Reanalysis of Historical Climate Data for Key Atmospheric Features

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KEY FINDINGS

- Reanalysis plays a crucial integrating role within a global climate observing system by producing comprehensive, long-term, objective, and consistent records of climate system components, including the atmosphere, oceans, and land surface (Section 2.1).
- Reanalysis data play a fundamental and unique role in studies that address the nature, causes, and impacts of global-scale and regional-scale climate phenomena (Section 2.3).
- Reanalysis datasets are of particular value in studies of the physical processes that produce high-impact weather and climate events such as droughts and floods, as well as other key atmospheric features that affect the United States, including climate variations associated with major modes of climate variability, such as the El Niño-Southern Oscillation (Section 2.3).
- Global and regional surface temperature trends in reanalysis datasets are broadly consistent with those obtained from temperature datasets constructed from surface observations not included in the reanalysis, particularly since the late 1970s. However, in some regions (e.g., Australia) the reanalysis trends show major differences with observations (Section 2.4).
- Reanalysis precipitation trends are less consistent with those calculated from observational datasets. The differences are likely due principally to current limitations in the reanalysis models and the methods used for integrating diverse datasets within models (Section 2.4).
- Current reanalysis data are extremely valuable for a host of scientific and practical applications; however, the overall quality of reanalysis products varies with latitude, altitude, time period, location and time scale, and quantity or variable of interest (Sections 2.1, 2.3).
- Current global reanalysis data are most reliable in Northern Hemisphere mid-latitudes, in the middle to upper troposphere (about 3 to 12 miles above Earth's surface), and for regional and larger areas. They are also most reliable for time periods ranging from one day up to several years, making reanalysis data well suited for studies of mid-latitude storms and short-term climate variability (Sections 2.1, 2.2, 2.3, 2.4).
- Present reanalyses are more limited in their value for detecting long-term climate trends, although there are cases where reanalyses have been usefully applied for this purpose. Important factors constraining the value of reanalyses for trend detection include: changes in observing systems over time; deficiencies in observational data quality and spatial coverage; model limitations in representing interactions across the land-atmosphere and ocean-atmosphere interfaces, which affect the quality of surface and near-surface weather and climate variables; and inadequate representation of the water cycle (Sections 2.2, 2.3, 2.4).
- At the present time, data sets constructed for an individual variable, for example, surface temperature or precipitation, are generally superior for climate change detection. However, the integrated and

comprehensive nature of reanalysis data provides a quantitative foundation for improving understanding of the processes that produce changes. These qualities make reanalysis data more useful than individual variable datasets for attributing the causes of climate variations and change (Section 2.4).

- Reanalysis data play an important role in assessing the ability of climate models to simulate basic weather and climate variables such as the horizontal winds, temperature, and pressure. In addition, the adjustments or analysis increments produced during the course of a reanalysis provide a method to identify fundamental errors in the physical processes and/or missing physics that create climate model biases (Sections 2.2, 2.3).
- Reanalyses have had substantial benefits for climate research and prediction, as well as for a wide range of societal applications. Significant future improvements are possible by developing new methods to address observing system inconsistencies, by developing estimates of the reanalysis uncertainties, by improving the observational database, and by developing integrated Earth system models and analysis systems that incorporate key climate elements not included in atmospheric reanalyses to date (Section 2.5).

2.1. CLIMATE REANALYSIS AND ITS ROLE WITHIN A COMPREHENSIVE CLIMATE OBSERVING SYSTEM

2.1.1 Introduction

Weather and climate vary continuously around the world on all time scales. The observation and prediction of these variations is important to many aspects of human society. Extreme weather events can cause significant loss of life and damage to property. Seasonal to interannual changes associated with the El Niño-Southern Oscillation (ENSO) phenomenon and other modes of climate variability have substantial effects on the economy. Climate change, whether natural or anthropogenic, can profoundly influence social and natural environments throughout the world, with impacts that can be large and far-reaching.

Determining the nature and predictability of climate variability and change is crucial to society's future welfare.

Determining the nature and predictability of climate variability and change is crucial to society's future welfare. To address the threats and opportunities associated with weather phenomena, an extensive weather observing system has been put in place over the past century (see Figure 2.1). Considerable resources have been invested in obtaining observations of the ocean, land, and atmosphere from satellite and surface-based systems, with plans to improve and expand these observations as a part of the Global Earth Observing System of Systems (GEOSS, 2005). Within this developing climate observing system, climate analysis plays an essential synthesizing role by combining data obtained from this diverse array of Earth system observations to enable improved descriptions and understanding of climate variations and change.

2.1.2 What is a Climate Analysis?

As discussed in Chapter 1, at its most fundamental level, an *analysis* is a detailed representation of the state of the atmosphere and, more generally, of other Earth climate system components, such as oceans or land surface, that is based on observations. A number of techniques can be used to create an analysis from a given set of observations.

One common technique for creating an analysis is based on the expertise of human analysts, who apply their knowledge of phenomena and physical relationships to estimate values of variables between observation locations, a technique referred to as interpolation. Such subjective analysis methods were used almost exclusively before the onset of modern numerical weather prediction in the 1950s and are still used for many purposes today. While these techniques have certain advantages, including the relative simplicity by which they may be produced, there are key inadequacies that limit their value for numerical weather prediction and climate research. An important practical limitation, recognized in the earliest attempts at numerical weather prediction (Richardson, 1922; Charney, 1951), was that the process of creating a detailed analysis, for example, of the global winds and temperatures through the depth of the atmosphere on a given day, is

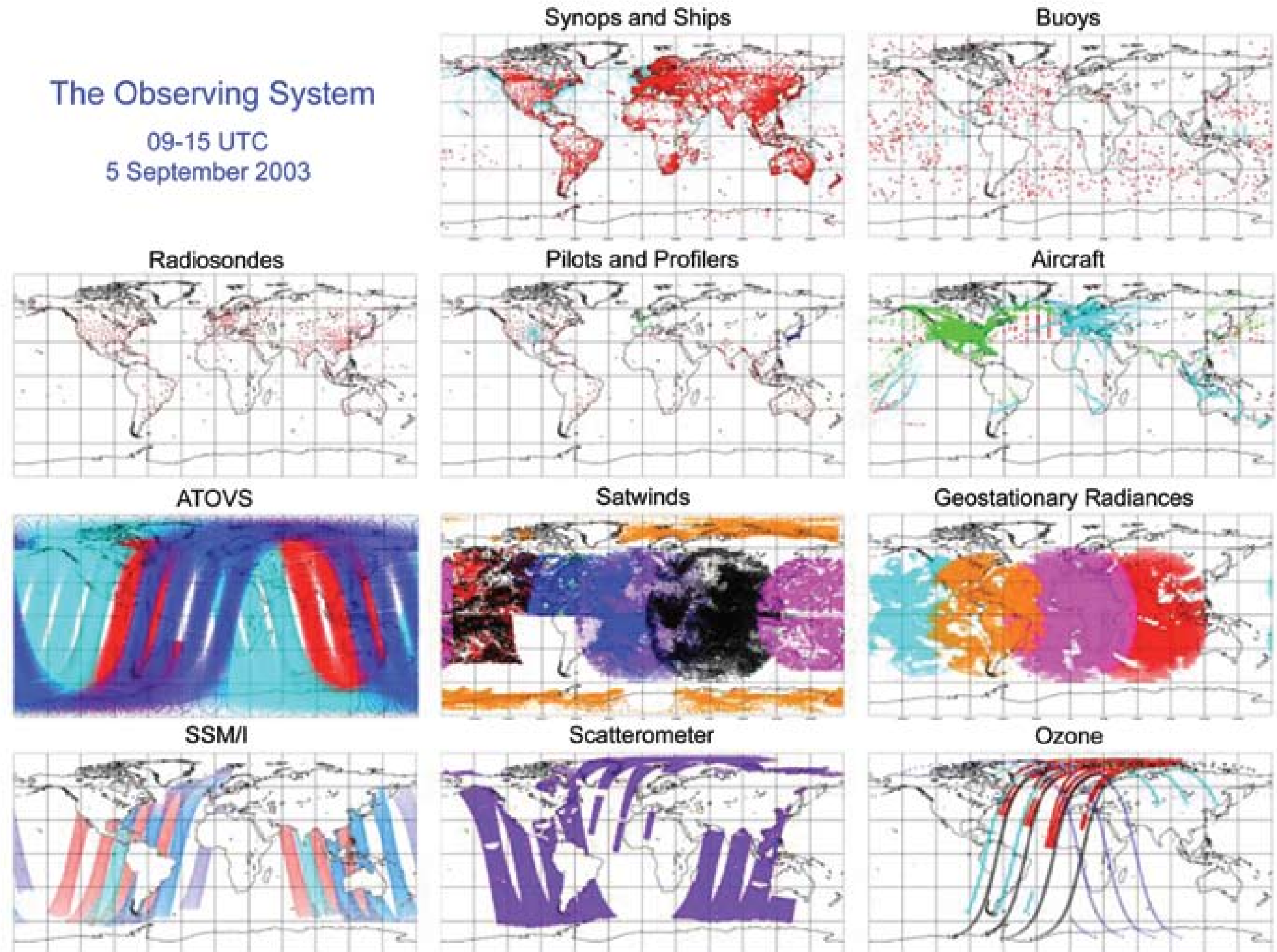

Figure 2.1 The atmospheric data coverage provided by the modern observing systems on 5 September 2003 for use in reanalysis. From Simmons (2006).

time consuming, often taking much longer to produce than the evolution of the weather itself. A second limitation is that physical imbalances between fields that are inevitably produced during a subjective analysis lead to forecast changes that are much larger than actually observed (Richardson, 1922). A third limitation is that this type of subjective analysis is not reproducible. In other words, the same analyst, given the same observational data, will generally not produce an identical analysis when given multiple opportunities.

Thus, by the early 1950s the need for an automatic, objective analysis of atmospheric conditions had become apparent. The important technological advance provided by the early computers of that time, while primitive by today's standards, could still perform calculations far faster than previously possible, making this a feasible goal.

The first objective analyses used simple statistical techniques to interpolate data values from the locations where observations were made onto uniform spatial grids that were used for the model predictions. Such techniques are still widely employed today to produce many types of analyses, such as global maps of surface temperatures, sea surface temperature (SST), and precipitation (Jones *et al*., 1999; Hansen *et al*., 2001; Doherty *et al*., 1999; Huffman *et al*., 1997; Xie and Arkin, 1997; Adler *et al*., 2003; Fan and Van den Dool, 2008). The purely statistical approaches are less well suited for the analysis of upper air conditions in that they do not fully exploit known physical relationships among different variables of the climate system, for example, among fields of temperature, winds, and atmospheric pressure. These relationships place fundamental constraints on how weather and climate evolve in time. Therefore, statistical analysis techniques are no longer used for applications that depend on relationships among

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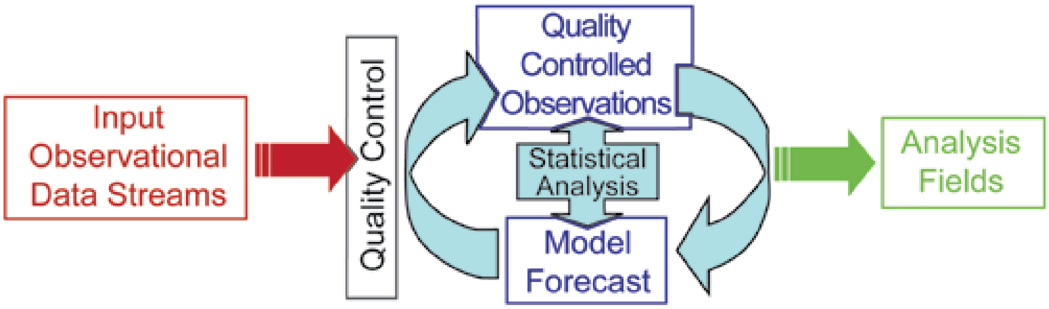

Figure 2.2 A schematic of data assimilation.

variables, as in numerical weather prediction or in research to assess detailed mechanisms for climate variability and change.

An alternative objective analysis method, which is the principal focus for this Product, is to estimate the state of the climate system (or of one of its components) by combining observations together within a numerical prediction model that mathematically represents the physical and dynamical processes operating within the system. This observations-model integration is achieved through a technique called data assimilation. One important aspect of a comprehensive climate observing system achieved through data assimilation is the ability to integrate diverse surface, upper air, satellite, and other observations together into a coherent, consistent description of the state of the global climate system. Figure 2.1 shows, for example, a snapshot of the coverage provided by the different atmospheric observing systems on 5 September 2003 that can be incorporated into such an analysis scheme.

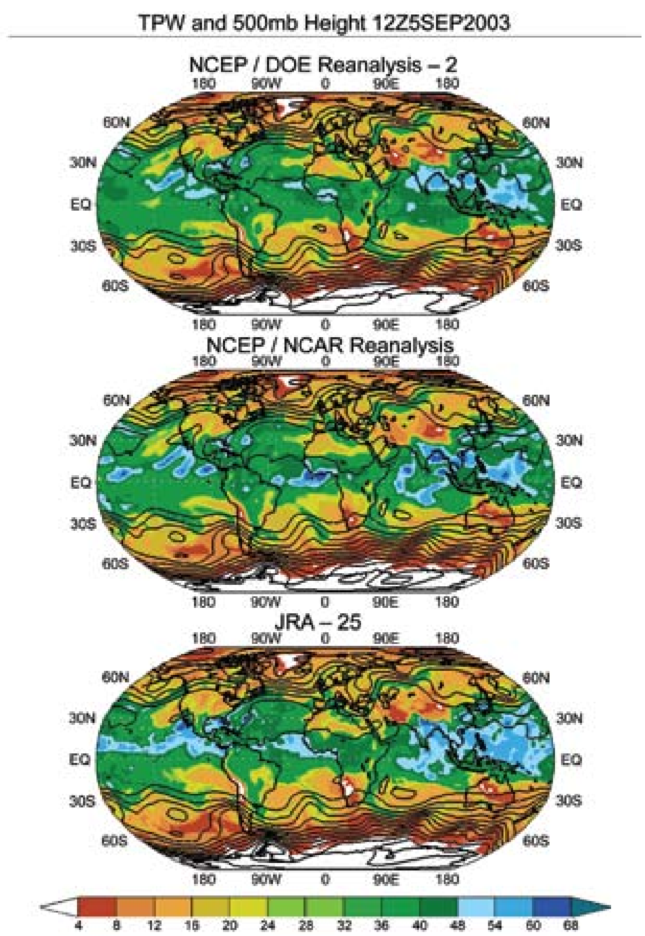

Figure 2.3 The global distribution of the mid-tropospheric pressure field (contours are of the 500 millibars [mb] geopotential height field) and total water vapor (shaded color; units are in millimeters) for 5 September 2003 from three different analyses.

How are observations combined that have such different spatial coverage, sampling density, and error characteristics? Data assimilation mathematically combines a background field or an initial estimate produced by a numerical prediction of the atmosphere (or oceans) with available observations using a method designed to minimize the overall errors in the analysis. Figure 2.2 schematically shows how data assimilation combines quality-controlled observations with a short-term model forecast (typically, in six-hour increments) to produce an analysis that attempts to minimize errors in estimates of the atmospheric state that would be present due to either the observations or model evaluated separately (for more details see Appendix A).

In practice, the quality of a global analysis is impacted by a multitude of practical decisions and compromises, involving the analysis methodology, quality control, the choice of observations and how they are used, and the model (see Appendix A and the discussion below). Figure 2.3 compares three different reanalyses produced from the observations available for 5 September 2003 (Figure 2.1) of the 500 millibars (mb) geopotential height distribution (the height of a mid-tropospheric pressure surface above mean sea level) and total water vapor fields. These are results from the National Centers for Environmental Prediction (NCEP)/National Center

Table 2.1 Characteristics of existing atmospheric reanlyses.

Organization	Time Period	Model	Analysis Scheme	Output	References
NASA Data Asssimilation Office (DAO)	1980 to 1994	2X2.5° Lat/lon- Δx~250 km, L20 (σ, top at 10mb), specified soil moisture	Optimal Interpolation (OI) with incremental analysis update	No longer available	Schubert *et al.* (1993)
NOAA NCEP and NCAR (R1)	1948 to present	T62 - Δx~200km L28 (σ, top at about 3mb)	Spectral Statistical Interpolation (SSI)	<http://www.cpc.ncep.noaa.gov/products/wesley/reanalysis.html>	Kalnay *et al.* (1996)
NOAA NCEP and DOE (R2)	1979 to present	T62 - Δx~200km L28 (σ, top at about 3mb)	Spectral Statistical Interpolation (SSI)	<http://www.cpc.ncep.noaa.gov/products/wesley/reanalysis2/>	Kanamitsu *et al.* (2002) (Fixes errors found in R1 including fixes to PAOBS, snow, humidity, etc.)
European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA-15)	1979 to 1993	T106 - Δx~125km L31(σ-p, top at 10mb)	Optimal Interpolation (OI), 1DVAR, nonlinear normal mode initialization	<http://data.ecmwf.int/data/d/era15/>	Gibson *et al.* (1997)
ECMWF (ERA-40)	1957 to 2001	T159 - Δx~100km L60 (σ-p, top at 0.1mb)	3D-Var, radiance assimilation	<http://data.ecmwf.int/data/d/era40_daily/>	Uppala *et al.* (2005)
JMA and CRIEPI (JRA-25)	1979 to 2004	T106 - Δx~125km L40 (σ-p, top at 0.4mb)	3D-Var, radiance assimilation	<http://jra.kishou.go.jp/index_en.html>	Onogi *et al.* (2005)
NOAA North American Regional Reanalysis (NARR)	1979 to present	Δx= 32km L45	3D-Var, precipitation assimilation	<http://nomads.ncdc.noaa.gov/#narr_datasets>	Mesinger *et al.* (2006)

for Atmospheric Research (NCAR) Reanalysis 1, the NCEP/Department of Energy (DOE) Reanalysis 2, and the Japanese Meteorological Agency (JMA)/Central Research Institute of Electrical Power Industry (CRIEPI) 25-year Japanese Reanalysis (JRA-25).

The two NCEP reanalyses were carried out with basically the same system (Table 2.1, the NCEP/DOE reanalysis system corrected some of the known errors in the NCEP/NCAR system).

The three analyses show substantial agreement in midlatitudes, especially for the pressure distribution; however, there is substantial disagreement in the tropical moisture fields between the NCEP and JRA data. The differences indicate that there are insufficient observations and/or inadequate representation of relevant physical processes incorporated into the models that are needed to tightly constrain the analyses. Consequently, the uncertainties in the tropical moisture field are relatively large.

The numerical prediction model used for data assimilation plays a fundamental role in the analysis. It ensures an internal consistency of physical relationships among variables such as temperatures, pressure, and wind fields, and provides a detailed, three-dimensional representation of the system state at any given time, including winds, temperatures, pressures, humidity, and numerous other variables that are necessary for describing weather and climate (Appendix A). Further, the physical relationships among atmospheric (or oceanic) variables that are represented in the mathematical model enable the model to transfer information from times or regions with more observations to other times or areas with sparse observations. At the same time, potential errors are introduced by the use of a model (Section 2.2).

The numerical prediction model used for data assimilation plays a fundamental role in the analysis.

Beginning in the 1970s, the sequence of initial atmospheric conditions or analyses needed for the emerging comprehensive global numerical weather prediction models were also used to study climate (Blackmon *et al*., 1977; Lau *et al*., 1978; Arkin, 1982). This unforeseen use of the analyses marked what could be considered a revolutionary step forward in climate science, enabling for the first time detailed quantitative analyses that were instrumental in advancing the identification, description, and understanding of many large scale climate variations, in particular, some of the major modes of climate variability described in Section 2.3. However, the frequent changes in analysis systems (*e.g.,* model upgrades) needed to improve short-range numerical weather forecasts also introduced false shifts in the perceived climate that rendered these initial analyses unsuitable for problems such as detecting subtle climate trends. Recognition of this fundamental issue led to recommendations for the development of a comprehensive, consistent analysis of the climate system, effectively introducing the concept of a model-based climate reanalysis (Bengtsson and Shukla, 1988; Trenberth and Olson, 1988).

Current methods of climate reanalyses evolved from methods developed for short-range weather prediction, and have yet to realize their full potential for climate applications.

2.1.3 What is a Climate Reanalysis?

A climate reanalysis is an analysis performed with a fixed (*i.e.*, not changing in time) numerical prediction model and data assimilation method that assimilates quality-controlled observational data over an extended time period, typically several decades, to create a long-period climate record. This use of a fixed model and data assimilation scheme differs from analyses performed for daily weather prediction. Such analyses are conducted with models using numerical and/or physical formulations as well as data assimilation schemes that are updated frequently, sometimes several times a year, giving rise to false changes in climate that limit their value for climate applications. Climate analysis also fundamentally differs from weather analysis in that observations throughout the system evolution are available for use, rather than simply those observations made immediately prior to the time when the forecast is initiated. While weather analysis has the goal of enabling the best short-term weather forecasts, climate analysis can be optimized to achieve other objectives such as providing a consistent description of the atmosphere over an extended time period. Current methods of climate reanalyses evolved from methods developed for short-range weather prediction, and have yet to realize their full potential for climate applications (see Chapter 4).

In the late 1980s, several reanalysis projects were initiated to develop long-term records of analyses better suited for climate purposes (Table 2.1). The products of these first reanalyses (*e.g.*, maps of daily, monthly, and seasonal averages of temperatures, winds, and humidity) have proven to be among the most valuable and widely used in the history of climate science, as indicated both by the number of scholarly publications that rely upon them and by their widespread use in current climate services (see Section 1.4). The reanalysis projects have produced detailed atmospheric climate records that have enabled successful climate monitoring and research to be conducted. They have also provided a testbed for improving prediction models on all time scales (see Section 2.2), especially for seasonal-to-interannual forecasts, as well as greatly improved basic observations and datasets prepared for their production. When extended to the present as an ongoing climate analysis, reanalysis provides decision makers with information about current climate events in relation to past events, and contributes directly to climate change assessments.

2.1.4 What Role Does Reanalysis Play within a Climate Observing System?

One of the key limitations of current and foreseeable observing systems is that they do not provide complete spatial coverage of all relevant components of the climate system. Because the observing system has evolved over the last half century mainly in response to numerical weather prediction needs, it is focused primarily on the atmosphere. The system today consists of a mixture of *in situ* and remotely sensed observations with differing spatial and temporal sampling and error characteristics (Figure 2.1). An example of the observations available for reanalysis during the modern satellite era is provided in Table 2.2.

A major strength of modern data assimilation methods is the use of a model to help fill in the gaps of the observing system. The assimilation methods act as sophisticated interpolators that use the complex equations governing the atmosphere's evolution together with all available observations to estimate the state of the atmosphere in regions with little or no observational coverage. Statistical schemes are used that ensure that, in the absence of bias with respect to the true state of the atmosphere, the observations and model first guess are combined in an optimal way to jointly minimize errors that are subject to certain simplifying assumptions such that the statistics follow a normal distribution. This can be as simple as the model transporting

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Table 2.2 An example of the conventional and satellite radiance data available for reanalysis during the satellite era (late 1970s to present). These are the observations used in the new NASA Modern Era Retrospective-Analysis for Research and Applications (MERRA) reanalysis (Section 2.5.2).

Data Source/Type	Period	Data Supplier
Conventional Data		
Radiosondes	1970 to present	NOAA/NCEP
PIBAL winds	1970 to present	NOAA/NCEP
Wind profiles	1992/5/14 to present	UCAR CDAS
Convetional, ASDAR, and MDCRS aircraft reports	1970 to present	NOAA/NCEP
Dropsondes	1970 to present	NOAA/NCEP
PAOB	1978 to present	NCEP CDAS
GMS, METEOSAT, cloud drift IR and visible winds	1977 to present	NOAA/NCEP
GOES cloud drift winds	1997 to present	NOAA/NCEP
EOS/Terra/MODIS winds	2002/7/01 to present	NOAA/NCEP
EOS/Aqua/MODIS winds	2003/9/01 to present	NOAA/NCEP
Surface land observations	1970 to present	NOAA/NCEP
Surface ship and buoy observations	1977 to present	NOAA/NCEP
SSM/I rain rate	1987/7 to present	NASA/GSFC
SSM/I V6 wind speed	1987/7 to present	RSS
TMI rain rate	1997/12 to present	NASA/GSFC
QuikSCAT surface winds	1999/7 to present	JPL
ERS-1 surface winds	1991/8/5 to 1996/5/21	CERSAT
ERS-2 surface winds	1996/3/19 to 2001/1/17	CERSAT
Satellite Data		
TOVS (TIROS N, N-6, N-7, N-8)	1978/10/30 to 1985/01/01	NCAR
(A)TOVS (N-9, N-10, N-11, N-12)	1985/01/01 to 1997/07/14	NOAA/NESDIS & NCAR
(A)TOVS (N-14, N-15, N-16, N-17, N-18)	1995/01/19 to present	NOAA/NESDIS
EOS/Aqua	2002/10 to present	NOAA/NESDIS
SSM/I V6 (F08, F10, F11, F13, F14, F15)	1987/7 to present	RSS
GOES sounder T_B	2001/01 to present	NOAA/NCEP
SBUV2 ozone (Version 8 retrievals)	1978/10 to present	NASA/GSFC/Code 613.3

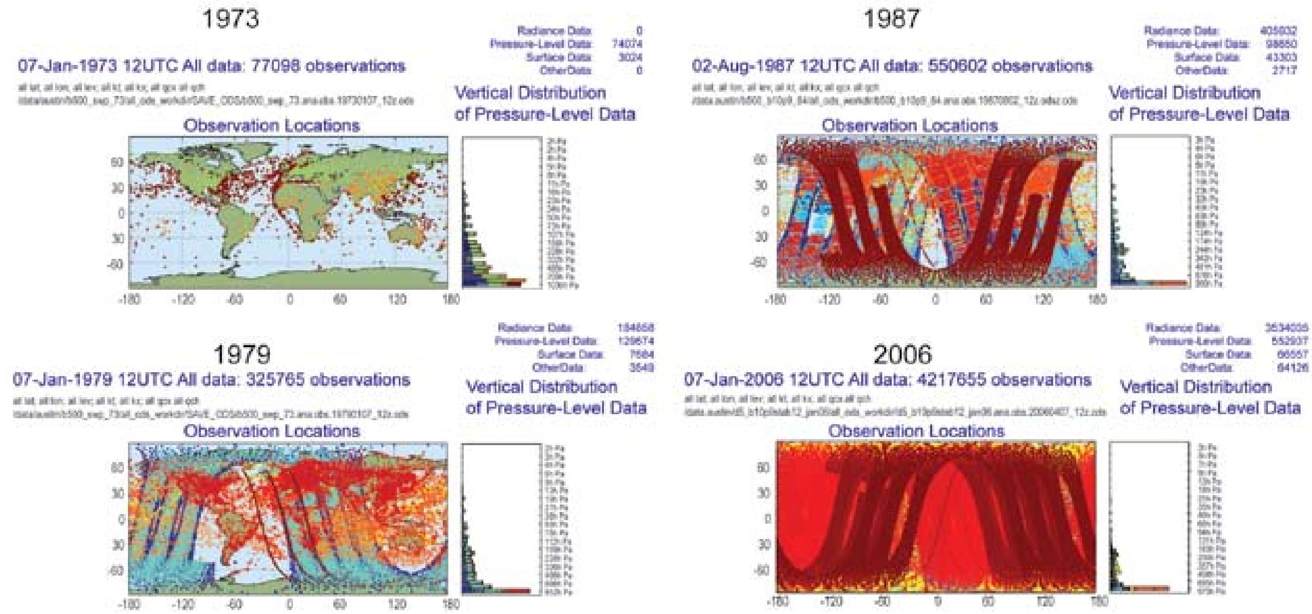

Figure 2.4 Changes in the distribution and number of observations available for NASA's Modern Era Retrospective-Analysis for Research and Applications (MERRA) reanalysis.

warm air from a region that has good observational coverage (*e.g.*, over the United States) to a region that has little or no coverage (*e.g.*, over the adjacent ocean), or a more complicated example, where the model generates a realistic low-level jet in a region where such phenomena exist but observations are limited. The latter is an example of a phenomenon that is largely generated by the model, and only indirectly constrained by observations. This example highlights both the advantages and difficulties in using reanalysis for climate studies. Through the use of a model, it allows climate scientists to estimate features that are indirectly or incompletely measured; however, the scientists have confidence in those estimates only if they are able to account for all model errors.

The use of a model enables estimates of quantities and physical processes that are difficult to observe directly, such as vertical motions, surface heat fluxes, latent heating, and many of the other physical processes that determine how the atmosphere evolves over time.

The use of a model also enables estimates of quantities and physical processes that are difficult to observe directly, such as vertical motions, surface heat fluxes, latent heating, and many of the other physical processes that determine how the atmosphere evolves over time. In general, the estimated quantities are model dependent and careful interpretation is required. Any incorrect representation of physical processes (called parameterizations) will be reflected in the reanalysis to some extent. Only recently have the models improved enough to be used with some confidence in individual physical processes. Previously, most studies using assimilated data have indirectly estimated physical processes by computing them as a residual of a budget that involves only variables that are well observed (Section 3.2.3). Thus, it is important to understand which quantities are strongly constrained by the observations, and which are indirectly constrained and depend on model parameterizations. In recognition of this problem, efforts have been made to document the quality of the individual products and categorize them according to how strongly they are observationally constrained (*e.g.*, Kalnay *et al*., 1996; Kistler *et al*., 2001).

Beyond their fundamental integrating role within a comprehensive climate observing system, climate analysis and reanalysis can also be used to identify redundancies and gaps in the climate observing system, thus enabling the entire system to be configured more cost effectively. By directly linking products to observations, a reanalysis can be applied in conjunction with other science methods to optimize the design and efficiency of future climate observing systems and to improve the products that the system produces.

Current reanalysis data are extremely valuable for a host of climate applications. However, there are also limitations. These are due, for example, to changes in the observing systems, such as the substantial increase in satellite

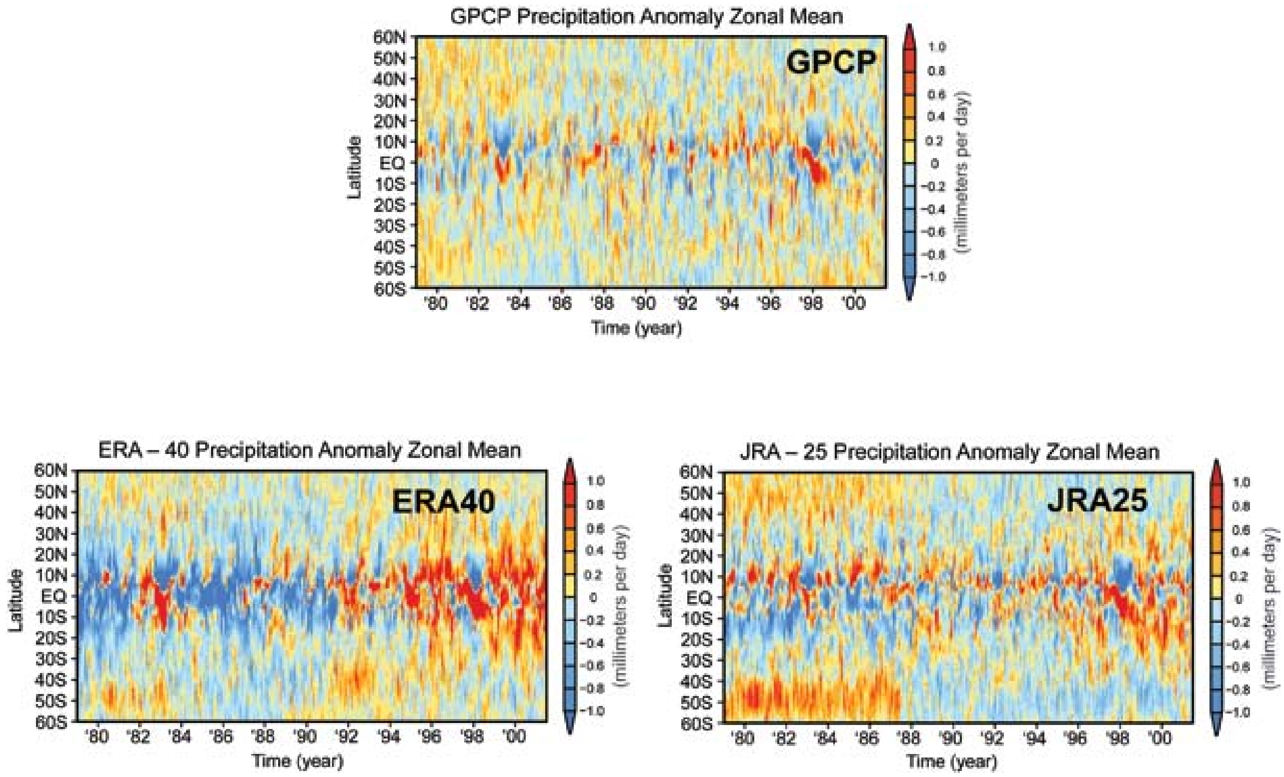

Figure 2.5 Trends and shifts in the reanalyses. The figures show the zonal mean precipitation from the GPCP observations (top panel), the ERA-40 reanalysis (bottom left panel), and the JRA-25 reanalysis (bottom right panel). Courtesy of Junye Chen and Michael Bosilovich, NASA Global Modeling and Assimilation Office (GMAO).

data in 1979 and other newer remote sensing instruments (Figure 2.4). Such changes to the observing system influence the variability that is inferred from reanalyses. Therefore, inferred trends and low frequency (*e.g.*, decadal) variability may be less reliable than shorter-term weather and climate variations (*e.g.*, Figure 2.5 and discussion in Sections 2.3.2.2 and 2.4.2).

The need to periodically update the climate record in order to provide improved reanalyses for climate research and applications has been strongly emphasized (*e.g.*, Trenberth *et al*., 2002b; Bengtsson *et al*., 2004a). There are several reasons for these updates: (1) to include important or extensive additional observations missed in earlier analyses; (2) to correct observational data errors identified through subsequent quality-control efforts; and (3) to take advantage of scientific advances in models and data assimilation techniques, including bias correction techniques (Dee, 2005), and to incorporate new types of observations, such as satellite data not assimilated in earlier analyses. In the following Sections, the strengths and limitations of current reanalyses for addressing specific questions defined in the Preface are discussed.

2.2 ROLE OF REANALYSIS IN UNDERSTANDING CLIMATE PROCESSES AND EVALUATING CLIMATE MODELS

2.2.1 Introduction

Global atmospheric data assimilation combines various observations of the atmosphere (see Figure 2.1) with a short-term model forecast to produce an improved estimate of the state of the atmosphere. The model used in the assimilation incorporates current scientific understanding of how the atmosphere (and more generally the climate system) behaves and can ideally forecast or simulate all aspects of the atmosphere at all locations around the world.

Atmospheric data assimilation and reanalysis, in particular, can be thought of as a model simulation of past atmospheric behavior that is continually updated or adjusted by available observations. Such adjustments are necessary because the model would otherwise evolve differently from nature since it is imperfect (*i.e.*,

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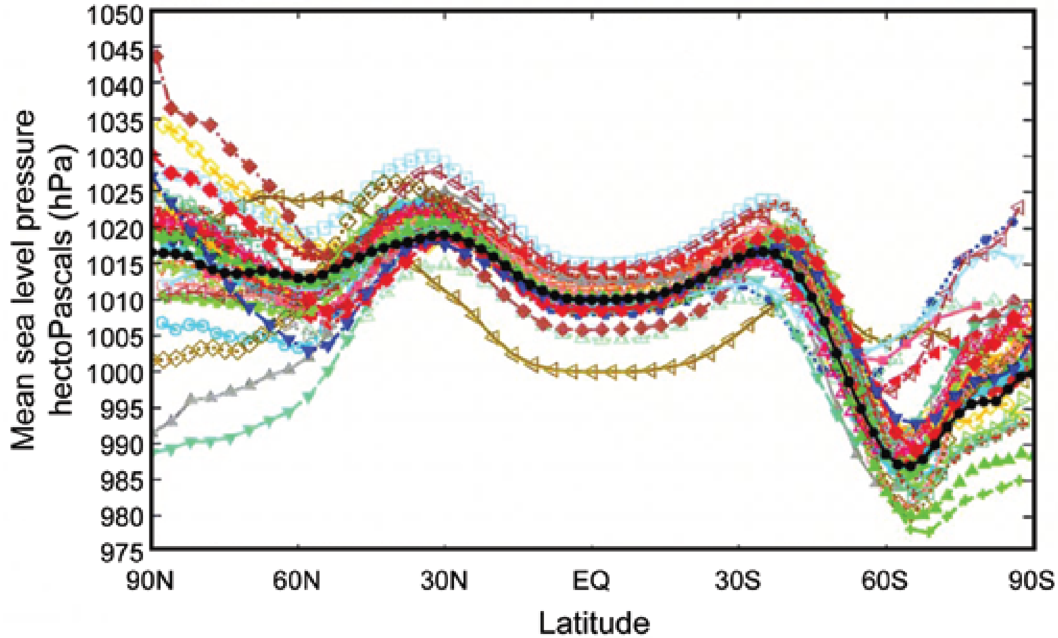

Figure 2.6 The distribution of zonally-averaged sea level pressure simulated by the various AMIP models for December, January, and February from 1979 to 1988 compared against the ECMWF (ERA-15) reanalysis (the black dots; Gibson *et al.*, 1997). From Gates *et al.*, 1999.

our understanding about how the atmosphere behaves and our ability to represent that behavior in computer models is limited). The adjustments must be made continually (or at least intermittently) because the information (observations) used to correct the model's time evolution at any instant are incomplete and also contain errors. In other words, all aspects of the climate system cannot be perfectly measured. Even with a perfect model and nearly perfect observations, adjustments are necessary because the model would still deviate from nature since the atmosphere is chaotic and even very small observational errors grow rapidly to impact the model forecast.

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The above model-centric view of data assimilation is useful when trying to understand how reanalysis data can be applied to evaluate how well climate models represent atmospheric processes. It highlights the fact that reanalysis products are a mixture of observations and model forecasts, and their quality will therefore be impacted by the quality of the model. In large geographic regions with little observational coverage, a reanalysis will tend to move away from nature and reflect more of the model's own behavior. Also, poorly observed quantities, such as surface evaporation, depend on the quality of the model's representation or parameterizations of the relevant physical processes (*e.g.*, the model's land surface and cloud schemes). Given that models are an integral component of reanalysis systems, how then can reanalyses be used to help understand errors in the climate models—in some cases the same models used to produce the reanalysis?

2.2.2 Assessing Systematic Errors

The most straightforward approach to assessing systematic errors is to compare the basic reanalysis conditions (*e.g.*, winds, temperature, moisture) with those that the model produces in free-running mode (a simulation that is not corrected by observations)[1]. The results of such comparisons, for example of monthly or seasonal average values, can indicate whether the model has systematic errors such as producing too cold or too wet in certain regions.

In general, such comparisons are only useful for regions and for quantities where the uncertainties in the reanalysis data are small compared to the model errors. For example, if the difference in the tropical moisture between two reanalysis products (*e.g.*, NCEP/NCAR R1 and ERA-40) is as large as (or larger than) the

[1] These are typically multi-year Atmospheric General Circulation Model runs started from arbitrary initial conditions and forced by the observed record of sea surface temperatures (SST).

differences between any one reanalysis product and the model results, then no conclusion can be reached about the model quality based on that comparison. This points to the need for obtaining reliable uncertainty and bias estimates of all reanalysis quantities (*e.g.*, Dee and Todling, 2000), something that has not yet been achieved in the current generation of reanalysis efforts. In the absence of such estimates, comparing the available reanalysis datasets can provide guidance regarding uncertainties and model dependence. Such comparisons with reanalysis data are now routine and critical aspects of any model development and evaluation effort. (*e.g.*, Atmospheric Model Intercomparison Project [AMIP] [Gates, 1992], the tropospheric-stratospheric GCM-Reality Intercomparison Project for SPARC [GRIPS] [Pawson *et al*., 2000], and coupled model evaluation conducted for the IPCC Fourth Assessment Report [IPCC, 2007]).

Figure 2.6 illustrates a comparison between various atmospheric models and the first European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis (ERA-15, Table 2.1).

The comparison shows considerable differences among the models in the zonal mean surface pressure, especially at high latitudes. Figure 2.7 shows an example of a more in-depth evaluation of the ability of Atmospheric General Circulation Model (AGCM) simulations forced by observed sea surface temperatures to reproduce that part of the variability associated with ENSO.

In this case the comparison is made with the NCEP/NCAR R1 reanalysis for December, January, and February from 1950 to 1999. The comparison suggests that the models produce a very good response to the ENSO-related sea surface temperature variations.

2.2.3 Inferences about Climate Forcing

While the above comparisons address errors in the description of the climate system, a more challenging problem is to address errors in the forcing or physical mechanisms (in particular the parameterizations) by which the model produces and maintains climate anomalies. This involves quantities that are generally only weakly or indirectly constrained by observations (*e.g.*, Kalnay *et al*., 1996; Kistler *et al*., 2001). Ruiz-Barradas and Nigam (2005), for example, show that land/atmosphere interactions may be too efficient (make too large a contribution) in maintaining precipitation anomalies in the U.S. Great Plains in current climate models, despite rather substantial differences in the reanalyses. Nigam and Ruiz-Barradas (2006) highlight some of the difficulties encountered when trying to validate models in the presence

Comparing available reanalysis datasets can provide guidance regarding uncertainties and model dependence.

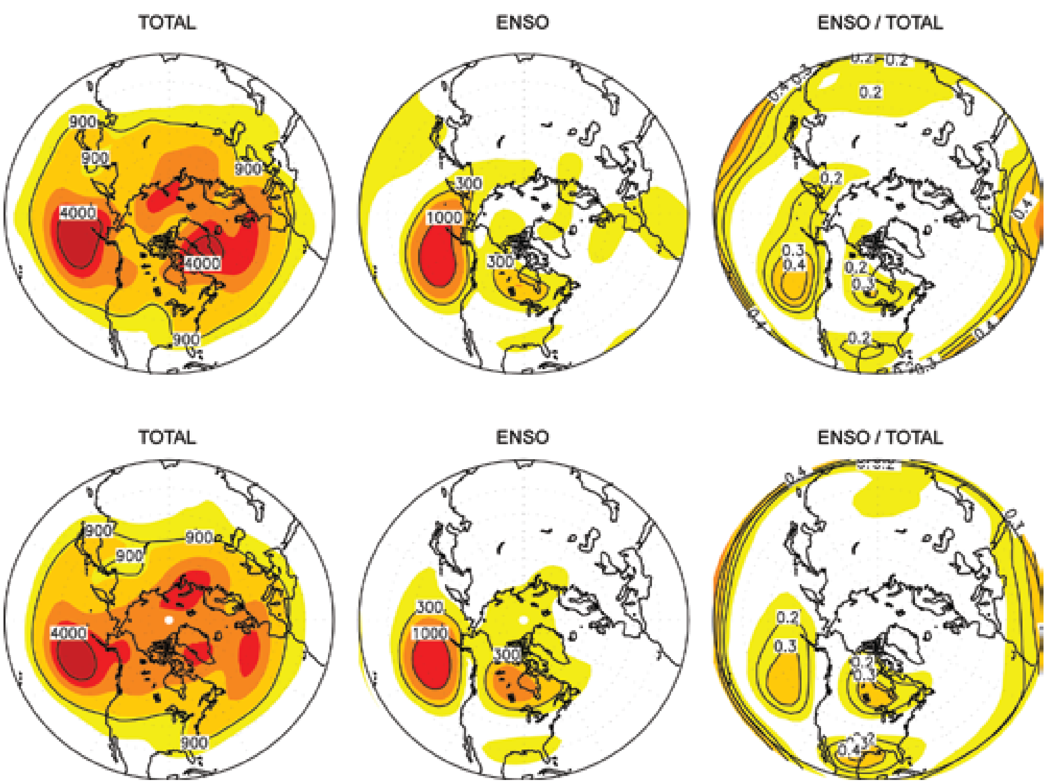

Figure 2.7 The left panels show the total variance of the winter average (December, January, February) 500mb height fields. The middle panels show that part of the total variance that is due to ENSO. The right panels show the ratio of the two variances (ENSO/Total). The top panels are from a reanalysis and the bottom panels are from atmospheric general circulation model (AGCM) simulations forced with observed sea surface temperatures. The results are computed for the period from 1950 to 1999, and plotted for the Northern Hemisphere polar cap to 20°N. The contour interval is 1000 (m^2) in the left and middle panels, and 0.1 in the right panels (taken from Hoerling and Kumar 2002).

of large differences between the reanalyses in the various components of the atmospheric water cycle (*e.g.*, precipitation and evaporation). This problem can be alleviated to some extent by indirectly estimating the physical processes from other related quantities that are better constrained by the observations (*e.g.*, Sardeshmukh, 1993). Nigam *et al*. (2000) show, for example, that the heating obtained from a residual approach appears to be of sufficient quality to diagnose errors in the ENSO-heating distribution in a climate model simulation.

Another approach to addressing errors in the forcing is to focus directly on the adjustments made to the model forecast during the assimilation (*e.g.*, Schubert and Chang, 1996; Jeuken *et al*., 1996; Rodwell and Palmer, 2007). These corrections can potentially provide substantial information about model limitations. Typically, the biases seen in fields, such as the monthly average temperature, are the result of complex interactions among small errors in different components of the model that grow over time. The challenge to modelers is to determine the individual potential sources of error, and ultimately to correct the inadequacies at the process level to improve long-term model behavior.

The development of a data assimilation system that provides unbiased estimates of the various physical processes inherent in the climate system is an important step in efforts to explain, or attribute, the causes of climate anomalies.

An important aspect of the corrections made during data assimilation is that they are applied frequently (typically every six hours), such that the impact of the adjustments can be seen before they can interact with the full suite of model processes. In other words, the corrections made during the course of data assimilation give a potentially direct method for identifying errors in the physical processes that create model biases (*e.g.*, Klinker and Sardeshmukh, 1992; Schubert and Chang, 1996; Kaas *et al*., 1999; Danforth *et al*., 2007; Rodwell and Palmer, 2007). They can also give insights into missing model physics such as dust-caused heating in the lower atmosphere (Alpert *et al*., 1998), radiative heating in the stratosphere from volcanic eruptions (Andersen *et al*., 2001), and impacts of land use changes (Kalnay and Cai, 2003)—processes not represented in the models used in the first reanalyses.

The development of a data assimilation system that provides unbiased estimates of the various physical processes inherent in the climate system (*e.g.*, precipitation, evaporation, cloud formation) is an important step in efforts to explain, or attribute (Chapter 3), the causes of climate anomalies. Therefore, reanalyses allow scientists to go beyond merely documenting what happened. Scientists can, for example, examine the processes that maintain a large precipitation deficit in some region. Is the deficit maintained by local evaporative processes or by changes in the storm tracks that bring moisture to that region, or some combination of such factors? As described in Chapter 3, reanalysis data provide the first steps in a process of attribution (how well the causes of climate variability are understood) that involves detection and description of the anomalies, and an assessment of the important physical processes that contribute to their development. Ultimately, scientists seek answers to questions about the causes that cannot be addressed by reanalysis data alone. Going back to the previous example, how can the role of local evaporative changes and changes in the storm tracks be separated? Model experimentation is required, as described in Chapter 3: here too, reanalyses play an important role in validating the model behavior.

2.2.4 Outlook

There are a number of steps that can be taken to increase the value of reanalyses for identifying model deficiencies, including: improving our estimates of uncertainties in all reanalysis products, balancing budgets of key quantities (*e.g.*, heat, water vapor, energy) (Kanamitsu and Saha, 1996; see also the next Section), and reducing the false model response to the adjustments made to the background forecast by the insertion of observations (the so-called model spin-up or spin-down problem), especially when the adjustments involve water vapor and the various components of the hydrological cycle (Kanamitsu and Saha, 1996; Schubert and Chang, 1996; Jeuken *et al*., 1996). For example, Annan *et al*. (2005) proposed an ensemble forecast approach to estimating model parameters. These, and other approaches, hold substantial promise for obtaining optimal estimates of uncertain model parameters from reanalyses, even for the current comprehensive climate models.

BOX 2.1: The Complementary Roles of Reanalysis and Free-Running Model Simulations in the Attribution Problem

Section 2.3 demonstrates the value of reanalysis for identifying and understanding climate variability. By providing best estimates of the circulation patterns and other weather elements, such as moisture transport, evaporation, precipitation, and cloudiness, which are present during observed extremes—estimates that are comprehensive and consistent over space and time—reanalysis offers a unique and profound contribution to the more general problem of attribution discussed in Chapter 3. Reanalyses are especially useful for providing a global picture of the prevailing anomalous circulation patterns such as those associated with a given drought. By studying reanalysis data, investigators can hypothesize linkages between the drought and climate anomalies in other parts of the world (*e.g.*, anomalies in sea surface temperatures [SSTs]).

Reanalysis is one tool for addressing the problem. A drawback of reanalysis in this context is its inability to isolate causality—to demonstrate unequivocally that one climate feature (*e.g.*, anomalous SSTs) causes another (*e.g.*, drought). This drawback can extend to any set of direct observations of the atmosphere. Climate model simulations that are unconstrained by the assimilation of observational data are needed in order to isolate causality, Climate models can be forced in different ways to determine whether a certain forcing will cause the model to reproduce a climate anomaly of interest. For example, if an investigator suspects, perhaps based on an analysis of reanalysis data, that anomalous SSTs caused the severe drought in the southern Great Plains during the1950s, he or she could perform two simulations with a free-running climate model, one in which the 1950s SST anomalies are imposed, and one in which they are not. If only the first simulation reproduces the drought, the investigator has evidence to support the hypothesized role of the SSTs. An additional step would be to determine the cause of the SST anomalies, which would require further experiments with a comprehensive atmosphere/ocean/land model.

These free-running modeling studies have their own deficiencies, most importantly the potential lack of realism in the climate processes simulated by an unconstrained (non-reanalysis) modeling system. This suggests an important additional role of reanalysis in the attribution problem. Not only can the reanalysis data help in the formulation of hypotheses to be tested with a free-running climate model, but it can (and should) be used to verify that the free-running model is behaving realistically, *i.e.*, that the variations in circulation and other climate processes in the free-running model are consistent with what we have learned from reanalysis (see Section 2.2). Reanalysis and free-running model simulations are complementary tools for addressing the attribution problem, each with their own strengths and weaknesses. Only the unconstrained parts of a model can be used to address attribution (causality), implying the need for free-running models, but those unconstrained parts must be evaluated for realism, implying the need for reanalysis. Arguably, the best approach to the attribution problem is to use the reanalysis and free-running model approaches in tandem.

2.3. USING CURRENT REANALYSES TO IDENTIFY AND UNDERSTAND MAJOR SEASONAL-TO-DECADAL CLIMATE VARIATIONS

In this Section the strengths and weaknesses of current reanalyses for identifying and understanding climate variability are examined. This is an important step for addressing the more general issue of attribution, which was introduced in Chapter 1 and is addressed more fully in Chapter 3. Understanding the connections between reanalysis, models, and attribution is crucial for understanding the broader path towards attribution, as outlined in Chapter 1 (see Box 2.1).

2.3.1 Climate Variability

The climate system varies greatly over space and time. The variability of the atmosphere in particular encompasses common, individual weather events, and longer-term changes affecting global weather patterns that can result in regional droughts or wet periods (pluvials) lasting many years. A primary research goal is to understand the causes of these long-term climate variations and to develop models that enable scientists to predict them.

On subseasonal to decadal time scales there are a number of key recurring global-scale patterns of climate variability that have pronounced impacts on the North American climate (Table 2.3), including the Pacific/North American pattern (PNA), the Madden-Julian

The variability of the atmosphere encompasses common, individual weather events and longer-term changes, affecting global weather patterns that can result in regional droughts or wet periods lasting many years.

Table 2.3 Characteristics of some of the leading modes of climate variability that are known to have a substantial impact on North American climate. The last column provides a subjective assessment of the quality of the atmospheric manifestations of these modes (and their impacts on regional climate) in current atmospheric reanalyses.

Phenomenon	Key reference	Time scale	Strength of link between atmosphere and ocean	Some impacts on North America	Consistency between atmospheric reanalyses
Pacific-North American (PNA) pattern	Wallace and Gutzler (1981)	Subseasonal-to-Seasonal	Weak to moderate	West coast storms	Good
Madden Julian Oscillation (MJO)	Madden and Julian (1994)	Approximately 30-60 days	Weak to moderate	Atlantic hurricanes	Fair to poor
North Atlantic Oscillation (NAO)	Hurrell *et al.* (2001)	Subseasonal-to-decadal	Moderate on long time scales	East coast winters	Good
Northern Annular Mode (NAM)	Thompson and Wallace (2000); Wallace (2000)	Subseasonal-to-decadal	Moderate on long time scales	East coast winters	Good to fair in stratosphere
El Niño-Southern Oscillation (ENSO)	Philander (1990)	Seasonal-to-inter-annual	Strong	Winter in west coast and southern tier of United States, Mexico, warm season regional droughts	Good to fair on longer time scales
Pacific Decadal Oscillation (PDO)	Zhang *et al.* (1997)	Decadal	Strong	Drought or pluvials over North America	Fair to poor
Atlantic Multi-decadal Oscillation (AMO)	Folland *et al.* (1986)	Decadal	Strong	Drought or pluvials over North America, Atlantic hurricanes	Fair to poor

Oscillation (MJO), the North Atlantic Oscillation (NAO) and the related Northern Annular Mode (NAM), the Quasi-Biennial Oscillation (QBO), El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the Atlantic Multi-decadal Oscillation (AMO). These patterns, sometimes referred to as modes of climate variability or teleconnection patterns, can shift weather patterns and disrupt local climate features (*e.g.*, Gutzler *et al.*, 1988; Hurrell, 1996).

As discussed in the following Sections, the quality of the representation of these phenomena in reanalyses vary and depend on the time scales, locations, and physical processes relevant to each of these modes of variability. The last column in Table 2.3 gives the authors' expert assessment of the consistency of the atmospheric manifestations of these modes (and their impacts on regional climate) in current reanalyses based on such general considerations.

Figures 2.8 and 2.9 show examples of the connection between the PNA and NAO patterns and North American surface temperature and precipitation variations. The spatial correspondence between the reanalysis tropospheric circulation and the independently-derived surface patterns show the potential value of the reanalysis data for interpreting the relationships between changes in the climate modes and regional changes in surface temperature and precipitation.

During the positive phase of the PNA pattern, surface temperatures over western North America tend to be above average; this can be related to an unusually strong high pressure ridge over the region as well as transport of warm Pacific air poleward along the West Coast extending to Alaska. An upper-level trough centered over the Southeast United States and the associated intensified north to south flow over the center of the continent facilitates the southward transport of Arctic air that produces a tendency toward below normal temperatures over the Gulf Coast states. This same flow pattern is associated with transport of relatively dry polar air and a tendency to produce descending motions in the middle troposphere over the Missouri and Mississippi regions, both of which favor below normal precipitation, as observed. In contrast, the positive phase of the NAO pattern is accompanied by above average temperatures over the eastern United States and above average precipitation in the Ohio Valley. The reanalysis data of tropospheric circulation help to interpret this relationship as resulting from a northward-shifted westerly flow regime over the eastern United States and North Atlantic that inhibits cold air excursions while simultaneously facilitating increased moisture convergence into the region.

The above patterns arise mainly, but not exclusively, as manifestations of internal atmospheric variability; that is, they owe their existence largely to processes that are confined to the atmosphere such as various atmospheric instabilities and nonlinear processes (*e.g.*, Massacand and Davies, 2001; Cash and Lee, 2001; Feldstein, 2002, 2003; Straus and Shukla, 2002, and as discussed in Chapter 3). They are, however, also linked in varying degrees to processes external to the atmosphere such as interactions with the land surface and ocean variations. Understanding subseasonal-to-decadal climate variability requires that we understand the physical processes that produce these large-scale patterns, including how they interact with each other, and their interactions with the different climate system components (Chapter 3).

A key factor that limits scientists' ability to fully understand such long-term variability is the lack of long-term comprehensive and consistent observations of the climate system, including observations of the land and ocean, which are critical to understanding and predicting atmospheric variability over seasonal and longer time periods. Observations of each of these climate system components, while improving with increased satellite usage, are not yet sufficient for addressing climate problems. In order to adequately address seasonal and longer period of variability, the observations need to continuously cover many decades, span the globe, include all key climate parameters, and be consistent with our best physical understanding.

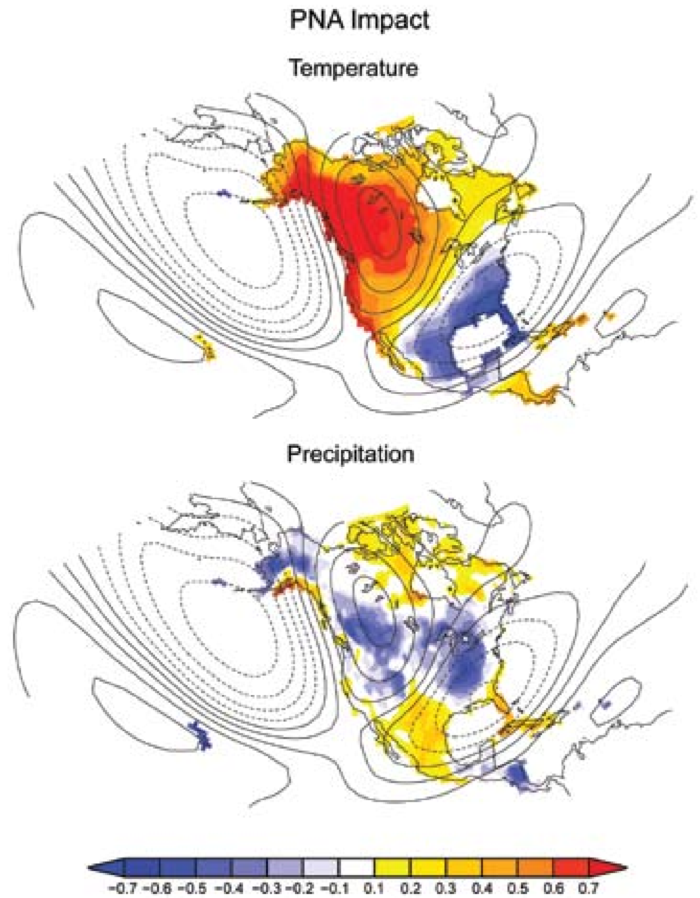

Figure 2.8 The contours indicate the correlation between the wintertime PNA index (Wallace and Gutzler, 1981) and 500 millibar height field. The color shading indicates the correlations between the PNA index and the surface temperature (top panel) and the precipitation (bottom panel). The 500millibar height is from the NCEP/NCAR R1 reanalysis. The surface temperature and precipitation are from independent observational datasets. The correlations are based on seasonally-averaged data from 1951 to 2006. The contours of correlation give an indication of the direction of the mid-tropospheric winds, and the positions of the troughs and ridges.

Among all components of the climate system, the atmospheric component possesses the most advanced observational capabilities. This system was developed primarily to support weather prediction, with major advances occurring first with the onset of a network of radiosondes in the 1950s and then with a near global observing system provided by satellite measurements beginning in the late 1970s. The present observing system is, however, still not fully adequate for many applications, and efforts continue to develop a true climate observing system that spans all climate system components and that provides continuity across space and time (GEOSS, 2005).

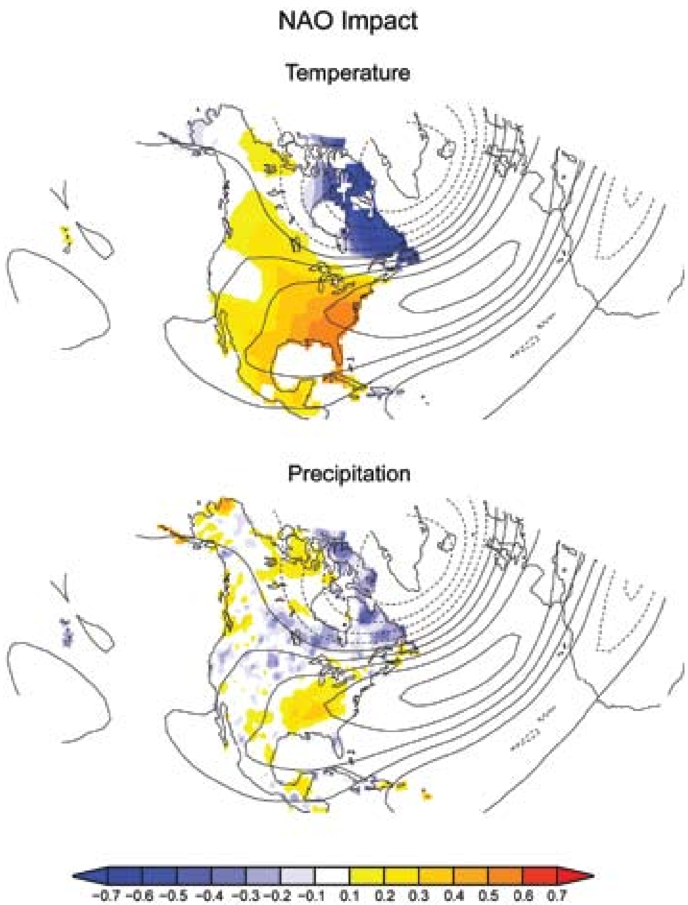

Figure 2.9 The contours indicate the correlation between the wintertime NAO index (Wallace and Gutzler, 1981) and 500 millibar height field. The color shading indicates the correlations between the NAO index and the surface temperature (top panel) and the precipitation (bottom panel). The 500 millibar height is from the NCEP/NCAR R1 reanalysis. The surface temperature and precipitation are from independent observational datasets. The correlations are based on seasonally-averaged data from 1951 to 2006. The contours of correlation give an indication of the direction of the mid-tropospheric winds, and the positions of the troughs and ridges.

2.3.2 Reanalysis and Climate Variability

One of the most important insights of the last few decades regarding the existing observational record was that the investment in operational weather prediction could be leveraged by harnessing the prediction infrastructure (the global models and data assimilation methods for combining various observations) to develop a more consistent historical record of the atmosphere (Bengtsson and Shukla, 1988; Trenberth and Olson, 1988). This insight led to the development of several atmospheric climate reanalysis datasets (Schubert *et al*., 1993; Kalnay *et al*., 1996; Gibson *et al*., 1997). These datasets provided the first comprehensive depictions of the global atmosphere that, in the case of the NCEP/NCAR reanalysis (Kalnay *et al*., 1996), now span over 60 years. This Section summarizes how these and several follow-on reanalyses (Kanamitsu *et al*., 2002; Uppala *et al*., 2005; Onogi *et al*., 2005; Mesinger *et al*., 2006)[2] have contributed to an improved understanding of seasonal to decadal variability of climate (Table 2.1).

The reanalysis data provide the most comprehensive picture to date of the state of the atmosphere and its evolution. The reanalyses also provide estimates of the various physical processes, such as precipitation, cloud formation, and radiative fluxes, that are required to understand the processes by which climate evolves. As the utility of current reanalyses for identifying and understanding atmospheric variability is examined, the critical roles of the model in determining the quality of the reanalysis must be recognized, and the impact of the observing system inconsistencies in both space and time must also be appreciated. When assessing the utility of the reanalyses, the nature of the problem that is being addressed must also be considered. What is the time frame? How big is the area coverage? Does the problem involve the tropics or Southern Hemisphere, which tend to be less well observed, especially before the onset of satellite observations? To what extent are water vapor and clouds or links to the land surface or the ocean important? These are important considerations because data assimilation systems used for the first reanalyses evolved from numerical weather prediction needs; however, these systems did not place a high priority on modeling links to the land and ocean, which were considered to be of secondary importance to producing weather forecasts from a day to a week in advance.

The capacity of current reanalyses to describe and understand major seasonal-to-decadal climate variations is addressed in Sections 2.3.2.1, 2.3.2.2, and 2.3.2.3 by examining three key aspects of reanalyses: their spatial characteristics, their temporal characteristics, and their internal consistency and scope. Key examples are given of where reanalyses have contributed to the understanding of seasonal-to-decadal

[2] While not global, the North American Regional Reanalysis (NARR) has played an important role for studying regional climate variability. Two of its key strengths are the enhanced resolution, and the fact that precipitation observations were assimilated.

variability and where improvement is needed. This Product builds on the results of two major international workshops on reanalysis (WCRP, 1997; WCRP, 1999) by emphasizing studies that have appeared in the published literature since the last workshop.

Spatial characteristics

The globally complete spatial coverage provided by reanalyses, along with estimates of the physical processes that drive the atmosphere, has greatly facilitated diagnostic studies that attempt to identify the causes of large-scale atmospheric variability that have substantial impacts on North American weather and climate (*e.g.*, the NAO and PNA). Substantial improvements have been made in understanding the nature of both the NAO and PNA through studies using reanalysis products. Thompson and Wallace (2000), for example, provide a global perspective on the NAO, using reanalysis data to link it to the so-called Northern Hemisphere Annular Mode (NAM), noting the similarities of that mode to another annular mode in the Southern Hemisphere. Reanalysis data have also been used to link the variability of the NAO to that in the stratosphere in the sense that anomalies developing in the stratosphere propagate into the troposphere, suggesting a source of potential predictability over subseasonal time periods (*e.g.*, Baldwin and Dunkerton, 1999, 2001). Detailed studies made possible by reanalysis data have contributed to the understanding that both PNA and NAO modes of variability are fundamentally internal to the atmosphere,;that is, they would exist naturally in the atmosphere without any anthropogenic or other "external" forcing (*e.g.*, Massacand and Davies, 2001; Cash and Lee, 2001; Feldstein, 2002, 2003; Straus and Shukla, 2002; see also Chapter 3 on attribution). Straus and Shukla (2002) emphasized the differences between the PNA and a similar pattern of variability in the Pacific/North American region that is forced primarily as an atmospheric response to the tropical sea-surface temperature changes associated with ENSO.

Reanalysis data also allow in-depth evaluations of the physical processes and global connections of extreme regional climate events such as droughts or floods. For example, Mo *et al*. (1997), building on several earlier studies (*e.g.*, Trenberth and Branstator, 1992; Trenberth and Guillemot, 1996), capitalized on the long record of the NCEP/NCAR global reanalyses to provide a detailed analysis of the atmospheric processes linked to floods and droughts over the central United States, including precursor events connected with large-scale wave propagation and changes in the Great Plains low level jet (LLJ). Liu *et al*. (1998) used reanalysis data in conjunction with a linear model to deduce the role of various physical and dynamical processes in the maintenance of the circulation anomalies associated with the 1988 drought and 1993 flood over the United States.

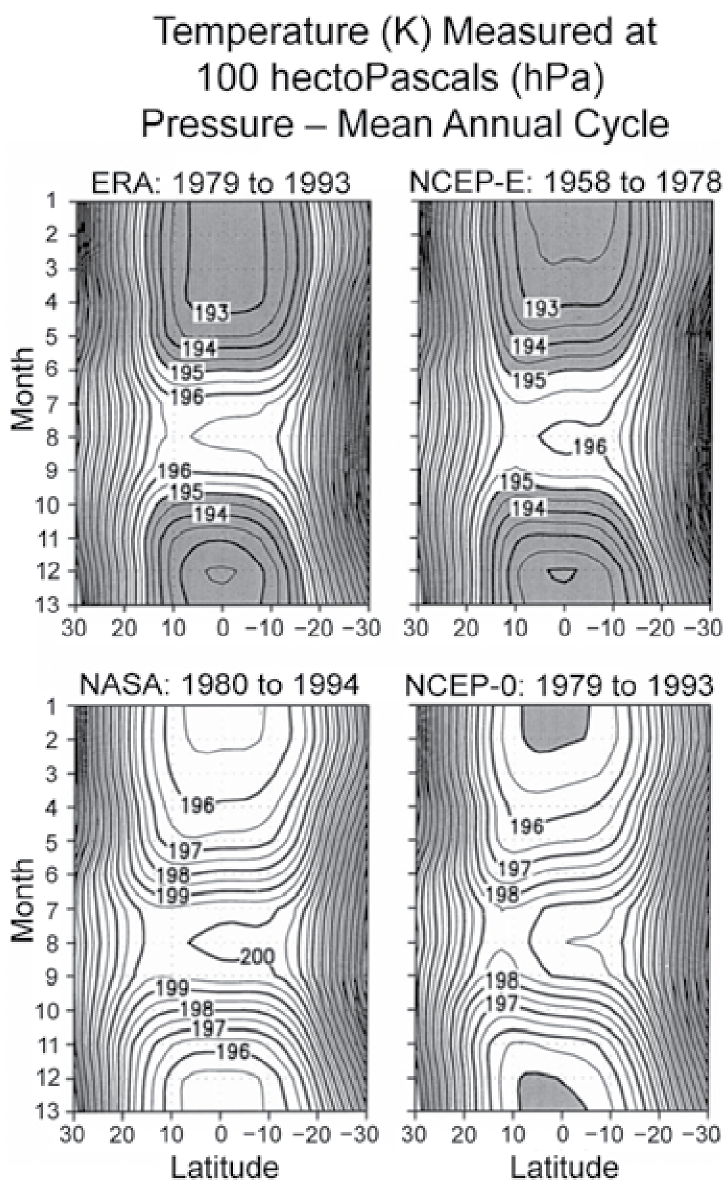

Figure 2.10 Latitudinal structure of the annual cycle in temperature (K; °C is equal to K - 273.15) at pressure of 100 hPa for ERA (top left), NCEP-E (top right), NASA/DAO (bottom left), and NCEP-O (bottom right). The contour interval is 0.5 K. Temperatures lower than 195 K are shaded. From Pawson and Fiorino (1999).

Process studies focused on North America have benefited from the high resolution and improved precipitation fields of the North American Regional Reanalysis (NARR). The studies examine, for example, the nature and role of the LLJ (*e.g.*, Weaver and Nigam, 2008), land-atmosphere interactions (*e.g.*, Luo *et al.*, 2007), and efforts to validate precipitation processes in global climate models (*e.g.*, Lee *et al.*, 2007). These studies highlight the leading role of reanalysis data in the diagnostic evaluation of large-scale climate variability and of the physical mechanisms that produce high impact regional climate anomalies.

Many recent studies that use reanalysis data include companion model simulation experiments, and the reanalyses are used to both characterize the atmospheric behavior and to validate the model results.

While reanalysis data have played a fundamental role in diagnostic studies of the leading middle- and high-latitude variability and of regional climate anomalies, there are inadequacies in the stratosphere—a region of the atmosphere particularly poorly resolved in initial reanalysis systems (*e.g.*, Pawson and Fiorino, 1998a,b, 1999; Santer *et al.*, 2003), but better represented in more recent reanalyses, such as the ERA-40 (Santer *et al.*, 2004). Figure 2.10 shows an example of the substantial differences between the reanalyses that occur in the tropical stratosphere even in such a basic feature as the annual cycle of temperature.

Another area of concern is in polar regions where the reanalysis models have limitations in both the numerical representation and the modeling of physical processes (*e.g.*, Walsh and Chapman, 1998; Cullather *et al.*, 2000; Bromwich and Wang, 2005; Bromwich *et al.*, 2007). In particular, reanalyses have been inadequate in the modeled polar cloud properties and associated radiative fluxes (*e.g.*, Serreze *et al.*, 1998).

Variations in tropical sea surface temperatures (SST), especially those associated with ENSO, are a major contributor to climate variability over North America on interannual time scales (*e.g.*, Trenberth *et al.*, 1998). Recent studies that use reanalysis data have contributed to important new insights on the links between tropical Pacific SST variability and extratropical circulation (*e.g.*, Sardeshmukh *et al.*, 2000; Hoerling and Kumar, 2002; DeWeaver and Nigam, 2002), the global extent of the ENSO response (*e.g.*, Mo, 2000; Trenberth and Caron, 2000), and its impact on weather (*e.g.*, Compo *et al.*, 2001; Gulev *et al.*, 2001; Hodges *et al.*, 2003; Raible, 2007; Schubert *et al.*, 2008). Many of these studies include companion model simulation experiments, and the reanalyses are used to both characterize the atmospheric behavior and to validate the model results. This is an important advance in climate diagnosis resulting from increased confidence in climate models, and it represents an important synergy between reanalysis and the attribution studies discussed in Chapter 3.

While the reanalyses are useful in many respects for addressing the problem of tropical/extratropical connections, there are limitations in representing tropical precipitation, clouds, and other aspects of the hydrological cycle (*e.g.*, Newman *et al.*, 2000). The Madden-Julian Oscillation is an example of a phenomenon in which the interaction between the circulation and tropical heating is fundamental to its structure and evolution (*e.g.*, Lin *et al.*, 2004)—an interaction that has not yet been well represented in climate models. Current reanalysis products are inadequate for validating models because those aspects of the MJO that appear to be important for proper simulation (*e.g.*, the vertical distribution of heating) are poorly constrained by observations and are therefore highly dependent on the models used in the assimilation systems (*e.g.*, Tian *et al.*, 2006). Indirect (residual) approaches to estimate the tropical forcing from reanalyses, however, can be useful, reflecting the greater confidence placed in the estimates of certain aspects of the large-scale tropical circulation (Newman *et al.*, 2000; Nigam *et al.*, 2000).

While the NAO, PNA and ENSO phenomena influence subseasonal-to-interannual climate variability, there is evidence that these modes also may vary over periods of decades or longer. Understanding that behavior, as well as other decadal-scale modes of variability such as the Pacific Decadal Oscillation and the Atlantic Multi-decadal Oscillation, require datasets that are consistent over many decades.

Temporal characteristics

The observing system over the last century varies greatly over time. Prior to the mid-twentieth century, the observing system was primarily surface-based and limited to land areas and ship reports, although some higher observations (*e.g.*, wind measurements from pilot balloons) have been made routinely since the early twentieth century (*e.g.*, Brönnimann *et al*., 2005). An upper-air radiosonde network of observations was initiated in the late 1940s but was primarily confined to land areas, and Northern Hemisphere midlatitudes in particular. A truly global observing system arose with the onset of satellite observations in the 1970s, with numerous changes made to the observing system as new satellites were launched with updated and more capable sensors, and older systems were discontinued (Figure 2.2). The changes in the observing system, together with improved sensors and the aging and degrading of existing sensors, makes combining all available observations into a consistent long-term global climate record a major challenge. Figure 2.11 provides an overview of the number of observations made at all latitudes from 1946 to 1998 that were available to the NCEP/NCAR reanalysis (Kistler *et al*., 2001). These changes, especially the onset of satellite observations, have impacted the reanalysis fields, often making it difficult to separate true climate variations from artificial changes associated with the evolving observing system.

The changes in the observing system have impacted the ability to study variability on interannual and longer time periods—the time scales at which changes to the observing system also tend to occur (*e.g.*, Basist and Chelliah, 1997; Chelliah and Ropelewski, 2000; Kistler *et al*., 2001; Trenberth *et al*., 2001; Kinter *et al*., 2004). The impact can be complicated, involving interactions and feedbacks with the

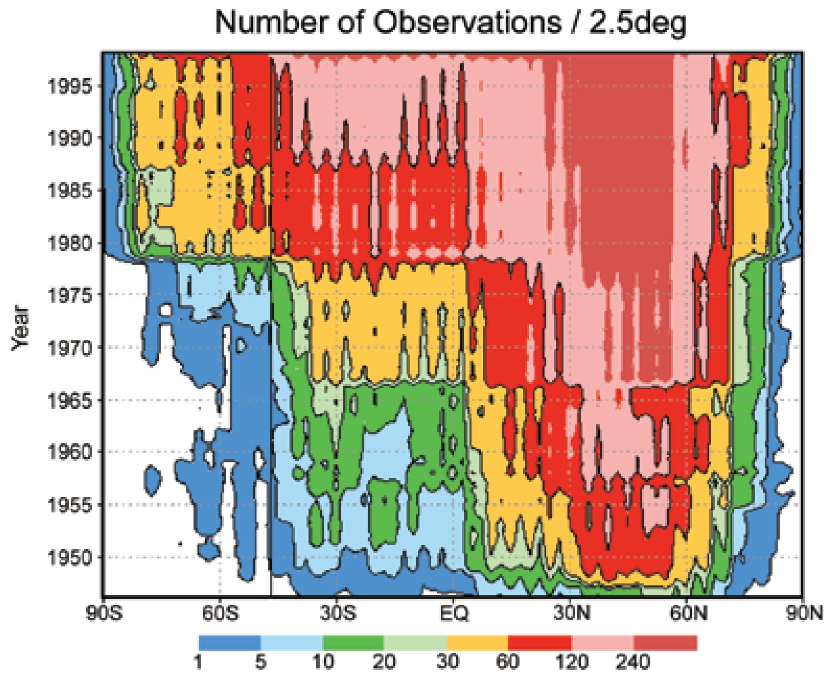

Figure 2.11 Zonal average number of all types of observations available to the NCEP/NCAR reanalysis per 2.5° latitude-longitude box per month from 1946 to 1998. A 12-month running average has been applied. From Kistler *et al.* (2001).

assimilation schemes. For example, Trenberth *et al*. (2001) show how discontinuities in tropical temperature and moisture can be traced to the bias correction of satellite radiances in the ECMWF (ERA-15) reanalyses. Changes in conventional radiosonde observations can also have impacts. For example, the Quasi-Biennial Oscillation, while clearly evident throughout the record of the NCEP/NCAR reanalysis, shows substantial secular changes in amplitude that are apparently the result of changes in the availability of tropical wind observations (Kistler *et al*., 2001). The major change in the observing system associated with the onset of satellite data in the 1970s represents a particularly difficult and important problem because it coincides with the time of a major climate shift associated with the Pacific Decadal Oscillation (*e.g.*, Pawson and Fiorino, 1999; Trenberth and Caron, 2000; Chelliah and Bell, 2004).

Despite these problems, reanalysis data can be valuable in understanding long-term atmospheric variability, particularly if used in conjunction with other independent observations. For example, Barlow *et al*. (2001) used NCEP/NCAR reanalyses of winds and stream function for the period 1958 to 1993, in conjunction with independent sea surface temperature, streamflow, precipitation, and other data to identify

The changes in the observing system, together with improved sensors and the aging and degrading of existing sensors, makes combining all available observations into a consistent long-term global climate record a major challenge.

three leading modes of SST variability affecting long-term drought over the United States.

In general, the quality of reanalysis tends to be best at weather time scales of a day to about a week, and degrades over both shorter and longer periods of time. The changes in quality reflect both the changes in the observing system and the ability of the model to simulate the variability at the different lengths of time. For time periods of less than a day, there are several factors that degrade the quality of the analysis. These include an observing system that does not fully resolve variations shorter than one day, and deficiencies in model's representation of the diurnal cycle (*e.g.*, Higgins *et al.*, 1996; Betts *et al.*, 1998a). This issue also contributes to errors in our estimates of seasonal and longer time averages of reanalysis quantities. It is not surprising that the quality is best for the weather time scales (*e.g.*, Beljaars *et al.*, 2006), since the analysis systems and models used thus far for atmospheric reanalyses were developed for global numerical weather prediction.

There are important connections between the atmosphere and the land and ocean systems on seasonal and longer periods of time that can limit reanalysis quality if they are not fully understood.

There are also important connections between the atmosphere and the land and ocean systems on seasonal and longer periods of time that can limit reanalysis quality if they are not fully understood. The assimilation systems for the land and ocean components are considerably less developed than for the atmosphere (discussed further in Section 2.5). The connection between the atmosphere and the ocean in the current generation of atmospheric reanalyses is made by specifying sea surface temperatures from reconstructions of historical observations; the land is represented in a simplified form, which can also contribute to limitations in representing the diurnal cycle because the cycle is interconnected with the land surface (*e.g.*, Betts *et al.*, 1998b).

Model errors can have particularly large impacts on quantities linked to the hydrological cycle, such as atmospheric water vapor (*e.g.*, Trenberth *et al.*, 2005) and major tropical circulations (*e.g.*, the Hadley Cell) that are relevant to understanding climate variations and change (Mitas and Clement, 2006). Any bias in the model can exacerbate false climate signals associated with a changing observing system, for example, a model that consistently produces conditions that are too dry in the lower atmosphere. Such a model may give a realistic tropical precipitation condition when there are few moisture observations available to constrain the model, but that same model might produce unrealistic rainfall for the satellite era when it is confronted with large amounts of water vapor information that is inconsistent with the model's average water vapor distribution (Figure 2.5).

The impacts of the changing observing systems on current reanalysis products indicate these changes have not yet been accounted for. To date, all available observations have been used in order to maximize the accuracy of the reanalysis products at any given time, but efforts to develop approaches that would reduce the inconsistencies over long time periods in the reanalysis products have been limited. This issue has been recognized, and efforts are currently underway to carry out reanalyses with a subset of the full observing systems to try to minimize the changes over time (*e.g.*, Compo *et al.*, 2006), as well as to conduct other observing system sensitivity experiments that could help to understand, if not reduce, the impacts (*e.g.*, Bengtsson *et al.*, 2004b,c; Dee, 2005; Kanamitsu and Hwang, 2006). Model bias correction techniques (*e.g.*, Dee and da Silva, 1998; Chepurin *et al.*, 2005; Danforth *et al.*, 2007), improvements to our models (Grassl, 2000; Randall, 2000), and improvements to historical observations including data mining, improved quality control and further cross calibration and bias correction of observations (Schubert *et al.*, 2006) may also help to reduce the impacts from the changing observing system.

Internal consistency and scope
An advantage of the reanalysis products mentioned earlier involves the role of the model in providing internal consistency, meaning that the model enforces certain dynamical balances that are known to exist in the atmosphere, such as the tendency for the atmosphere to be in geostrophic balance (an approximate balance of the Coriolis and pressure gradient forces) in the midlatitudes. One important implication is that the different state variables (the quantities that define the state of the atmosphere—*e.g.*, the winds, temperature, and pressure) depend strongly on one other. That such constraints are satisfied in the reanalysis products is important for many studies that attempt to understand the physical processes or forcing mechanisms by which the atmosphere evolves (*e.g.*, the various patterns of variability mentioned above).

A fundamental advantage of model-based reanalysis products over single variable analyses of, for instance, temperature or water vapor observations, is that reanalysis products provide a comprehensive, globally complete picture of the atmosphere at any given time, together with the various forcings that determine how the atmosphere evolves over time. In principle it is possible to diagnose all aspects of how the climate system has evolved over the time period covered by the reanalyses; however, the results depend on the quality of the model as well as model characteristics and observational errors used in the reanalysis. As mentioned earlier, the models used in the current generation of reanalyses were largely developed for midlatitude numerical weather prediction and have known limitations, especially in various components of the hydrological cycle (clouds, precipitation, evaporation) that are necessary for understanding such important phenomena as monsoons, droughts, and various tropical phenomena.

Given that models are imperfect, can model-based reanalysis products be used to validate model simulations (see also Section 2.2)? For example, by forcing models with the historical record of observed sea surface temperatures, can some of the major precipitation anomalies that occurred over the last century be accurately reproduced (*e.g.*, Hoerling and Kumar, 2003; Schubert *et al*., 2004; Seager *et al*., 2005; Chapter 3)? As these simulations are examined for clues about how the climate system operates, there is an increasing need to validate the physical processes that produce the regional climate anomalies (*e.g.*, drought in the Great Plains of the United States). There is a question as to whether the reanalyses used in the validations are themselves compromised by model errors. However, evidence is growing that, at least in regions with relatively good data coverage, the reanalyses can be used to identify fundamental errors in the model forcing of hydrological climate anomalies (*e.g.*, Ruiz-Barradas and Nigam, 2005).

On global scales, the limitations in the assimilation models are shown as biases in, for example, monthly averaged heat and moisture budgets, introducing uncertainties in the physical processes that contribute to them (*e.g.*, Trenberth and Guillemot, 1998; Trenberth *et al*., 2001; Kistler *et al*., 2001). There has been success in looking at variability of the energy budgets associated with some of the major climate variations such as ENSO (*e.g.* Trenberth *et al*., 2002a); however, inconsistencies in certain budgets (especially the atmospheric energy transports) limit their usefulness for estimating overall surface fluxes (Trenberth and Caron, 2001)—quantities that are important for linking the atmosphere and the ocean, as well as the atmosphere and land surface. Limitations in model-estimated clouds (and especially short wave radiation) appear to be a primary source of the problems in model fluxes both at the surface and at the top of the atmosphere (*e.g.*, Shinoda *et al*., 1999). Figure 2.12 shows an ex-

A fundamental advantage of model-based reanalysis products is that reanalysis products provide a comprehensive, globally complete picture of the atmosphere at any given time, together with the various forcings that determine how the atmosphere evolves over time.

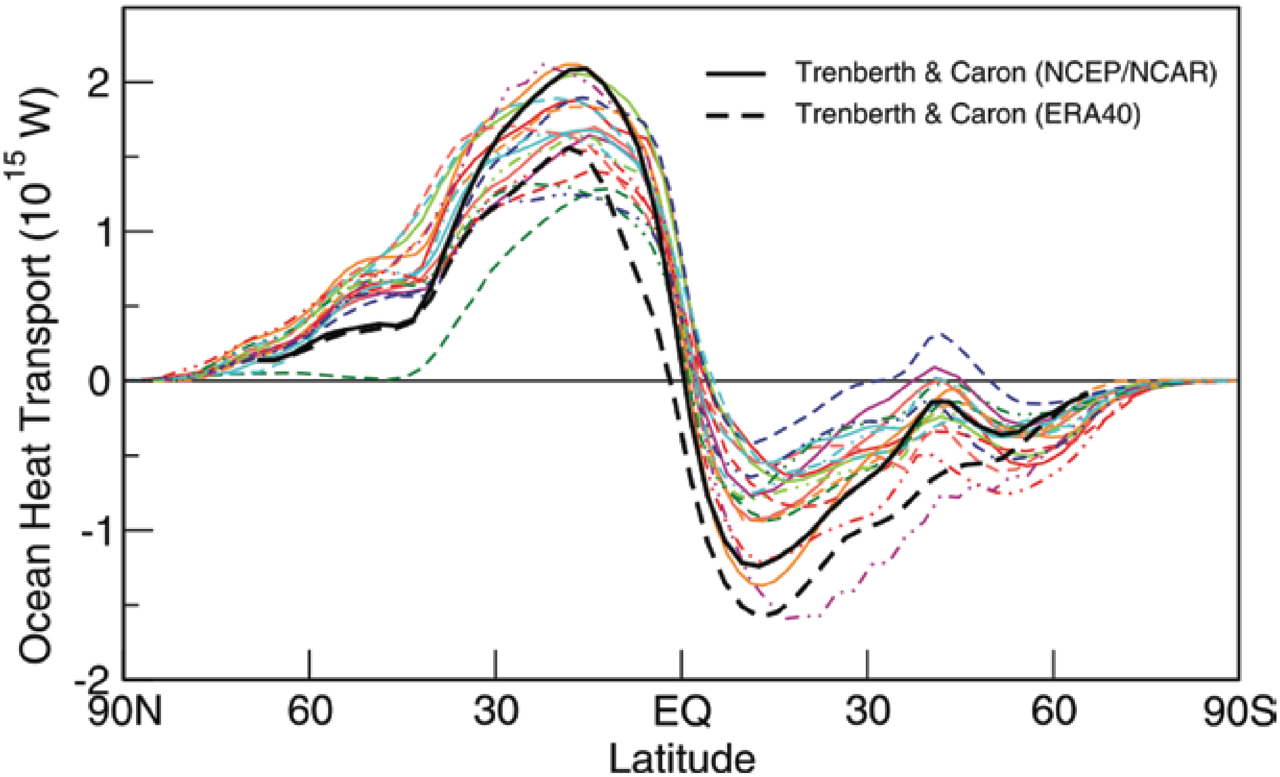

Figure 2.12 Annual mean, zonally-averaged oceanic heat transport implied by net heat flux imbalances at the sea surface, under an assumption of negligible changes in oceanic heat content. The observational based estimate, taken from Trenberth and Caron (2001) for the period February 1985 to April 1989, originates from reanalysis products from NCEP/NCAR (Kalnay *et al.*, 1996) and European Centre for Medium Range Weather Forecasts 40-year reanalysis (ERA40; Uppala *et al.*, 2005). The model averages are derived from the years 1980 to 1999 in the twentieth century simulations in the Multi-Model Dataset at the Program for Climate Model Diagnosis and Intercomparison (PCMDI). The legend identifying individual models appears in Figure 8.4 of the IPCC Fourth Assessment Report (IPCC, 2007).

The climate of a region is defined by statistical properties of the climate system evaluated over an extended period of time, typically over decades or longer.

ample of implied ocean heat transport estimates provided by two different reanalyses and how they compare with the values obtained from a number of different coupled atmosphere-ocean model simulations.

Current atmospheric reanalysis models do not satisfactorily represent interactions with other important components of the climate system (ocean, land surface, cryosphere). As a result, various surface fluxes (*e.g.*, precipitation, evaporation, radiation) at the interfaces between the land and atmosphere, cryosphere and atmosphere, and the ocean and atmosphere, are generally inconsistent with one other and therefore limit the ability to fully understand the forcings and interactions of the climate system (*e.g.*, Trenberth *et al.*, 2001). While there are important stand-alone land (*e.g.*, Reichle and Koster, 2005) and ocean (*e.g.*, Carton *et al.*, 2000) reanalysis efforts currently either in development or underway (Section 2.5), the long-term goal is a fully coupled climate reanalysis system (Tribbia *et al.*, 2003).

2.4 CLIMATE TRENDS IN SURFACE TEMPERATURE AND PRECIPITATION DERIVED FROM REANALYSES *VERSUS* FROM INDEPENDENT DATA

The climate of a region is defined by statistical properties of the climate system (*e.g.*, averages, variances, and other statistical measures) evaluated over an extended period of time, typically over decades or longer. If these underlying statistical values do not change with time, the climate would be referred to as "stationary". For example, in a stationary climate the average monthly rainfall in a specific region during the twentieth century, for instance, would be the same as that in the nineteenth, eighteenth, or any other century (within statistical sampling errors). Climate, however, is non-stationary; the underlying averages (and other statistical measures) do change over time. The climate system varies through ice ages and warmer periods with a timescale of about 100,000 years (Hays *et al.*, 1976). The "Little Ice Age" in the

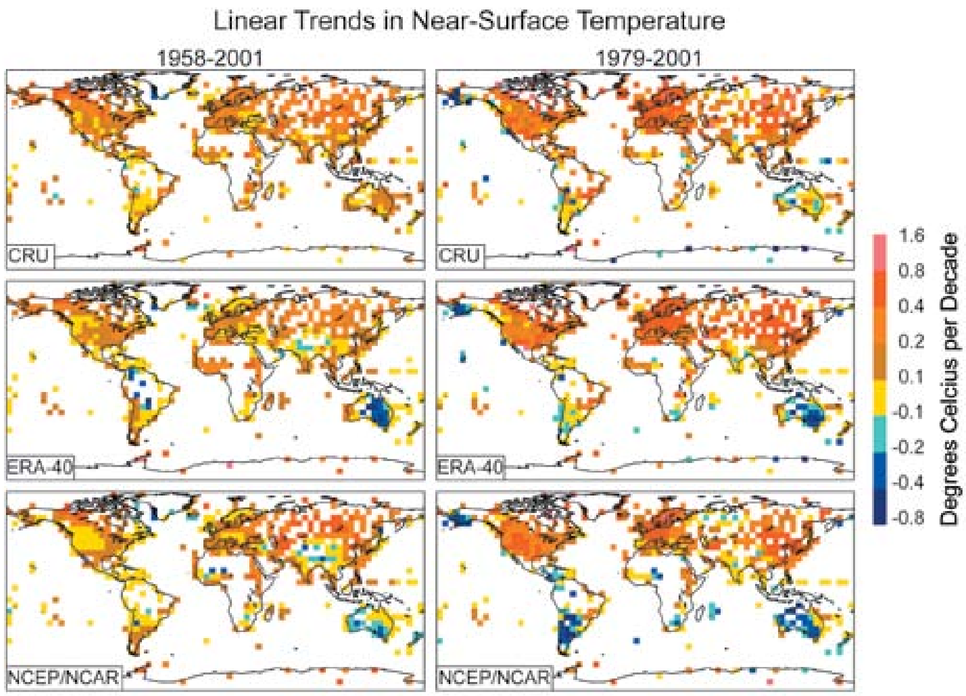

Figure 2.13 Calculated trends in near-surface (2 meter) temperature from an observational dataset (top), the ERA-40 reanalysis (middle), and the NCEP/NCAR reanalysis (bottom). Reproduced from Simmons *et al.* (2004).

fifteenth to nineteenth centuries (Bradley *et al*., 2003) is an example of a natural climate variation (non-stationarity) with a much shorter timescale of a few centuries. Humans may be affecting climate even more quickly through their impact on atmospheric greenhouse gases (Hansen *et al*., 1981).

The search for trends in climatic data is an attempt to quantify the non-stationarity of climate, as reflected in changes in long-term average climate values. There are various methods for accomplishing this task (see CCSP, 2006: Appendix A for a more detailed discussion). Perhaps the most common approach to calculating a trend from a multiple decade dataset is to plot the data value of interest (*e.g.*, rainfall) against the year of measurement. A line is fit through the points using standard regression techniques, and the resulting slope of the line is a measure of the climatic trend. A positive slope, for example, suggests that the "underlying climatic average" of rainfall is increasing with time over the period of interest. Such a trend calculation is limited by the overall noisiness of the data and by the length of the record considered.

2.4.1 Trend Comparisons: Reanalyses *Versus* Independent Measurements

Reanalysis datasets now span several decades, as do various ground-based and space-based measurement datasets. Trends can be computed from both. A natural question is: How well do the trends computed from the reanalysis data agree with those computed from independent datasets? This question has been addressed in many independent studies. Calculating trends is one method for assessing the adequacy of reanalysis data for evaluating climate trends. The focus here is on trends in two particular variables: surface temperature at a height of two meters, referred to here as T_{2m}, and precipitation.

Simmons *et al.* (2004) provide the most comprehensive evaluation to date of reanalysis-based trends in surface temperature, T_{2m}. Figure 2.13, reproduced from that work which uses linear regression techniques, shows comparison of T_{2m} from observations (the CRUTEM2v dataset of Jones and Moberg, 2003), with two reanalyses (ERA-40 and NCEP/NCAR).

The period from 1958 to 2001 (left) and from 1979 to 2001 (right) were considered. All three

Calculating trends is one method for assessing the adequacy of reanalysis data for evaluating climate trends.

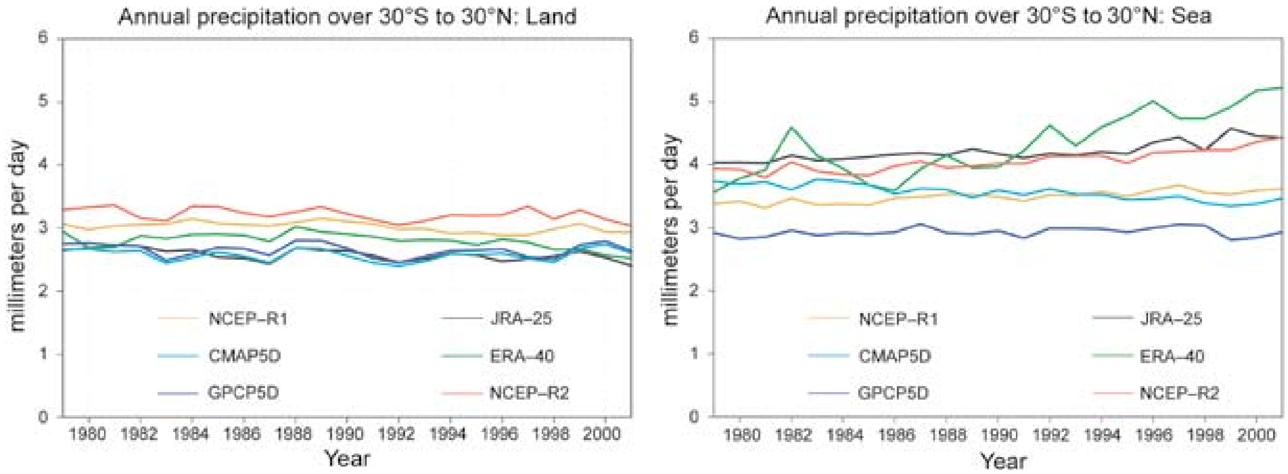

Figure 2.14 Annual tropical precipitation over land (left) and ocean (right) from four reanalyses (NCEP-R1, NCEP-R2, JRA-25, and ERA-40) and from two observational datasets (CMAP5D and GCPC5D). Reprinted from Takahashi *et al.* (2006).

datasets show generally positive trends. The reanalyses-based trends, however, are generally smaller, particularly for the longer time period. The average trend for 1958 to 2001 in the Northern Hemisphere, is 0.19°C per decade for the observations, 0.13°C for ERA-40, and 0.14°C for NCEP/NCAR. For the shorter and more recent period, the Northern Hemisphere averages are 0.30°C for the observations, 0.27°C for ERA-40, and 0.19°C for NCEP/NCAR. Simmons *et al*. (2004) consider the latter result for ERA-40 to be particularly encouraging because "the agreement is to within about 10 percent in the rate of warming of the land areas of the Northern Hemisphere since the late 1970s". Stendel *et al*. (2000) note that for the ERA-15 reanalysis, which covers 1979 to 1993 using an earlier version of the modeling system, the trend in T_{2m} over North America and Eurasia is too small by 0.14°C per decade, relative to observations. Thus, the later ERA-40 reanalysis appears to improve significantly over the earlier ERA-15 reanalysis for T_{2m} temperature trends. Figure 2.13 shows that the performance of

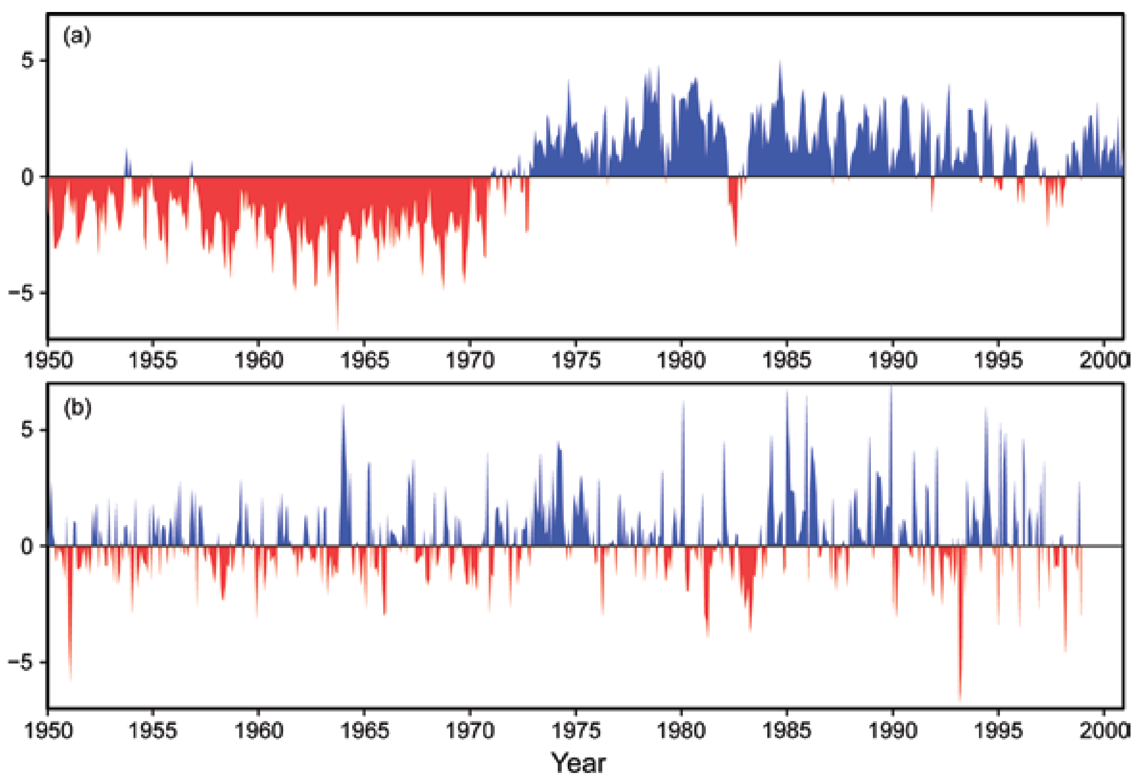

Figure 2.15 Precipitation averaged over 10°S-equator, 55°-45°W with respect to time, from (a) the NCAR/NCEP reanalysis, and (b) from an observational precipitation dataset. Reprinted from Kinter *et al.* (2004).

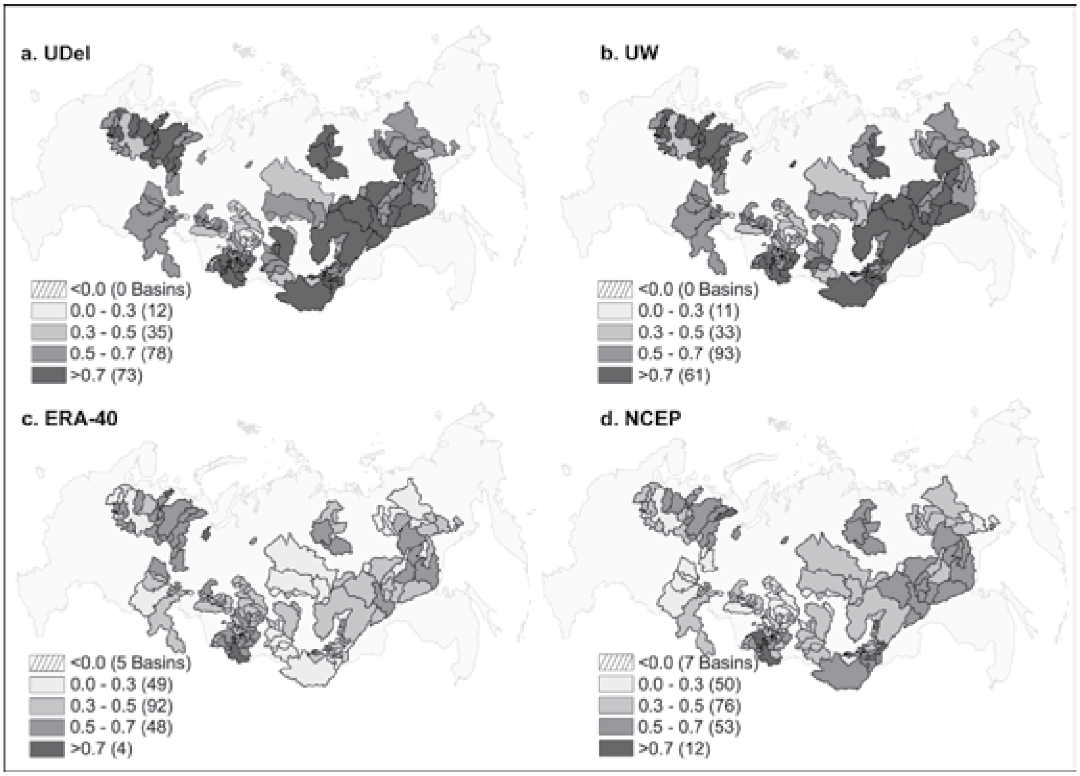

Figure 2.16 Identification of northern Asia river basins for which the computed precipitation trend is positive (a wetting trend) or negative (a drying trend), for four datasets: (top left) a dataset based on ground-based measurements of rainfall; (top right) a modified (improved) version of the first dataset; (bottom left) ERA-40 reanalysis; and (bottom right) NCEP/NCAR reanalysis. From Pavelsky and Smith (2006).

ERA-40 and NCEP/NCAR varies with region, with some clear areas of large discrepancies that most likely represent reanalysis errors. Both reanalyses underestimate trends in India and Australia. The NCEP/NCAR reanalysis in particular does not adequately reproduce trends in southern South America, a problem also noted by Rusticucci and Kousky (2002).

A similarly comprehensive evaluation of precipitation trends from reanalyses has not been published. Takahashi *et al*. (2006), however, do summarize the trends in total tropical (30°S to 30°N) precipitation over the period of 1979 to 2001 (Figure 2.14) based on two sets of observational data and four reanalyses.

The biggest discrepancy between the observations and reanalyses is the large positive trend over the ocean for the ERA-40 reanalyses and the smaller but still positive trends for the other reanalyses, trends that are not found in the observations. Similarly, Chen and Bosilovich (2007) show that the reanalyses indicate a positive precipitation trend in the 1990s when global precipitation totals are considered, whereas observational datasets do not. By starting in 1979, the tropical analysis of Takahashi *et al*. (2006) misses a problem discovered by Kinter *et al*. (2004), who demonstrate a false precipitation trend produced by the NCEP/NCAR reanalysis in equatorial Brazil. As shown in Figure 2.15, the NCEP/NCAR reanalysis produces a strong, apparently unrealistic, increase in rainfall starting in about 1973, and thus, an unrealistic wetting trend.

Pohlmann and Greatbatch (2006) found that the NCEP/NCAR reanalysis greatly overestimates precipitation in northern Africa before the late 1960s, resulting in an unrealistic drying trend. Pavelsky and Smith (2006), in an analysis of river discharge to the Arctic Ocean, compared precipitation trends in the ERA-40 and NCEP/NCAR reanalyses with those from ground-based observations and found the reanalyses trends to be much too large, particularly for ERA-40. Figure 2.16 qualitatively summarizes these results.

River basins with an increasing precipitation trend and those with a decreasing precipita-

Compared with temperature trends, reanalysis-based precipitation trends appear to be less consistent with those calculated from observational datasets.

tion trend are identified for each dataset. For ERA-40, the vast majority of basins show an unrealistic (relative to ground observations) wetting trend.

Reanalyses that rely solely on atmospheric data may miss real trends in surface temperature that are associated with land usage, such as urbanization, cropland conversion, changing irrigation practices, and other land use changes.

2.4.2 Factors Complicating the Calculation of Trend

The previous studies indicate that observed temperature trends are captured to a large extent by the reanalyses, particularly in the latter part of the record, although some area trends (*e.g.*, Australia) have been more difficult to reproduce. Compared with temperature trends, reanalysis-based precipitation trends appear to be less consistent with those calculated from observational datasets. As described below, many studies have identified sources for errors with the reanalyses that at least partly explain these inadequacies; however, trends produced from the observational datasets are also subject to errors for several reasons (see CCSP, 2006, and discussed below), such that the true inadequacies of the reanalyses-based trends cannot be fully measured.

First, and perhaps most importantly, a false trend in the reanalysis data may result from a change in the observations being assimilated. In particular, with the onset of satellite data in the late 1970s, global-scale observations of highly variable quality increased dramatically. Consider a model that tends to "run cold" (has a negative temperature bias) when not constrained by data. If this model is used to perform a reanalysis of the last 50 years but by necessity only ingests satellite data from the late 1970s onward, then the first half of the reanalysis will be biased cold relative to the second half, leading to an artificial positive temperature trend (Figure 2.17).

Bengtsson *et al.* (2004a) use this reasoning to explain an apparently false trend in lower troposphere temperature (not surface temperature) produced by the ERA-40 reanalysis. Kalnay *et al.* (2006), when computing trends in surface air temperature from the NCEP/NCAR reanalysis, separate the 40-year reanalysis period into a pre-satellite and post-satellite period to avoid such issues. However, reanalyses can also be affected by non-satellite measurement system changes. Betts *et al.* (2005) note in reference to the surface temperature bias over Brazil that "the Brazilian surface synoptic data are not included [in the ERA-40 reanalysis] before 1967, and with its introduction, there is a marked shift in ERA-40 from a warm to a cool bias in two meter temperature".

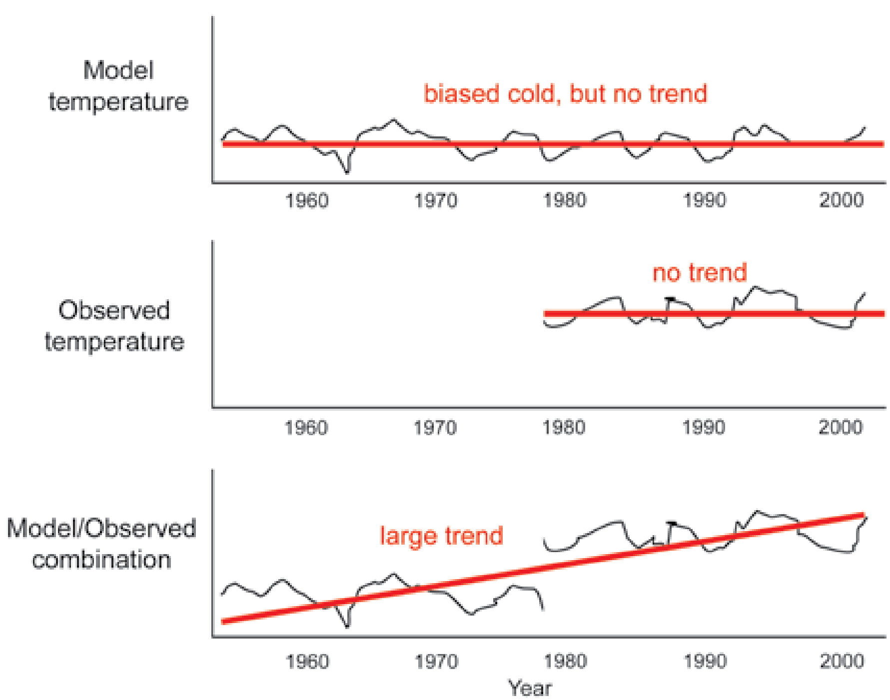

Figure 2.17 Idealized example showing how the correction of biased model data with observational data during only one part of a reanalysis period, from 1979 onward, can lead to a spurious temporal trend in the reanalysis product.

Reanalyses that rely solely on atmospheric data may miss real trends in surface temperature that are associated with land usage, such as urbanization, cropland conversion, changing irrigation practices, and other land use changes (Pielke *et al.*, 1999; Kalnay *et al.*, 2006). The ERA-40 reanalysis, which assimilates some station-based air temperature measurements made at the surface, is less affected by this issue than the NCEP/NCAR reanalysis, which does not. This difference in station data assimilation may partially explain why ERA-40 reanalysis performs better compared with NCEP/NCAR reanalysis, as shown in Figure 2.13 (Simmons *et al.*, 2004).

As mentioned above, calculating trends from observational datasets also involves errors, and introduces additional uncertainties when compared with reanalysis products, in which values are provided on regular grids. An important and challenging issue is estimating the appropriate grid-cell averaged temperature and precipitation values from point observations so that they can be directly compared with reanalysis products. Errors in representation may play an important role. For example, rainfall at one observation point may not be representative of rainfall over the corresponding model grid cell, which represents an area-average value. Rainfall measurements are often sparse and distributed non-randomly, *for example*, in the mountainous western United States, much of the precipitation falls as snow at high elevations, while most direct measurements are taken in cities and airports located at much lower elevations, and are therefore not representative of total precipitation in that region. Simmons *et al.* (2004) note that the gridded observational values along coastlines reflect mostly land-based measurements, whereas reanalysis values for coastal grid cells reflect a mixture of ocean and land conditions. Also, producing a gridded data value from multiple stations within the cell can lead to significant problems for trend estimation because the contributing stations may have different record lengths and other inhomogeneities over space and time (Hamlet and Lettenmaier, 2005). Jones *et al.* (1999) note that urban development over time at a particular sensor location can produce a positive temperature trend at the sensor that is real, but is likely unrepresentative of the large grid cell that contains it.

Observational datasets that span multiple decades are also subject to changes in measurement systems. Takahashi *et al.* (2006) suggest that the use of a new satellite data product (introduced in 1987) in an observational precipitation dataset led to a change in the character of the data. Kalnay *et al.* (2006) found an artificial trend in observational temperature data induced by changes in measurement time-of-day, measurement location, and thermometer type. Jones *et al.* (1999) discuss the need to adjust or omit station data as necessary to ensure a minimal impact of such changes before computing trends.

Figure 2.18 shows the uncertainty inherent in trend computations from various observational datasets, and compared with NCSEP/NCAR reanalysis.

Observational datasets that span multiple decades are subject to changes in measurement systems.

The top six maps show the annual temperature trends across regions over the continental United States, as computed from six different observational datasets from 1951 to 2006, and the bottom map shows the trend computed from the NCEP/NCAR reanalysis. Of the seven maps, the reanalysis-derived map is clearly different from the other maps; the six observations-based maps all show a warming trend in all regions except the South, whereas

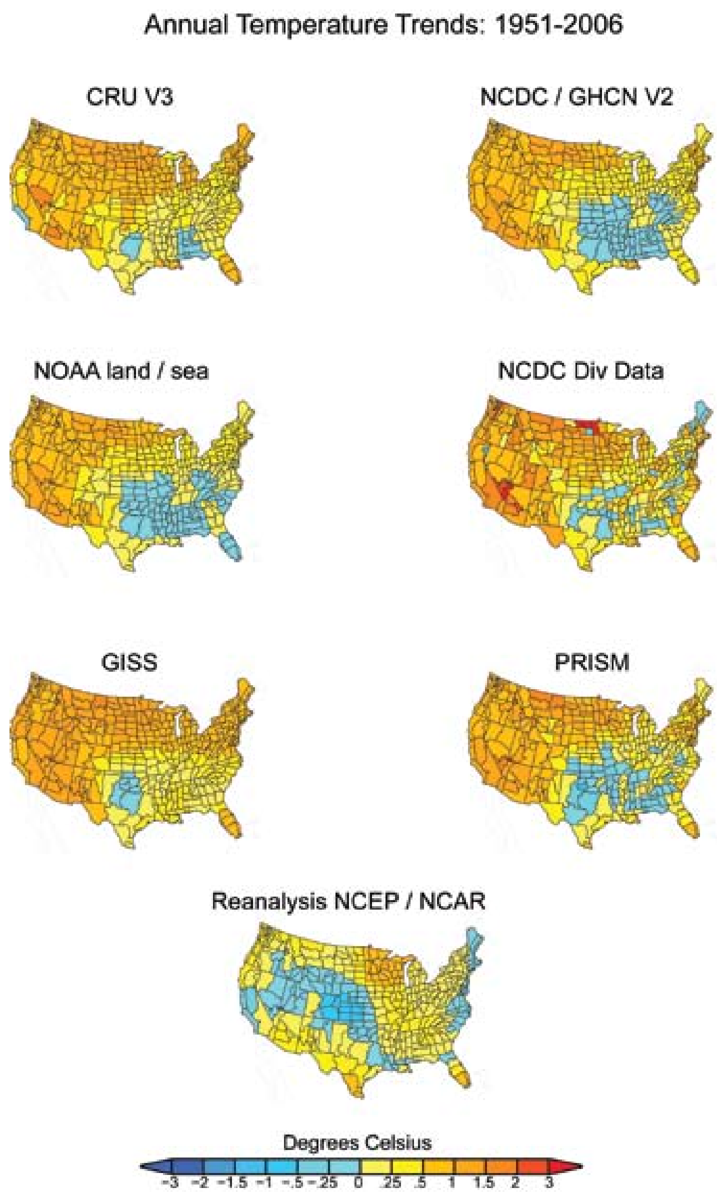

Figure 2.18 Annual temperature trends across the continental United States, as determined with six observational datasets and the NCEP/NCAR reanalysis (M. Hoerling, personal communication).

the reanalysis shows a general warming in the South and cooling toward the West. However, the six observations-based maps do not fully agree with one another. For example, the area of cooling in the South is smaller in the GISS and CRU datasets than in the National Climatic Data Center (NCDC)/Global Historical Climatology Network (GHCN) dataset. The NCDC climate division data show relatively high temperature trends in the West. These maps illustrate the fact that there is no perfect "truth" against which to evaluate the reanalysis-based trends.

There are also other sources of uncertainty for both observations-based trends and reanalysis-based trends. The mathematical algorithm used to compute trends is important. Jones (1994a) uses the linear regression approach and the "robust trend method" of Hoaglin *et al.* (1983), thereby computing two similar, but not identical, sets of trend values from the same dataset. Also, part of the trend estimation problem is determining whether a computed trend is real, that is, the degree to which the trend is unlikely to be the result of statistical sampling variations. Groisman *et al.* (2004) describe a procedure they used to determine the statistical significance of computed trends, which can help alleviate this problem. Even if all surface temperature data were perfect and the trend estimation technique was not an issue, the time period chosen for computing a trend can result in sampling variations, depending, for example, on the relationship to transient events such as ENSO or volcanoes (Jones, 1994b).

A proper analysis of the mechanisms of climate trends requires substantial data, and only a reanalysis provides self-consistent datasets that are complete in space and time over several decades.

2.4.3 Outlook

While limitations hamper the accurate estimation of trends from either reanalyses or observational datasets, it is the authors' assessment that it is likely that most of the trend differences shown in Figures 2.13 to 2.16 are related to limitations of the model-based reanalyses. Datasets that originate directly from surface and/or satellite observations, such as surface air temperature, precipitation, and atmospheric water vapor, will continue, at least for the near-term, to be the main tool for quantifying decadal and long-term climate changes. The observations-based trends are likely to be more reliable, in part because the relevant limitations in the observational data are better known and can, to a degree, be accounted for prior to trend estimation. This is less the case for existing reanalyses, which were not optimized for trend detection. Bengtsson *et al.* (2004a), examining various reanalysis products (though not surface temperature or precipitation), find that "there is a great deal of uncertainty in the calculation of trends from present reanalyses". Reanalysis-based precipitation (for ERA-40 and NCAR/NCEP) and surface air temperature (for NCAR/NCEP) are derived solely from the models (*i.e.*, precipitation and surface temperature observations are not assimilated). Therefore, these fields are subject to inadequacies in model parameterization. The North American Regional Reanalysis is an important example of a reanalysis project that did employ the assimilation of observed precipitation data (Mesinger *et al.*, 2006), producing, as a result, more realistic precipitation products.

Reanalyses have some advantages in analyzing trends. The complexity of describing and understanding trends is multi-faceted, and involves more than simply changes in average quantities over time. Precipitation trends, for example, can be examined in the context of the details of precipitation probability distributions rather than total precipitation amount (Zolina *et al.*, 2004). Observed precipitation trends in the United States reflect more than just an increase in the average itself, being largely related to increases in extreme and heavy rainfall events (Karl and Knight, 1998). Heavier rainfall events seem to be decreasing over tropical land during the last 20 years, a trend that appears to be captured by reanalyses (Takahashi *et al.*, 2006). Warming trends often reflect nighttime warming rather than warming throughout the full 24-hour day (Karl *et al.*, 1991). Precipitation and temperature statistics are fundamentally tied together (Trenberth and Shea, 2005); therefore, their trends should not be studied in isolation.

Given these and other examples of trend complexity, one advantage of a reanalysis dataset becomes clear: a proper analysis of the mechanisms of climate trends requires substantial data, and only a reanalysis provides self-consistent datasets that are complete in space and time over several decades. Given Figures 2.13 to 2.16, future reanalyses need to be improved to support robust trend estimation, particularly for precipitation. However, for many purposes, the comprehensive fields generated by reanalyses, together with their continuity (*i.e.*, no gaps in time, which are a common feature in observational data) and area coverage, provide value for understanding the causes of trends beyond what can be gained from observational datasets alone. For example, by providing trend estimates for midlatitude circulation patterns and other weather elements (features that tend to have a robust signal in reanalyses; see Section 2.4), reanalyses can provide insights into the nature of observed surface temperature and/or precipitation trends.

2.5 STEPS NEEDED TO IMPROVE CLIMATE REANALYSIS

As discussed previously, there are several reasons why the current approaches to assimilating observations for climate reanalysis can lead to false trends and patterns of climate variability. The instruments used to observe the climate may contain systematic errors, and changes in the types of instruments over time may introduce false trends into the observations. Even if the instruments are accurate, the sampling of the instruments across space and time changes over time and thus may improperly introduce shorter time scale or smaller space scale features, or introduce false jumps into the climate record. In addition, the numerical models used to provide a background estimate of the system state contain systematic errors that can project onto the climate analysis. In the case of the ocean, changes in the quality of the surface meteorological forcing will be an additional source of false trends. The following Section address issues of systematic instrument and data sampling errors as well as model and data assimilation errors as a backdrop for recommending improvements in the way future reanalyses are performed. Specific recommendations are given in Chapter 4.

2.5.1 Instrument and Sampling Issues

Prior to the middle of the twentieth century the atmosphere and ocean observing systems consisted mainly of surface observations of variables such as sea level pressure, winds, and surface temperature, although some upper air observations were already being routinely made early in the twentieth century (Brönnimann *et al*., 2005). Much of the marine surface data are contained in the International Comprehensive Ocean-Atmosphere Dataset (ICOADS) (Worley *et al*., 2005) but more still needs to be included. Considerable surface land data also exist, although these are currently scattered throughout several data archives, including those at the National Climatic Data Center and National Center for Atmospheric Research, and many additional surface datasets still need to be digitized. The state of this surface land data should improve as various land data recovery efforts begin (Compo *et al*., 2006). Attempts to reconstruct climate for the first half of the twentieth century must rely on these surface observations almost exclusively and thus these data recovery efforts are very important (Whitaker *et al*., 2004; Compo *et al*., 2006).

Attempts to reconstruct climate for the first half of the twentieth century must rely on land surface observations almost exclusively and thus data recovery efforts are very important.

In 1936, the U.S. Weather Bureau began operational use of the balloon-deployed radiosonde instrument, providing routine information for atmospheric pressure, temperature, humidity, and wind direction and speed used in daily weather forecasts. By the time of the International Geophysical Year of 1958, the radiosonde network expanded globally to include Antarctica and became recognized as a central component of the historical observation network that climate scientists could use to study climate. As a climate observation network, radiosondes suffer from two major types of problems. First, the instruments contain internal systematic errors (Haimberger, 2007). For example, the widely used Vaisala radiosondes exhibit a tendency toward dryness that needs to be removed (Zipser and Johnson, 1998; Wang *et al*., 2002). Second, some radiosonde stations

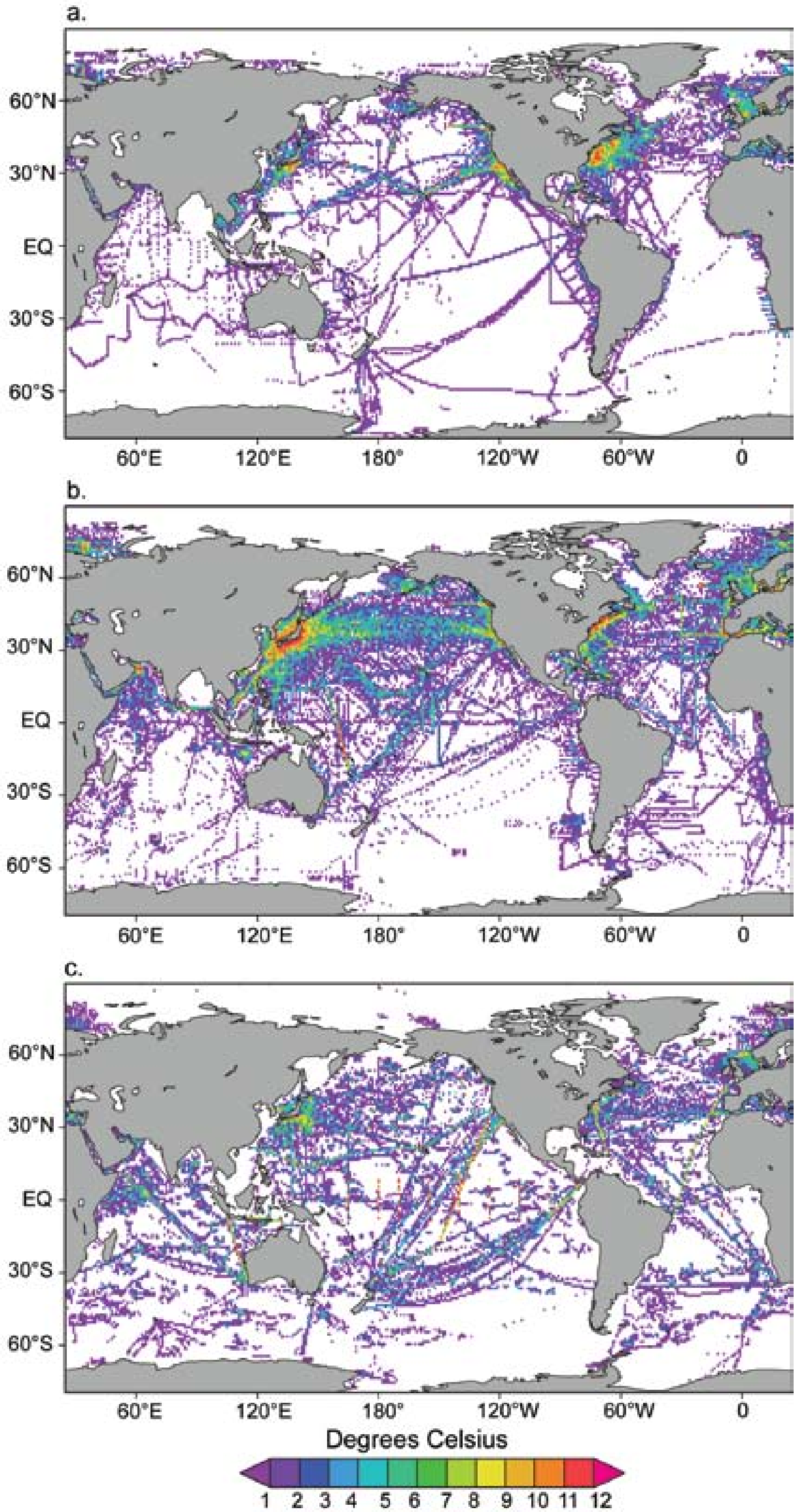

Figure 2.19 Distribution of temperature profile observations in the World Ocean Database extending from the surface of the ocean to 150 meter depth showing 40,000 profiles for 1960 (panel a), 105,000 profiles for 1980 (panel b), and 106,000 profiles for 2004 (panel c) (<http://www.nodc.noaa.gov/OC5/indprod.html>).

have moved to different locations, introducing inconsistencies into the record (Gaffen, 1994).

Two additional observing systems were added to the existing system in the 1970s. Aircraft observations increased in 1973, along with some early satellite-based temperature observations. In 1978, the number of observations increased dramatically in preparation for the First GARP Global Experiment, known as FGGE. The increased observation coverage included three satellite-based vertical temperature sounder instruments (MSU/HIRS/SSU), cloud-tracked winds, and the expansion of aircraft observations and surface observations from ocean drifting buoys. The impact of these additional observations (especially in the Southern Hemisphere) has been noted in the NCEP/NCAR and NCEP/DOE reanalyses (Kalnay *et al*., 1996; Kistler *et al*., 2001).

Currently the global radiosonde network consists of about 900 stations, although most radiosondes are launched from continents in the Northern Hemisphere. Of these, there are approximately 600 sonde ascents at 00:00 UTC (Coordinated Universal Time) and 600 ascents at 12:00 UTC, with many from stations that launch the radiosondes only once per day. Most of these launches produce vertical profiles of variables that extend only into the lowest levels of the stratosphere (about six miles above the Earth's surface), at which height the balloons burst. A further troubling aspect of the radiosonde network is the recent closure of stations, especially in Africa, where the network is especially sparse.

As indicated above, the number of atmospheric observations increased dramatically in the 1970s with the introduction of remote sensed temperature retrievals, along with a succession of ancillary measurements (*e.g.*, Figure 2.1). Temperature retrievals are made by observing the intensity of upwelling radiation in the microwave and infrared bands and then using physical models to relate these intensity measurements to a particular temperature profile. The issue of unknown systematic errors in the observations and the need for redundant observations has been highlighted in recent years by a false cooling trend detected in microwave tropospheric temperature retrievals. This false cooling trend has recently been corrected by properly accounting for the effects of orbital decay (Mears *et al*., 2003).

The ocean observing system has also undergone a gradual expansion of *in situ* observations (*i.e.*, measurements obtained through direct contact with the ocean), followed by a dramatic increase of satellite-based observations (Figures 2.19 and 2.20).

Prior to 1970, the main instrument for measuring subsurface ocean temperature was the mechanical bathythermograph, an instrument primarily deployed along trade shipping routes in the Northern Hemisphere, which recorded temperature only in the upper 280 meters, well above the oceanic thermocline (a thin layer in which temperature changes more rapidly with depth than it does in the layers above or below) at most locations. In the late 1960s the expendable bathythermograph (XBT) was introduced. In addition to being much easier to deploy, the XBT typically records temperature to a depth of 450 meters or 700 meters. Since the late 1980s, moored thermistor arrays have been deployed in the tropical oceans, beginning with the TAO/Triton array of the tropical Pacific, expanding into the Atlantic (PIRATA) in 1997, and most recently into the tropical Indian Ocean. These surface moorings typically measure temperature and, less often, salinity at depths to 500 meters.

Two major problems have been discovered in the historical ocean temperature sampling record. First, much of the data were missing from the oceanographic centers; however, this problem is improving. The 1974 version of the World Ocean Atlas contained 1.5 million profiles. Thanks to great efforts by Global Oceanographic Data Archaeology and Rescue (GODAR) the latest release of the World Ocean Database (WOD2005) contains nearly 8 million profiles (Boyer *et al*., 2006). Such data archaeology and rescue work needs to be continued. Second, similar to the atmospheric radiosonde, the XBT instrument was not designed for climate monitoring. It is now known that XBT profiles underestimate the depth of the measurement by 1 to 2.5 percent of the actual depth (Hanawa *et al*., 1995). Unfortunately, the compensating drop-rate correction differs for different varieties of XBTs, and less than half of the XBT observations identify the variety used. Some of the XBT observations collected since the late 1990s have had a drop-rate correction applied without accompanying documentation, while there is evidence that the drop-rate error has changed over time, being higher in the 1970s compared with other time periods (AchutaRao *et al*., 2007).

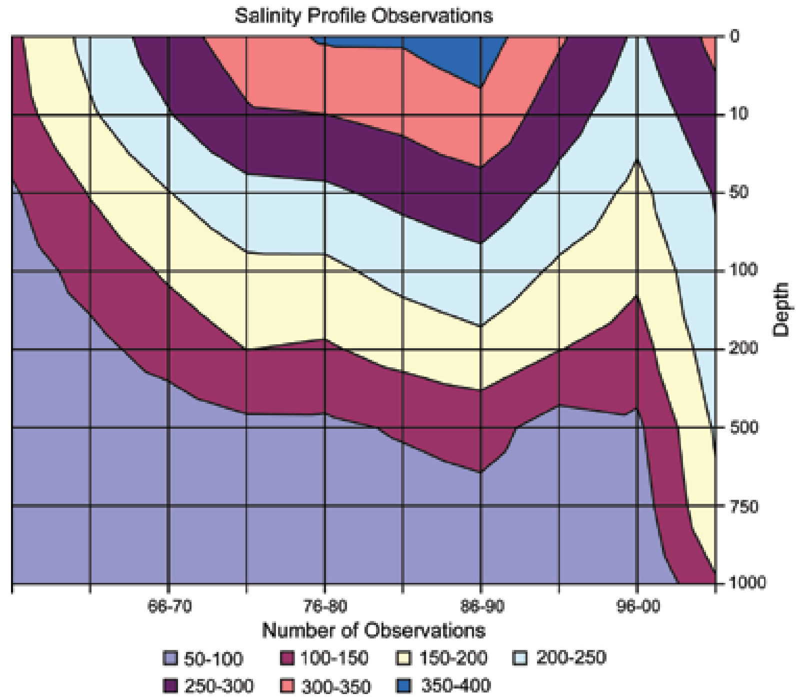

Figure 2.20 Distribution of salinity observations as a function of depth and time in the upper 1000 meters from the World Ocean Database 2001 (Carton and Giese, 2008). The decrease in salinity observations in 1974 resulted from the closure of ocean weather stations, while the decrease in the mid 1990s resulted from the end of the World Ocean Circulation Experiment and from the effects of the time delay in transferring salinity observations into the data archives. The recent increase in salinity observations is due to the deployment of the Argo array. Argo is a global array of free-drifting profiling floats that measures the temperature and salinity of the upper 2000 meters of the ocean.

Scientists can to al large extent only speculate about the historical changes in deep ocean circulation for the last half of the twentieth century.

For the last half of the twentieth century the main instrument for collecting deep ocean temperature and salinity profiles was the Salinity Temperature Depth or Conductivity Temperature Depth (CTD) sensor. The CTD profiles are accurate, but there are five times fewer CTD profiles compared to the number of XTB profiles. As a result, scientists can to a large extent only speculate about the historical changes in deep circulation.

Since 2003 a new international observing program called Argo (Roemmich and Owens, 2000) has revolutionized ocean observation. Argo consists of a set of several thousand autonomous drifting platforms that are mainly located at about 1000 meter depth. At regular intervals, generally ten days, the Argo drifters sink and then rise to the surface, recording a profile of temperature and salinity, which is then transmitted via satellite to data archival centers. The introduction of Argo has greatly increased ocean coverage in the Southern Hemisphere as a whole and at mid-depths everywhere, and also greatly increased the number of salinity observations. Argo is gradually being expanded to measure variables such as oxygen levels, which are important for understanding the movement of greenhouse gases .

Satellite remote sensing has further expanded the ocean observing system. This process began in the 1980s with the introduction of infrared and microwave sensing of sea surface temperature, followed by the introduction of continuous radar observations of sea level in the early 1990s, and then by regular surface wind observations from satellite-based scatterometers in the late 1990s. Scatterometers use the radar backscatter from wind-driven ripples on the ocean surface to provide information on wind speed and direction.

The availability of ocean datasets as well as general circulation models of the ocean has led to considerable interest in the development of ocean reanalyses (see Table 2.3). The techniques used are analogous to those used for the atmosphere. One example is the Simple Ocean Data Assimilation (SODA) ocean reanalysis by Carton *et al.* (2000). Like its atmospheric counterpart, this reanalysis shows distinctly different climate variability when satellite data is included.

It is important to address issues regarding the collection and interpretation of reanalysis-relevant land surface data. First, global *in situ* measurements of land states (*e.g.*, soil moisture, snow, ground temperature) are essentially non-existent. Scattered measurements of soil moisture data are available in Asia (Robock *et al.*, 2000), and snow measurement networks provide useful snow information in certain regions (*e.g.*, SNOTEL, <www.wcc.nrcs.usda.gov/snotel/>), but grid-scale *in situ* averages that span the globe are unavailable. Satellite data provide global coverage; however, they have limitations. Even the most advanced satellite-based observations can only measure soil moisture several centimeters into the soil, and not at all under

BOX 2.2: Modern Era Retrospective-Analysis for Research and Applications (MERRA)

The NASA/Global Modeling and Assimilation Office (GMAO) atmospheric global reanalysis project is called the Modern Era Retrospective-Analysis for Research and Applications (MERRA). MERRA (Bosilovich *et al.*, 2006) is based on a major new version of the Goddard Earth Observing System Data Assimilation System (GEOS-5), that includes the Earth System Modeling Framework (ESMF)-based GEOS-5 AGCM and the new NCEP unified grid-point statistical interpolation (GSI) analysis scheme developed as a collaborative effort between NCEP and the GMAO.

MERRA supports NASA Earth science by synthesizing the current suite of research satellite observations in a climate data context (covering the period 1979 to present), and by providing the science and applications communities with of a broad range of weather and climate data, with an emphasis on improved estimates of the hydrological cycle.

MERRA products consist of a host of prognostic and diagnostic fields including comprehensive sets of cloud, radiation, hydrological cycle, ozone, and land surface diagnostics. A special collection of data files are designed to facilitate off-line forcing of chemistry/aerosol models. The model or native resolution of MERRA is 0.67° longitude by 0.5° latitude with 72 levels extending to a pressure of 0.01 hectoPascals (hPa). Analysis states and two-dimensional diagnostics will be made available at the native resolution, while many of the three-dimensional diagnostics will be made available on a coarser 1.25° latitude, 1.25° longitude grid. Further information about MERRA and its status may be found at <http://gmao.gsfc.nasa.gov/research/merra/>.

dense vegetation (Entekhabi *et al*., 2004). Also, existing satellite-based estimates of surface soil moisture, as produced from different sensors and algorithms, are not consistent (Reichle *et al*., 2007), implying the need for bias correction. Time-dependent gravity measurements may provide soil moisture at deeper levels, but only at spatial scales much coarser than those needed for reanalysis (Rodell *et al*., 2007). Snow cover data from satellite are readily available, but the estimation of total snow amount from satellite data is subject to significant uncertainty (Foster *et al*., 2005).

There are now a number of recommendations that have been put forth by the scientific community (*e.g.*, Schubert *et al*., 2006) in order to make progress on issues regarding data quality and improvement of the world's inventories of atmospheric, ocean, and land observations. These include the need for all major data centers to prepare inventories of observations needed for reanalysis, to form collaborations that can sustain frequent data upgrades and create high quality datasets from all instruments useful for reanalyses, to develop improved record tracking control for observations, and to further improve the use of information about the quality of the reanalyses targeted especially for data providers/developers. Furthermore, the observational, reanalysis, and climate communities should take a coordinated approach to further optimizing the usefulness of reanalysis for climate. These recommendations have now been considered by the WCRP Observations and Assimilation Panel (WOAP) and the Global Climate Observing System (GCOS)/WCRP Atmospheric Observations Panel for Climate.

2.5.2 Modeling and Data Assimilation Issues

False trends may be introduced into the reanalyses by systematic errors in the models used to provide background estimates for data assimilation and by incomplete modeling of those systematic errors in the data assimilation algorithm. Atmospheric models include numerical representations of the primitive equations of motion along with parameterizations of small-scale processes such as radiation, turbulent fluxes, and precipitation. Model integrations begin with some estimate of the initial state, along with boundary values of solar radiation and sea surface temperature, and are integrated forward in time. While initial global reanalyses (Table 2.1) had resolutions of about 100 to 200 kilometers, the latest reanalysis efforts, NASA's Modern Era Retrospective-Analysis for Research and Applications, MERRA, (see Box 2.2), and NOAA's Reanalysis and Reforecasts of the NCEP Climate Forecast System, CFSRR, (see Box 2.3) have horizontal resolutions of about 50 kilometers or less. Regional models have much finer resolution, currently approaching one kilometer, and time steps of seconds. Improvements in resolution have improved representation of physical processes such as the strength and position of storm tracks and thus have improved simulation of local climate variability and reduced model bias.

Improvements in model resolution have improved representation of physical processes such as the strength and position of storm tracks and thus have improved simulation of local climate variability and reduced model bias.

Despite these increases in resolution, many important physical processes still cannot be explicitly resolved in current global models, such as convection, cloud formation, and precipitation in the form of both water and ice. Therefore, these processes must be parameterized, or estimated from other, presumably more accurately simulated, model variables. Inaccuracies in these parameterizations are a major source of uncertainty in numerical simulation of the atmosphere and are a cause of false trends, or bias, in atmospheric models. In addition, the presence of atmospheric instabilities (*e.g.*, Farrell, 1989; Palmer, 1988) will lead to model forecast errors.

Ocean models also include representations of primitive equations, with parameterizations for processes such as mixing and sea ice physics. Ocean models exchange thermodynamic, radiative, and momentum fluxes with the atmosphere. Horizontal resolution of current global ocean models is approaching 10 kilometers in order to resolve the complex geometry of the ocean basins and the oceanic mesoscale. Despite this fine resolution, such models still exhibit systematic errors, suggesting that the small horizontal and vertical scales upon which key processes such as vertical mixing, convection, and sea ice formation are still not being resolved (Smith *et al*., 2000).

In most analyses, the fluxes between ocean and atmosphere are one way because the ocean reanalysis is controlled partly by atmospheric

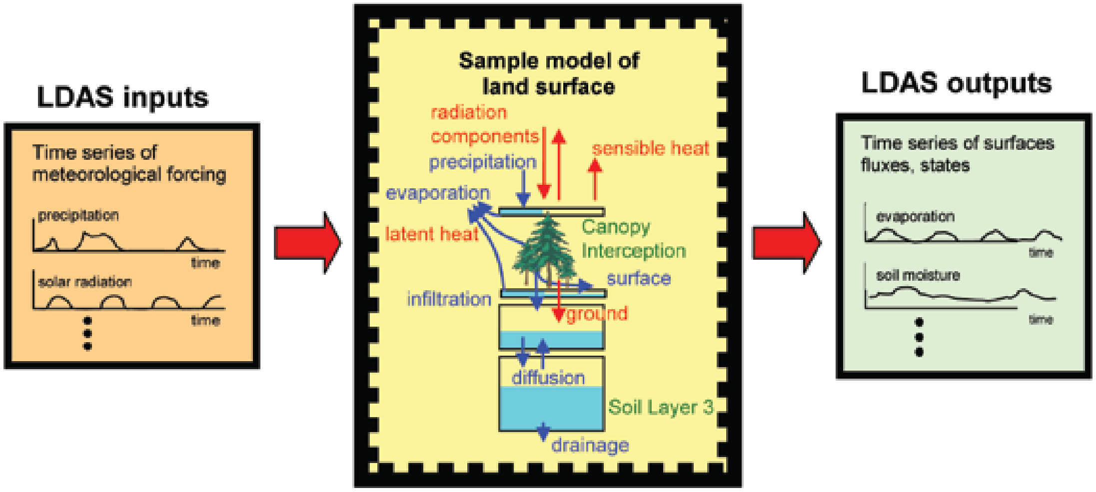

Figure 2.21 Schematic showing the inputs and outputs of a typical Land Data Assimilation System (LDAS) project.

Data assimilation provides a general way to correct a background estimate of the state of the atmosphere, ocean, and land surface that is consistent with available observations.

fluxes, while the atmospheric reanalysis is controlled partly by sea surface temperatures that are specified from observations. Thus, the fluxes in the reanalyses computed for the ocean and for the atmosphere, which should be identical, are in practice substantially different. Carrying out both reanalyses in a fully interconnected atmosphere/ocean model would ensure consistency; however, the surface exchanges are less constrained and thus, initial efforts at a combined analysis have been found to contain considerable systematic errors in both the atmosphere and the ocean (Collins *et al.*, 2006; Delworth *et al.*, 2006). A major challenge in the future will be to correct these systematic errors and subsequently develop consistent and accurate atmosphere/ocean reanalyses. NCEP is currently carrying out the first weakly coupled ocean-atmosphere reanalysis; results are encouraging but it is too early to know the extent to which the fluxes and trends are reliable (Box 2.3).

The land surface component of an atmospheric model also provides fluxes of heat, water, and radiation at the Earth's surface. The major difficulty in producing realistic land fluxes is the large amount of variability (*e.g.*, in topography, vegetation character, soil type, and soil moisture content) across areas (relative to that found in the atmosphere or ocean) in the properties that control these fluxes. These variabilities are difficult to accurately model for two reasons. First, given the area resolutions used for global reanalyses (now and in the foreseeable future), the physical processes that control the land surface fluxes cannot be properly resolved and therefore the small-scale processes must be parameterized. Second, there are few high resolution global measurements, which are required for many of the relevant land properties.

Despite these limitations, land models have been used in numerous Land Data Assimilation System (LDAS) projects. The current LDAS approach is to drive regional or global arrays of land surface models with observations-based meteorological forcing (*e.g.*, precipitation, radiation) rather than with forcing from an atmospheric model. This allows the land models to evolve their soil moisture and temperature states to presumably realistic values and to produce surface moisture and heat fluxes for diagnostic studies (Figure 2.21).

A list of some current LDAS projects is provided in Table 2.4. The LDAS framework is amenable to true assimilation, in which satellite-derived fields of soil moisture, snow, and temperature are incorporated into the gridded model integrations using new techniques (*e.g.*, Reichle and Koster, 2005; Sun *et al.*, 2004).

Data assimilation provides a general way to correct a background estimate of the state of the atmosphere, ocean, and land surface that is consistent with available observations (Kalnay, 2003; Wunsch, 2006). However, most current data assimilation algorithms make several assumptions either for efficiency or from lack of information, limiting their effectiveness. These assumptions include: (1) that any systematic

Table 2.4 A partial list of current Land Data Assimilation System (LDAS) projects.

Project	Sponsor(s)	Spatial Domain	Unique Aspects	Reference	Project website
GSWP-2	GEWEX	Global, 1°	Separate datasets produced by at least 15 land models for the period 1986 to 1995	Dirmeyer *et al.* (2006)	<http://www.iges.org/gswp2/>
GLDAS	NASA, NOAA	Global, .25° to ~2°	Multiple land models; near-real-time data generation	Rodell *et al.* (2004)	<http://ldas.gsfc.nasa.gov/>
NLDAS	Multiple Institutions	Continental U.S., 0.125°	Multiple land models; near-real-time data generation	Mitchell *et al.* (2004)	<http://ldas.gsfc.nasa.gov/>
ELDAS and ECMWF follow-on	European Commission	Europe, 0.2°	True data assimilation of air temperature and humidity in some versions	Van den Hurk (2002); Van den Hurk *et al.* (2008)	<http://www.knmi.nl/samenw/eldas/>

trends or biases in the observation measurements or sampling have been identified and corrected; (2) that the forecast model is unbiased; and (3) that the error statistics, such as the model forecast error, have linear, Gaussian (normally distributed) characteristics.

Several changes can be made to improve these assumptions. Systematic errors introduced by expansions of the observing system can be reduced by repeating the reanalysis with a reduced, but more consistent dataset, excluding, for example, satellite observations. An extreme version of this approach is to use only surface observations (Compo *et al.*, 2006). In this case, atmospheric reanalysis methods would need to make better use of historical surface observations from land stations and marine platforms. These records include existing climate datasets, such as daily or monthly air temperature, pressure, humidity, precipitation, and cloudiness, which have already undergone extensive quality control for the purpose of climate variability and trend applications.

BOX 2.3: Climate Forecast System Reanalysis and Reforecast Project (CFSRR)

The New Reanalysis and Reforecasts of the NCEP Climate Forecast System (CFSRR) is a major upgrade to the coupled atmosphere/ocean/land Climate Forecast System (CFS; Saha *et al.*, 2006). This upgrade is planned for January 2010 and involves changes to all components of the CFS, including the NCEP atmospheric Gridded Statistical Interpolation scheme (GSI), the NCEP atmospheric Global Forecast System (GFS), the NCEP Global Ocean Data Assimilation System (GODAS), which includes the use of the new GFDL MOM4 Ocean Model, and the NCEP Global Land Data Assimilation System (GLDAS), which includes the use of a new NCEP NOAA Land model.

There are two essential components to this upgrade: a new reanalysis of atmosphere, ocean, land, and sea ice, and a complete reforecast of the new CFS. The new reanalysis will be conducted for the 31-year period (1979 to 2009). The reanalysis system includes an atmosphere with high horizontal (spectral T382, about 38 km) and vertical (64 sigma-pressure hybrid levels) resolution, an ocean with 40 levels in the vertical to a depth of 4737 meters and a horizontal resolution of 0.25° at the tropics, tapering to a global resolution of 0.5° northwards and southwards of 10°N and 10°S, respectively, an interactive sea ice model, and an interactive land model with four soil levels.

In addition to the higher horizontal and vertical resolution of the atmosphere, the key differences from the previous NCEP global reanalysis are that the guess forecast will be generated from an interconnected atmosphere-ocean-land-sea ice system, and that radiance measurements from the historical satellites will be assimilated.

Systematic errors in the models may be explicitly accounted for and thus potentially corrected in the data assimilation algorithm (*e.g.*, Dee and da Silva, 1998; Danforth *et al*., 2007). However, additional work is needed to improve bias modeling. In addition to estimating and reducing bias, there is a need to improve the representation of error covariances, and to provide improved estimates of the uncertainties in all reanalysis products. New techniques (*e.g.*, the Ensemble Kalman Filter) are being developed that are both economical and able to provide such estimates (*e.g.*, Tippett *et al*., 2003; Ott *et al*., 2004).

As scientists continue to improve coupled models, joint assimilation between atmosphere, ocean, and land components should ensure greater consistency of model states across the components because the states of the systems would be allowed to evolve together.

Looking ahead, a promising pathway for improved reanalyses is the development of coupled data assimilation systems, along with methods to correct for the tendency of coupled models to develop bias. In this case, the observed atmosphere, ocean, and land states are assimilated jointly into the atmosphere, ocean, and land components of a fully coupled climate system model; however, the substantial bias in current coupled models makes this a significant challenge. Nevertheless, as scientists continue to improve coupled models, this joint assimilation should ensure greater consistency of model states across the components because the states would be allowed to evolve together. For example, a satellite-based correction to a soil moisture value would be able to impact and thereby potentially improve overlying atmospheric moisture and temperature states. The overall result of coupled assimilation would presumably be a more reliable and more useful reanalysis product. Several efforts are moving toward coupled data assimilation in the United States. These are focused primarily on developing more balanced initial conditions for the seasonal and longer forecast problem, and include the Climate Forecast System Reanalysis and Reforecast (CFSRR, see Box 2.3) project at NCEP and an ensemble-based approach being developed at NOAA's Geophysical Fluid Dynamics Laboratory (GFDL) (Zhang *et al*., 2007). Also, the GMAO is utilizing both the MERRA product (Box 2.2) and an ocean data assimilation system to explore data assimilation in a fully coupled climate model.