

Data Assimilation

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Data assimilation is an exercise in the calculation of conditional probabilities in which short-term model forecasts are combined with observations to best estimate the state of, for example, the atmosphere. Since there are limitations in model resolution and errors associated with parameterization of unresolved physical processes, and the behavior of the atmosphere is chaotic, forecast accuracy is described by a probability distribution, as is observation accuracy. These probability distributions are combined to form conditional probabilities, which are simplified by assuming these distributions are Gaussian (normally distributed). The conditional probabilities are used to create a more accurate *analysis* than can be obtained solely from either the forecasts or the observations. The same approach can be applied to the ocean, land surface, or cryosphere.

Atmospheric data assimilation proceeds through a succession of (typically) six hour *analysis cycles*. At the beginning of each cycle, a six-hour model forecast is carried out starting from initial conditions of atmospheric pressure, temperature, humidity, and winds provided by the previous analysis cycle, with observed boundary conditions such as sea surface temperature and snow cover. At the end of each cycle all available current observations are quality controlled, and the differences between the observations and the model forecast of the same variables, referred to as observational increments or innovations, are computed. The observations may include the same variables observed with different systems (*e.g.*, winds measured from airplanes or by following the movement of clouds). They may also include observations of variables that do not directly enter the forecast such as satellite radiances, which contain information about both temperature and moisture.

If the evolving probability distributions of the model forecasts and observations are known, then it is possible to construct an analysis that is optimal because the expected error variance, which is the difference between the analysis of a variable and its true value, is minimized. In practice, the probability distributions are unknown. In addition, it is not possible to solve the computational problem of minimizing the error variance for realistic complex systems. In order to address these problems, several simplifying assumptions are needed. The observational increments are generally assumed to be Gaussian. With this assumption a cost function can be constructed whose minimization, which provides us with the optimal analysis, leads to the Kalman Filter equations. A bigger assumption that the probability distribution of the forecast errors does not depend on time, gives rise to the widely used and more simplistic three-dimensional variational type of data assimilation (3DVAR). Four-dimensional variational data assimilation (4DVAR) is a generalization of the cost function approach that allows the forecast initial conditions (or other control variables such as diffusive parameters) to be modified based on observations within a time window.

Despite the use of simplifying assumptions, the Kalman Filter and 4DVAR approaches still lead to challenging computational problems. Efforts to reduce the magnitude of the computational problems and exploit physical understanding of the physical system have led to the development of Monte Carlo approaches known as Ensemble Kalman Filter (EnKF). EnKF methods, like 4DVAR, can be posed in such a way that the analysis at a given time can be influenced by past, present, and future observations. This property of time symmetry is especially desirable in reanalyses since it allows the analysis at past times to benefit to some extent from future enhancements of the observing system.

Table A.1 Characteristics of some existing global ocean model-based reanalyses of ocean climate
(extracted from: <<http://www.clivar.org/data/synthesis/directory.php>>)

Organization/System	Model	Analysis Method	Time Period	Weblinks
NCEP, Météo France, CERFACS	OPA8.2, 2°x2°x31 Lev (~0.5°x2° tropics) ERA40 forcing	Multivariate 3D-Var (OPAVAR) for T & S profiles	1962 to 2001	< fr/globc/overview.html >
ECMWF	HOPE, 1°x1°x29 Lev (1/3°x1° tropics)	OI	1959 to 2006	< ecmwf.int/products/forecasts/d/charts/ocean/reanalysis/ >
ECCO-GODAE	MITgcm 1°x1°	4DVAR	1992 to 2004	< www.ecco-group.org >
ECCO-JPL	MITgcm and MOM4 1°x1°x50 lev	Kalman filter and RTS smoother	1993 to present	< ecco.jpl.nasa.gov/external/ >
ECCO-SIO	1°x1°	4DVAR	1992 to 2002	< ecco.ucsd.edu >
ECCO2	MITgcm, 18kmx50 Lev	Green's functions	1992 to present	
ENACT consortium			1962 to 2006	< www.ecmwf.int/research/EU_projects/ENACT/ >
FNMOC/GODAE				< www.usgodae.org >
GECCO			1950 to 2000	< www.ecco-group.org >
GFDL			1960 to 2006	< www.gfdl.noaa.gov/ >
UK Met Office GloSea	GloSea OGCM 1.25°x1.25°x40 Lev (0.3°x1.25° tropics) daily ERA40 fluxes with corrected precipitation	OI	1962 to 1998	< www.metoffice.gov.uk/research/seasonal/glosea.html >
NASA Goddard GMAO	Poseidon, 1/3°x5/8°	MVOI, Ensemble KF	1993 to present	< gmao.gsfc.nasa.gov >
INGV	OPA8.2 2°x2°x31 Lev (0.5°x2° tropics) ERA40 and operational ECMWF fluxes	Reduced Order MVOI with bivariate T and S EOFs	1962 to present	
MEXT K-7	MOMv3 1°x1°x36 Lev NCEP2 reanalysis, ISCCP data	4DVAR	1990 to 2000	< www.jamstec.go.jp/frcg/k7-dbase2/eng/ >
MERCATOR-3	OPA8.2 2°x2°x31 Lev (~0.5° meridional at the tropics)	Single Evolutive Extended Kalman (SEEK) filter	1993 to 2001	< www.mercator-ocean.fr/html/systemes_ops/psy3/index_en.html >
JMA MOVE/MRI.COM			1949 to 2005	< www.mri-jma.go.jp/Dep/oc/oc.html >
NOAA/NCEP GODAS	MOMv3 1°x1°x40 Lev (1/3°x1° tropics) NCEP Reanalysis2	3DVAR	1980 to present	< www.bom.gov.au/bmrc/ocean/JAFOOS/POAMA/ >
BoM, CSIRO, POAMA	ACOM2 (based on MOM2), 2°x2°x27 Lev (0.5°x2° at high latitudes) ERA40	MVOI, ensemble KF	1980 to 2006	< www.atmos.umd.edu/~ocean/ >
SODA	POPI.4, POP2.01, global ave	MVOI with evolving error	1958 to 2005	