for entire weather fields and multiple parameters simultaneously (desirable for aviation)
- BMA is the basis for `Probcast`, the first operational PDF-based calibrated probabilistic forecasting website
  - up since June 25, 2004
  - currently for the Pacific Northwest,

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters
  - for entire weather fields and multiple parameters simultaneously (desirable for aviation)
- BMA is the basis for `Probcast`, the first operational PDF-based calibrated probabilistic forecasting website
  - up since June 25, 2004
  - currently for the Pacific Northwest,
  - temperature and precip

Basic Idea

- Forecast ensembles:
  - The dominant approach to probabilistic forecasting
  - They contain useful information (spread-skill relationship)
  - BUT they tend to be underdispersed, especially at the surface
  - uncalibrated
- Bayesian Model Averaging (BMA) provides calibrated and sharp probabilistic forecasts
  - based on an ensemble
  - for temperature, PoP, quantitative precip, wind speeds, wind directions, vector winds
  - and potentially other parameters
  - for entire weather fields and multiple parameters simultaneously (desirable for aviation)
- BMA is the basis for `Probcast`, the first operational PDF-based calibrated probabilistic forecasting website
  - up since June 25, 2004
  - currently for the Pacific Northwest,
  - temperature and precip
  - wind speed soon to be added

Outline

Outline

- Bayesian model averaging

Outline

- Bayesian model averaging
- BMA for exchangeable ensembles

Outline

- Bayesian model averaging
- BMA for exchangeable ensembles
- BMA for precipitation

Outline

- Bayesian model averaging
- BMA for exchangeable ensembles
- BMA for precipitation
- BMA for wind

Outline

- Bayesian model averaging
- BMA for exchangeable ensembles
- BMA for precipitation
- BMA for wind
- EMOS

Bayesian Model Averaging for Ensembles

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.
- Good results with a 25-day "moving window" training period.

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.
- Good results with a 25-day "moving window" training period.
- Potential improvement with reforecasting and longer training periods

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.
- Good results with a 25-day "moving window" training period.
- Potential improvement with reforecasting and longer training periods
- BMA better calibrated and more accurate than the raw ensemble:

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.
- Good results with a 25-day "moving window" training period.
- Potential improvement with reforecasting and longer training periods
- BMA better calibrated and more accurate than the raw ensemble:
    - For the UWME, 2000–2009

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.
- Good results with a 25-day "moving window" training period.
- Potential improvement with reforecasting and longer training periods
- BMA better calibrated and more accurate than the raw ensemble:
  - For the UWME, 2000–2009
  - For Canada (Wilson et al 2007)

Bayesian Model Averaging for Ensembles

- The overall (BMA) forecast probability distribution is a mixture of distributions, each one centered on one of the forecasts after bias correction.
- The weights are the estimated probabilities of the models, and reflect the relative predictive performance of the models during a training period.
- The BMA point or deterministic forecast is just a weighted average of the forecasts in the ensemble.
- For each grid point, the model is estimated from a training set of recent data at similar and close stations by maximum likelihood.
- Good results with a 25-day "moving window" training period.
- Potential improvement with reforecasting and longer training periods
- BMA better calibrated and more accurate than the raw ensemble:
  - For the UWME, 2000–2009
  - For Canada (Wilson et al 2007)
  - For Europe (KNMI/DWD experiments)

UW Ensemble Bayesian Model Averaging

User's Guide

Param: Max 2m Temp (24-48 hrs)

Valid for 24 hours ending at:

Wed May 27, 2009 5 PM

Jump to new date

Toggle Contour Lines OFF

Plot Size: Big Medium Small

Units: Celsius Fahrenheit

Grid Forecast:

Deterministic

Upper bound of interval .9

Lower bound of interval .1

Half-width of interval

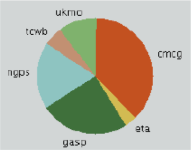
Prob. param exceeds threshold 0

Greater than Less than

Probability Distribution:

Latitude: 47.68049 Longitude: -122.2244

Retrieve Data

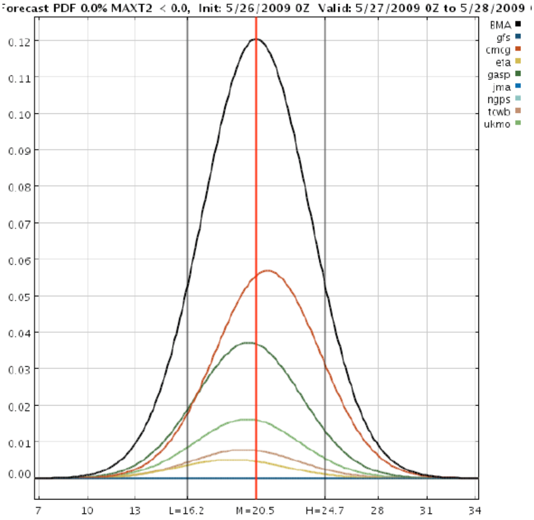


BMA Weights

Forecasts Error: NORMAL: 2.16

BMA Forecast Verification

Prob of freezing | Prob of precip > 0 | Prob of precip > 1/4" | Prob of precip > 1" | Prob of high winds | Prob of gale winds



About this page.

BMA for Ensembles with Exchangeable Members

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member
    - But often ensembles have subsets of exchangeable members:

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member
  - But often ensembles have subsets of exchangeable members:
  - ECMWF: 2 groups: control (1); singular vector perturbations (50)

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member
  - But often ensembles have subsets of exchangeable members:
  - ECMWF: 2 groups: control (1); singular vector perturbations (50)
  - NCEP 2006 SREF: 21 members divided into 13 groups

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member
  - But often ensembles have subsets of exchangeable members:
  - ECMWF: 2 groups: control (1); singular vector perturbations (50)
  - NCEP 2006 SREF: 21 members divided into 13 groups
- Exchangeable BMA forces the weights for exchangeable members to be the same.

BMA for Ensembles with Exchangeable Members

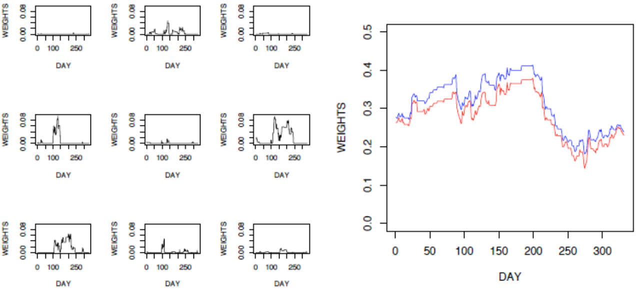
- "Traditional" BMA gives a different weight to each ensemble member
    - But often ensembles have subsets of exchangeable members:
    - ECMWF: 2 groups: control (1); singular vector perturbations (50)
    - NCEP 2006 SREF: 21 members divided into 13 groups
- Exchangeable BMA forces the weights for exchangeable members to be the same.
- Example: 89-member ensemble combining UWME (8 individual members) and UW-EnKF (experimental: 80 exchangeable members).

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member
  - But often ensembles have subsets of exchangeable members:
  - ECMWF: 2 groups: control (1); singular vector perturbations (50)
  - NCEP 2006 SREF: 21 members divided into 13 groups
- Exchangeable BMA forces the weights for exchangeable members to be the same.
- Example: 89-member ensemble combining UWME (8 individual members) and UW-EnKF (experimental: 80 exchangeable members).

BMA for Ensembles with Exchangeable Members

- "Traditional" BMA gives a different weight to each ensemble member
  - But often ensembles have subsets of exchangeable members:
  - ECMWF: 2 groups: control (1); singular vector perturbations (50)
  - NCEP 2006 SREF: 21 members divided into 13 groups
- Exchangeable BMA forces the weights for exchangeable members to be the same.
- Example: 89-member ensemble combining UWME (8 individual members) and UW-EnKF (experimental: 80 exchangeable members).



Exchangeable BMA: Results for 2007

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)		
UW EnKF (80 exchangeable)		
Combined (89)		

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	
UW EnKF (80 exchangeable)		
Combined (89)		

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	
UW EnKF (80 exchangeable)	3.32	
Combined (89)		

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	
UW EnKF (80 exchangeable)	3.32	
Combined (89)		

- UW EnKF worse than UW ME (experimental)

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	
UW EnKF (80 exchangeable)	3.32	
Combined (89)	3.25	

- UW EnKF worse than UW ME (experimental)

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	
UW EnKF (80 exchangeable)	3.32	
Combined (89)	3.25	

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	2.15
UW EnKF (80 exchangeable)	3.32	
Combined (89)	3.25	

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	2.15
UW EnKF (80 exchangeable)	3.32	2.49
Combined (89)	3.25	

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	2.15
UW EnKF (80 exchangeable)	3.32	2.49
Combined (89)	3.25	2.09

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	2.15
UW EnKF (80 exchangeable)	3.32	2.49
Combined (89)	3.25	2.09

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME
- BMA improves all 3 ensembles

Exchangeable BMA: Results for 2007

	MAE	
	Raw	BMA
UW ME (8)	2.31	2.15
UW EnKF (80 exchangeable)	3.32	2.49
Combined (89)	3.25	2.09

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME
- BMA improves all 3 ensembles
- With BMA, combined ensemble *better* than UW ME alone!

Exchangeable BMA: Results for 2007

	MAE		CRPS	
	Raw	BMA	Raw	BMA
UW ME (8)	2.31	2.15	1.96	1.55
UW EnKF (80 exchangeable)	3.32	2.49	2.84	1.76
Combined (89)	3.25	2.09	2.64	1.48

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME
- BMA improves all 3 ensembles
- With BMA, combined ensemble *better* than UW ME alone!

Exchangeable BMA: Results for 2007

	MAE		CRPS	
	Raw	BMA	Raw	BMA
UW ME (8)	2.31	2.15	1.96	1.55
UW EnKF (80 exchangeable)	3.32	2.49	2.84	1.76
Combined (89)	3.25	2.09	2.64	1.48

- UW EnKF worse than UW ME (experimental)
- Combined *raw* ensemble worse than UW ME
- BMA improves all 3 ensembles
- With BMA, combined ensemble *better* than UW ME alone!
- Same conclusion with MAE (deterministic) and CRPS (probabilistic)

BMA for Precipitation

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative
  - its distribution, given that it is not zero, is strongly skewed

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
    - precip has a nonzero probability of being exactly zero
    - it is constrained to be nonnegative
    - its distribution, given that it is not zero, is strongly skewed
- For probabilistic forecasting of precipitation, we replace the normal distribution by a mixture of

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative
  - its distribution, given that it is not zero, is strongly skewed
- For probabilistic forecasting of precipitation, we replace the normal distribution by a mixture of
  - a point mass at zero, whose probability is specified by logistic regression given the forecast

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative
  - its distribution, given that it is not zero, is strongly skewed
- For probabilistic forecasting of precipitation, we replace the normal distribution by a mixture of
  - a point mass at zero, whose probability is specified by logistic regression given the forecast
  - a gamma distribution, whose mean and variance depend on the forecast

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative
  - its distribution, given that it is not zero, is strongly skewed
- For probabilistic forecasting of precipitation, we replace the normal distribution by a mixture of
  - a point mass at zero, whose probability is specified by logistic regression given the forecast
  - a gamma distribution, whose mean and variance depend on the forecast
- We then proceed with maximum likelihood estimation as before

BMA for Precipitation

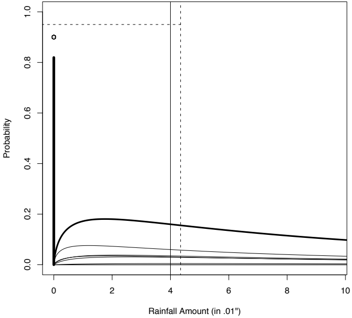
- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative
  - its distribution, given that it is not zero, is strongly skewed
- For probabilistic forecasting of precipitation, we replace the normal distribution by a mixture of
  - a point mass at zero, whose probability is specified by logistic regression given the forecast
  - a gamma distribution, whose mean and variance depend on the forecast
- We then proceed with maximum likelihood estimation as before
- Recently extended to wind speeds:

BMA for Precipitation

- The normal-based BMA used for temperature doesn't work for precipitation because:
  - precip has a nonzero probability of being exactly zero
  - it is constrained to be nonnegative
  - its distribution, given that it is not zero, is strongly skewed
- For probabilistic forecasting of precipitation, we replace the normal distribution by a mixture of
  - a point mass at zero, whose probability is specified by logistic regression given the forecast
  - a gamma distribution, whose mean and variance depend on the forecast
- We then proceed with maximum likelihood estimation as before
- Recently extended to wind speeds:
  - Zero component not needed in the Pacific Northwest

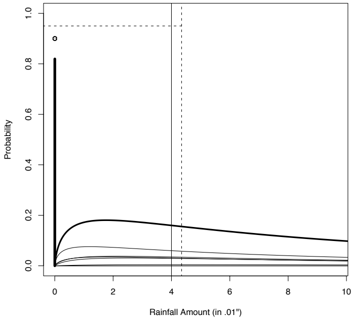
BMA Predictive Distributions for Precipitation

BMA Predictive Distributions for Precipitation

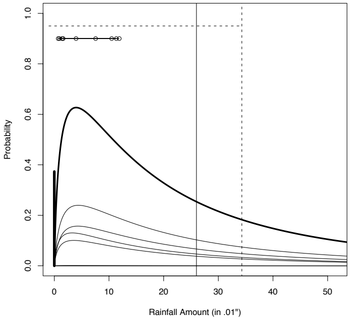


Renton, 19th May, 2003

BMA Predictive Distributions for Precipitation



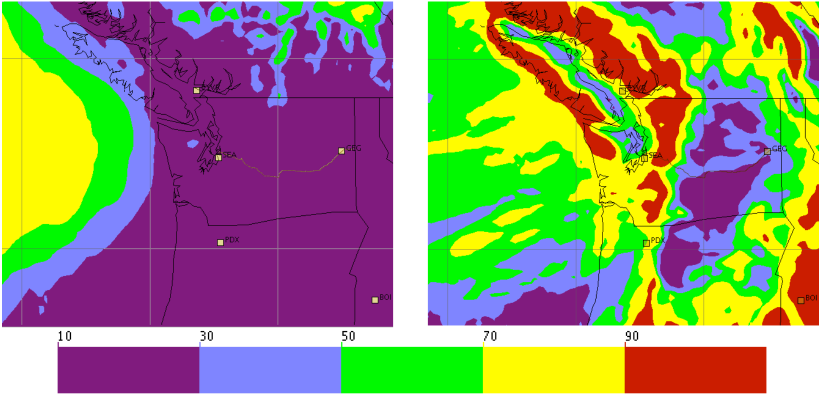
Renton, 19th May, 2003



Station KPWT, 26th January, 2003

BMA Probability of Precipitation

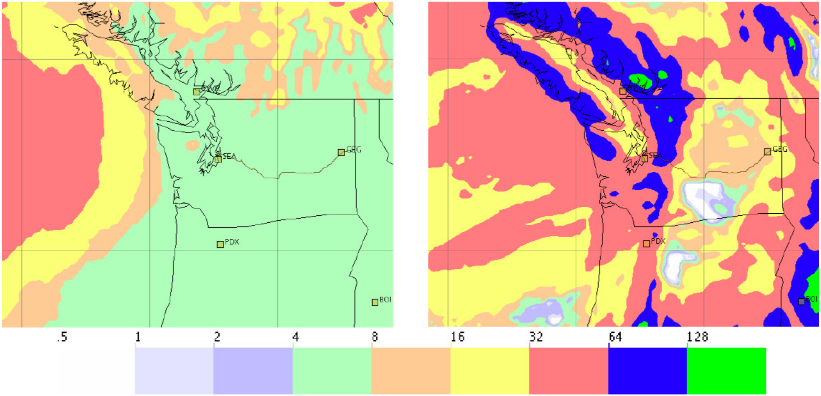
BMA Probability of Precipitation



(a) 19th May, 2003 (b) 26th January, 2003

BMA 90% Upper Bound forecast

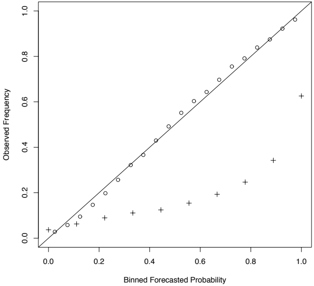
BMA 90% Upper Bound forecast



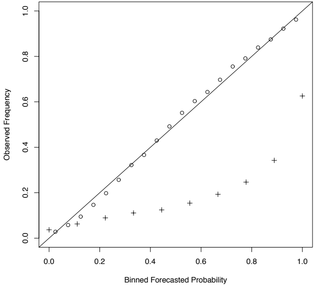
(a) 19th May, 2003 (b) 26th January, 2003

Calibration of Forecasts of the *Probability* of Precipitation

Calibration of Forecasts of the *Probability* of Precipitation

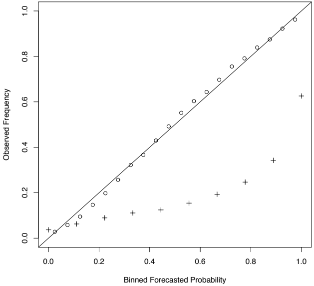


Calibration of Forecasts of the *Probability* of Precipitation



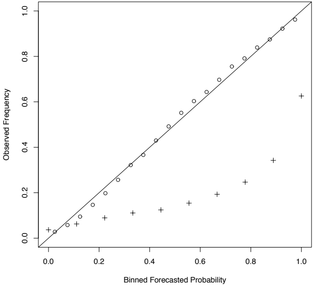
- x-axis shows the forecast probability of precipitation (PoP)

Calibration of Forecasts of the *Probability* of Precipitation



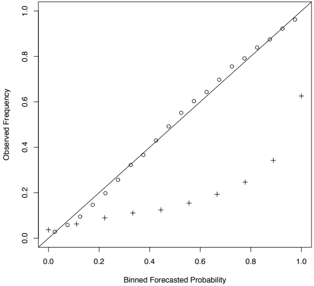
- x-axis shows the forecast probability of precipitation (PoP)
- y-axis shows the observed relative frequency of precipitation, based on 2 years of data, 2003–2004 (100K obs)

Calibration of Forecasts of the *Probability* of Precipitation



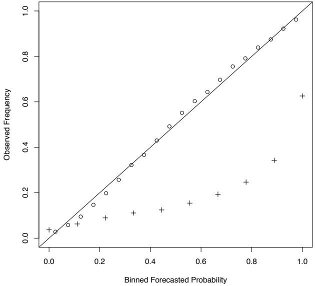
- x-axis shows the forecast probability of precipitation (PoP)
- y-axis shows the observed relative frequency of precipitation, based on 2 years of data, 2003–2004 (100K obs)
- Thus a good PoP forecast would be on the diagonal (solid line)

Calibration of Forecasts of the *Probability* of Precipitation



- x-axis shows the forecast probability of precipitation (PoP)
- y-axis shows the observed relative frequency of precipitation, based on 2 years of data, 2003–2004 (100K obs)
- Thus a good PoP forecast would be on the diagonal (solid line)
- Crosses show the proportion of the ensemble members that predict precipitation, i.e. the raw ensemble PoP forecast. Poorly calibrated

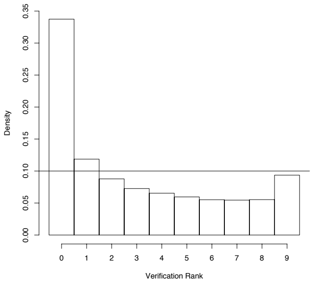
Calibration of Forecasts of the *Probability* of Precipitation



- x-axis shows the forecast probability of precipitation (PoP)
- y-axis shows the observed relative frequency of precipitation, based on 2 years of data, 2003–2004 (100K obs)
- Thus a good PoP forecast would be on the diagonal (solid line)
- Crosses show the proportion of the ensemble members that predict precipitation, i.e. the raw ensemble PoP forecast. Poorly calibrated
- Circles show the BMA PoP forecast. Much better.

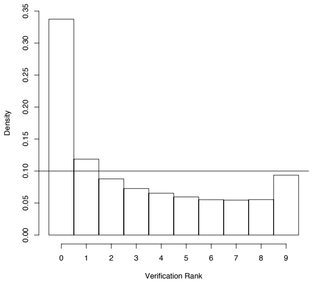
Calibration of Forecasts of the *Amount* of Precipitation

Calibration of Forecasts of the *Amount* of Precipitation



Verification rank histogram
for ensemble forecast

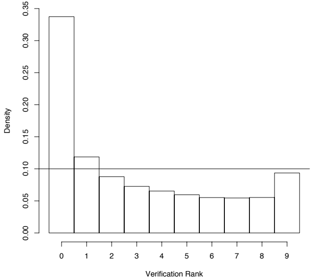
Calibration of Forecasts of the *Amount* of Precipitation



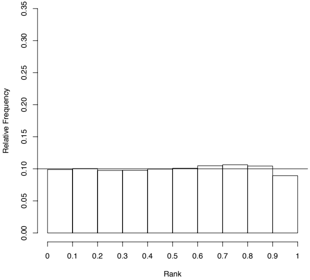
Verification rank histogram
for ensemble forecast

- The raw ensemble is poorly calibrated

Calibration of Forecasts of the *Amount* of Precipitation



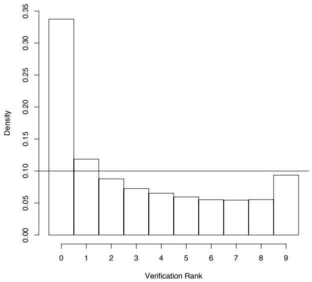
Verification rank histogram
for ensemble forecast



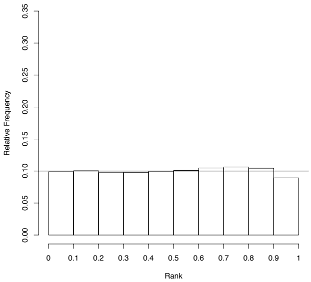
PIT histogram for
BMA forecast distribution

- The raw ensemble is poorly calibrated

Calibration of Forecasts of the *Amount* of Precipitation



Verification rank histogram
for ensemble forecast



PIT histogram for
BMA forecast distribution

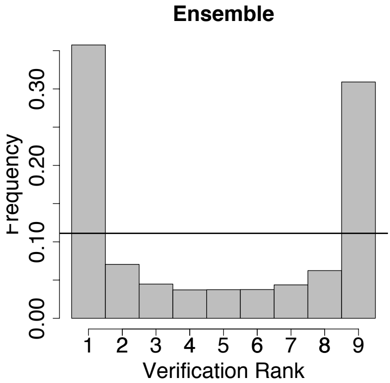
- The raw ensemble is poorly calibrated
- The BMA forecast distribution is much better calibrated

Wind Speeds

(similar model to quantitative precip)

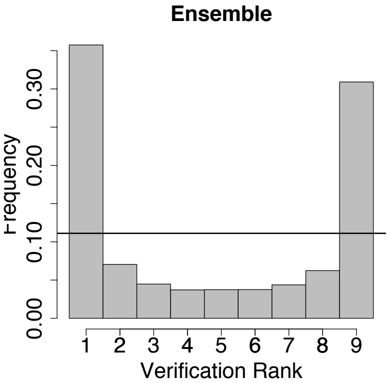
Wind Speeds

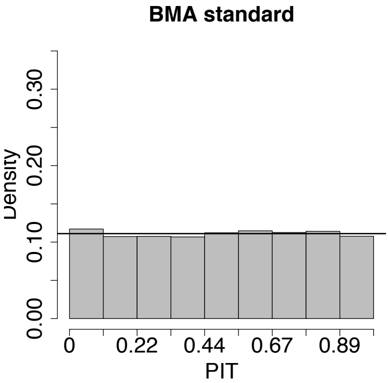
(similar model to quantitative precip)



Wind Speeds

(similar model to quantitative precip)





Ensemble MOS

Ensemble MOS

- Conditional PDF for temperature:

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution
  - Mean a linear combination of ensemble members

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution
  - Mean a linear combination of ensemble members
  - Variance a linear function of the ensemble variance

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution
  - Mean a linear combination of ensemble members
  - Variance a linear function of the ensemble variance
  - Conditional distribution very similar to BMA

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution
  - Mean a linear combination of ensemble members
  - Variance a linear function of the ensemble variance
  - Conditional distribution very similar to BMA
  - performance similar to BMA

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution
  - Mean a linear combination of ensemble members
  - Variance a linear function of the ensemble variance
  - Conditional distribution very similar to BMA
  - performance similar to BMA
- Applied to wind speeds: truncated normal distribution

Ensemble MOS

- Conditional PDF for temperature:
  - Normal distribution
  - Mean a linear combination of ensemble members
  - Variance a linear function of the ensemble variance
  - Conditional distribution very similar to BMA
  - performance similar to BMA
- Applied to wind speeds: truncated normal distribution
- Hard to apply to precip, wind directions

Summary

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds
- External validation:

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds
- External validation:
  - Published articles developing BMA: 6 in MWR, 2 in *Journal of the American Statistical Assocation*, several in W&F and BAMS

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds
- External validation:
  - Published articles developing BMA: 6 in MWR, 2 in *Journal of the American Statistical Assocation*, several in W&F and BAMS
  - Cited in 2006 National Research Council Report

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds
- External validation:
  - Published articles developing BMA: 6 in MWR, 2 in *Journal of the American Statistical Assocation*, several in W&F and BAMS
  - Cited in 2006 National Research Council Report
  - Developed with $7M of recurring funding from NSF and ONR

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds
- External validation:
  - Published articles developing BMA: 6 in MWR, 2 in *Journal of the American Statistical Assocation*, several in W&F and BAMS
  - Cited in 2006 National Research Council Report
  - Developed with $7M of recurring funding from NSF and ONR
- Free R software packages: EnsembleBMA, ProbForecastGOP

Summary

- BMA gives sharp and calibrated probabilistic forecasts for temperature, PoP, PQPF, wind speed, wind direction, vector wind
- BMA has been extended to ensembles with exchangeable members such as NCEP SREF
  - With BMA, adding a bad ensemble to a better one improved performance!
- BMA has been extended to provide forecasts of entire fields
- Real-time probabilistic forecasting site based on BMA up since 2004
- EMOS an alternative statistical formulation: gives similar results to BMA for temperature and wind speeds
- External validation:
  - Published articles developing BMA: 6 in MWR, 2 in *Journal of the American Statistical Assocation*, several in W&F and BAMS
  - Cited in 2006 National Research Council Report
  - Developed with $7M of recurring funding from NSF and ONR
- Free R software packages: EnsembleBMA, ProbForecastGOP
- Web sites: www.stat.washington.edu/raftery/Research/dsm.html www.stat.washington.edu/MURI www.probcast.washington.edu bma.apl.washington.edu