Illustration of a Processes-Based Evaluation System for Tracing Systematic Forecast Error Evolutions in a NWP model

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Outline

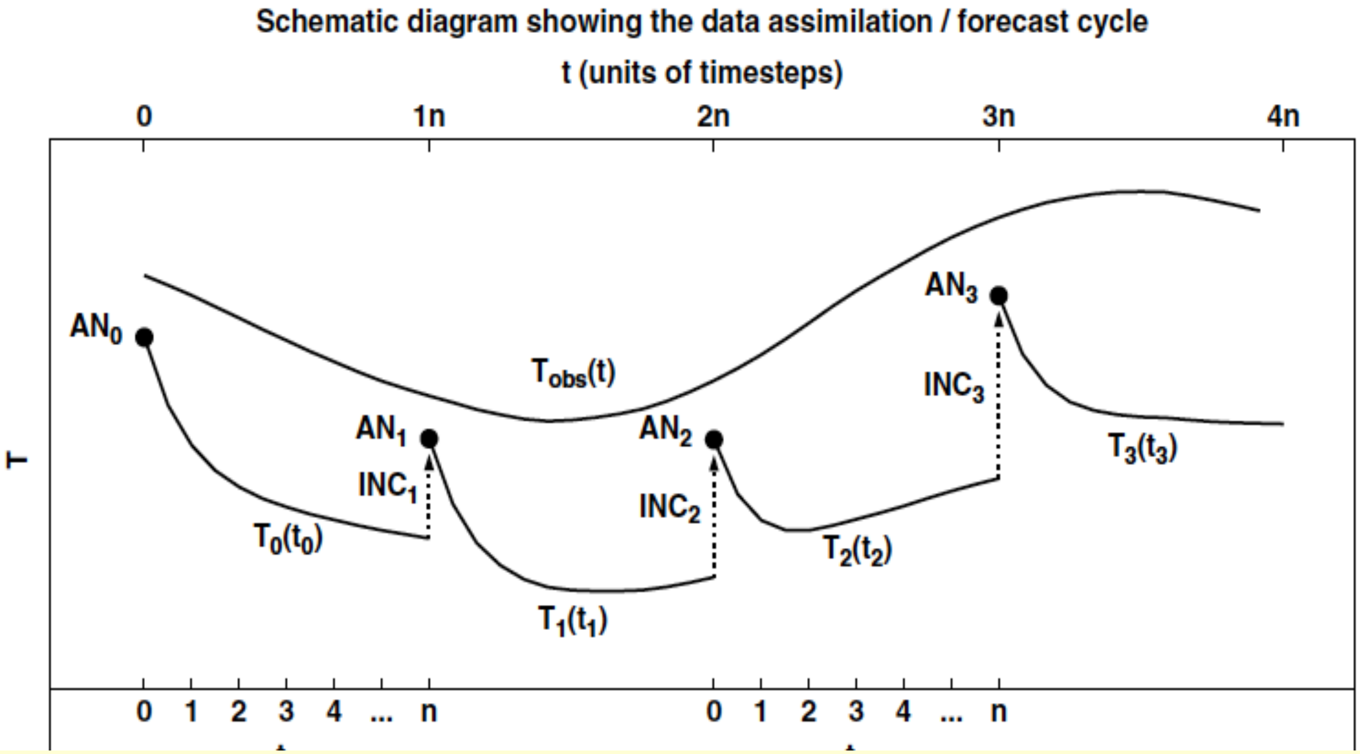
1. Goal of the project
2. NWP technique to assess (systematic) model errors
3. The process-based error tracking system
4. Illustration
5. Examples of other applications

Goal of the project

- The ultimate goal of the proposed study is to deliver to the NCEP a revolutionary diagnostics system that is capable of tracing the sources of systematic errors and the evolutions of these errors’ 3-dimensional (3D) structures with the forecast lead time in the operational forecast system.

Using NWP technique to assess model error

- First proposed by Rodwell and Palmer (2007, Q. J. Royal Met. Soc.) that extends the work of Klinker and Sardeshmukh (1992)



Using NWP technique to assess model error

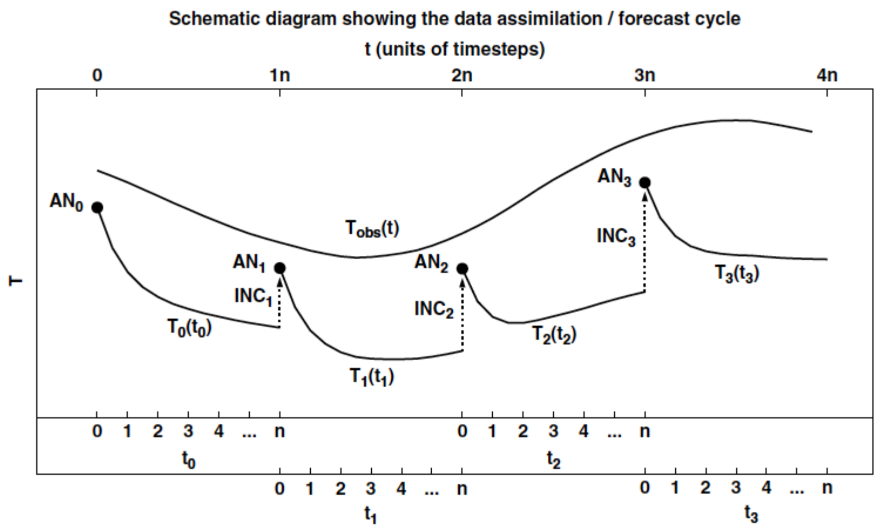


Figure 1. Schematic diagram showing the data assimilation and forecast integration aspects of numerical weather prediction. $T_{\mathrm{obs}}(t)$ represents an observed time series (e.g. of temperature at some specified location). For each i, $T_i(t_i)$ represents the model forecast initiated from analysis AN_i. For the purposes of explaining our methodology, the role of systematic forecast error (in this case a cooling) has been emphasized over random error. See the main text for further explanation.

$$
\begin{aligned}
INC_1 &= AN_1 - T_0(n) \\
&= T_1(0) - T_0(n).
\end{aligned}
$$

$$INC_i = T_i(0) - T_{i-1}(n).$$

INC = analysis increment

- Perfect model and perfect observations: INC = 0 at each data assimilation (DA) cycle.
- Assuming the time mean observational errors is zero: the time mean of INC (over many DA cycles) is zero for perfect model.
- Therefore, the non-zero value of the average of INC over many DA cycles is associated with model errors.

Using NWP technique to assess model error

$$\frac{1}{m}\sum_{i=1}^{m} INC_i = \frac{1}{m}\sum_{i=1}^{m}(T_i(0) - T_{i-1}(n))$$

$$= -\frac{1}{m}\sum^{m}(T_i(n) - T_i(0)) + \frac{1}{m}(T_m(n) - T_0(n)).$$

$$\frac{1}{m}\sum_{i=1}^{m} INC_i \approx -\frac{1}{m}\sum_{i=1}^{m}(T_i(n) - T_i(0))$$

$$= -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n}(T_i(j) - T_i(j-1)) \quad = -\frac{1}{m}\sum_{i=1}^{m}\sum_{i=1}^{n}\dot{T}_i(j) \equiv -\overline{\dot{T}},$$

- $(T_i(n) - T_i(0)) = (T_i(n) - An_{i-1})$ corresponds to forecast tendency at the DA cycle i, starting at the initial time ending at the n steps after.
- $(T_i(j) - T_i(j-1))$ corresponds to forecast tendency between step j and step (j-1) at at the DA cycle i.

Using NWP technique to assess model error

$$\frac{1}{m}\sum_{i=1}^{m} INC_i \approx -\frac{1}{m}\sum_{i=1}^{m}(T_i(n) - T_i(0))$$

$$= -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n}(T_i(j) - T_i(j-1)) \quad = -\frac{1}{m}\sum_{i=1}^{m}\sum_{i=1}^{n}\dot{T}_i(j) \equiv -\overline{\dot{T}},$$

- As in Klinker and Sardeshmukh (1992), they only considered the mean forecast tendency at the first time step starting each DA cycle: $\frac{1}{m}\sum_{i=1}^{m}\dot{T}_i(0).$

$$\dot{T}_i(0) = \dot{T}_i^{dyn}(0) + \dot{T}_i^{rad}(0) + \dot{T}_i^{con}(0) + \dot{T}_i^{lsp}(0) + \ldots.$$

- Therefore the average of the initial tendency at each DA cycle, whose non-zero value is due to model errors can be related into individual processes

Using NWP technique to assess model error

$$\dot{T}_i(0) = \dot{T}_i^{dyn}(0) + \dot{T}_i^{rad}(0) + \dot{T}_i^{con}(0) + \dot{T}_i^{lsp}(0) + \ldots.$$

- However, the average of each term on the right hand side over many DA cycles by itself does NOT have to represent error, although their sum corresponds to model error.

- Therefore, the method proposed by Rodwell and Palmer (2007, Q. J. Royal Met. Soc.) is not very effective for identifying the source(s) of model errors.

Proposed Process-based Error Tracking System

- The proposed error tracking system follows the same idea as Rodwell and Palmer (2007), i.e., using NWP technique to assess model errors except each term on the RHS of the forecast tendency equation also represents the error associated with a specific process, and their sum corresponds to the total error (i.e., the LHS of the forecast tendency equation.) .
- This new functionality of the proposed process-based error tracking system is built upon the climate feedback response analysis method (CFRAM, Lu and Cai 2008 and Cai and Lu 2008)

Proposed Process-based Error Tracking System

We consider

$$\Delta T_\tau = \overline{(T_\tau - T_0)}^{t} \quad (1)$$

τ is the lead time of the forecast and subscript "0" corresponds to initial condition (or analysis), and the overbar with superscript "*t*" represents an averaging over a period of time (e.g., a seasonal mean).

Let τ be 6 hours, then the average of the 6-hour forecast tendencies over a period of time (t) is the same as the average of all DA cycles for the period of time. => (1) represents the average of analysis increment, which should be zero for perfect model and random observational errors. Therefore, all we need to do is to make each term on the right hand side of the forecast tendency equation represent error.

Proposed Process-based Error Tracking System

Using the CFRAM technique (linearization of radiative transfer model

$$\left(\frac{\partial \mathbf{R}}{\partial \mathbf{T}}\right)\Delta \mathbf{T}_\tau = \begin{Bmatrix} \Delta^{ghs}(\mathbf{S}-\mathbf{R})_\tau + \Delta^{O_3}(\mathbf{S}-\mathbf{R})_\tau + \Delta^{wv}(\mathbf{S}-\mathbf{R})_\tau + \Delta^{c}(\mathbf{S}-\mathbf{R})_\tau + \Delta^{alb}\mathbf{S}_\tau \\ +\Delta \mathbf{Q}^{LH}{}_\tau + \Delta \mathbf{Q}^{SH}{}_\tau + \Delta \mathbf{Q}^{conv}{}_\tau + \Delta \mathbf{Q}^{adv}{}_\tau + \Delta \mathbf{Q}^{ocn\_dyn+storage}{}_\tau \end{Bmatrix} (2)$$

- The terms in red cannot be evaluated directly purely by offline calculations without adding more output fields to the standard output fields. But they can be evaluated indirectly (as the residual).

$$\Delta \mathbf{T}_\tau = \begin{Bmatrix} \Delta^{ghs}\mathbf{T}_\tau + \Delta^{O_3}\mathbf{T}_\tau + \Delta^{wv}\mathbf{T}_\tau + \Delta^{c}\mathbf{T}_\tau + \Delta^{alb}\mathbf{T}_\tau \\ +\Delta^{LH}\mathbf{T}{}_\tau + \Delta^{SH}\mathbf{T}{}_\tau + \Delta^{conv}\mathbf{T}{}_\tau + \Delta^{adv}\mathbf{T}{}_\tau + \Delta^{ocn\_dyn+storage}\mathbf{T}{}_\tau \end{Bmatrix} (3)$$

- Note that left and right hand sides of (3) can be interpreted as the systematic errors as well as systematic forecasts tendency errors for τ = 6 hours (DA cycle time interval)

Proposed Process-based Error Tracking System

- The systematic error definition implies that all terms on the right hand side can be evaluated at a much longer lead time, or τ does not have to be 6 hours with similar accuracy as long as linearization is still valid (we can estimate the errors due to linearization as a function of lead time).

- This would allow us to exam the evolution of individual error terms, which may help to understand the “causal” relationships among individual error terms.

Data required

- GEFS: ftp.ncep.noaa.gov/pub/data/nccf/com/gens/prod/
- GFS: ftp.ncep.noaa.gov/pub/data/nccf/com/gfs/prod/

lack of surface fields or not all required variables are available in both analysis (initial conditions) and forecast outputs.

- CFS: ftp.ncep.noaa.gov/pub/data/nccf/com/cfs/prod/

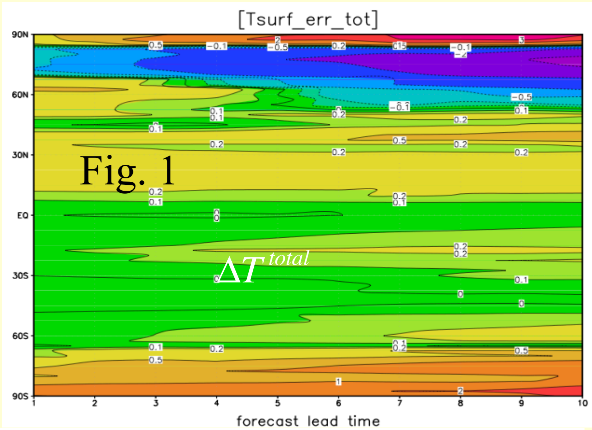
  Surface analysis and forecasts (4 times per day; 181x360)

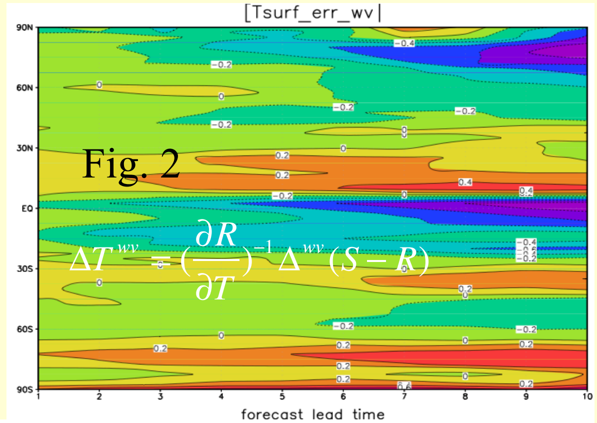
  Incoming solar flux, down/up SW and LW at surface, Ps, Ts, albedo, SH, LH

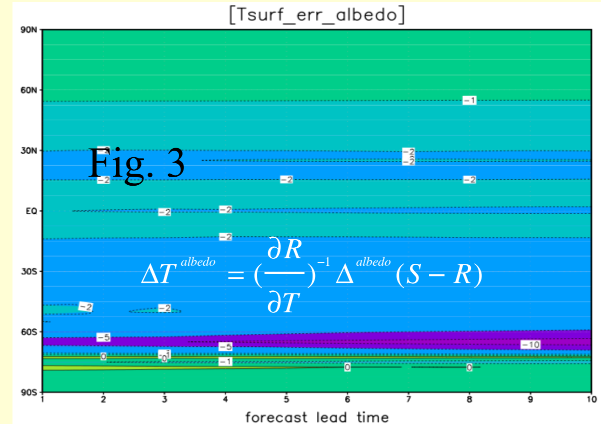
  Pressure analysis and forecasts (4 times per day; 181x360; 37 levels)

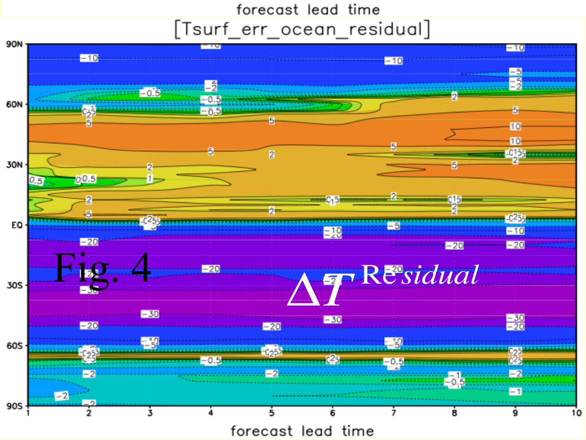
  3D Temp, water vapor, clouds (liquid water/ice, area), ozone
- Period of study: 10/01/2016 – 09/30/2017

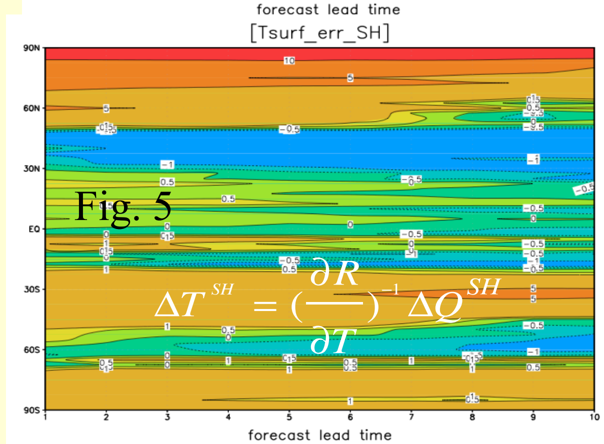
Illustration (surface temp. in a winter month)

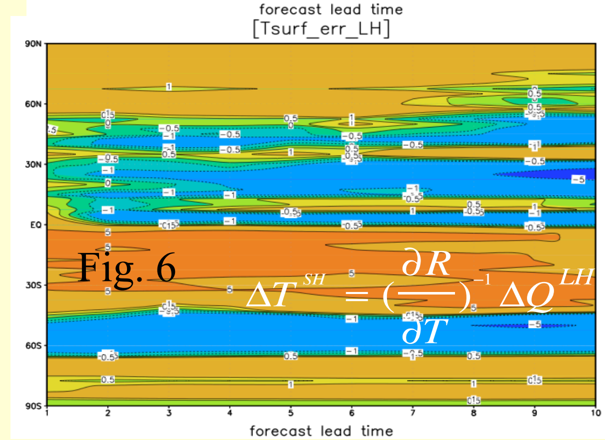


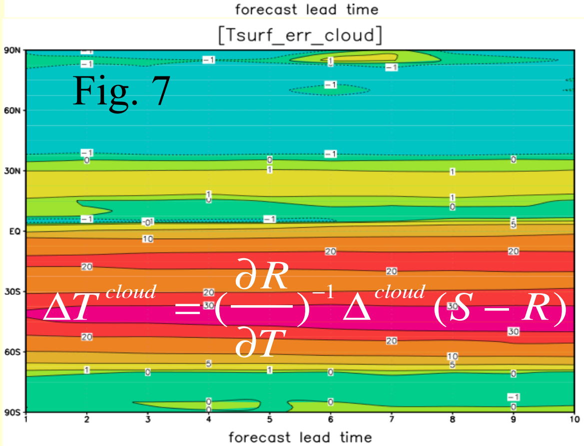


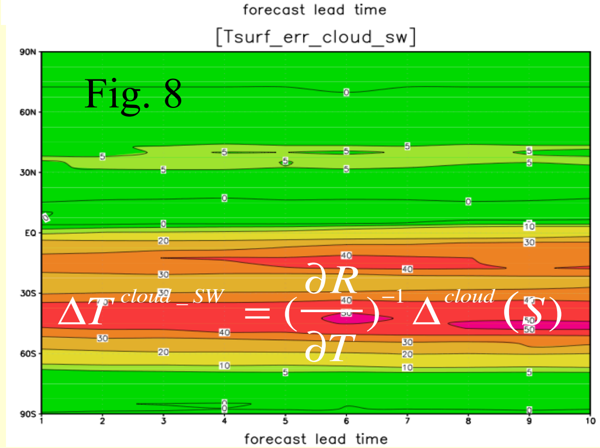


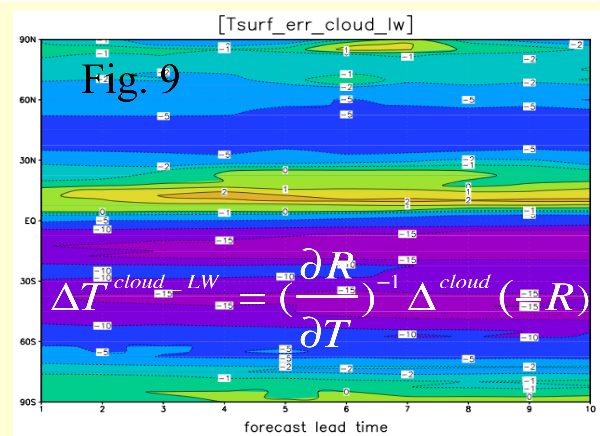












Preliminary Summary

- The meridional pattern of systematic errors remains largely unchanged from day 1 and the amplitude of systematic errors grow weakly as lead time increases (except over Arctic where errors grow in time pronouncedly).
- Warm biases over most latitudes except over Arctic where CFS has cold biases.
- There are large cancellations of errors due to different processes. Mostly noticeable cancellations are found between warm biases caused by less-cloud biases over mid-latitudes of Southern Hemisphere and cold biases from stronger ocean heat storage term.
- Dry biases contribute to cold biases over Arctic that grow as the lead time increases.

2^{nd} Year Research Plan

- examine (lead time) evolution of model systematic errors (up to 1 month) and their relations with forecast tendency errors.
- examine the seasonal dependence of model errors.
- examine the diurnal cycle of model errors from forecast tendency perspective

Examples of future applications

- It is *flexible* since it allows quantitative evaluations of the impacts of single or multiple, simultaneous model updates on forecast skill and can also be seamlessly expanded to evaluate models of both global and regional domain.

Examples of future applications

- It can be used to test one new parameterization scheme for a given physical process or a set of new parameterization schemes for several physical processes. This helps to shorten the model development cycle.

Examples of future applications

- It can be used to understand the spread of ensemble forecasts or contributions to the spread of ensemble forecasts from individual processes, as a function of lead time.