Appendix: Chapter 8

The invention of the telegraph in 1845 ushered in the era of real-time weather data. By the end of the 19th century, hand-drawn *synoptic charts* summarizing surface weather conditions at many different stations were being used by national weather services in many different countries as a basis for issuing weather forecasts. The growth of aviation during the early decades of the 20th century created a demand for upper air charts. It was also becoming increasingly apparent that forecasting the movement of weather systems requires a knowledge of the winds aloft that steer them. Early upper air charts were based on reports of aircraft pilots, kites and the paths of pilot balloons, which could be optically tracked to around the 3 km (700-hPa) level, weather permitting. By the late 1940s, radar tracked radiosondes bearing disposable instrument packages were being launched on a regular schedule from hundreds of stations around the world and synoptic charts were being prepared for a standard set of pressure levels extending all the way up into the lower stratosphere.

The launch of Sputnik, the first unmanned satellite, by the Soviet Union in 1958 paved the way for remote sensing of the global atmosphere from space. Coincidentally, this launch took place during the International Geophysical Year, a venture that demonstrated the feasibility of international cooperation on a scale that had not previously been attempted in the physical sciences. By 1980, satellite-based remote sensing had become the backbone of a truly global network for observing weather systems. Today, despite the wide disparity between the density of in situ weather observations in the northern and southern hemispheres, satellite data provide so much information that the skill of hemispheric weather forecasts for the two hemispheres is comparable (Fig. 1.1).

Figure 8.80 provides an indication of the scope of the observing system that existed in support of numerical weather prediction in 2004. Each panel shows the locations or geographical domain of one of the components of the observing system during a 6 hour interval around noon on a typical day. In situ data are shown in the top two rows and remotely sensed data from satellite-borne instruments in the bottom two rows. These observations are blended to produce a single, dynamically consistent, four dimensional (space/time) analysis of global fields such as pressure, wind, temperature and moisture, making use of *data assimilation* schemes. The analyzed fields are represented as numerical values at regularly spaced grid-points on a set of pressure surfaces at regular time intervals. Unlike the raw data from which they are constructed, the analyzed fields provide complete coverage in space and time. Hence, based on analyzed fields it is relatively straightforward to produce horizontal maps, vertical cross-sections and other graphical representations of the analyzed data.

Short-range forecast fields derived from state-of-the-art numerical weather prediction models are used as *first-guess* fields for the analysis. Each observation is used to "nudge" the first-guess field toward the true state of the atmosphere within some surrounding "region of influence". For example, if a temperature measurement is lower than the first guess temperature at that particular place and time, the analyzed temperatures will be adjusted downward at nearby grid

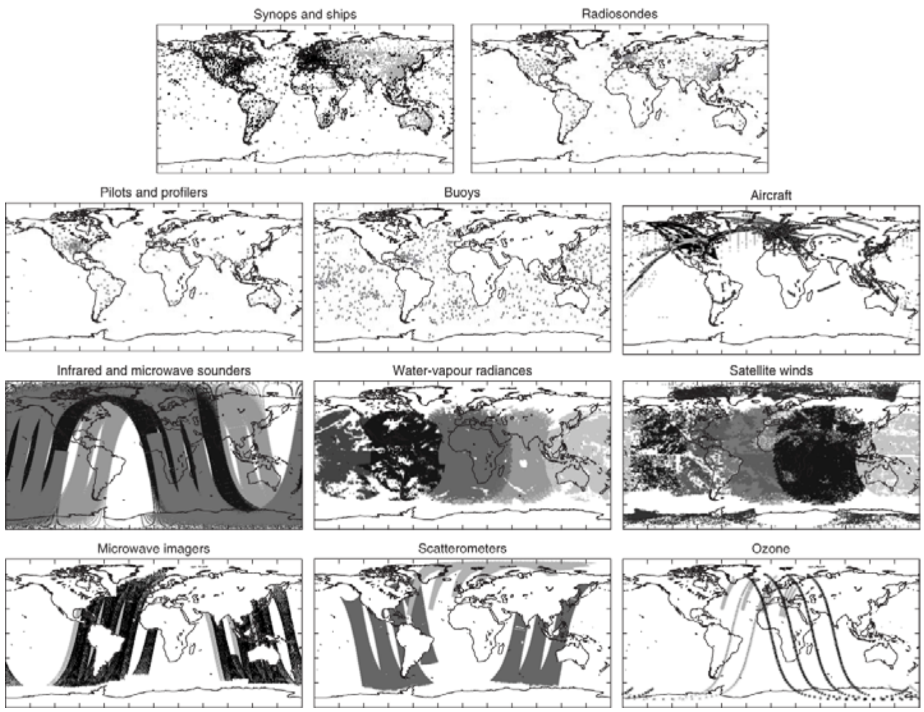

Fig. 8.80 Operational data coverage for the 6-hour interval centered at 1200 UTC Nov. 21, 2004. [From A. Simmons, "Observations, assimilation, and the improvement of global weather prediction—Some results from operational forecasting and ERA-40," in *Predictability of Weather and Climate*, edited by T.N. Palmer and R. Hagedorn, in press, Cambridge University Press. Courtesy of T.N. Palmer, ECMWF.]

points. A stronger correction will be applied to grid points very close to the site of the measurement than to grid points farther away, and little or no correction will be applied to grid points that lie outside the region of influence. The weight that is assigned to each observation also depends upon the performance characteristics of the instrumentation: for example, a temperature measurement from a sensor that is known to be highly reliable is assigned a higher weight than one from a less reliable sensor. Through the dynamical constraints built into in the forecast model, information from data-rich regions trends to propagate into surrounding data-void regions.

Figure 8.81 shows how such a data assimilation scheme could be implemented by running a forecast model through a series of discrete (e.g. 6-hour) time steps. Let us suppose that the first short term (e.g. 6-hour) forecast F_1 is generated starting with a crude initial analysis A_0 (e.g., the climatological mean fields).

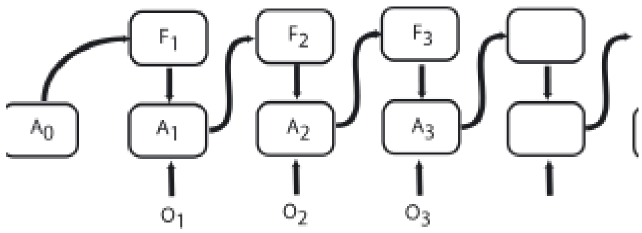

Fig. 8.81 Implementation of a data assimilation scheme through a sequence of time steps 1, 2...etc. that might be 6 or 12 hours apart. At each time step the observational data O available at that time are used to "nudge" the first guess field F. toward the true state of the atmosphere, yielding analysis A. The forecasts are based on a state-of-the-art numerical weather prediction model, initialized with the analysis produced at the previous time step.

Data assimilation is performed, for the first time, at the end of the first time step to produce an improved analysis A_1. Since the first guess forecast field F_1 for this first updated analysis bears little relation to the true state of the atmosphere, A_1 will be crude but, thanks to the assimilated data, it should be much closer to the true state of the atmosphere than A_0 was a time step ago. It follows that the first guess F_2 for the data assimilation carried out at the end of the second time step should be substantially closer to the true state of the atmosphere than F_1 and, accordingly, A_2 should be closer to the true state of the atmosphere than A_1. Through this bootstrap process, the quality of the analysis improves over the course of a week or so of simulated time, by which time the "memory" of the crude initial analysis A_0 is almost entirely lost, and the current analysis A_n depends only upon the recent history of the observations.

Modern atmospheric data assimilation is *multivariate* in the sense that a measurement of, say, temperature affects not only the analyzed temperature field in the vicinity of the observation, but also the fields of geopotential height, wind, and surface pressure. In the above example, the geopotential height field will be adjusted downward locally, in accordance with the hypsometric equation, above the region in which the negative temperature adjustment is applied. The data assimilation scheme will also ensure that wherever the heights are locally lowered, the winds at the surrounding gridpoints will be adjusted to make the wind field more cyclonic. Satellite radiances that relate to temperature or the mixing ratio of water vapor or ozone are compared with radiances computed from the first guess fields of temperature, water vapor or ozone, and the first guess field is "nudged" in a dynamically consistent manner so as to reduce the discrepancy. This transfer of information between different fields makes much more effective use of the measurements than is possible in a *univariate* scheme, in which each field is analyzed in isolation.

Data assimilation schemes may be either three or four dimensional. Three-dimensional (3D) schemes assign all the observations within a specified interval (typically 6 hours long) to a common reference time, regardless of when they were actually taken, and use them to update the first guess fields to produce the analysis. More sophisticated and much more computationally intensive four dimensional (4D-VAR) schemes take into account the timing, as well as the spatial position of the observations. Relying on inverse modeling techniques based on the calculus of variations, these schemes nudge the atmospheric fields at the start of the interval so as to minimize the root-mean-squared difference between the observations and the forecasts during the interval.

Other things being equal, the more skillful the forecast model, the smaller the nudging required to bring the first guess field into optimal agreement with the observations, and the more accurate the final analysis. Hence, today's reanalysis of the state of the atmosphere that existed at an instant in time, say, a decade ago is more accurate than the operational analysis that was made back at that time based on the same observations, simply because today's forecast model is more skillful than the forecast models that were in use a decade ago. For analyses made with the same forecast model, the more complete and accurate the observations, the more closely the analyzed fields will track the true state of the atmosphere, and the smaller the nudging required to bring the first guess field into optimal agreement with the observations at each time step. In terms of mean squared 500-hPa height increment, the amount of nudging required has decreased by roughly a factor of 2 since the pre-satellite era.

Data assimilation is performed in real time in support of operational numerical weather prediction, and a delayed time mode, for the purpose of producing more uniform, quality controlled data sets for climate research. Data assimilation yields, as a by-product, diagnostic fields such as vertical velocity, diabatic heating and surface fluxes, which are not directly measured. In interpreting such fields it should be borne in mind that they are model-dependent, at least to some degree. Most of the figures presented in Section 8.1 are based on model-assimilated data.