SHORT RANGE FORECAST
BIAS CORRECTION
BY
SEQUENTIAL DATA ASSIMILATION

Kaustubha Bhattacharya
NCMRWF
NCMRWF operational analysis scheme (SSI)

- obs residuals analyzed in spectral space
- analysis variables same as model variable
- Any type of obs can be used – provision for observation operator
- No data selection – single global problem
- Analysis performed on sigma surface
NCMRWF Operational Forecast Model

- Global Spectral Model  T80L18 Sigma
- Dep variables: vor, div, tv, ps, sh
- Time integration:
  Semi implicit: for div, temp, pressure
  Explicit:       for vor, moisture
- Time step : 15 mins
- Horizontal diffusion: fourth order
- Orography: Mean orography
- Physics: surface processes, boundary layer, convection, radiation, clouds
PRELIMINARIES: SEQUENTIAL

Analysis

\[ w^a - w^f = k \left[ y - h(w^f) \right] \]

Linearize about \( w = w^f \):

\[ h \rightarrow H \quad k \rightarrow K \]

Define errors

\[ e^f = w^f - w \quad \text{forecast} \]
\[ e^o = w^o - w \quad \text{observation} \]
\[ e^a = w^a - w \quad \text{analysis} \]
WHERE

\( w_k = \) truth at time \( t_k \)

\( w^f_k = \) biased state vector at time \( t_k \)

\( \hat{w}^f_k = \) unbiased state vector at time \( t_k \)

\( w^o_k = \) vector of unbiased observations at time \( t_k \)

\( H_k = \) linearized observation operator at time \( t_k \)

\( K_k = \) gain matrix at time \( t_k \)

\( R_k = \) observation error covariance matrix
EFFECTS OF BIAS ON ANALYSIS

Bias affects innovation

\[ < y - h(w_f^*) > \sim < e^o > - < H e^f > \]

Bias affects analysis increment

\[ < w^a - w^f > \sim < K e^o > - < K H e^f > \]

Bias affects analysis error

\[ < e^a > \sim < K e^o > + < [ I - KH] e^f > \]
LET

$\hat{c}_k^-$ = predicted bias estimate at time $t_k$

$\hat{c}_k$ = updated bias estimate at time $t_k$

$S^f_k$ = covariance matrix of forecast errors

$S^{c-}_k$ = covariance matrix of bias prediction

$L_k$ = bias gain matrix
SEPARATE BIAS ESTIMATION ALGORITHM

BIAS PREDICTION:

\[ \hat{c}_k^- = \hat{c}_{k-1} + g(\hat{c}_{k-1}, w_{k-1}^a) \]

\[ \hat{w}_k^f = w_k^f - \hat{c}_k^- \]

BIAS UPDATE:

\[ \hat{c}_k = \hat{c}_k^- - L_k [w_0^o - H_k \hat{w}_k^f] \]

WHERE

\[ L_k = S_{c-k}^c H_k^T [H_k S_{c-k}^c H_k^T + H_k S_k^f H_k^T + R_k]^{-1} \]

for optimality (DEE AND TODLING, 2000)

ASSUME

\[ S_{c-k}^c = \gamma \cdot S_k^f \]
Separate Bias Estimation Algorithm

- Statistical - gives no clue about origin of bias
- Needs unbiased observations – a non trivial requirement
- Full bias estimation requires about same amount of computation as the analysis
- Can be used in on-line or off-line mode
Practical Implementation

- NCMRWF runs Spectral Statistical Interpolation for operational assimilation, so the scheme used in off-line mode
- Subsets of full data used to reduce computation
- Scheme tested on radiosonde temperature observations from Australia, USA and India
- Tuning parameter ‘gamma’ controls time scale and magnitude of bias corrections
CONCLUSIONS

• The separate bias algorithm works for constant or slowly changing bias
• It is adaptive - bias adjusts to change
• Faster bias correction needs a model for bias prediction
• Application to actual forecasts needs online computation of forecast error covariance matrix for bias corrected state