Introduction to initialization of NWP models

- weather forecasting an initial value problem

- traditionally, initialization comprised

    - "objective analysis" of obs at a fixed "synoptic time", i.e. 00Z or 12Z: data quality control; interpolation* onto a grid; use of a "background" (or "first guess") field, i.e. climatology, or a short range forecast from an earlier initialization, to fill in data-sparse regions

    - "initialization," entailing modification of the above field to obtain a field consistent with the resolvable *meteorologically-relevant* motions of the particular forecast model (e.g. exclusion of high waveno. gravity waves)

- most NWP centres now use "four-dimensional variational data assimilation" permitting optimal use of data available at off-synoptic times (Holton, p475)

- "a practical definition of the best analysis is that which gives the best subsequent forecast. However, forecast models are imperfect and subject to improvements, so it is better to define the best analysis so as to exclude the possibility of the analysis compensating for errors in the forecast model. It is necessary, however, to consider the particular forecast model to be used" (Lorenc, 1986, Quart. J. R. Met. Soc. Vol. 112

*typically nearby obsv. were weighted by the inverse of their distance to the gridpoint

• important that the model not be initialized too far out of balance. It would be unduly simplistic to (e.g.) demand that at the initial time the atmosphere be hydrostatic and in Geostrophic equilibrium – and obviously unrealistic to set it uniform in its potential temperature

• on the other hand we don't want the initial state to be drastically out of hydrostatic and Geostrophic balance (unless the model resolution were so high it was expected to resolve motions on scales less than circa. 10 km – presently not the case)

• there are more sophisticated and less drastic measures of "balance" (e.g. Holton), but these are of limited generality, possibly pertaining only to the wind & height field, ignoring topography, etc. These are no longer relevant to initialization of modern global NWP models – though note (L03) NCEP's addition of a penalty term (failure to satisfy the linear balance eqn) to the cost function as a "weak constraint" in 3D-Var

• today's initialization process uses diverse and non-simultaneous observations (within a time bracket called the "assimilation window") to start the model in a state that approximates reality. But not all observations have equal accuracy, nor equal value – they have to be accordingly weighted

• "data assimilation comprises combining all available sources of information about the atmosphere to produce the best possible forecast. Sources of information are of two types: observations of the atmosphere and the physical laws governing its evolution" (Talagrand & Courtier, 1987, QJRMS Vol. 113)

• "It became clear rather early in the history of NWP that, in addition to the observations, it was necessary to have a complete first guess estimate of the state of the atmosphere at all gridpoints (also known as the *background field* or *prior information*)" (Kalnay, 2003, *Atmos. Modeling, Data Assimilation & Predictability;* "K03"). This is because "the number of degrees of freedom in a modern NWP model is of the order of 10^7… (far fewer than the number of obs available)" – problem of under-determination – "as forecasts became better, use of short range forecasts as a first guess was universally adopted"… a practice known as "four-dimensional data assimilation (4DDA)"

• "in data rich regions, the analysis is dominated by information contained in the observations. In data poor regions, the forecast benefits from information upstream" (K03)

• we shall not cover specifics; modern methods all have a close connection to the elementary notion of a "best least squares fit**"

**Given a set of values of an independent variable (x_i, i =1...N) and a corresponding set of y_i, find the linear model $y_i^{\text{pred}} = \alpha \; x_i + \beta$ that minimizes the sum of squares of the errors

$$SS = \Sigma_i \left(y_i^{\text{pred}} - y_i \right)^2$$

Improvements in ECMWF forecasts and identified cause

 (2002; QJRMS Vol. 128)

TABLE A.1. REDUCTIONS IN R.M.S. 1-DAY FORECAST ERRORS MEASURED IN PRE-OPERATIONAL TRIALS OF RECENT CHANGES TO THE ECMWF FORECASTING SYSTEM

	Cycle	18r1	18r6	19r2	21r1	21r4	22r1	22r3	23r1	23r3
	Principal changes (see below)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Start date of trial period	9 Oct 1997	16 Apr 1998	1 Jan 1999	10 Mar 1999	7 May 1999	5 Feb 2000	1 Mar 2000	1 Jul 2000	1 Jul 2000
	Date implemented	25 Nov 1997	29 Jun 1998	9 Mar 1999	5 May 1999	12 Oct 1999	8 Apr 2000	27 Jun 2000	12 Sep 2000	21 Nov 2000
NH	Z500	0.5	0.4	0.4	0.2	1.5	−0.1	0.6	0.4	0.8
	MSLP	0.06	0.02	0.01	0.00	0.13	0.00	0.07	0.04	0.07
SH	Z500	1.8	0.0	0.4	0.8	2.3	0.5	1.9	0.7	0.7
	MSLP	0.27	0.02	0.01	0.09	0.39	0.02	0.19	0.08	0.07

SH and NH are the southern and northern hemispheres, respectively. Z500 is the 500 hPa height forecast error (m). MSLP is the mean-sea-level pressure forecast error (hPa).

1. 4D-Var replaces 3D-Var (with 6-hourly cycling).
2. Introduction of coupling with ocean-wave model. Improved utilization of radiosonde data. Use of hourly surface data. Assimilation of humidity from SSM/I.
3. Increased vertical resolution in the stratosphere.
4. Assimilation of raw MSU and AMSU-A radiances.
5. Increased vertical resolution in PBL and improved representation of clouds, convection and orography. New background-error statistics for 4D-Var. Corrected processing of humidity observations. Assimilation of marine winds from SSM/I.
6. Improved quality control of SSM/I data and assimilation of the data from a second satellite. Corrected stratospheric humidity analysis
7. New background- and observation-error variances. Assimilation of additional ATOVS radiance data. Improved representation of the land surface, sea-ice and radiation
8. Twelve-hourly cycling of 4D-Var.
9. T511 horizontal resolution for atmospheric model and T159 analysis increments. Doubled angular resolution for ocean-wave model.

Variational data assimilation

• variational approach – find the solution of the assimilating model which minimizes a given scalar function measuring the “distance” between a model solution and the available observations. The “adjoint equations” of the model** can be used to compute explicitly the “gradient” of the distance function with respect to the model’s initial conditions. Computation of the gradient requires one forward integration of the full model equations over the time interval on which the observations are available, followed by one backward integration of the adjoint equations. Successive gradients thus computed are introduced into a descent algorithm in order to determine the initial conditions which define the minimizing model solution (Talagrand & Courtier, 1987, QJRMS Vol. 113)

• variational formulation leads to a natural framework for the direct assimilation of (e.g.) satellite radiances instead of retrieved temperature and humidity profiles. This is also true for any other indirect measurement of the state of the atmosphere (G07)

• use of the adjoint of a numerical model makes it possible to determine the initial conditions leading to a forecast that would best fit data available over a finite time interval (assimilation window)(G07)

• these are the two key elements of “4D-VAR,” as now used at CMC, ECMWF and most other centres (Gauthier et al., 2007; Monthly Weather Review Vol. 135; G07)

** essentially a linearization of the model about the present state of the atmosphere

The notion of "linearizing" a model (or more simply, an equation)

Suppose the model, which is non-linear, is: $y = f(t) = a t^2 + b$

Suppose we know the state at time t_0 and want the state at a later time $t_0 + \Delta t$. A Taylor series expansion gives:

$$y(t_0 + \Delta t) \approx y(t_0) + \left.\left(\frac{\partial y}{\partial t}\right)\right|_{t_0} \Delta t + \frac{1}{2!}\left.\left(\frac{\partial^2 y}{\partial t^2}\right)\right|_{t_0} \Delta t^2 + \ldots$$

"Linearizing" means the neglect of all terms that are non-linear in Δt, viz.

$$y^{\text{tlm}}(t_0 + \Delta t) \approx y(t_0) + \left.\left(\frac{\partial y}{\partial t}\right)\right|_{t_0} \Delta t \; = \; a t_0^2 + b \; + \; (2 a t_0) \; \Delta t$$

This can be called the "tangent linear model" (TLM – thus the superscript "tlm") corresponding to the original non-linear model. The basic idea can be extended to a numerical weather model as an ensemble of equations – one linearizes about a basic state (which may be a forecast from a few hours earlier). Some processes may be neglected. The "adjoint model" is basically a version of the TLM that is valid for going *backwards* in time.