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eWater Technical Report

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These organisations are partners in eWater CRC

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Executive summary

The aim of research undertaken in eWater CRC Project D1 (‘Enhanced stream flow forecasting’) is to develop and facilitate prediction and forecasting of stream flow through improvements in the coupling of observations with hydrologic models. Better forecasting skill by catchment models will enable better management decisions by river managers and planners. A key element in this project is to improve catchment-scale hydrologic models through utilisation of multiple types of high frequency spatial data including: (1) reflective, thermal and microwave remote sensing; (2) ground-based radar-rainfall; (3) gauge measurements of stream flow; (4) distributed observations of soil moisture; and (5) 0–7 day forecasts from Numerical Weather Prediction models. Outputs from this work will deliver into two eWater CRC Product Development Programs, being: (1) River OPerationS (RiverOPS); and (2) the Water and Constituent Accounting Simulation Tool (WaterCAST).

There are multiple benefits for developing an improved capability for stream flow forecasting. These include improved efficiencies of water use through better anticipation of river inflows (particularly associated with flows from unregulated tributaries); a concomitant reduction in water losses and shortfalls on irrigation orders; better targeting of environmental flows by augmenting releases with natural flow events; basin wide consistency in management operations based on a thorough knowledge of variation in inflows and off-takes in time and space; an enhanced capability for predicting and monitoring flood events; and a better understanding of past catchment water dynamics through reanalysis studies.

While the benefits of an integrated stream flow forecasting system are great, current infrastructure and methodologies are not technologically mature enough to support a fully operational system at this time. Furthermore, institutional and technological barriers exist which maintain the *status quo* in river operations. To realise the benefits of improved flow forecasting, directed investment into specific research and development is needed to improve hydrologic modeling and prediction. The focus of this research and development effort should be on:

1. improved synthesis of precipitation data products from satellite, ground and numerical weather models;
2. development of improved spatially explicit hydrologic models with internal flow routing schemes to provide prognostic estimates of flow at catchment exit points;
3. acquisition and processing of relevant satellite data products in near real-time from operational and research satellites across a range of wavelengths;
4. development of computationally efficient numerical algorithms for minimising differences between observed and model ‘target’ variables (including state and flux variables and model parameters);
5. quantitative treatment of errors in the different types of data and the models; and
6. establishment of implementation pathways for adoption and use of flow forecast products by river management agencies and in policy development.

This document has a dual purpose. First, it examines the current status of data, models and model-data assimilation methods from a hydrologic viewpoint. It lays out the various sources of observational information, the range and structure of catchment models, the mathematical data assimilation techniques currently in use, and the observational and modeling framework needed to develop an operational stream flow forecasting system. It also provides background for those not familiar with the application of model-data assimilation methods.

The second purpose of this document is to provide a blueprint for the research direction of eWater CRC project D1 ‘Enhanced Stream Flow Forecasting’. This blueprint draws on the spectrum of options in the observation, model and assimilation domains. Outputs from this research will be adopted in both the RiverOPS and WaterCAST Product Development Programs in the eWater CRC and in river management agencies. As such, this document provides a way forward for promoting the development and adoption of data assimilation and forecasting methods in hydrology.

1 Introduction

Over the last 25 years, the variety and number of observations used to quantify water stores and fluxes in landscapes has grown increasingly. The motivation for a more thorough measurement of landscape water status ranges from improving prediction of stream flow for urban, agricultural and environmental applications, to understanding groundwater recharge rates and to improve irrigation efficiencies. *In situ* sensor technologies, direct measurements, new and more sophisticated satellite based sensors and advances in flux observations have all provided new insights into the dynamics of the hydrological cycle and the impacts of water resources management on water availability at a range of spatial and temporal scales.

While there are now a large number of hydrological data sets and models available, none of these independently provide sufficient information on which to base sound decisions because the data are not unified and they contain gaps, models are incomplete, and inconsistencies between the data and models abound (Walker et al. 2003; Barrett et al. 2007). The challenge for the research community is to develop approaches to synthesize the information contained in these different data types and model predictions for the purpose of improved forecasting of water stores and flows. Such approaches need to account for data collected at different spatial scales and temporal frequencies, their inherent errors and biases.

The term 'model-data assimilation' (DA) refers to a set of mathematical algorithms which enable measured observations (and errors) to be incorporated into models of dynamical systems for the estimation of current and future model state variables and fluxes taking into account the errors in each. A simple example is the use of distributed profile soil moisture measurements to constrain a soil water balance model forced by precipitation data (e.g. Walker et al. 2002). Ongoing developments in model-data assimilation in the atmospheric, oceanographic and geophysical sciences (Daley 1991; Bennett 1992; Berliner 2003) have made demonstrable improvements in the forecasting capability of complex models forced with satellite and ground based data. These techniques provide researchers with a range of mathematical tools capable of:

1. improved model parameterisation;
2. analysis of model structure and model sensitivity to perturbations;
3. diagnosis of system background state and initial conditions;
4. development of efficient sample designs and observation networks; and
5. improved forecasts with quantitative measures of forecast uncertainties.

In the last five years, considerable attention has been directed towards the development of model-data assimilation techniques in hydrology (e.g. Walker et al. 2001a, b; Walker and Houser 2001; Reichle et al. 2002; MacKay et al. 2003; Heathman et al. 2003; Sun et al 2004; Pipunic et al. 2007) with heavy utilisation of remote sensing data (e.g. Crosson et al. 2002; Kim and Barros 2002; Ni-Meister et al. 2005, 2006; Dong et al. 2007). Many studies have focused on assimilating separate and independent datasets such as microwave data of surface soil moisture or *in situ* soil moisture observations (Ceballos et al. 2005). More recently attempts have been made to synthesize information from multiple sources in the one assimilation scheme (Rudiger 2007). For example, Aubert et al. (2003) demonstrated substantial improvement in modeled stream flow when both *in situ* soil moisture observations and stream flow data were assimilated, compared to using stream flow data alone. Their attempts at also assimilating active microwave data from the European Earth Resources Satellite – Synthetic Aperture Radar (ERS SAR) were limited by the update frequency of those satellite data (1 week). They concluded that considerable advantage for hydrologic forecasting could be gained by a more frequent update cycle of 1–3 days.

Attempts at developing operational land surface model-data assimilation schemes capable of forecasting stream flow and other water balance components for the continental United States (North American Land Data Assimilation Scheme, NLDAS) have had variable success in prediction of runoff and actual evapotranspiration (Burke et al. 2001; Mitchell et al. 2004; Lohmann et al. 2004). These studies attempted to diagnose the hydrometeorology of the land surface at the mesoscale (10^2–10^3 km^2) resolved to 1/8° (~12.5 km) by coupling remote sensing observations of snow cover, land surface temperature, soil moisture storage and snowpack, with daily streamflow observations from a range of catchments.

Results from these studies have identified a range of biases and errors in models and data including:

1. substantial inter-model errors in surface evaporation, runoff, and soil moisture;
2. poor estimation of model parameters at fine resolution over large regions;
3. inadequate understanding of the interaction between non-linear models, their parameters and calibration; and
4. errors in forcing data particularly precipitation.

These errors and biases need to be addressed in the development of operational hydrologic forecasting to avoid propagation of these errors and biases into forecasts. Part of the objective of Project D1 'Enhanced stream flow forecasting' is to generate methodologies capable of providing the best possible forecasts of stream flow through the integration of model prediction and observations. By confronting a model with observations, we are also able to improve our understanding of the relevant hydrological processes such as runoff generation, surfacewater and groundwater interactions, and transport processes, in addition to improving the predictive capability of the model.

The scope of research in the 'Enhanced Stream Flow Forecasting' project is the establishment of a model-data assimilation framework for water yield forecasts and river operations. This project will deliver research *via* two practical tools for stream flow modeling that will allow river operators, planners and managers to work from a common platform (Figure 1.1):

1. RiverOPS, which is designed for operational forecasting of stream flow and real-time decision making; and,
2. WaterCAST, which is designed for long-term planning including scenario assessment to support decisions for water resources management.

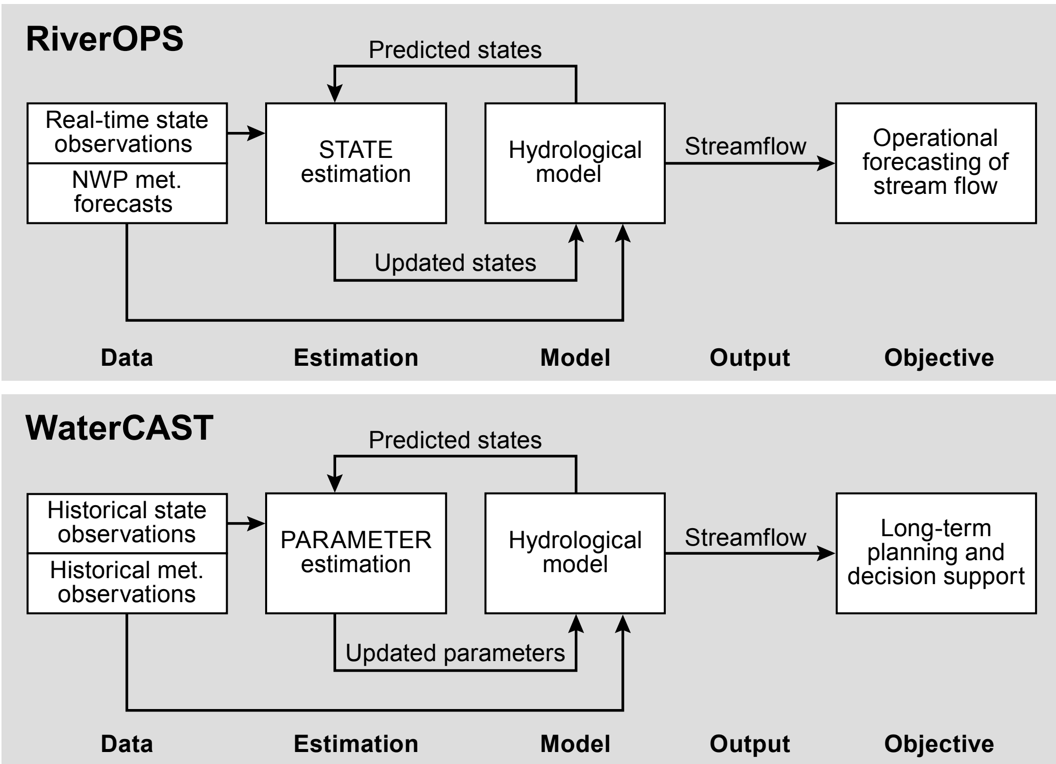


Figure 1.1. Schematic of proposed hydrologic modeling in eWater CRC Project D1 'Enhanced Stream Flow Forecasting' and its interaction with WaterCAST and RiverOPS Product Development Programs.

In RiverOPS applications, near real time observations of state variables and forcing data, and current forecasts from Numerical Weather Prediction (NWP) models are ingested into a hydrologic model simulating catchment water balance, hillslope runoff and stream flow to generate better estimates of flow for operational decision making through improved model state estimation. In WaterCAST applications, archived historical observations will be used in the model data assimilation scheme to generate best estimates of model parameters to generate improved understanding of stream flow dynamics for long term decision making (including scenario assessment) and setting of policies.

In order that these tools provide a consistent and coordinated approach to water management, they must be built within a comprehensive system requiring: (1) high quality regular forcing, observational and validation data; (2) a robust and reliable hydrological model; and (3) a computationally efficient data assimilation scheme.

In this document, we survey the available data products, hydrological models and data assimilation methods that make up the various components of DA system for forecasting stream flow. Our aim here is to assemble a blueprint for research from the current range of data and modeling products and DA methods. This report serves two purposes. Firstly, it documents the survey of data and methods and our choices made in establishing the blueprint which is likely to be of use to others. Secondly, it serves as a starting point for the planning and execution of an operational stream flow forecasting system for practical use by river management agencies.

The report is structured as follows: Section 2 examines the type and availability of a range of data sources for use in hydrologic forecasting; Section 3 documents a range of suitable hydrologic models purposefully focusing on those readily available and accepted within the eWater CRC community *via* the Catchment Modeling Toolkit; Section 4 reports on the different types of data assimilation schemes available for hydrologic forecasting; and Section 5 concludes with the D1 blueprint or research pathway using the Murrumbidgee River catchment in southeastern Australia for demonstration.

How to read this document

This document contains a considerable amount of technical detail across a wide range of topics pertaining to data sets, hydrologic models and data assimilation methods. These details may be familiar to some but unknown to others; for example, researchers concerned with measurement may be unfamiliar with the range and function of catchment hydrologic models. Furthermore, detailed technical considerations are important when choosing the most appropriate components of an operational hydrologic forecasting system. However, this exhaustive detail can obscure the ‘bigger picture’ when trying to understand the layout of a hydrological forecasting scheme. To blend these two conflicting objectives (sufficient technical detail versus schematic overview) into a single document we suggest approaching this report in one of two ways. First, to develop a high-level overview, the reader should focus on sections 2.1, 2.2, 3.1, 3.2, 4.2, 5.2, and 5.3. Second, where greater detail regarding available data sources is required the reader is referred to sections 2.3, 2.4, and 2.5. Third, if more detail regarding the range hydrologic models is required the reader is referred to section 3.3 and the references therein. Finally, specifics about model-data assimilation methods are found in section 4.3.

2 Data

2.1 Introduction

Data used in applied physical models can be divided into three categories:

1. forcing data, which define external variables that influence system state and fluxes and include archival and prognostic data;
2. parameters, which summarise information about system processes that operate outside the time or space scale considered by the model; and
3. observations of model states and fluxes which provide information on the current state of the system or can be used for verification and assessment of forecast skill.

Table 2.1. Summary of data types and data sources applicable to stream flow forecasting. The source category 'other' refers to archival and static data sets.

	Data type			Source			
Data Name	Model forcing	Model parameters	State or flux observation	Remote sensing	Surface observation	Numerical weather model	Other
Precipitation	✓			✓	✓	✓	
Actual evapotranspiration	✓			✓	✓	✓	
Potential evapotranspiration	✓			✓	✓	✓	
Short-wave radiation	✓			✓	✓	✓	
Long-wave radiation	✓			✓	✓	✓	
Surface air temperature	✓				✓	✓	
Dew point temperature	✓				✓	✓	
Surface pressure	✓				✓	✓	
Surface wind speed	✓				✓	✓	
Leaf Area Index *		✓		✓			
Normalised Difference Vegetation Index		✓		✓			
Vegetation type		✓		✓	✓		
Greenness		✓		✓			
Albedo		✓		✓			
Soil properties		✓					✓
Elevation		✓					✓
Catchment area		✓					✓
Catchment shape		✓					✓
Connectivity of stream network		✓					✓
Normalised Difference Temperature Index			✓	✓	✓		
Soil moisture			✓	✓	✓		
Groundwater			✓	✓	✓		
Surface temperature			✓	✓			
Surfacewater			✓	✓			
Runoff / discharge			✓		✓		
Snow coverage / Snow Water Equivalent			✓	✓			

* Other metrics of vegetation such as fraction Absorbed (by vegetation) Photosynthetically Active Radiation (fAPAR) and percent vegetation cover may be used depending on the model formulation, and these like Leaf Area Index, can be derived from remote sensing.

In the hydrologic context, examples of forcing data are historical meteorological records and output from numerical weather prediction models, an example of a parameter is soil hydraulic conductivity which comprises aggregate information about processes governing flow of water through the soil matrix, and examples of observations are measurements of surface states and fluxes (such as evapotranspiration and soil moisture) using *in situ* or remote sensing approaches.

For model-data assimilation purposes, information is required on the errors associated with each data type. This is because the quality of the analysis is directly dependent on the error covariances among data. Another important issue is the presence of bias in observations. Bias violates important assumptions in data assimilation theory and distorts the outcome of the analysis. Much effort has been expended in removing biases and characterising observation error covariances in meteorological and oceanographic data assimilation in order to ensure that the best possible results are achieved. Similar efforts are underway in hydrological applications of data assimilation (e.g. Reichle and Koster 2005; Ni-Meister et al. 2005; Foster et al. 2005; Dong et al. 2005) but much further work is required.

In this section of the report, we examine the range of data sources available for use in DA schemes from the viewpoint of the D1 ‘Streamflow Forecasting’ project; a summary of these data are presented in Table 2.1. Firstly, an overview of ground based, remote sensing and numerical weather prediction products is given, followed by a detailed summary of available forcing data, parameters and observations. These observations are currently accessible and could be used with little overhead costs in an operational hydrologic data assimilation system.

2.2 Overview of data sources

The available data sources for hydrologic model-data assimilation are divided here into three categories and a summary is given of each category before being discussed in detail. These categories are: (1) ground based data; (2) remote sensing observations; and (3) products from numerical weather prediction models.

2.2.1 Ground based observations

Meteorological data are the primary source of forcing data in hydrologic models. These data are supplied by the observation, communications and data processing system developed, maintained and undergoing continual improvement by the Australian Bureau of Meteorology (hereafter the ‘Bureau’) as part of a global network coordinated under international data exchange programs administered by the World Meteorological Organisation. The observing system includes a network of 50 surface-to-upper air (radiosonde) stations, a surface network of more than 800 automatic weather stations (AWS) (Figure 2.1) with 550 operated by the Bureau and the remainder by other organisations, a volunteer daily 9am precipitation network of 6000 contributors, and a range of other specialised networks and facilities such as ground based radars and relevant satellite observations. The Bureau’s network of AWS typically collects observations of air temperature, dew point, relative humidity, wind speed and direction, pressure and precipitation on 1 minute, 10 minute and hourly intervals. The currently available meteorological data are presented in Table 2.3, along with a listing of desired NWP outputs. Additional details regarding data types, their temporal and spatial resolutions and archiving systems are provided by Kuzmin et al. (2007).

2.2.2 Remote sensing data

Remote sensing is the measurement or acquisition of information by a recording device not in physical contact with a surface and can utilise the gamma ray, reflective, thermal, microwave or radio portions of the electromagnetic spectrum. Measurements from satellite, aircraft or from ground-based instruments provide information on the reflectance or radiance properties of the Earth’s surface at spatial resolutions from metres to kilometres and time-series extending back 30 years. Remote sensing imagery is now routinely recorded by sensors on board satellites which vary in altitude from ~700 km for polar orbiters to ~36,000 km for geostationary satellites. Errors in observations are due to the Earth’s atmosphere, sub-pixel

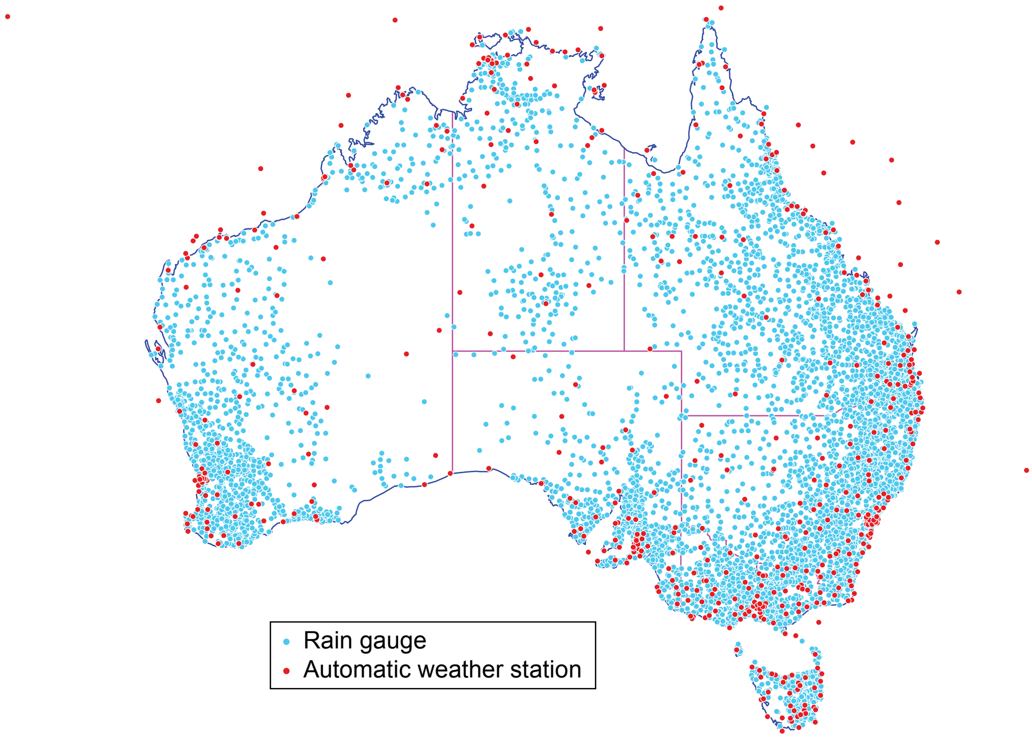


Figure 2.1. Meteorological observational network of Australia.

heterogeneity, sensor drift and calibration problems, and through interactions between these errors. Physical models (also called scene-based or direct interpretation models) are used to compensate for errors and to transform reflectance and radiances into 'Level 2' data (e.g. O'Brien et al. 2000). In the hydrologic context, a summary of important satellite derived observational data is given in Table 2.2. The considerable potential for satellite observations to provide timely and relevant information regarding key components of the water balance of the Earth's surface is evident by the extensive spatial coverage and rapid update frequencies now routinely available; as such it is increasingly used by operational users in a variety of disciplines (including hydrology) in near real-time systems across the globe.

Table 2.2. Hydrologic observations available from satellite sensors (adapted from Walker et al. 2003).

Hydrologic quantity	Remote-sensing technique	Frequency of acquisition	Spatial resolution
Surface soil moisture	Passive microwave	1–3 d	50 km
	Active microwave	3 d, 30 d	3 km, 10 m
	Thermal infrared	1 h, 1 d, 15 d	60 m, 1 km, 4 km
Surface skin temperature	Thermal infrared	1 h, 1 d, 15 d	60 m, 1 km, 4 km
Snow cover	Visible / thermal infrared	1 h, 1 d, 15 d	30–60 m, 0.5–1 km, 4 km
Snow water equivalent	Passive microwave	1–3 d	50 km
	Active microwave	3 d, 30 d	10 m
Total water storage changes	Gravity changes	30 d	1,000 km
Evapotranspiration	Thermal infrared and/or reflective	1 h, 1 d, 15 d	60 m, 1 km, 4 km

2.2.3 Numerical weather prediction (NWP) products

The Bureau generates a wide range of forecast products that are based on different numerical weather prediction models operating at a range of temporal and spatial resolutions, different spatial domains, and with varying forecast lead times. These include: (1) the Limited Area Prediction System (LAPS) 375 model out to 72 hours with a spatial resolution 0.375° (~37.5 km) for all of Australia; (2) MesoLAPS 125 model with a spatial resolution 0.125° (~12.5 km) for all of Australia; and (3) MesoLAPS 05 model with a spatial resolution 0.05° (~5 km) for parts of Australia only. Domains of the MesoLAPS 05 model are shown in Figure 2.2.

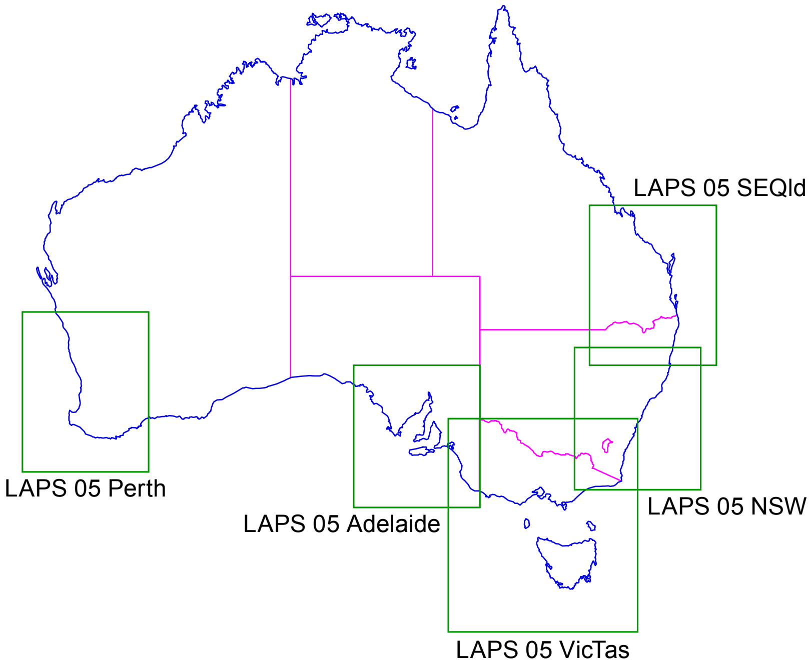


Figure 2.2. Domains and names for the MesoLAPS 05 systems (Bureau of Meteorology).

Table 2.3. Numerical Weather Prediction forecasts required for hydrological prediction (from Kuzmin et al. 2007). Currently available and 'desired' products for improved forecasting are shown.

Meteorological fields	Current					Desired			
	Lead time, h	Spatial resolution, km	Forecasting step, h	Deterministic (D) or ensemble (E)	Source	Lead time, h	Spatial resolution, km	Forecasting step, h	Deterministic (D) or ensemble (E)
Precipitation	72	37.5	1	D	LAPS 375	144	12.5	1	E
	72	100	12	E	LAPS EPS				
Actual evapotranspiration	72	37.5	1	D	LAPS 375	96	12.5	1	E
Potential evapotranspiration	72	37.5	1	D	LAPS 375	96	12.5	1	E
Surface pressure	72	37.5	1	D	LAPS 375	96	12.5	1	E
Wind speed	72	37.5	1	D	LAPS 375	96	12.5	1	E
Surface air temperature	72	37.5	1	D	LAPS 375	96	12.5	1	E
Dew point temperature	72	37.5	1	D	LAPS 375	96	12.5	1	E
Long-wave downward radiation	72	37.5	1	D	LAPS 375	96	12.5	1	E
Short-wave downward radiation	72	37.5	1	D	LAPS 375	96	12.5	1	E

Table 2.3 summarises important meteorological fields from numerical weather models that have application in hydrological forecasting. The utilisation of these products will enable the extension of catchment models into the forecasting domain on 1 to 7 day timescales. Forecast lead time out to 3 days at a spatial and temporal resolution of 37.5 km and 1 hour are available from the operational forecast model of the Bureau of Meteorology; the Limited Area Prediction System (LAPS). Ongoing advances in numerical modelling at higher spatial resolution and statistical downscaling techniques will enable ensemble predictions at 12.5 km which will greatly improve prediction of stream flow by hydrologic models.

The remainder of Section 2 provides detailed summaries of the three categories of data sources introduced at the start of this section, that are available for hydrologic forecasting applications.

2.3 Detailed summary of available forcing data

2.3.1 Precipitation

Precipitation data are a primary driver and significant source of uncertainty in hydrologic models (Milly and Dunne 2002) and so improvements in understanding the spatial and temporal distribution of precipitation are important for stream flow forecasting. There is considerable effort underway (summarised below) to fully exploit existing technology to improve the monitoring and forecasting of precipitation which will facilitate improved performance by hydrologic models.

Precipitation data can be obtained from three sources: (1) remote sensing observations; (2) surface observations; and (3) NWP products. The first two of these sources provide diagnostic information on past to current precipitation while the third provides prognostic information on present to future precipitation. An active area of research is the combining of precipitation data products (e.g. gauge and radar data) to maximise the benefits of multiple information sources and minimise errors (Seed 2004)

Remote sensing of precipitation

Remote sensing provides information to augment the existing gauged precipitation network, by filling gaps in data between gauge locations. In return, the gauge network provides point observations for calibration and validation of remote sensing algorithms (McVicar and Jupp 1998). There are several remote sensing techniques which have potential to assist in the mapping of precipitation patterns (Lakshmi et al. 2001). The most promising are thermal and microwave.

High frequency thermal remote sensing imagery, such as that available from Geostationary Meteorology Satellites (GMS), provides information on cloud top temperatures which are correlated with the size of precipitation droplets in clouds and, hence, the likelihood of rain. For example, Ebert and Le Marshall (1995) used a rule-based algorithm to estimate precipitation rates based on infrared data from a Japanese GMS. Cloud top temperatures associated with rain-bearing frontal activity are usually warmer and closer to ground temperature than the very cold temperatures measured in convective clouds, which makes detecting precipitation more difficult. However, this approach is useful for identifying precipitation likelihood (Tait et al. 1998). Furthermore, GMS data can be used as a covariate in spatial interpolation to distribute rain gauge observations and to discriminate convective precipitation events missed by the gauge network.

There are several integration techniques which may allow precipitation to be better predicted by combining thermal GMS data with other data sets. These include:

1. Use of pattern recognition or visible data to determine cloud type (Ebert 1987);
2. Relating shortwave infrared (SWIR) based inferences of cloud top droplet size to precipitation rate (Rosenfield and Gutman 1994); and
3. Coupling outputs from Numerical Weather Prediction (NWP) to information about current meteorological conditions (Grassotti and Garand 1994). Herman et al. (1997)

have developed an operational system using this approach for Africa to provide 10-day precipitation estimates for the entire continent.

Microwave observations provide information on the presence of precipitation-sized water and ice particles present in clouds (Petty 1995) which are related to surface precipitation intensity; although, there is some uncertainty associated with the interaction between droplet size, shape, microwave signal and precipitation intensity. Passive microwave remote sensing of rainfall over land has been ongoing since 1987 with the launch of the Special Sensor Microwave Imager (SSM/I) on board the U.S. Defence Meteorological Satellite Program (DMSP). There are numerous examples of the use of the SSM/I to estimate rainfall (e.g. Grody 1991; Spencer et al. 1989). The skill of SSM/I data to estimate instantaneous rainfall over land for a 1.25 degree resolution cell is as high as 0.82 (Petty 1995).

In November 1997, the Tropical Rainfall Mapping Mission (TRMM) was launched, to better monitor precipitation events in tropical and subtropical latitudes. The frequent (3 hour) repeat cycle provides multi-pass daily coverage of precipitation rate for all of Australia at 0.25° (3B42 product), and a higher resolution swath product (2B31) of precipitation rate at 5 km resolution and 247 km width. A range of blended precipitation products are also available which utilise gauge observations and GMS data (see http://trmm.gsfc.nasa.gov/publications_dir/regional_asia.html).

Ground based radar precipitation observation

Another source of precipitation data is the Bureau ground-based radar network (Figure 2.3). The Bureau of Meteorology 'Rainfields' server generates quantitative precipitation estimates for South-East Australia within 256 km square regions centred on radars at Adelaide, Brisbane, Canberra, Melbourne, Sydney and Yarrawonga. The primary product is 10-minute rainfall accumulation at 1 km spatial resolution, but hourly and daily accumulation products are also available (image products available at http://mirror.bom.gov.au/weather/radar/). These data can potentially improve estimation of infiltration excess runoff in models (Giannoni et al. 2003). However, residual problems exist with accurately interpreting precipitation rate (particularly in heavy rain) due to differences in droplet shape, the obscuration of storms by near station rainfall or by topographic features, and the dissipation of signal with distance from station (Bargo 2002).

Gauge network of precipitation observations

Gridded daily rainfall products are available for all Australia at 0.25° (~25 km) resolution based on point observations from the surface observation network with an initial pass based on the AWS network and a subsequent pass with observer data. It is important to note that these products record precipitation data in the 24 hours preceding 9:00 AM local time rather than the calendar date (Ebert and Weymouth 1999, Lee 2006; Weymouth and Le Marshall 1999, Weymouth and Le Marshall 2001). The Bureau and Queensland Department of Natural Resources and Water also provide a gridded daily precipitation product (along with daily maximum and minimum air temperature, and daily shortwave incoming radiation) at 0.05° (~5 km) from the SILO Web site (http://www.bom.gov.au/silo/) and a lag time of 1 day (Jeffery et al. 2001) and also from the Bureau's 'Water and the Land' Web page with the same lag time (http://www.bom.gov.au/watl/).

Numerical weather prediction products

In addition to ground-based and remotely sensed precipitation observations, NWP system products, such as deterministic and probabilistic forecasts of precipitation can be used to force hydrologic models. Most deterministic forecasts are obtained from the Limited Area Prediction System (LAPS) numerical model and its variations. Currently these forecasts have spatial resolution 0.375° (~37.5 km) and lead time up to 72 hours. For the whole continent, precipitation forecasts with resolution 0.125° (~12.5 km) are available, but their lead time is only 48 hours. Other NWP products are available from the Global AnalysiS and Prediction system (GASP), which provides long-range, low resolution forecasts over the entire globe

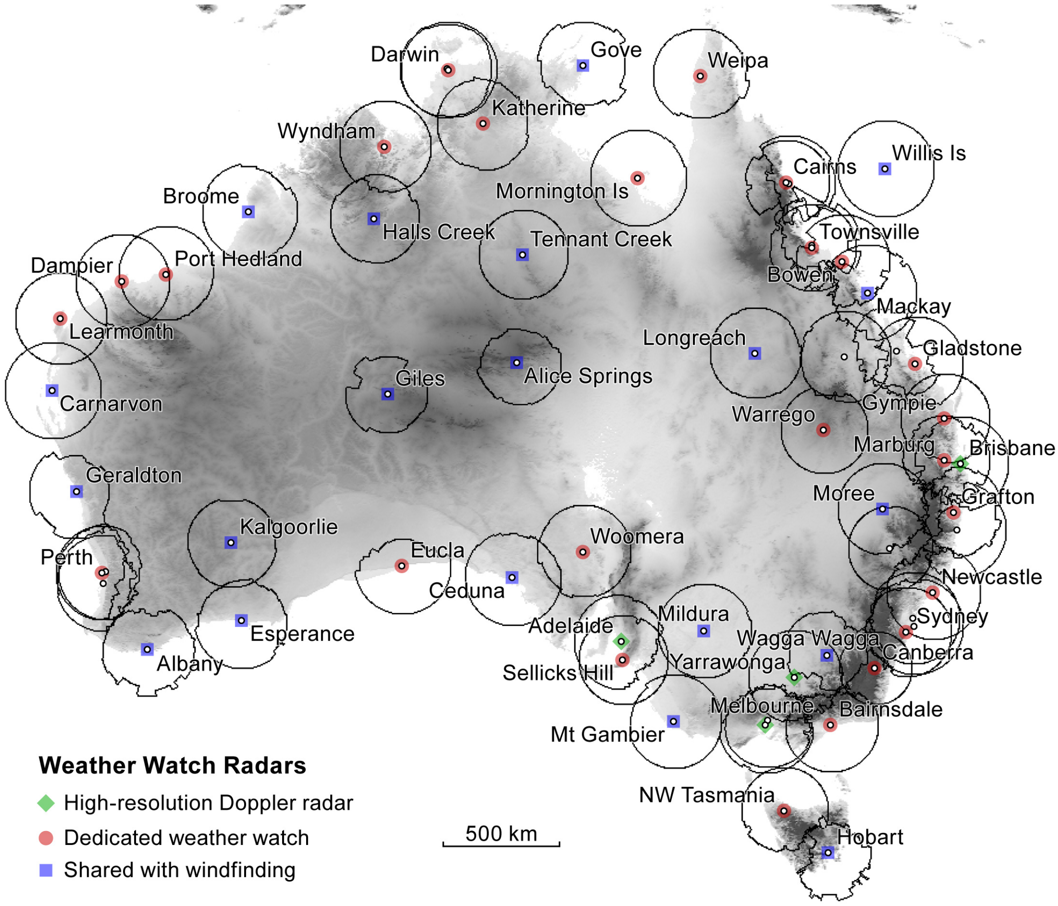


Figure 2.3 The distribution of ground based radars operated by the Bureau of Meteorology weather radar network. The high resolution Doppler radars yield the best rainfall estimates. Radars that are shared with wind finding are less suitable for rainfall estimation. The region around each radar is the simulated coverage at 3000 m generated by the program Radio Mobile (http://www.cplus.org/rmw/rme.html) from elevation data; it does not take into account local obstructions such as buildings and trees. (After Bureau of Meteorology 2008a,b).

(spatial resolution 1° and lead time up to 10 days). However, it should be noted that significant errors exist in the 24 hour forecast, particularly in the spatial distribution of precipitation, and that the skill in precipitation forecasting from 3 to 5 days is low.

For high resolution short-term forecasts, the Short-Term Ensemble Prediction System (STEPS is capable of generating ensemble forecasts of precipitation forward to a limit of 6 hours (Bowler et al. 2003) by combining the information that exists in MesoLAPS NWP forecasts with current weather radar observations. This model has been developed jointly by the Australian Bureau and the UK Met Office to generate forecasts based on radar rainfall observations and NWP forecasts from MesoLAPS. STEPS currently generates deterministic forecasts for precipitation accumulation over the next 30, 60, and 90 minutes and estimates the probability that the precipitation accumulation in the next 60 minutes will exceed 1, 2, 5, 10, 20, 50 mm.

2.3.2 Actual evapotranspiration

Evapotranspiration (ET) is a collective term for the transfer of water vapour from the soil and vegetation to the atmosphere and is affected by the surface energy balance, soil moisture content and biophysical properties of the surface. Various approaches to estimating ET exist and these differ on the spatial scale over which ET is calculated and the primary controlling mechanism for vegetation transpiration. Non-linearity in the processes driving ET and feedback between the land surface and atmosphere means that it is not straightforward to downscale large scale estimates of ET to local scale catchment studies.

Numerical weather models provide latent heat fluxes and an important development for stream flow forecasting is the planned availability via Bureau of hourly ensemble forecasts of actual ET at 12.5 km resolution in 2008 (Kuzmin et al. 2007). The ensemble forecasts will provide time-relevant forcing data with uncertainties. This type of forecast will become an important input to operational stream flow prediction within the RiverOPS system and for water demand forecasting by irrigators. However, research effort is required to develop adequate downscaling approaches for individual catchments and sub-catchments.

There is also a range of actual ET remote sensing products being developed by several research groups in CSIRO and elsewhere based on a range of different methods. These include: (1) resistance energy balance method; (2) crop coefficient method; (3) inversion of the surface energy balance; and (4) parameterisation of Penman-Monteith equation. All of these methods have been applied using regional (1 km) resolution high frequency satellite remote sensing data such as the MODerate resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR).

The first method, resistance energy balance, requires that meteorological data are available at the time of satellite overpass (e.g. McVicar and Jupp 1999). Evapotranspiration estimates are made at the locations of meteorological observing stations and remotely sensed data are used to interpolate between stations (McVicar and Jupp 2002).

The second approach is based on the premise of mapping actual ET as a function of potential ET modified by a ‘crop coefficient’. Given that potential ET is readily available from sources such as SILO on a daily time-step, this method is straightforward to implement. Recently, Van Dijk et al. (2006) have used observations in the SWIR bands from MODIS for estimating vegetation moisture content to calibrate the ‘crop coefficient’ based on the relationship between absorptance in shortwave infra red wavelengths and canopy moisture content.

The third method involves inverting a surface energy balance model to solve for latent heat fluxes given satellite observations of land surface temperature. Recently, Renzullo et al. (2007) coupled a surface-energy balance (SEB) and microwave radiative transfer model to retrieve latent heat flux from MODIS thermal data and AMSR-E (Advanced Microwave Scanning Radiometer - Earth observing system) microwave observations. The application of these methods to multiple sensors with observations throughout the day yields daily actual ET estimates.

The fourth approach involves parameterising the surface conductance term of the Penman-Monteith equation by establishing relationships with remotely-sensed LAI (Leaf Area Index) at flux tower sites (Cleugh et al. 2007). Remotely sensed estimates of LAI are then used to spatially infill between flux towers the calibrated Penman-Monteith model given readily available meteorological data.

2.3.3 Short-wave radiation fluxes

Solar radiation is a major determinant of the surface energy balance and hence evapotranspiration. Reflective measurements acquired by GMS (Japanese MTSAT-IR) are used by the Bureau to estimate incoming short-wave and net radiation over the Australian region on a daily basis. These estimates are within 4.3% of ground based observations under clear sky conditions. Under heavy cloud conditions the error between GMS based estimates compared to ground based pyranometer measurements is ~15% (Le Marshall 1994); while a relatively higher error it should be noted that the amount of incoming shortwave radiation is lower during these times.

In addition to satellite observations, the short-wave downward radiation (SWDR) products available from the Bureau are:

1. deterministic forecasts obtained from the LAPS 375 model at a spatial resolution of ~37.5 km and a lead time 72 h;

2. ensemble forecasts obtained from the GASP EPS model at a spatial resolution of ~50 km and lead time of 10 days; and
3. ensemble forecasts obtained from MesoLAPS 05 model in experimental mode at a spatial resolution ~5 km and lead time of 36 h (K. Puri, personal communication).

Hourly ensemble forecasts of SWDR with the same lead time and a spatial resolution of 12.5 km are expected to be available in 2008 and will be important forcing data for use in stream flow forecasting models (Kuzmin et al. 2007).

2.3.4 Long-wave radiation fluxes

Multiple empirical functions exist for estimating the downward flux of long-wave radiation (LWDR) to an accuracy of ~20% (Garratt 1992) and these are routinely used in surface energy balance modeling. Long-wave downward fluxes are influenced by cloud cover, and temperature and humidity profiles of the lower atmosphere, and also by CO_2 and O_3 concentrations. Prata (1996) compared 5 historical methods with a new method he proposed and showed using observational measurements of down welling long-wave radiation that his method had the lowest bias on cloud-free days. Upward long-wave fluxes are calculated according to grey body emissions using Planck's function, surface emissivities and estimates of surface temperature from either energy balance considerations or satellite surface temperatures (Pinker et al. 2003).

The Bureau numerical weather models also provide hourly forecasts of LWDR obtained from the LAPS 375 model to 72 hours lead time and a spatial resolution of 37.5 km. For several smaller domains (shown in Figure 2.2), LWDR data can be obtained from the MesoLAPS systems at a spatial resolution of 125 km and 5 km. A planned upgrade of the LAPS Ensemble Prediction System (LAPS EPS) will produce hourly ensemble forecasts of LWDR with the same lead time at a spatial resolution of 12.5 km and is scheduled to be available in 2008.

2.3.5 Air temperature

Near surface air temperatures are routinely measured at 2 m height and are available from a subset of the Bureau surface observational network (Figure 2.1) with latency of less than 1 hour. Daily maximum and minimum air temperatures are spatially interpolated to 0.05° (~ 5 km) using a partial thin plate spline (Jeffrey et al. 2001) and are available from the SILO Web site (http://www.bom.gov.au/silo/). The Bureau has recently developed a similar gridded product, additionally providing daily error surfaces (Jones et al. 2006). In addition, surface air temperatures are available as a range of NWP products by the Bureau. These include output from the LAPS model (including MesoLAPS 125 and MesoLAPS 05; Figure 2.3) and from the Global AnalysiS and Prediction system (GASP) with a 10 day lead time and a 1.5° (~150 km) spatial resolution. In stream flow forecasting, these prognostic air temperatures are important for estimating actual evapotranspiration in catchment hydrologic models.

2.3.6 Dew point temperature

Dew point temperature provides a measure of atmospheric moisture content (humidity) in the mixed surface layer derived from dry and wet-bulb temperatures with a correction for site elevation as part of the Bureau meteorological observation network (Figure 2.1). The Bureau NWP system also provides a wide range of dew point data products (Kuzmin et. al. 2007). These include:

1. LAPS 375 deterministic hourly forecasts (3 days, 37.5 km grid over Australia). As planned, the spatial resolution of this type of forecast will be increased to 12.5 km.
2. MesoLAPS 125 hourly forecasts (for several smaller domains shown on Figure 2.3).
3. MesoLAPS 05 hourly forecasts (for corresponding smaller domains also shown on Figure 2.3).

2.3.7 Wind speed

Wind speed is an important forcing variable of surface energy balance models determining aerodynamic and boundary layer resistances of water vapour and heat. Wind speed and direction at 2 m height is routinely observed by the Bureau observation network and is available from AWS data feeds. Prognostic wind speed data are available as numerical weather model output at a lead time of 72 hours and resolution of 125km. Wind run is also a widely recorded variable, with day-time average wind speed being readily calculated from it. (McVicar and Jupp 1999; Smith et al. 1991). Two studies conducted at Bureau stations recently illustrated that that a long-term decline in wind speed is the primary factor causing reduction in pan evaporation rates across Australia (Rayner 2007; Roderick et al. 2007). Rayner (2007) conclusively showed that two grid-based proxies of wind speed did not capture the observed decrease in wind speed. The two proxies were: (1) NCEP-NCAR reanalysis products of wind analyses that have a coarse 2.5° (~250 km) resolution; and (2) a daily wind-run model forced by pressure gradients at a 0.05° (~5 km) resolution. McVicar et al. (2007) have interpolated daily day-time average wind speed surface at a ~1 km resolution from 1975 onwards; with the wind speed trends captured in these surfaces on a monthly, seasonal, and annual basis. Jones et al. (2006) are developing short range meso-scale forecasts modified with real-time wind observations to provide hourly and daily estimates of wind-speed at a 0.04° (~4 km) resolution from late 2004 onwards.

2.4 Model physical parameters

2.4.1 Vegetation type

Data on vegetation and land use are available from the Australian Natural Resources Data Library (http://adl.brs.gov.au). The AUSLIG digital vegetation Atlas of Australia provides vector coverage of vegetation classes for regional-continental studies at a scale of 1:2.5 million. The 'Land Use of Australia' digital data set (1992–2002) provides rasterised land use information based on the Bureau of Statistics Agricultural Census information interpreted using AVHRR NDVI imagery. An additional source of land surface information is the Australian woody-vegetation data set produced by the Australian Greenhouse Office. These data map all vegetation across the continent that qualifies as 'forest' cover (defined as > 20% tree crown cover, > 2m height at maturity, and a minimum mapping area of 0.2 ha) and is derived from Landsat imagery on 3–5 year update cycle from 1977 to present. There are also a myriad of local catchment and regional studies for particular applications but these suffer from inconsistencies between vegetation categories among classification schemes. Many classification products are also available for limited areas from high resolution imagery such as Landsat (Van Niel and McVicar 2004a,b), ASTER, SPOT or from synthetic aperture radar (e.g. JERS, ALOS).

2.4.2 Normalised Difference Vegetation Index (NDVI) and Leaf Area Index (LAI)

The normalised difference vegetation index (NDVI) is a direct measure of sunlit leaf area of the vegetation canopy and typically ranges from 0.05 for bare soil to ~0.8 for dense green vegetation. It is a widely used measure of vegetation, specifically the sunlit leaf area. In hydrological models, NDVI provides information on canopy cover for the estimation of actual evapotranspiration and surface energy budget calculations. It is also widely used to estimate leaf area index (LAI), fractional cover, absorbed photosynthetically active radiation, and vegetation 'greenness' (i.e., the proportion of vegetation that is actively transpiring). Canopy LAI is an important term which determines canopy conductance in evapotranspiration models and hence the partitioning of sensible and latent heat fluxes at the land surface.

Leaf area index can be derived from empirical relationships between observed optical reflectance data (expressed as a 'simple ratio' of NIR/Red reflectances or as NDVI) and measured LAI for different crops and pastures or woody vegetation (e.g. McVicar et al. 1996a;

McVicar et al. 1996c). It has been shown (Lu et al. 2003) that the simple ratio is linearly related to LAI, whereas NDVI is a linear function of fractional vegetation cover (proportion of land area covered by green vegetation). Additionally, Donohue et al. (2007a, b) have developed a method to consistently derive fraction of photosynthetically active radiation (fPAR) that is absorbed by green vegetation from two AVHRR data sources for all Australia from July 1981 onward. Alternatively, LAI can be retrieved by applying inverse methods to optical radiative transfer models of canopies with specified geometries (Woodcock et al. 1982; Woodcock 1986; Jupp et al. 1989) or by employing empirical functions relating LAI to NDVI or fractional cover (e.g. Choudhury 1989). Recent advances in estimation of LAI by remote sensing include utilisation of blue wavebands to remove residual background (soil) and aerosol artefacts (e.g. the Soil Adjusted Vegetation Index, SAVI (Heute 1988)), adjusting for sun-target-sensor geometry artefacts via calibration of the bidirectional reflectance distribution function and back-correction of canopy reflectances, and improved characterisation of canopy physical properties through the optimisation of parameters by integration of models and observations.

2.4.3 Albedo

Albedo is an important parameter in determining the surface energy balance and hence evapotranspiration, but obtaining accurate estimates of albedo is difficult. A number of practical solutions have been devised including Saunders (1990) who showed that a broadband surface albedo, suitable for use in surface energy balance models, could be generated from the reflective channels of the AVHRR sensor. Apart from *ad hoc* albedo products derived from research projects, there are a range of remote sensing derived albedo products now available on-line for ingestion into hydrologic models with regular weekly to monthly updates. Available products include:

1. The MODIS Level 3, 8 day Albedo Product (MOD43) which provides data products at 500 m, 1km, and 5km resolution, available from the NASA Goddard Space Flight Center.
2. Geostationary meteorological satellites (Pinty et al. 2000).

2.4.4 Soil properties

Currently, very limited information is available on spatially distributed soil hydraulic properties over large regions of Australia. This is despite the fact that the partitioning of rainfall between infiltration and runoff is highly dependent on soil hydraulic conductivity which can vary by four orders of magnitude between adjacent soil classes (Saxton et al. 1986). The Atlas of Australian Soils (1:2.5 million) is the primary source of soils information providing continental coverage of soil classes. In addition, a technical report by McKenzie and Hook (1992) enables interpretation of these classes into soil physical properties for hydrological applications but, as noted by the authors, with critical uncertainties. These interpreted classes were updated for the 2000 National Land and Water Resources Audit.

Existing regional soils information for Australia and local surveys held by state agencies (including radiometric aerial surveys) are currently being assembled in the Australian Soil Resource Information System which will become an increasingly important source of soil properties data for hydrologic modeling in the future (http://www.asris.csiro.au).

Another potential source of soil hydrologic information can be retrieved from ‘off-line’ inversion studies of well instrumented catchments. An example is the study of Jhorar et al. (2002) who used observations of actual evapotranspiration from a cotton crop on three soil types to constrain Van Genuchten soil hydraulic functions. They retrieved optimal estimates of soil hydraulic parameters for each soil type from the model inversion.

2.5 Hydrometric observations

2.5.1 Soil moisture

Remote sensing of soil moisture

Advances in remote sensing capability in the next 5 years will see rapid improvement in the monitoring of surface and profile soil moisture contents and of surfacewater and flood events. Table 2.4 summarises the range of remote sensing techniques available for measuring and monitoring soil surface and profile moisture content. The visible and shortwave infrared based methods provide information on the presence of surfacewater and on vegetation moisture content, yet they are not currently used to force or constrain hydrologic models.

Microwave based techniques provide the most promising approach to routinely observing shallow soil moisture directly, particularly for observations made at frequencies <10 GHz as they are relatively unaffected by cloud cover and vegetation, sense a deeper layer of soil, and have a stronger physical basis for interpretation. The basis of microwave estimation of soil moisture is the relationship between the dielectric constant of the soil (a measure of the soil's

Table 2.4. Summary of remote sensing techniques for measurement of surface and profile soil moisture content (partially adapted from Walker 1999). The most commonly used remote sensing instruments for optical and thermal data are the Multi-Spectral Scanner (MSS), Landsat Thematic Mapper (TM), Le Systeme Pour l'Observation de la Terre (SPOT), the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). Available microwave radiometers include the Scanning Microwave Multichannel Radiometer (SMMR), the Tropical Rainfall Measurement Mission Microwave Imager (TRMM-TMI), the Advanced Microwave Scanning Radiometer (AMSR), and microwave scatterometers on the European Resources Satellite (ERS) or Japanese Earth Resources (JERS) satellites. Upcoming missions aimed at direct measurement of surface soil moisture using microwave sensors include the European Soil Moisture and Ocean Salinity (SMOS) mission and the US Soil Moisture Active-Passive (SMAP) microwave mission.

RS techniques	Property observed	Advantages	Limitations	Noise sources	Sensors
Visible	Soil albedo	Simple method, extensive coverage	Many noise sources. Needs spectral reference dataset.	SZA[1], cloud, soil colour, vegetation	AVHRR, MODIS, MSS, TM, SPOT
Shortwave infrared	Surface and vegetation moisture	Very sensitive to surface moisture	Vegetation signal strong. Needs interpretation.	Cloud, vegetation cover	MODIS, ASTER
Thermal infrared	Surface temperature	High resolution, large swath, coverage frequency, physics well understood	Cloud cover limits frequency of coverage. Needs interpretation.	Meteorological conditions	TM, AVHRR, MODIS
Active microwave	Backscatter coefficient, dielectric properties	Low atmospheric noise, high resolution	Limited swath width, calibration of SAR	Roughness, surface slope, vegetation cover	ERS, JERS
Passive microwave	Brightness and soil temperature, dielectric properties	Low atmospheric noise, moderate to good vegetation penetration	Low resolution, radio interference	Roughness, vegetation cover, temperature. mobile phone, TV and radio	SMMR, TRMM AMSR, SMOS[2], SMAP[2]

[1] SZA: solar and view zenith angle effects encapsulated in the bidirectional reflection distribution function which describes variation in reflectance as a function of view and solar angles.
[2] SMOS and SMAP sensors operate at L-Band Frequencies (1.4 GHz), which minimize radio frequency interference

electrical properties) and soil water content. The absolute value of the dielectric constant varies from 4 for pure water to 80 for dry soil and the emission of microwave radiation is directly dependent on the dielectric constant. Hence, microwave emissions are a sensitive measure of soil moisture content at the source depth of the radiation (10–25% of the wavelength, depending on the soil moisture). The future planned mission of the European Space Agency called the Soil Moisture Ocean Salinity (SMOS) Mission will carry a purpose built radiometer to improve the availability and penetration depth of soil moisture.

Currently, good coverage of the Australian continent is achieved approximately daily with the AMSR-E sensor at a nominal resolution of 25 km. For the 6.9 GHz (4.3 cm) channel, the derived soil moisture fields represent approximately the top ~1–2 cm of soil. Figure 2.4 demonstrates the AMSR-E level 1B product for the Murrumbidgee catchment alongside interpolated rain gauge data for the same period. Currently, there are two soil moisture products routinely produced from AMSR-E data: one at the National Aeronautical and Space Administration (NASA) (following Njoku and Chan 2006), and one at the Free University of Amsterdam (Vrije Universiteit Amsterdam – VUA), following the algorithm described by Owe et al. (2001). While verifying remotely sensed soil moisture is difficult, comparisons between AMSR-E derived soil moisture and estimates from ground-stations are encouraging (McCabe 2005; De Jeu 2003; Wagner 2007; Draper et al. 2007).

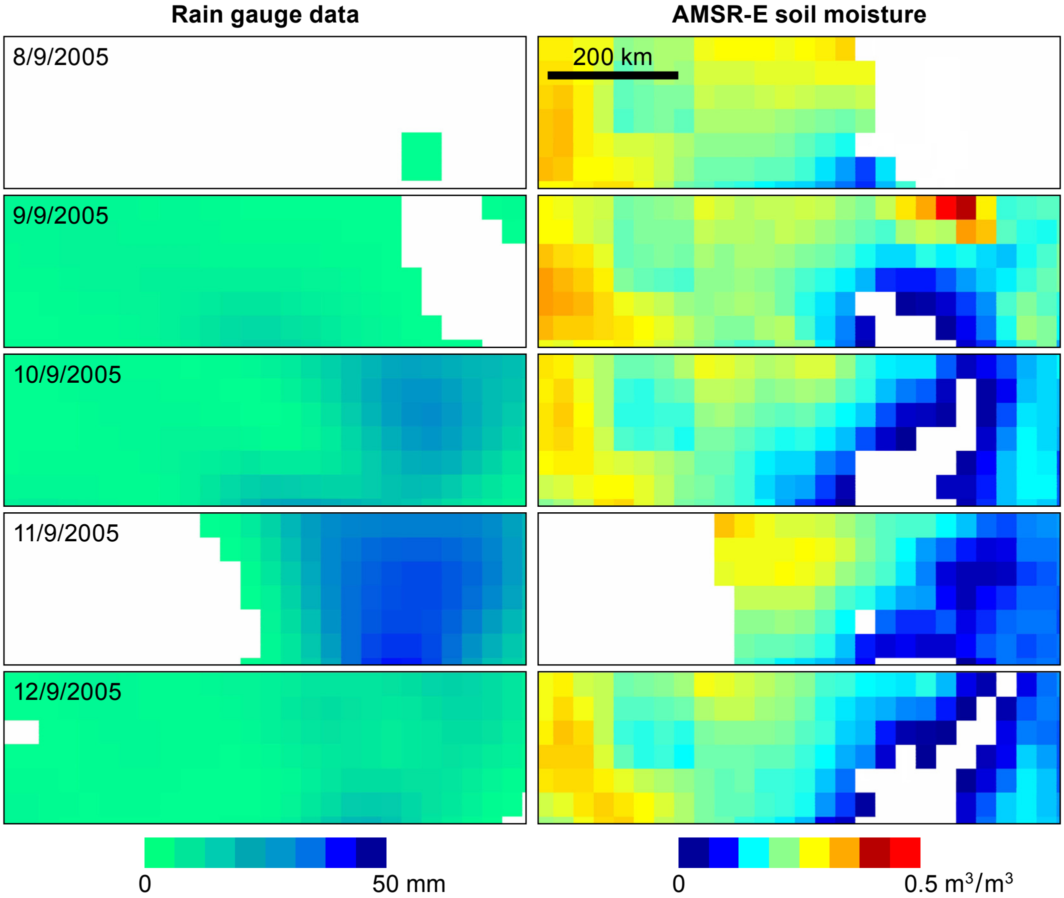


Figure 2.4. A sequence of spatial plots derived from Bureau of Meteorology rain gauge analysis and AMSR-E surface soil moisture (Owe et al. 2001) for the region of Australia containing the Murrumbidgee River catchment. The box bounds latitudes and longitudes of 36.6°S, 143.0°E to 35.0°S, 149.6°E. White areas in each plot are missing data values due to failure of rainfall or soil moisture analyses to yield meaningful estimates or due to limited coverage of the image swath. Failure to acquire soil moisture retrievals from AMSR-E observations may be due to presence of surfacewater, active rainfall at time of overpass, or exceedence of the threshold for vegetation cover.

The Vienna University of Technology (Technische Universität Wien – TUW) produces a 'global surface degree of saturation' index (SSDS) from European Remote Sensing (ERS) scatterometer data at 50 km resolution, using an empirical change detection approach (Wagner 1999). The SSDS represents the layer between 0.5 and 2 cm from the surface and can be converted to volumetric soil moisture if the wilting point and saturation moisture content of the soil are known. The product compares well to other estimates of soil moisture (Bartalis 2004), however, coverage over Australia has been extremely poor due to loss of data storage capacity on ERS. Coverage has recently improved since TUW updates their SSDS product from the ASCAT scatterometer launched in October 2006.

Other approaches to develop soil moisture products from remotely sensed thermal data have been explored. Soil moisture has been estimated by combining METEOSTAT geostationary imagery and precipitation data, and while this product compares well to other estimates of soil moisture (Wagner 2007), it is not available over Australia. Another approach developed by McVicar and Jupp (1999, 2002), combined spatially dense thermal remotely sensed data with temporally dense surface meteorological observations (maximum and minimum temperature, and precipitation) to produce the Normalised Difference Temperature Index (NDTI), a metric of moisture availability (McVicar et al. 2007). It is also possible to retrieve information on profile soil moisture, at least to the depth of plant roots, by inverting a surface energy balance model constrained by observations of land surface temperature. This approach requires knowing the vegetation stomatal response to soil moisture availability (Renzullo et al. 2007). In contrast to the microwave wavelengths, the thermal signal needs to be corrected for atmospheric effects and cannot penetrate cloud.

Ground based observations of soil moisture

Spatially distributed real-time observations of profile soil moisture content are an important observational constraint and/or source of verification data in a hydrologic forecasting scheme. These data coupled with satellite observations of surface soil moisture and real-time rainfall observations are critical elements of an improved ability to forecast stream flow. A current example of the type of *in situ* observation network required is the Murrumbidgee catchment monitoring network (see www.oznet.unimelb.edu.au). This prototype network has been established to specifically illustrate the benefits that continuous *in situ* soil moisture monitoring affords hydrology and coupled land surface – atmosphere climate models.

In 2001, a network of 18 soil moisture monitoring sites were installed across the 80,000 km^2 Murrumbidgee Catchment, with the aim of evaluating the land surface component of the Bureau's operational weather forecasting model. Since then, the Murrumbidgee Monitoring Network has evolved to include 46 sites for continuous measurement of root-zone soil moisture, soil temperature and precipitation, with a second instalment of sites in 2003, and a significant upgrade in 2006 to include near-surface soil moisture and temperature measurements together with telemetry. Data is currently being archived at http://www.oznet.unimelb.edu.au.

The Murrumbidgee Monitoring Network is critical to a range of eWater related research where it will underpin development and testing of the RiverOPS and WaterCAST Products. First, it will enable proper evaluation of emerging soil moisture remote sensing products from passive microwave. These products will be used to enhance RiverOPS partitioning of rainfall into runoff, the prediction of irrigation demand, and in Numerical Weather Prediction improvements of synoptic forecasts out to 7 days. Second, it will allow evaluation of the RiverOPS product within the catchment, and evaluation of the Numerical Weather Prediction land surface model component. Third, it will support improved understanding of catchment water balance and run-off, which are key issues for water resources quantity and quality prediction by WaterCAST.

2.5.2 Groundwater

The launch of the NASAs Gravity Recovery And Climate Experiment (GRACE) satellites in 2002 has provided the potential to infer changes in terrestrial water storage (soil moisture, groundwater, snow, ice, lake, river and vegetation) (Rodell and Famiglietti 1999, 2001). The Earth's gravity field varies both in time and space, with most spatial variations resulting from variations in the density of rocks from place to place, while the dominant causes of temporal variations are changes in mass distribution caused by post-glacial rebound, solid earth tide, crustal movements caused by gravity fields of the sun and the moon, and erosion. Besides geologic density variations, the Earths density is impacted by changes in terrestrial water storage, including soil moisture, groundwater, snow, river, reservoir and vegetation, and changes in the Earths atmosphere. It is the time-varying component of the gravity field that yields information on terrestrial water storage changes. GRACE provides a sequence of maps showing changes in the gravity field over time, which can be inverted to estimate the absolute magnitude of changes in water storage on Earth at monthly timescales with a spatial resolution in the order of approximately 1000 km, with the potential to constrain hydrologic model predictions at sub-basin scale (Ellett et al. 2006).

2.5.3 Surface temperature

Land surface temperature provides an important observational constraint in daytime surface energy balance (SEB) models and hence on the partitioning of daytime latent and sensible heat fluxes, on estimation of daily evapotranspiration of vegetation (Norman et al. 2003; Anderson et al. 2003) and hence regional water budgets. This partitioning is directly related to soil profile moisture content through the canopy and soil conductance terms of the SEB model and so from knowledge of land surface temperature, soil profile moisture content can be deduced (Pipunic et al. 2007). Methods which infer soil moisture from thermal data include data assimilation, inverting surface energy balance models (Renzullo et al. 2007, McVicar and Jupp 2002), calculating day-night surface to air temperature variation (which is related to profile total water storage; Bravo et al. 2002), and determining the morning rate of change of land surface temperature (which is a function of energy partitioning itself dependent on soil moisture availability; Norman et al. 2003).

A common and widely used algorithm for the estimation of land surface temperature based on satellite radiance observations is the 'split-window' algorithm (Sobrino et al. 1991; Prata 1996; Wan and Dozier 1996) which is based on the brightness temperatures (i.e. the surface temperature of an equivalent black body emitting at the surface) in two thermal channels. The simplest form of this algorithm is

$$T_S = T_1 + A(T_1 - T_2) + B$$

where T_S is the surface temperature and T_1 and T_2 are the brightness temperatures of two infrared radiometer channels. Conversion of brightness temperature to land surface temperature requires consideration of component emissivities of the land surface. The basis for this method is the differential absorption by the atmosphere in these adjacent infrared wavebands which allows for correction of atmospheric artefacts at view angles up to 42°. The coefficient A corrects for water vapour absorption in both channels and coefficient B accounts primarily for the near constant surface reflectance in both channels (Sobrino et al. 1991). Most algorithms function within an error bound of ±1.6 K at atmospheric water vapour concentrations <4 g cm^{-2} (surface area), but errors increase to ±3 K at higher water contents because virtually all algorithms have not been calibrated above 4 g cm^{-2} (Ouaidrari et al. 2002).

Significant errors in land surface temperature can still be introduced through partial cloud contamination of pixels, large air to ground temperature differential and differences in ground surface emissivity between the two channels. Most methods of ground surface emissivity rely on using NDVI to determine fraction vegetation cover and then calculate total emissivity as a linear combination of soil and vegetation emissivities (e.g. McVicar and Jupp 2002).

2.5.4 Snow

The appropriate sensors for snow monitoring include (1) visible sensors and (2) passive microwave sensors. Visible sensors are only able to provide information on presence or absence of snow under cloud free sunlit conditions. However, they have moderate to high resolution (250 m in the visible) and daily repeat frequency.

Passive microwave sensors provide an all weather and regional capability for snow pack monitoring using the 19 and 37 GHz channels, and are also able to provide information on the snow water equivalent (SWE) at an update rate of one to three days, but they are limited by their low spatial resolution of 25 km to 50 km. Suitable sensors include the Advanced Micro-wave Scanning Radiometer for the Earth observing system (AMSR-E), the Special Sensor Microwave Imager (SSM/I), and the historic Scanning Multichannel Microwave Radiometer (SMMR). The performance of microwave sensors in estimating SWE is affected by forest cover, signal saturation (above SWE of 100 mm), and pixel contamination by liquid water (e.g. Robinson et al. 1993; Tait and Armstrong 1996; Foster et al. 2005; Dong et al. 2005). Although this limits the use of remotely sensed SWE estimates to inland locations for times of moderate snow pack amount, it is these times and locations that the snow pack is typically the most dynamic and model estimates on their own are the poorest (e.g. Slater et al. 2001).

2.5.5 Stream flow observations

A major source of observational data on aggregate catchment hydrologic status is the approximately 5,000 stream-flow stations that are operated and maintained by the State and Territory-based water agencies. The water resources assessment undertaken by the National Land and Water Resources Audit (NLWRA) and published as Australian Water Resources Assessment 2000 (AWRA), used a subset of these networks to define the extent, quantity, use and quality of Australia's water resources. The processed data are available through the Web-based Australian Natural Resource Atlas (http://www.anra.gov.au/). A data management infrastructure (Water Resources Observation Network) is proposed to link the Atlas with State and Territory agencies' data archives thus enabling the NLWRA data and products to be more readily updated in time. The quality of the surfacewater and groundwater data available from the AWRA stations varies according to the primary use of each station. While the standards adopted by each of the agencies are considered to be good, the suitability of the data for use as observations in a forecasting scheme has not yet been assessed. A catalogue of the Australian stream gauges is available at the Bureau Web site (http://www.bom.gov.au/hydro/wrsc).

2.6 Verification data sets

Verification data sets to test model skill at forecasting state variables and fluxes such as evapotranspiration, soil moisture, snow depth, surface temperature and stream flow are needed. At present few resources are dedicated to establishing the observing systems needed for developing verification data sets. In some cases, dedicated observations will be needed such as evapotranspiration (and other scalar fluxes) from micrometeorological measurements at eddy flux tower sites and profile soil moisture contents. In other cases, 'jack-knifing' methods can be used to diagnose sources of error in forcing, model and initial conditions by sequentially withholding individual data points to assess and formulate bias correction. These methods can be applied to archived time series of observations such as stream flow records, satellite observations of surface temperature, and snow depth records.

2.7 Section summary

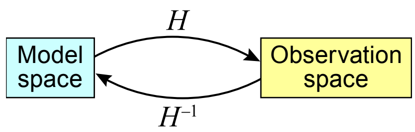
In this section of the report, we have noted that data can be divided into three categories for use in a model-data assimilation scheme: forcing, parameters and observations. Errors and biases associated with each of these data types have a strong influence over the analysis from a model-data assimilation scheme and so special care is needed to remove bias and quantify errors (see Section 2.1). The majority of this section of the report was devoted to a comprehensive overview and summary of all the important sources of data currently available to underpin a hydrologic forecasting scheme. These data sets include a range of products from surface observations, satellite datasets and output products from numerical weather prediction. The role of observations in a model-data assimilation scheme is revisited in section 4 of the report ('Model-Data Assimilation'). The next section discusses the hydrologic models that are suited for use in such a scheme.

3 Models

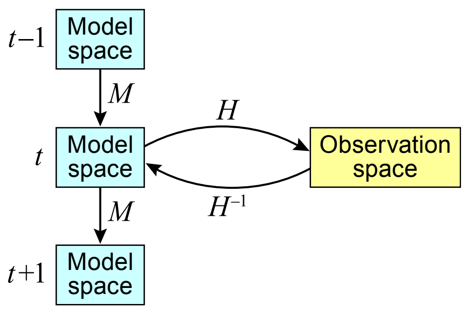
3.1 Introduction

The general requirements of applied mathematical models are: (1) they must realistically reproduce the dynamics of the system they are simulating; (2) be parsimonious; and (3) consider scale effects arising from interactions between model non-linearity and heterogeneity. In hydrologic applications, this means that the dynamics of infiltration and surface runoff (overland and interflow), base flow, drainage, and evapotranspiration must be represented with minimum complexity by the 'forward model', M, without degrading predictive capability. The forward model consist of differential equations that evolve state variables in time utilizing forcing data, model states and initial conditions. More pragmatic considerations are that forcing data and parameters must be available at an appropriate scale (in both space and time) and extent that covers the application of the model (see the previous Data section).

A critical additional requirement of data assimilation is another model that explicitly represents the relationship between model state variables or parameters and observations. This is required to evaluate the distance metric of the cost function that minimizes the deviation between model and observations during the assimilation. The constraint imposed on model state variables by observations is achieved through the mapping of information between state and observation spaces by means of an 'observation operator', H. The observation operator describes the phenomenological relationship between the model and observations, and its role is to generate modeled 'observations' for direct comparison against true observations, i.e.:



An example in the hydrologic context is a model which relates surface physical properties (e.g. land surface temperature or moisture) to satellite radiances. In this case, H could potentially include blackbody emission, radiative transfer, solar and orbital geometry, and instrument performance models. Moreover, the hydrologic model, M, would need to explicitly contain a state variable representing shallow surface soil layer of depth 1 to 5 cm (depending on sensor used) with associated soil moisture and temperature state estimates. Thus, the role of H is to connect observations with state variables in M and the role of M is to propagate those variables forward in time, i.e:



A further requirement of models used in DA schemes is the characterisation of model errors. The various DA schemes (see Section 4) differ in their treatment of model errors, ranging from ignoring it (e.g. statistical correction) to explicit tracking of its spatial and temporal evolution (e.g. Kalman filter). Although, characterisation of model errors can be particularly difficult, recent developments in DA have attempted to tackle this problem. 'Ensemble' methods based on Monte Carlo sampling of the variable and parameter errors and multi-model ensembles that combine output from multiple models driven with equivalent forcing data are relatively new methods used to characterize model errors (e.g. Liang et al 1996, 2001; Turner et al. 2007).

A final consideration of models used in DA schemes is whether the model is continuous and differentiable. This is because the most appropriate DA method is dependent on the availability of the Jacobian of observation and forward models (i.e. $\partial M/\partial x$ and $\partial H/\partial x$, where x represents relevant model states or parameters). The most computationally efficient methods utilise these derivatives to rapidly converge on solutions. For discontinuous models, computation is more expensive, and computational overheads can quickly overwhelm hardware capability even with relatively small scale applications (e.g. for single catchments). This is an important consideration in the operational context for applications at regional to continental scales.

To adapt existing catchment scale rainfall-runoff models to model-data assimilation applications capable of exploiting spatial remote sensing and ground based data sets it will be necessary to (1) establish appropriate observation models that relate observations to forward model state variables; (2) adapt existing forward models where necessary to better utilise new types of observations; and, (3) invest in the development of software code of the derivatives of model functions ($\partial M/\partial x$ and $\partial H/\partial x$) in order to maximise computational efficiency of the assimilation scheme.

In this section, we examine six catchment models of which the first four are included in the eWater CRC Catchment Modeling Toolkit, E2. These models are:

1. SACramento Soil Moisture Accounting model (SAC-SMA);
2. Australian Water Balance Model (AWBM);
3. Simplified HYDROLOG model (SimHYD);
4. Soil Moisture Accounting Runoff model (SMAR);
5. Variable Infiltration Capacity macro-scale hydrologic model (VIC); and
6. Probability Distributed Model (PDM).

Potentially any of these models could be utilized in an DA scheme given suitable modifications. After presenting an intercomparison of model features we discuss our reasoning for choosing the Sacramento model as most suitable for our purposes at the present stage.

3.2 Summary of catchment-scale hydrologic models

A wide range of hydrological models are available from which to infer stream flow from catchments each developed to address specific problems at particular time and space scales (Table 3.1). These models can be classified according to whether they provide deterministic or stochastic outputs; whether they represent solely the water balance or additional processes (e.g. surface energy balance); are fundamentally physically based, conceptual, or statistical; and whether they are spatially distributed, semi-distributed or lumped catchment models.

The models examined here included are a mix of conceptual and deterministic, physically based and statistical catchment water balance models. We compared these models for: (1) their suitability for application in a spatially distributed manner in order to utilise satellite observations; (2) the ease with which state variables of the model can be related to observations; (3) the explicit representation of routing used to generate peak stream flow and base flow; (4) the information requirements of forcing, parameter and observation data sources; and (5) the number of 'free' parameters required to be constrained by observations. We did not perform a general and exhaustive review of these models and their suitability. Rather, we made an assessment based on the authors' collective experience and judgment of their suitability for use in a hydrologic assimilation system given available data sources. We also considered the expected requirements in an operational context based on discussions with river management agencies.

Another consideration of the appropriateness of models is their internal routing scheme for surface flow. It is possible, for example, that model errors associated with incorrect routing could swamp estimates of stream flow even if rainfall distribution in time and space, and runoff generation are accurately known. In lumped models, routing is (by definition) not explicitly considered and error will emerge as unexplained variation in the unit hydrograph (catchment impulse-response function). An important outcome of the present research is whether routing errors in spatially explicit models can be reduced to manageable levels in order that DA methods are useful.

In comparing these catchment models and assessing their suitability for coupling with satellite observations , it was necessary to consider whether these models could couple water and energy balances. Coupled models can account for such variables as surface brightness temperature, temperature of vegetation, and temperature of soil derived from satellite, thereby making it easier to relate remotely sensed observations with model predictions. However, the greater number of parameters in a coupled water-energy model may lead to an under-determined problem and, hence, the need for more data. In some cases, simpler models may perform better than more complicated models provided that the simpler models can adequately capture catchment moisture dynamics and have sufficiently robust relationships between model state variables and observations. Simple models usually require less parameters to be estimated and often require less observational data to force the model. Depending on interactions between errors and biases in both parameters and data, simple models may provide better predictive skill compared to complex models but cannot benefit from constraints imposed by satellite observations. A benefit of developing a model-data assimilation approach is that predictive skill can be quantified with and without these new data sets to assess their utility.

Table 3.1. A summary of the features of six catchment models.

Model	E2-toolkit	Energy balance	Water balance	Lumped version	Distributed version	Routing scheme	Calibration	Number of parameters	Land cover / land use	Time step (hours)	States				
											Surface moisture	Land surface temperature	Groundwater	Stream flow	Snow water equivalent
Sacramento	✓		✓	✓	✓	✓	✓	11	✓	1, 6, 24	✓		✓	✓	✓
AWBM	✓		✓	✓	✓	✓	✓	8	✓	24	✓		✓	✓	
SIMHYD	✓		✓	✓				7	✓	24	✓		✓	✓	
SMAR	✓		✓	✓				9		24	✓		✓	✓	
VIC		✓	✓	✓	✓	✓		36	✓	1, 24	✓	✓	✓	✓	✓
PDM			✓	✓		✓	✓	13		1, 24	✓		✓	✓	

In this study, we selected the Sacramento (SAC-SMA) model as our starting point for the model-data assimilation scheme. This widely used model is easy to calibrate, it has more options for temporal resolution (provided forcing data are available), and includes the relevant components of stream flow (direct runoff, interflow and base flow). The advantages of the Sacramento model are that it is computationally inexpensive to calibrate, its forcing data requirements are less than VIC and Sacramento has been shown to yield good results of modelling stream flow in the United States (Koren et al. 2006; Kuzmin et al. 2008).

In the remainder of this section of the report, we briefly overview each of the 6 catchment models from Table 3.1.

3.3 Overview of catchment models

This section provides a brief overview of each of the catchment models examined in the intercomparison (Table 3.1). More details are available from the references cited for each model.

3.3.1 Sacramento Soil Moisture Accounting model (SAC-SMA)

The Sacramento model is a conceptual catchment water balance model developed for the U.S. National Weather Service (NWS) that relates runoff to rainfall at daily, 6-hourly or 1-hourly time steps (Figure 3.1) (Burnash et al. 1973; Armstrong 1978). Currently, the version of the Sacramento model available in E2 operates with daily data and a daily time-step. The model contains five stores (Figure 3.1); two surface stores with surface evaporation, surface runoff and interflow. The three base flow stores are used to represent soil evaporation and two stages of base flow. The original version of the Sacramento model has 16 parameters that can be estimated from soil moisture observations and soil type data (the parameter ranges are given in Table 3.2); however, in most cases 5–7 parameters can be replaced with constants without any loss of quality (Kuzmin et al. 2008). The model is available in lumped and distributed modes. However, its distributed version is potentially difficult to calibrate and, as a result, it does not necessarily provide better forecasts than the lumped version (Reed et al. 2004). Due to its reliability Sacramento has been widely used operationally by the U.S. National Weather Service and in Australia (Boughton 2005).

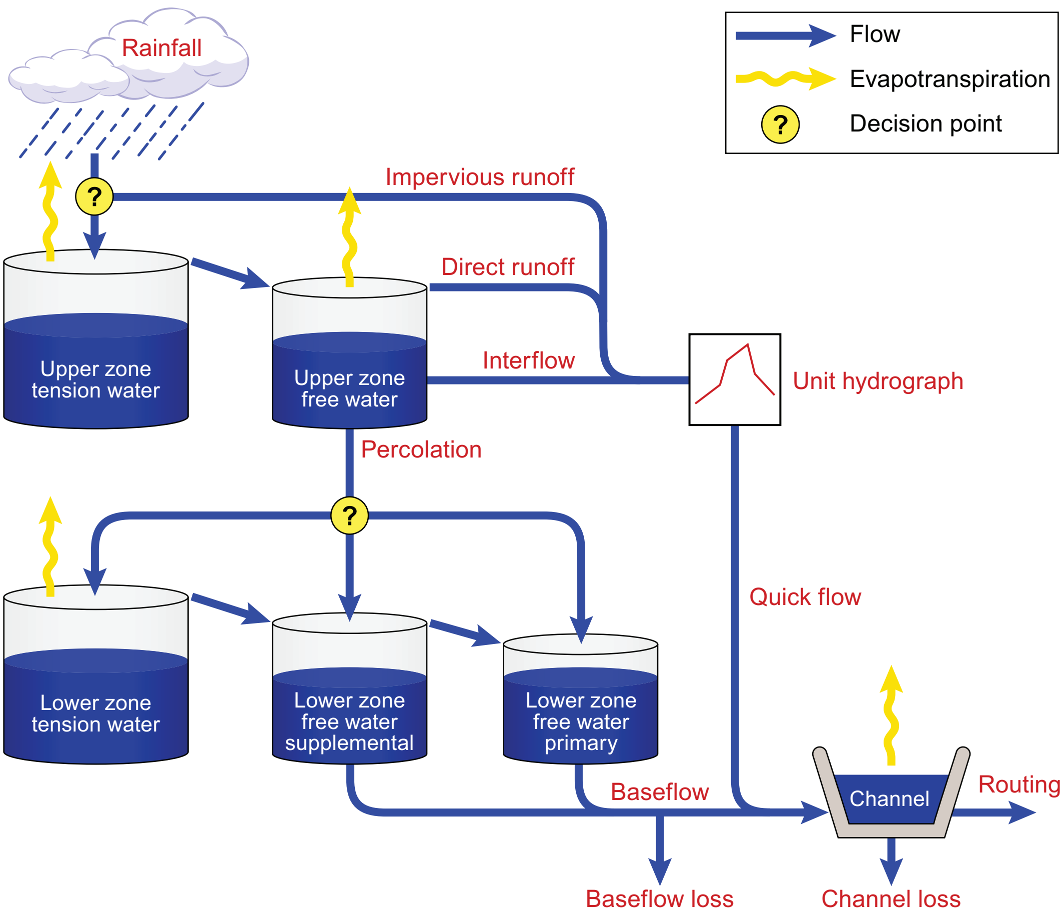


Figure 3.1. National Weather Service Sacramento Soil Moisture Accounting Model (SAC-SMA) (http://www.toolkit.net.au/cgi-bin/WebObjects/toolkit).

In a data assimilation scheme, the Sacramento model can assimilate soil moisture content in the upper soil layer (although some modification of the model is needed to relate this to microwave observations of surface soil moisture) and stream flow data. It can also assimilate actual evapotranspiration and snow observations if these are available or utilise these products as forcing if created offline. Another advantage is an efficient automated calibration tool developed specifically for it, which can be used for model state and flux estimation through both sequential and non-sequential optimisation (Kuzmin et al. 2008).

Table 3.2. SAC-SMA model parameters and their feasible ranges (adapted from Koren et al. 2003).

Parameter	Description	Units	Min	Max
UZTWM	The upper layer tension water capacity	mm	10	300
UZFWM	The upper layer free water capacity	mm	5	150
UZK	Interflow depletion rate from the upper layer free water storage	day^{-1}	0.10	0.75
ZPERC	Ratio of maximum and minimum percolation rates	–	5	350
REXP	Shape parameter of the percolation curve	–	1	5
LZTWM	The lower layer tension water capacity	mm	10	500
LZFSM	The lower layer supplemental free water capacity	mm	5	400
LZFPM	The lower layer primary free water capacity	mm	10	1000
LZSK	Depletion rate of the lower layer supplemental free water storage	day^{-1}	0.01	0.35
LZPK	Depletion rate of the lower layer primary free water storage	day^{-1}	0.001	0.05
PFREE	Percolation fraction that goes directly to the lower layer free water storages	–	0.0	0.8

3.3.2 Australian Water Balance Model (AWBM)

The Australian Water Balance Model (AWBM) is a catchment water balance model based on conceptual relationships that relate runoff to rainfall at an hourly or daily time-step, by calculating losses from rainfall for flood hydrograph modelling (Figure 3.2) (Marston et al. 2002; Boughton 2004).

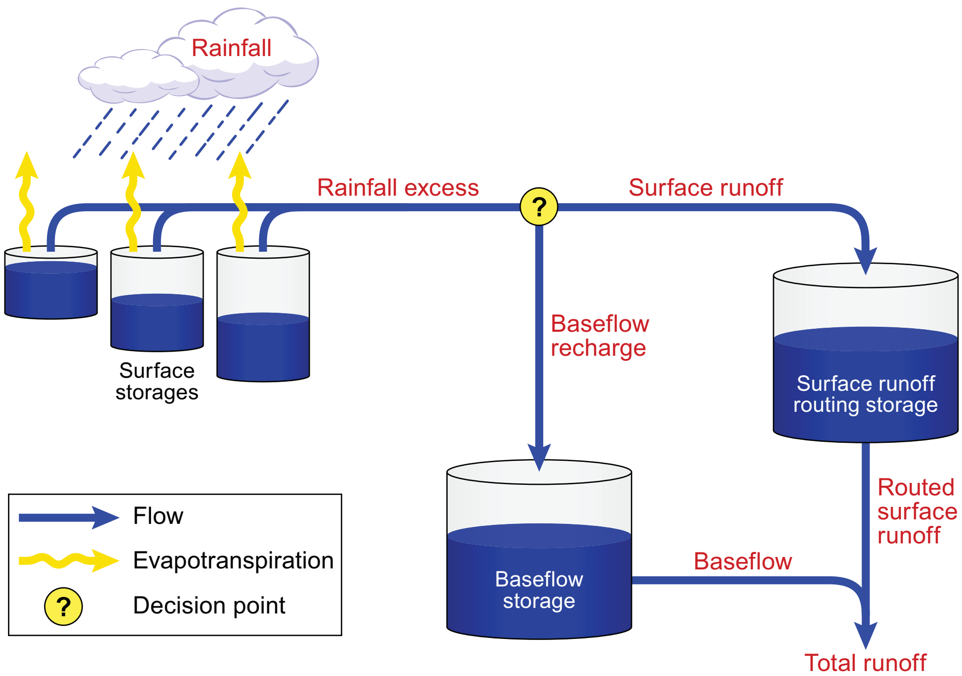


Figure 3.2. Structure of the AWBM model (http://www.toolkit.net.au/cgi-bin/WebObjects/toolkit).

The model calculates the moisture balance for three separate surface stores to simulate partial areas of runoff. At each time step, rainfall is added to each of the three surface moisture stores and evapotranspiration is subtracted. When surface stores fill, surface flow occurs. This 8 parameter model is disaggregated into 5 stores comprising 3 surface stores ,a base flow store and a surface runoff routing store (parameters are defined in Table 3.3). AWBM is provided with a model-specific automatic calibration tool. This model is included in the E2 modelling toolkit.

Advantages of the AWBM are that it requires only three types of input data (precipitation, evapotranspiration, and proportional source areas for runoff generation) and it simulates surface and baseflow runoff. On the other hand, this model does not incorporate process equations for transpiration, direct evaporation from the water surface and water transfers among deep stores.

This model has three potential state/flux variables for assimilation which could improve water balance estimation. These are:

1. the adjustment factor for precipitation;
2. the adjustment factor for evapotranspiration; and
3. stream flow at catchment exit point.

Table 3.3. The AWBM model parameters, their defaults values and limits.

Parameter	Description	Units	Default	Min	Max
A_1	Partial area of surface store 1	m^2/m^2	0.134	0	1
A_2	Partial area of surface store 2	m^2/m^2	0.433	0	1
A_3	Partial area of surface store 3	m^2/m^2	0.433	0	1
C_1	Capacity surface store 1	mm	7	0	50
C_2	Capacity surface store 2	mm	70	0	200
C_3	Capacity surface store 3	mm	150	0	500
BFI	Base flow index	none	0.35	0	1
K	Base flow recession	day^{-1}	0.95	0	1
KS	Surface flow recession	day^{-1}	0.35	0	1

3.3.3 The Simplified HYDROLOG model (SimHYD)

SimHYD is a daily conceptual hydrologic model based on relationships that relate daily stream flow to daily rainfall and potential evapotranspiration data (Chiew et al. 2002; Figure 3.3).

In SimHYD, daily rainfall first fills the interception store, which is fully emptied each day by evaporation. Excess rainfall is then subjected to an infiltration function that determines infiltration capacity. Excess rainfall that exceeds infiltration capacity becomes infiltration excess runoff. The model has 9 parameters to be estimated and contains three stores for interception loss, soil moisture and groundwater (Table 3.4).

Table 3.4. SIMHYD model parameters, their defaults values and limits.

Description	Units	Default	Min	Max
Baseflow coefficient	mm/mm	0.3	0	1
Impervious threshold	none	1	0	5
Infiltration coefficient	day^{-1}	200	0	400
Infiltration shape	none	3	0	10
Interflow coefficient	day^{-1}	0.1	0	1
Pervious fraction	mm/mm	0.9	0	1
Rainfall interception store capacity	mm	1.5	0	5
Recharge coefficient	day^{-1}	0.2	0	1
Soil moisture store capacity	mm	320	1	500

This model is more flexible than the AWBM and it better captures the processes of evapotranspiration and water transfers between groundwater stores (Boughton 2005). In a data assimilation scheme the partitioning of precipitation between evapotranspiration and infiltration as well as soil moisture storage are candidate target variables to be constrained by observations.

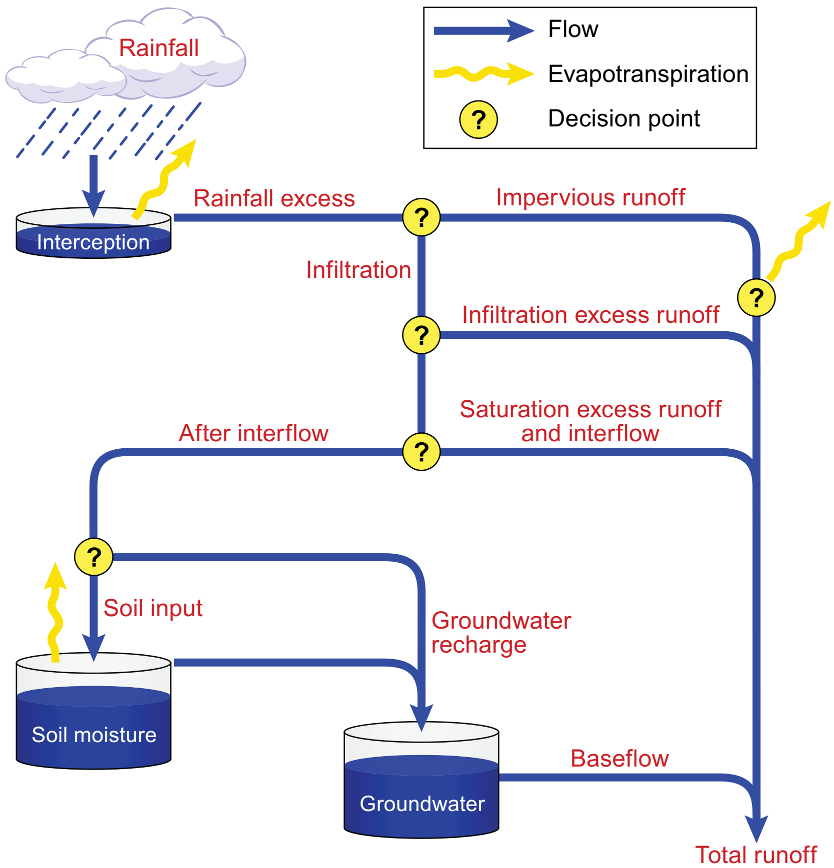


Figure 3.3. Structure of the SIMHYD model (http://www.toolkit.net.au/cgi-bin/WebObjects/toolkit).

3.3.4 The Soil Moisture Accounting Runoff model (SMAR)

The Soil Moisture Accounting Runoff model (SMAR) is simpler than the Sacramento model. It is a lumped conceptual hydrologic water balance model which aims to also resolve the soil moisture profile at 3 levels (O'Connel et al. 1970; Kachroo 1992). The model provides daily estimates of surface runoff, groundwater discharge, evapotranspiration and leakage from the soil profile for the catchment as a whole. The surface runoff component comprises overland flow, saturation excess runoff and saturated through-flow from perched groundwater. SMAR consists of two components in sequence, a water balance component and a routing component that simulate the associated lags between rainfall events and flow out of the catchment (Figure 3.4). The model has 11 parameters (Fazal et al. 2005), shown in Table 3.5, but the E2 modelling toolkit contains a simplified version of the model with 9 parameters (Argent et al. 2006).

Unlike the Sacramento model, the SMAR includes its own routing scheme based on approximation of flood waves. In a data assimilation scheme, SMAR could assimilate soil moisture content in the upper soil layer, actual evapotranspiration and stream flow at internal stream gauges.

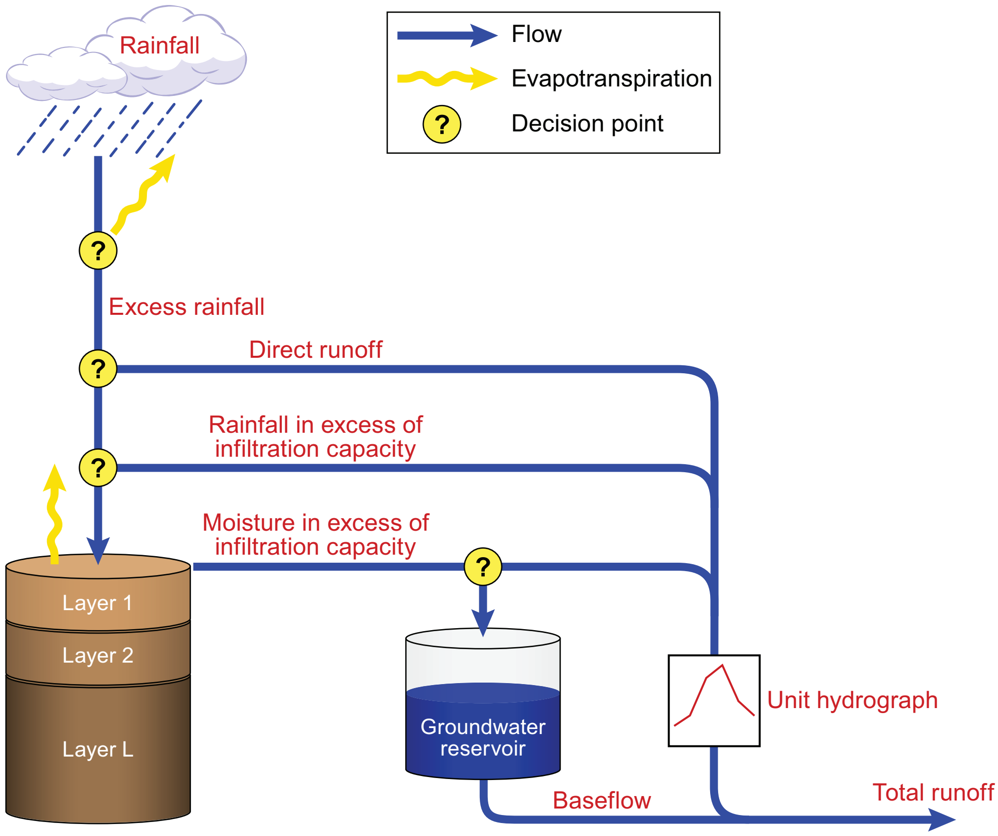


Figure 3.4. Structure of the SMAR rainfall-runoff model (http://www.toolkit.net.au/cgi-bin/WebObjects/toolkit). Blue stores and arrows depict water flows through catchment. Brown stores indicate soil water store which is a function of soil porosity used to model deep drainage in the profile.

Table 3.5. SMAR model parameters.

Parameter	Description	Units	Min	Max
C	Discounting factor of the remaining potential evaporation rate	0–1	0	1
E	Evapotranspiration rate	mm/mm	0	1
H	Direct runoff area index	m^2/m^2	0	1
G	Groundwater runoff coefficient	mm/mm	0	1
Kg	Number of time step for groundwater routing	days	0	20
N	Number of days	days	1	6
NK	Ordinates of gamma-function	none	0.01	1.00
P	Rainfall rate	mm/day	0	1
T	Potential evapotranspiration factor	mm/mm	0	1
Y	Soil infiltration capacity	mm	0	5000
Z	Total soil moisture capacity	mm	0	5000

3.3.5 Variable Infiltration Capacity macro-scale hydrologic model (VIC)

VIC is an energy and water balance model commonly used as a land surface scheme in climate models, which simulates several elements of the surface hydrologic cycle: vegetation fraction cover, evapotranspiration, runoff, snow water equivalent, soil moisture storage, and total storage of water (Figure 3.5). The model can operate using hourly to daily time steps. A routing sub-model, which works with daily runoff and base flow fluxes, is available (Liang et al. 1996; D. Lettenmaier, personal communication). The VIC model has 36 parameters (25 soil and climate parameters, 5 location parameters and 6 vegetation parameters). More information on model structure and function is available at http://www.hydro.washington.edu/Lettenmaier/Models/VIC/References/References.html.

VIC is not available as part of E2.

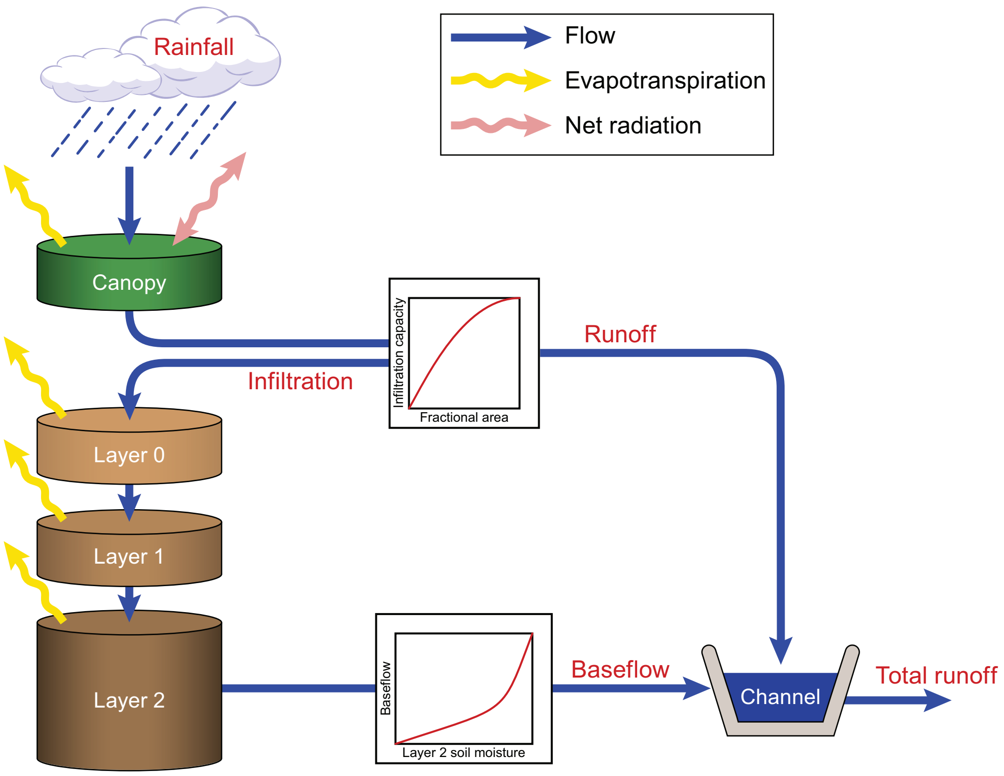


Figure 3.5. VIC model structure (http://www.hydro.washington.edu/Lettenmaier/Models/VIC/VIChome.html). Note that this is a spatially distributed model where each grid cell has a specified fraction coverage by vegetation with varying canopy characteristics. Transpiration from sub-surface layers is lost through the canopy (yellow arrows).

Table 3.6. VIC model vegetation, climate and soil parameters. Note max/min range is not supplied, as this varies depending on location.

Parameter	Description	Units
infilt	Variable infiltration curve parameter	–
Ds	Fraction of max velocity of base flow at which base flow begins	–
Dsmax	Max velocity of base flow	mm/d
Ws	Fraction of max soil moisture at which base flow begins	–
C	Base flow curve exponent (nominally = 2)	–
expt	Parameter describing variation in Ksat with soil moisture	–
Ksat	Saturated hydraulic conductivity	mm/d
phi_s	Soil moisture diffusion parameter	–
init_moist	Initial layer soil moisture content	mm
elev	Mean elevation of model grid cell	m
depth	Thickness of each soil layer in model	m
avg_T	Value for constant temperature at depth	^oC
dp	Soil depth at constant temperature	m
bubble	Bubbling pressure of soil	cm
quartz	Quartz content of soil	–
bulk_density	Soil bulk density of layer	kg/m^3
soil_density	Soil particle density (nominally 2685 kg/m^3)	kg/m^3
Wcr_FRACT	Fraction of soil moisture at 70% field capacity	–
Wpwp_FRACT	Fraction of soil moisture at wilting point	–
Rough	Surface roughness: bare soil	m
snow_rough	Surface roughness: snow	m
annual_prec	Mean annual precipitation	mm
resid_moist	Fraction of soil moisture as residual per layer	–
fs_active	Switch for frozen soil	–
July_Tavg	Average July soil temperature	^oC
vegetat_type	Number of vegetation types in model grid cell	–
veg_class	Vegetation classification identifier	–
Cv	Fraction of model grid cell per vegetation class	–
root_depth	Root zone thickness	m
root_fract	Fraction of total root biomass in soil layer	–
GLOBAL_LAI	Canopy leaf area index	monthly

3.3.6 Probability Distributed Model (PDM)

The Probability-Distributed Model (PDM) is a conceptual hydrologic model, which transforms rainfall and evaporation data to flow at the catchment outlet (Moore 2007). The model formulation is based on probability-distributions of soil moisture store and the translation of runoff and drainage via routing stores. PDM represents groundwater storage under the influence of pumped abstractions, spring flows and underflows (Moore 1985). The PDM software supports the following functions:

1. a toolkit of model functions capable of representing a broad range of catchment runoff behaviour using a minimum number of model parameters;
2. a choice of time-step, from15 minutes through 1 hour to daily;
3. model calibration by automatic optimisation and by interactive visualization;
4. error response function plots to investigate parameter interdependence;
5. calibration across separate storm events, maintaining a daily water balance between events; and
6. forecast updating for real-time applications, using state correction or error prediction techniques.

The PDM model represents water stores and transfers among surface and groundwater storages is shown on Figure 3.6. Parameters are defined in Table 3.7. In a data assimilation scheme, it would be possible to optimise the moments of the parameter probability distribution functions while minimising differences between modelled water stores and observations; although, such an approach has not been attempted to the authors' knowledge. In practice, model states (stores) are adjusted to match total runoff as observed by stream flow. PDM is not included in the E2 modelling toolkit.

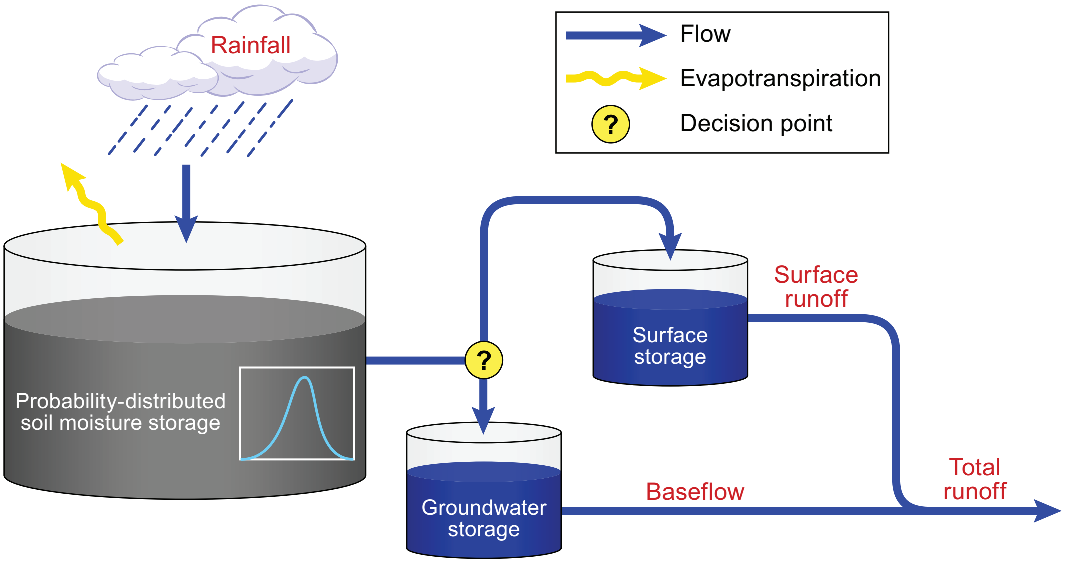


Figure 3.6. The PDM rainfall-runoff model (http://www.toolkit.net.au/cgi-bin/WebObjects/toolkit).

Table 3.7 PDM model parameters (Moore, 2007). Note max/min range is not supplied as this varies depending on location.

Parameter	Description	Units
fc	Rainfall factor	–
td	Time delay	hr
cmin	Minimum store capacity	mm
cmax	Maximum store capacity	mm
b	Exponent controlling variability of store capacity	–
be	Exponent of actual evaporation function	–
kg	Groundwater recharge time constant	–
bg	Exponent of recharge function	–
St	Soil tension storage capacity	mm
alpha	Groundwater deficit ratio threshold	–
beta	Exponent in groundwater demand function	–
qsat	Maximum rate of recharge	mm/hr
k1	Time constants of cascade of first linear reservoir	hr
k2	Time constants of cascade of second linear reservoir	hr
kb	Baseflow time constant	–
m	Exponent of baseflow non-linear storage	–
qc	Constant flow representing returns/abstractions	m^3/s

3.4 Section summary

In this section, we have noted that the hydrological models used for stream flow forecasting must be capable of simulating the dynamics of infiltration, runoff, flows, and evapotranspiration with minimal complexity, using forcing data and parameters acquired at scales appropriate to model application. An additional consideration for models used in a DA scheme is the ability to formulate an observation operator that can relate the model state variables and observations. In a survey of six widely used catchment hydrologic models, the Sacramento model was chosen as most suitable for use in a catchment scale stream flow forecasting scheme in this work because it is computationally straightforward to calibrate, forcing data are readily available, the potential for incorporating satellite observations of surface moisture as constraints and its demonstrated ability to model stream flow dynamics. The next section discusses the model-data assimilation schemes.

4 Model-data assimilation

4.1 Introduction

Model-data assimilation describes a set of mathematical algorithms used to optimally combine the information contained in models and observations. The underlying principle is to minimise the mismatch between model predictions and observations through direct adjustment of model states ('state estimation') or through adjustment of model parameters ('parameter estimation'). The output from an assimilation scheme is estimates of 'target variables' of the model (state variables, parameters and/or fluxes) obtained when the mismatch between model and observations is minimal. While simple in principle, there are numerous difficulties to overcome. However, the outcome of implementing a successful assimilation scheme is a quantifiable improvement in predictive capability even in systems dominated by chaotic processes.

The last decade has seen rapid development of model-data assimilation methods for hydrologic, hydrometeorological, remote sensing and terrestrial biogeochemical applications (e.g. Walker et al. 2001a, b; Walker and Houser, 2001; Barrett 2002; Walker et al. 2002; Walker et al. 2003; Quegan et al. 2003; Barrett et al. 2005; Raupach et al. 2005) based on techniques initially developed in the atmospheric, oceanographic and geophysical sciences (Giering 2000). In this time, hydrologically relevant remote sensing methods have become well-defined, theoretically established, and technologically supported. In the next five years, it is expected that widespread application of data assimilation techniques to the forecasting of water availability will invoke major changes in water resources management.

In this section, we provide by way of background, a short primer on DA methods. We then list the full range of methods available for potential application to hydrologic problems; readers are referred to Walker and Houser (2005) for a more complete introduction to DA in hydrology. These methods have been developed as solutions to problems with particular characteristics and so no single method will be suitable to solving all problems in the hydrologic domain. The primary difference among these approaches lies in the algorithms used to solve the assimilation problem which can involve inversions of large matrices or gradient searches in high-dimensional spaces. Technical development of algorithms has proceeded in direct relation to the size of the assimilation problem. To provide context, modern operational meteorological data assimilation schemes may assimilate 10^7 model states using 10^5 observations within a 6 hour forecast period. This application of DA methods is computationally demanding requiring significant IT infrastructure and algorithms specifically adapted to the application.

4.2 Background

The term 'model-data assimilation' refers to a suite of mathematical techniques based on Bayesian statistical theory that couple observations and physical models with the aim of generating improved accuracy in model predictions by estimation of optimal model state variables. The mathematical formalism of these techniques provides a framework within which different types of data can be brought together within physical models to generate inferences of system state. Both the model and data have intrinsic uncorrelated errors. Through the application of statistical methods it's possible to generate model predictions in which we have a higher confidence than from either the data on its own or from unconstrained model predictions. Modern approaches to data assimilation do not consider a single observation type, but rather attempt to 'blend' information from a range of sources; so called 'multiple constraints model-data assimilation'.

In the 'initial value' problem, an observation field derived from measurements made in real time and the 'best guess' of system conditions from a model are combined using data assimilation methods to reveal an estimate of the current system state given errors in observations and the model (Figure 4.1; this is also termed the 'analysis' or forecast initialisation step; Zupanksi and Kalnay (1999)). For hydrological applications, this may refer to the background state of moisture in the soil profile, present state of flow in a stream network or current rate of evapotranspiration over a region. From the initial condition, forecasts of future states may be made utilising output products (and their errors) from numerical weather prediction.

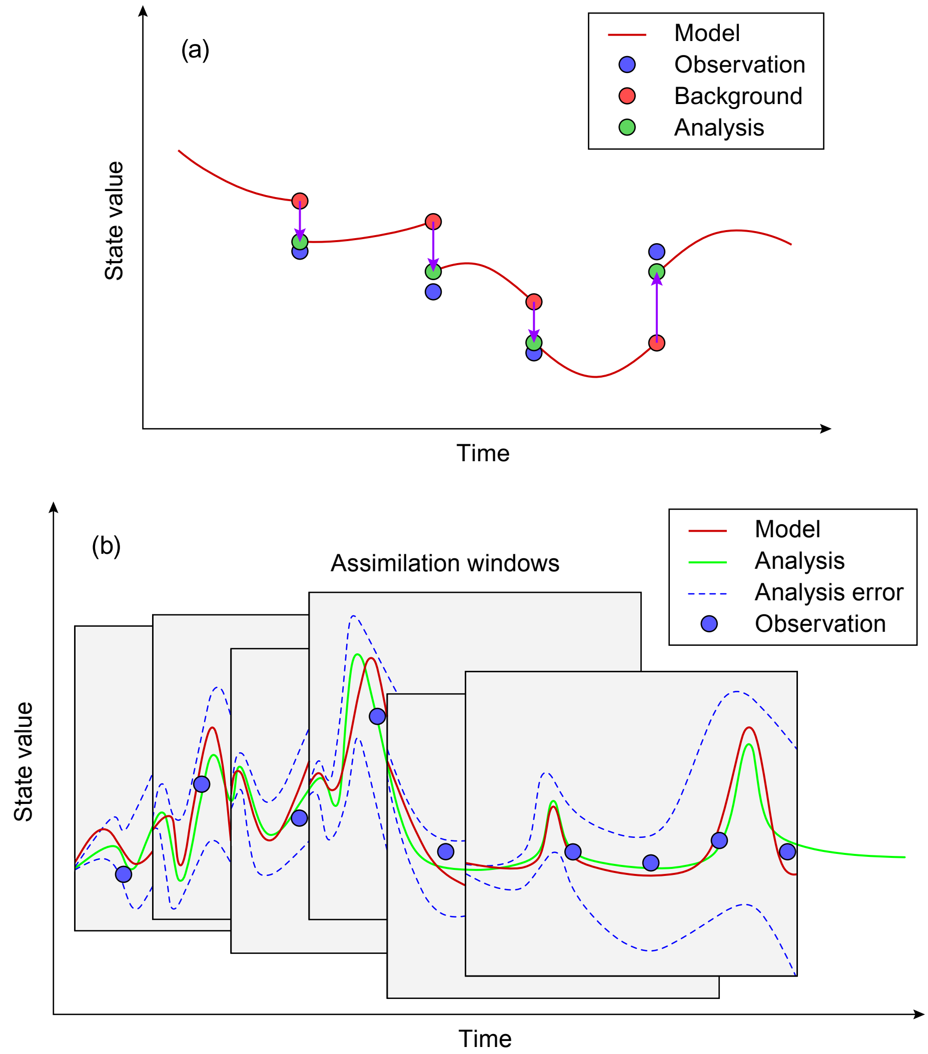


Figure 4.1. Schematics of sequential data assimilation application. (a) Sequential or direct observer assimilation by application of the Kalman filter, 3-D variational or related methods. (b) Non-sequential or indirect observer assimilation by 4-D variational, 'smoother' or related methods.

As time advances into a new forecast period, the previous model forecast is utilised as the best guess for the next assimilation cycle because it represents the best prior information available about the current state of the system. Forecast accuracy is largely a function of observation coverage (in time and space), model adequacy, whether the model can be linearised, knowledge of the characteristics of observation errors, and adherence to assumptions of the underpinning statistical theory. However, despite the wide variation among different applications, all DA schemes have seven common elements. These are:

1. a physical model (or models);
2. a set of initial conditions;
3. multiple types of forcing data;
4. a set of parameters;
5. a set of model states;

6. potentially multiple types of observations;
7. an assessment of observation and model error; and
8. an optimisation scheme to combine model and observations considering the errors.

In the hydrologic context, these elements comprise lumped, semi-distributed or fully spatially distributed hydrologic models, a network of observations (hydrograph, *in situ* ground based and satellite data) to provide forcing, model parameters, observational data and their errors, and a data assimilation scheme capable of minimising deviations between model predictions and system observations while considering their relative errors. Additionally, ancillary observations of model state variables are needed, such as from intensively studied catchments, for verification, to test forecasting skill and to identify where improvements are needed. These can be additional observations of stream flow kept in reserve for validation or ancillary datasets used for verifying internal state variables (e.g. point soil moisture observations).

As discussed in Section 2 ('Data'), bias-free observations and their errors are used in the DA scheme to constrain model dynamics. The challenge in hydrologic data assimilation is how best to utilize available observations that may only be indirectly related to the hydrologic variables of interest. For example, satellite radiances are indirectly related to model internal variables of evapotranspiration, surface temperature and soil moisture which themselves are related through the conservation equations of the forward model, M, to stream flow using the observation operator, H (section 3: Models). The range of possible observations to assimilate is large and includes networks of soil moisture measurements and of stream hydrographs, observations of scalar fluxes from eddy covariance sites, and satellite data products of land surface temperature, surface soil moisture, snow cover, vegetation water content, vegetation cover and soil physical properties. It is necessary to transform the information contained within these observations into constraints on the state variables in the model. The role of the DA scheme is to infer hydrologically relevant information from indirect and noisy observations. Where it is possible to observe a hydrologic variable (more or less) directly (e.g. evapotranspiration at a flux tower site), spatial variation and gaps in data make it difficult to accurately interpolate these values. The role of the assimilation scheme is also to propagate information from observing sites to locations in space and time where observations are missing.

As noted in section 3, the key link between observations and model variables in a data assimilation scheme is achieved through the 'observation operator', H, which maps observations to model state variables. Various observation operators are shown in Table 4.1. For example, (in increasing order of complexity) rating curves are used to transform the direct measurement of stream height to volumetric flow, radiative transfer models are used to convert the primary satellite observation of radiance to surface temperature or moisture, and eddy covariance functions calculate scalar fluxes from observations of concentrations and velocity. The success of a model-data assimilation scheme is dependent on accurately linking available observations with state variables in the forward model through the observation operators.

In Table 4.1, gauge measurement of precipitation is a direct measure at a point location (albeit with adjustment to remove artefacts) and requires spatial interpolation to regions. River or stream height gauges require rating curves for conversion to fluxes and provide an integrated measure over catchment area. Thermal and microwave radiance measurements from satellite require consideration of atmospheric and geometric artefacts. Finally, the conversion of microclimate observations at an eddy flux tower, to scalar fluxes take into consideration the atmospheric turbulence in the vicinity of the tower. Thus, the observation operator can take on various roles from interpolation from model grid to location of measurement through to describing the physical relationships between observation and state variable.

Table 4.1. Examples of key observational data, observation operators and hydrologic variables constrained by the observations. H **= observation operators (model) which include** SI **= spatial interpolation;** RC **= rating curve function;** RT **= radiative transfer model (thermal or microwave);** EC **= eddy covariance functions.**

Constrained hydrologic variable	H	Primary observation
Precipitation (regional)	$\xrightarrow{SI}$	Precipitation (gauge)
Stream flow	$\xrightarrow{RC}$	River height
Soil profile moisture and evapotranspiration	$\xrightarrow{RT}$	Radiance (thermal)
Surface (<2.5 cm) moisture	$\xrightarrow{RT}$	Radiance (microwave)
Evapotranspiration	$\xrightarrow{EC}$	Air temperature Vapour pressure Wind speed Leaf Area Index Radiation terms

4.3 Summary of model-data assimilation methods

Detailed background discussion and derivation of the theory and application of model-data assimilation methods can be found in Tarrantola (1987), Bouttier and Courtier (1999), Prinn (2000), Giering (2000), Toddling (2000), Holm (2003), and Walker and Houser (2005), so these details won't be repeated here. We commence this discussion from the perspective of a discrete formulation of the analysis problem in which values of model 'target variables', are sought given a model (+ model error) and observations (+ observation error). Target variables of the analysis may include model states or initial conditions (e.g. soil moisture, evapotranspiration or runoff/discharge), or model parameters (e.g. coefficients partitioning rainfall among stores, physical parameters, or time constants). These techniques provide a framework within which to test model dynamics and predictions against observations, to interchange disparate and scarce data types, to fill gaps in data records, improve constraints on model behaviour, infer parameters that are not directly observable and predict the dynamics of physical model(s) with associated quantitative error estimates.

4.3.1 Sequential assimilation

The sequential assimilation techniques update the model forecast using the difference between observation $\mathbf{z}$ and the modeled observation, $\hat{\mathbf{z}}$, as soon as observations become available (see Figure 4.1a). This difference is termed the 'innovation'. If we let the background vector be $\mathbf{x}^b$, then the optimal least squares estimator of the analysis state, $\mathbf{x}^a$, is

$$\mathbf{x}_k^a = \mathbf{x}_k^b + \mathbf{K}\left(\mathbf{z}_k - \hat{\mathbf{z}}_k\right) \tag{4.1}$$

where

$$\hat{\mathbf{z}}_k = H\left(\mathbf{x}_k^b\right) \tag{4.2}$$

is the observation operator (see section 3 'Models'), k refers to the time of update, and $\mathbf{K}$ is the gain matrix given by

$$\mathbf{K} = \mathbf{\Sigma}\mathbf{H}^T\left(\mathbf{H}\mathbf{\Sigma}\mathbf{H}^T + \mathbf{R}\right)^{-1} \tag{4.3}$$

where $\mathbf{H}$ is the linearised Jacobian of H (called the 'tangent linear operator') and $\mathbf{\Sigma}$ is the covariance matrix of background errors.

In a hydrologic context, $\mathbf{x}^b$ might be a vector of runoff, stream flow, soil moisture, evapotranspiration state variables, or parameters of any one of the rainfall-runoff models described in section 3 ('Models'), $\mathbf{z}$ might be observations of stream heights, land surface temperature, microwave emissions, or soil moisture measurements, and H a set of functions which maps the state vector, $\mathbf{x}^b$, to observation space (Table 4.1). Given this we can make the following comments.

1. The analysis, $\mathbf{x}^a$ (equation 4.1), is derived from the background state plus a term which represents differences between the model ($H(\mathbf{x}^b)$) and observations ($\mathbf{z}$) weighted by the gain matrix ($\mathbf{K}$).
2. The gain matrix is entirely dependent on the background and observation error covariances ($\mathbf{\Sigma}$ and $\mathbf{R}$) and the sensitivity of the model predictions to error in the state variables ($\mathbf{H}$).
3. The analysis covariance is dependent only on the error covariances and sensitivity of the model ($\mathbf{\Sigma}$, $\mathbf{R}$ and $\mathbf{H}$) and not on the values of the state variables.

These comments lead to several important considerations in the application of DA methods. Firstly, the analysis is as much dependent on the relative errors in $\mathbf{\Sigma}$ and $\mathbf{R}$ as it depends on the observations ($\mathbf{z}$). Secondly, the gain matrix represents confidence in the observations relative to the model. And thirdly, the uncertainty of the analysis depends only on the combined uncertainty of the model and observations. These considerations emphasise the importance of understanding and characterising the nature of model and observations errors in a DA scheme.

The commonly used sequential assimilation methods are:

1. Direct Insertion;
2. Statistical Correction;
3. Successive Correction;
4. Optimal Interpolation/Statistical Interpolation;
5. Analysis Correction;
6. Nudging;
7. 3D Variational; and
8. Kalman Filter and its variants.

While approaches like direct insertion, nudging and optimal interpolation are computationally efficient and easy to implement, the updates do not account for observation uncertainty or utilise system dynamics in estimating model background state uncertainty, and information on estimation uncertainty is limited. The Kalman filter, while computationally demanding in its pure form, can be adapted for near real-time application in hydrologic forecasting and provides information on estimation uncertainty. However, it has only limited capability to deal with model errors, and necessary linearisation approximations can lead to unstable solutions. The ensemble Kalman filter, while it can be computationally demanding (depending on the size of the ensemble) is well suited for near real-time applications to forecasting soil moisture and streamflow, is robust, very flexible and easy to use, and is able to accommodate a wide range of model error descriptions.

4.3.2 Non-sequential assimilation

The non-sequential assimilation techniques differ from sequential methods by considering all observations at once rather than at the time the observations become available (see Figure 4.1b). These methods find the best fit between forecast model state and observations, subject to the initial state vector uncertainty Σ and observation uncertainty $\mathbf{R}$, by minimising an objective function J. The objective function has the form

$$J = \frac{1}{2}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right)^{\mathrm{T}} \mathbf{\Sigma}_0^{b^{-1}} \left(\mathbf{x}_0 - \mathbf{x}_0^b\right) + \frac{1}{2}\sum_0^{N-1}\left(\mathbf{z}_k - \hat{\mathbf{z}}_k\right)^{\mathrm{T}} \mathbf{R}_k^{-1}\left(\mathbf{z}_k - \hat{\mathbf{z}}_k\right), \tag{4.4}$$

where the superscript b refers to the initial or 'background' estimate of the state vector, the subscript *k* refers to the number of observations within the time step, and N is the number of time steps of the analysis. To minimise the objective function over time, an assimilation time 'window' is defined and an 'adjoint' model is typically used to yield the derivatives of the objective function with respect to the initial model state vector $\mathbf{x}_0$. The adjoint is a mathematical operator that allows one to determine the sensitivity of the objective function to changes in the solution of the state equations by a single forward and backward pass over the assimilation window. While an adjoint is not strictly required (i.e., a number of forward passes can be used to numerically approximate the objective function derivatives with respect to each state), it makes large problems computationally tractable by limiting the number of iterations needed to find a solution. The non-sequential techniques can be considered simply as an optimisation or calibration problem, where the state vector – rather than the model parameters – at the beginning of each assimilation window is 'calibrated' to the observations over that time period. The non-sequential techniques can be formulated with:

1. a strong constraint (variational) where the model is assumed perfect, as in equation 4.4; and
2. a weak constraint (dual variational or representer methods) where errors in the model formulation are taken into account as process uncertainty.

In representer methods, model uncertainty is included in the objective function as an additional term in equation 4.4 so that

$$J = \frac{1}{2}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right)^{\mathrm{T}} \boldsymbol{\Sigma}_0^{b-1}\left(\mathbf{x}_0 - \mathbf{x}_0^b\right) + \frac{1}{2}\sum_0^{N-1}\left(\mathbf{z}_k - \hat{\mathbf{z}}_k\right)^{\mathrm{T}} \mathbf{R}_k^{-1}\left(\mathbf{z}_k - \mathbf{z}_k\right) + \frac{1}{2}\sum_0^{N-1}\mathbf{w}_k^{\mathrm{T}}\mathbf{Q}_k^{-1}\mathbf{w}_k \,, \tag{4.5}$$

where $\mathbf{w}$ is the model error vector and $\mathbf{Q}$ is the model error variance-covariance matrix.

Non-sequential assimilation methods are well suited for smoothing problems,such as reanalysis of time series of hydrologic variables, but provide information on estimation accuracy only at considerable computational cost. Moreover, adjoints (operators that map between observation and forward model spaces) are not available for many existing hydrologic models, and the development of robust adjoint models is difficult due to the nonlinear nature of hydrologic processes and can require as much investment in generation of computer code as the original model itself. A further disadvantage lies in generating the model derivatives which can be complicated and costly for large models. Derivative free optimisation methods (e.g. Genetic Algorithms, Simulated Annealing, Markov Chain Monte Carlo and Stepwise Line Search (SLS) methods) avoid calculating the gradient of the cost function allowing $\mathbf{x}^a$ to be determined for almost any model (but with an associated computational overhead).

4.4 Section summary

In this section we have described the motivation underlying the application of DA methods to hydrologic problems; viz, improving the predictive capability of catchment hydrology models through optimising the information contained in both observations and models weighted by the relative magnitude of their errors. We then presented a brief overview of DA methods and the evolution of these methods for application to large hydrological problems. These methods along with data (Section 2) and models (Section 3) form the components of a stream flow forecasting system to be outlined in the blueprint for research in 'Enhanced Streamflow Forecasting' in Section 5.

Prior to implementation, development work is still required to couple the system components, code the data assimilation algorithms, link the real-time data access, implement models and develop the forecasting capability and skill to meet user requirements and specifications. Research is still required to develop accurate characterisation of errors, minimise bias in data sources, improve hydrologic model functions for spatial application, blend different types of precipitation observations and assess the utility of various data sources to improve model forecast skill.

5 Conclusion: a blueprint for stream flow forecasting

5.1 Introduction

In Section 1 ('Introduction'), we presented a schematic showing the structure of a stream flow forecasting system for water yield and river operations (Figure 1.1). The outcome of research undertaken in project D1 'Enhanced stream flow forecasting' of eWater CRC will be the generation of two practical tools for stream flow modeling: RiverOPS, a tool for operational real-time forecasting of stream flow; and WaterCAST, a tool for long term planning and decision support (including scenario assessment) for water resources management. The material covered in Sections 2, 3 and 4 of this report have described in detail the components needed to develop these tools. The rest of this section is concerned with recasting Figure 1.1 as a detailed schema for an operational stream flow forecasting system.

5.2 The focus catchment

The Murrumbidgee River catchment in NSW has been selected for developing and testing the RiverOPS and WaterCAST tools. This catchment (Figure 5.1) is one of eWater CRC's five focus catchments (the others are Brisbane River, Fitzroy River, Goulburn Broken River, and Yarra River) and is the largest catchment of the Murray Darling Basin at 73,400 km^2. It is bounded on the east by the Great Dividing Range, the Lachlan and Murray rivers on the north and south, and riverine plains to the west, and has 14 major dams, 8 large weirs, and 10,000 km of irrigation channels (Figure 5.1). Flows are regulated by dams and weirs as well as the Snowy River Hydroelectric Scheme, but a number of tributaries are unregulated. The catchment is highly variable in its physical characteristics, land use and hydrology. Land use varies from sheep and cattle grazing, conservation reserves and residential areas in the upper catchment to irrigated agriculture, horticulture, dry land cropping and grazing, and forestry in the mid and lower areas of the catchment. The Murrumbidgee catchment is one of the most

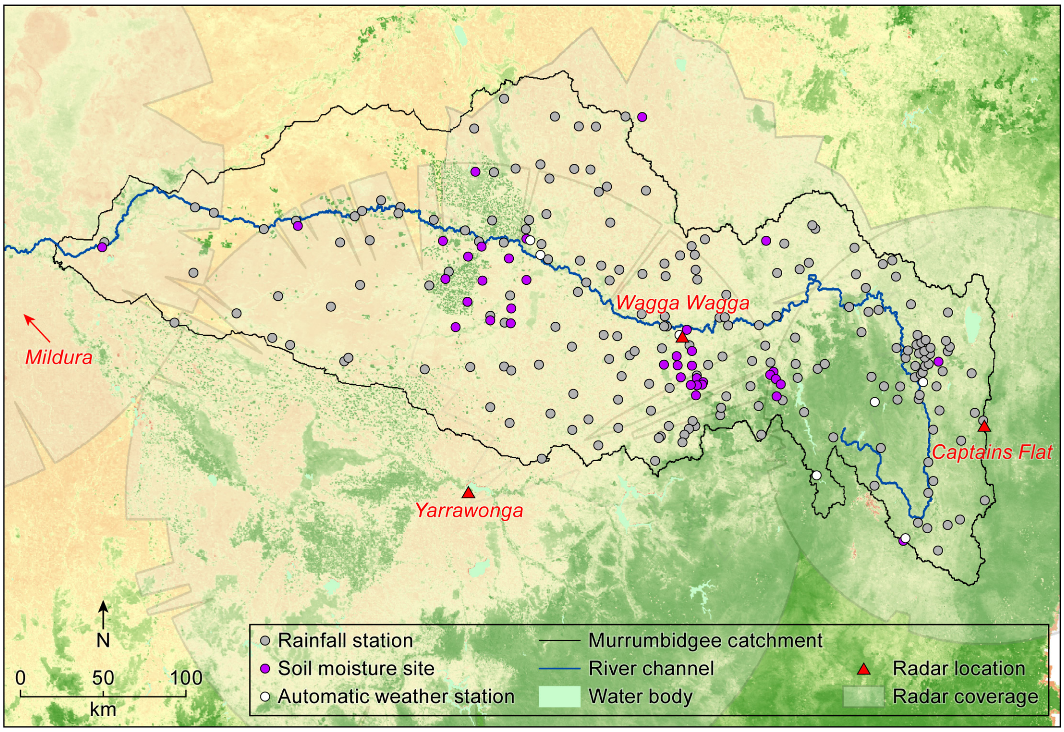


Figure 5.1. Map of the Murrumbidgee River catchment.

densely populated regions of rural Australia with over 520,000 people and a growth rate of 1.5% pa.

The catchment is also covered by a wide range of data sources including (Figure 5.1):

1. dedicated 'Weather Watch' ground based precipitation radars in Canberra and Yarrawonga, and a part-time radar in Wagga Wagga
2. historical and real-time time-series of stream flow (discharge) observations at multiple gauging stations
3. a network of meteorological stations and stations to record soil profile moisture; and
4. coverage by spatial data including satellite observations of soil moisture, snow cover, actual evapotranspiration and surface temperature, soil and vegetation maps and terrain information.

5.3 The blueprint

The blueprint of the stream flow forecasting scheme for the Murrumbidgee catchment is shown in Figure 5.2. This blueprint assembles into a single schematic diagram: the data, model, and DA scheme needed for state and parameter estimation of hydrologic variables. Such a scheme could be used by an operational agency to predict flows, and soil moisture throughout the catchment on 1–5 day lead times (RiverOPS) or reconfigured to generate time-series reanalysis of catchment water availability (i.e. inflows to storages) for trend analysis, decision making and long term water planning (WaterCAST). All components of the scheme are currently in existence and all data sets in Figure 5.2 are accessible in real-time. However, the assembly, testing and improvement of such a system is not a trivial task.

The forward model of this scheme is the Sacramento model used operationally by several projects sponsored by the United States National Oceanic and Atmospheric Administration (NOAA) (e.g. INFORM; a forecasting system for rivers and dams in northern California; Georgakakos et al. 2006) and is included in the E2 catchment modeling toolkit. It has been chosen because of its E2 legacy, its existing stream flow forecasting capabilities, and its suitability for assimilation of streamflow observations and remotely sensed soil moisture, evapotranspiration, surface temperature and snow. This model can be run on hourly, 6-hourly or daily time steps to generate estimates of soil moisture content and stream flow. Sacramento captures all relevant physical processes that impact on the generation of stream flow within a catchment. The vector of background state variables ($\mathbf{x}^b$) include surface soil moisture in upper soil layers, actual evapotranspiration, surface temperature and stream flow. The observation model (or operator, H) converts surface moisture content to brightness temperatures in microwave wavebands. The target variables of the analysis ($\mathbf{x}^a$) include state variables for stream flow forecasting in RiverOPS or the 11 Sacramento model parameters for reanalysis studies in WaterCAST. There is an already established efficient procedure for obtaining prior parameter estimates based on Koren et al. (2003) and Kuzmin et al. (2008), they have developed a fast and efficient calibration procedure (stepwise line search, SLS) for this model. To reduce the computational burden associated with spatial parameterising of Sacramento, the optimisation of the 11 parameters in Table 3.2 can be replaced with 7 'primary' parameters (percentage of sand, percentage of clay, saturated moisture content, field capacity, wilting point, saturated hydraulic conductivity, and specific yield) which will increase computational efficiency by up to 50–80% (Kuzmin et al. 2008). The full procedure for computation of prior estimates of the Sacramento model parameters using soil properties is given in (Koren et al. 2003).

Observations of model states and fluxes for the assimilation will include satellite observations of soil moisture from AMSR-E based on the retrieval scheme of Owe et al. (2001) and De Jeu and Owe (2003) and stream flow data from the gauge network. Where the geographic location of observations and model states do not coincide, interpolation routines will be used as required. Observations of snow extent and soil water equivalent will be trialled in the forecasting scheme during ongoing improvements over time. Future developments will include the assimilation of land surface temperatures (from MODIS and AVHRR sensors) in a coupled surface energy balance – microwave radiative transfer model to better estimate profile surface soil moisture. Verification of flows will be achieved against existing hydrograph observations

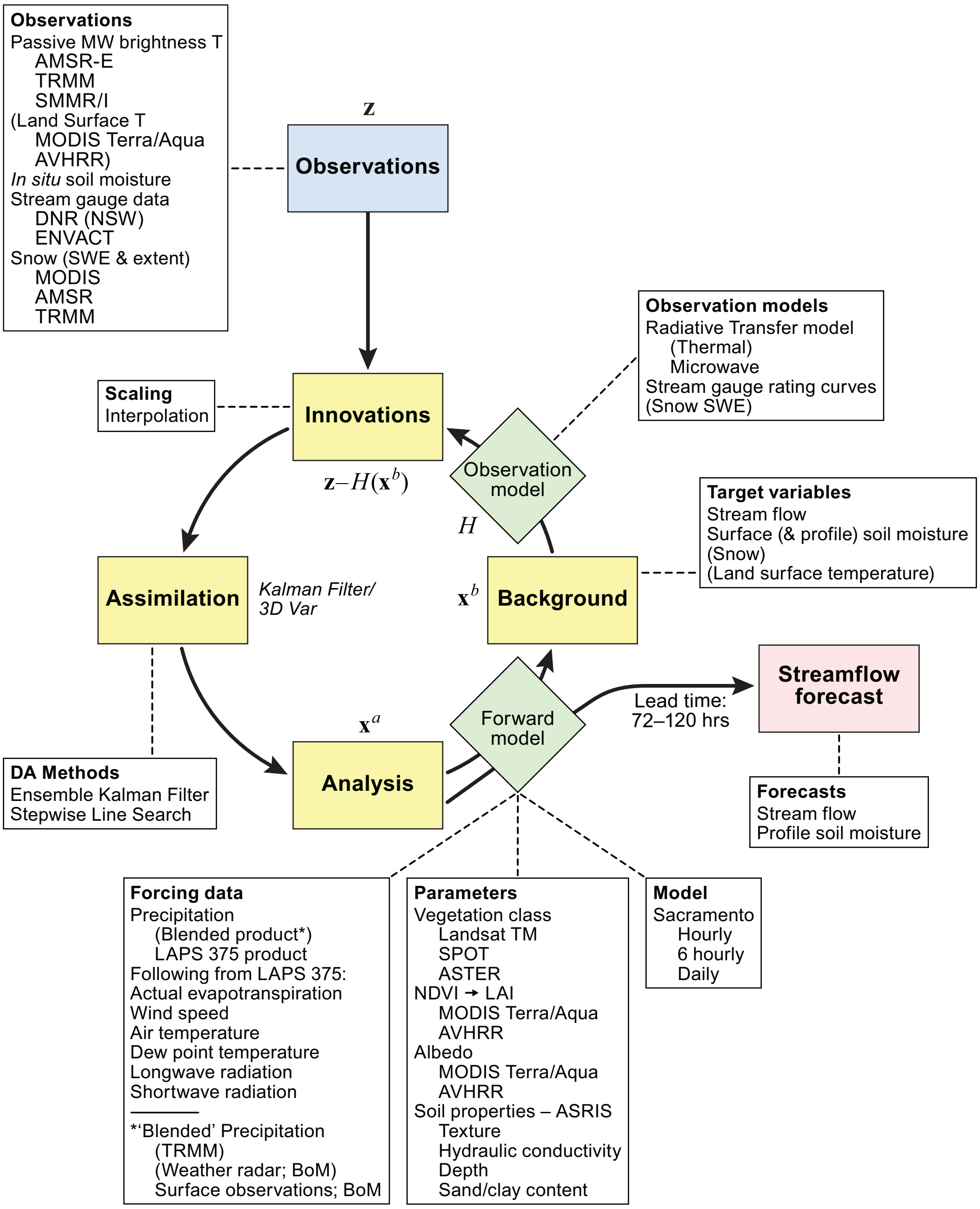


Figure 5.2. Blueprint of a generic streamflow forecasting scheme capable of predicting flow on 1–5 day leadtimes for river management purposes (RiverOPS). The analysis provides optimal estimates of state variables and parameters based on the minimisation of differences between observed values and modelled 'observations' (called 'innovations') for the forecasting of stream flow, soil profile moisture content and actual evapotranspiration with a lead time of up to 72 hours. Components in parentheses are improvements for later addition.

and soil moisture observations from the Murrumbidgee catchment Soil Moisture Monitoring Network (see section 2.5.1, and they are located on Figure 5.1).

The assimilation of observations into a hydrologic model will be conducted using three proposed methods to compare results and computational efficiency at reaching a solution for each of the RiverOPS and WaterCAST applications. These methods are:

1. the ensemble Kalman Filter;
2. a 3-D variational method; and,
3. a brute-force variational approach (viz. Stepwise Line Search method).

The 3-D variational method will be applied to a spatially distributred coupled surface energy balance/runoff model to examine the utility of satellite observations of surface temperature in constraining profile soil moisture and runoff by explicit representation of the land surface energy balance. The Stepwise Line Search (SLS) method will be used to generate parameters of the Sacramento model by successive minimisation (Press et al. 1986) using the simplification of Kuzmin et al. (2008) that can increase computation speed by up to four times. The SLS method is straightforward to apply, computationally efficient and will generate physically realistic posterior model parameter estimates. It will also assist exploration of the influence of a nonlinear and irregular cost function surface on the estimation of model parameters. The cost function to be minimised will be designed to emulate the multiple time-scale of observations including peak flow, base flow and flow recession periods (Parada et al. 2003).

5.4 Section summary

In this section, we outlined a blueprint of a stream flow forecasting scheme being developed and tested for the Murrumbidgee Catchment. The blueprint integrates data (Section 2), models (Section 3) and DA methods (Section 4) to provide catchment wide forecasts of stream flow, profile soil moisture content and actual evapotranspiration.

Prior to implementation, development work is required to couple the system components, code the data assimilation algorithms, establish links to real-time data access, implement models and develop the forecasting capability and skill to meet user requirements and specifications. Research is still required to develop accurate characterisation of errors, minimise bias in data sources, improve hydrologic model functions for spatial application, blend different types of precipitation observations and assess the utility of various data sources.

Once implemented, engineering a basin-wide operational forecasting of stream flow is possible by scaling-up the resources used for application in the Murrumbidgee catchment; albeit with the efficiency gained through multiple reuse of components. A regional scale system would realise multiple benefits afforded by improved skill in forecasting flows in river systems, including; improved efficiencies of water use, better anticipation of high flows and flooding, a reduction in river system losses or shortfalls in supply; better targeting of environmental flows and basin-wide consistency in river management.

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Glossary

AC. Analysis Correction (a method of data assimilation).
ALOS. Advanced Land Observing Satellite.
AMSR-E. Advanced Microwave Scanning Radiometer (a sensor onboard Aqua satellite, launched in May 2002).
ASCAT. Advanced SCATterometer (a sensor onboard MetOp satellite, launched in October 2006).
ASTER. Advanced Spaceborne Thermal Emission and Reflection Radiometer.
AUSLIG. AUStralian Surveying and Land Information Group (a Federal Government Department based in Canberra).
AVHRR. Advanced Very High Resolution Radiometer (a sensor onboard the NOAA series of satellites first launched in 1981).
AWBM. Australian Water Balance Model.
AWRA. Australian Water Resources Assessment.
AWS. Automatic Weather Station.
BoM. The Australian Government Bureau of Meteorology (http://www.bom.gov.au).
Bureau. The Australian Government Bureau of Meteorology (http://www.bom.gov.au).
CABLE. CSIRO Atmosphere Biosphere Land Exchange model.
CRC. Cooperative Research Centre (an Australian Federal Government programme, established to bring together researchers and research users; eWater is one such CRC).
CSIRO. Commonwealth Scientific and Industrial Research Organisation (Australia).
CRCCH. CRC for Catchment Hydrology.
DA. Data Assimilation.
DI. Direct Insertion (a method of data assimilation).
Discontinuous model. A models that contains a discontinuity and hence is not differentiable.
DMSP. Defense Meteorological Satellite Program.
E2. A modeling shell for semi-distributed catchment software developed by CRCCH.
EKF. Extended Kalman Filter (a sequential method of data assimilation).
EMS. ElectroMagnetic Spectrum.
EnKF. Ensemble Kalman Filter (a sequential method of data assimilation).
ERIN. Environmental Resources Information Network (Australian Government Departmet of Environment and Water Resources).
ERS. European Remote Sensing scatterometer data (a sensor onboard ERS-2 satellite, launched in April 2005).
EST. (Australian) Eastern Standard Time.
ET. EvapoTranspiration.
FU. Functional Units (spatial elements ,usually the result of Boolean-GIS overlay, of E2).
GASP. Global AnalysiS and Prediction (providing long-range, low resolution forecasts over the entire globe).
GASP EPS. Global AnalysiS and Prediction Ensemble Prediction System (based on 32 international climate models).
GDA94. Geocentric Datum of Australia, a coordinate system established in 1994.
GMS. Generic Geostationary Meteorological Satellites.
GRACE. Gravity Recovery and Climate Experiment (twin satellites launched separately in March 2002).
GRV. Gaussian Random Variable.
GUI. Graphical User Interface.
JERS. Japanese Earth Resources Satellite (a project of the National Space Development Agency of Japan).
LAI. Leaf Area Index.
LAPS. Limited Area Prediction System (a numerical weather prediction model).
LAPS 375. LAPS model with spatial resolution 0.375° (~37.5 km).

LAPS EPS. LAPS Ensemble Prediction System (perturbs the boundary conditions and some of the model physics to produce a 25-member ensemble with a 0.5° resolution out to a lead time of 72 hours).
LP DAAC. Land Processes Distributed Active Archive Centre.
LWDR. Long-Wave Downward Radiation.
MesoLAPS. Meso-scale LAPS numerical weather prediction model.
MesoLAPS 05. LAPS model configuration with spatial resolution 0.05° (~5 km).
MesoLAPS 125. LAPS model configuration with spatial resolution 0.125° (~12.5 km).
METEOSTAT. METEOrological SATellite (a European satellite, first launched in 1977; current satellite launched 1997).
MetOp. The satellite carrying ASCAT sensor (launched October 2006).
MODIS. MODerate resolution Imaging Spectrometer (a sensor onboard the NASA Terra and Aqua satellites, launched in December 1999 and May 2002, respectively).
MSOF. Multi-Scale Objective Function (an optimisation criteria, which reflects different frequencies of the stream flow).
MSS. Multi-Spectral Scanner (a sensor onboard the US Landsat series of satellites, first launched in 1972).
MTSAT-IR. The Japan Meteorological Agency MultI-functional Transport SATellite.
NASA. National Aeronautic and Space Agency (USA).
NDVI. Normalised Difference Vegetation Index.
NDTI. Normalised Difference Temperature Index.
NIR. Near InfraRed (portion of the electromagnetic spectrum).
NLDAS. North American Land Data Assimilation Scheme.
NLWRA. National Land and Water Resources Audit (Australia).
NOAA. National Oceanic and Atmospheric Administration (USA).
NPOESS. The National Polar-orbiting Operational Environmental Satellite System (USA).
NRT. Near Real Time.
NWP. Numerical Weather Prediction model.
NWS. National Weather Service (USA).
OCF. Operational Consensus Forecasts.
OHD. Office of Hydrologic Development (jointly involves NOAA and NWS).
OI. Optimal Interpolation (a method of data assimilation).
PDF. Probability Distribution Function.
PDM. Probability Distributed Model.
Profile soil moisture content. Measurements made of soil water distribution over the soil profile (i.e. with depth).
RiverOPS. River OPerationS (one of the eWater CRC Product Development Programs which will be used for operational forecasting stream flow and decision making in real-time by operational water resources management agencies).
RMSE. Root Mean Square Error (a commonly used optimisation criteria).
RS. Remote Sensing.
Runoff. Runoff is flow across the surface (or just below the surface) that reaches a stream line. Runoff is unlikely to be observed directly by remote sensing, but can be ‘observed’ by a hydrograph as discharge. Cf. ‘surfacewater’.
SAC-SMA. SACramento Soil Moisture Accounting model.
SAR. Synthetic Aperture Radar.
SAVI. Soil Adjusted Vegetation Index.
SC. Successive Correction (a method of data assimilation).
SCE. Shuffled Complex Evolution (a quasi-global method of parameters optimization).
SI. Statistical Interpolation (a method of data assimilation).
SEB. Surface Energy Balance.
SILO. Special Information for Land Owners, http://www.bom.gov.au/silo/ (a rich source of historic and real-time meteorological and agricultural data of particular interest to anyone involved in the agricultural arena).
SimHYD. Simplified HYDROLOG model.
SLS. Stepwise Line Search(a modification of the pattern search (model calibration approach)).
SMAR. Soil Moisture Accounting and Routing model.

SMMR. Scanning Multichannel Microwave Radiometer (a sensor onboard Nimbus 7 satellite, launched in October 1978; finished 1987).

SMOS. Soil Moisture Ocean Salinity (an ESA planned mission for 2008 onboard a standard 'Proteus' spacecraft).

SSM/I. Special Sensor Microwave / Imager (a sensor onboard a Defense Meteorological Satellite Program satellite, launched in July 1987).

SSDS. Surface Degree of Saturation index.

SSTP. Stochastic Self-Training Procedure (a sequential approach of data assimilation).

StC. Statistical Correction (a method of data assimilation).

STEPS. Short-Term Ensemble Prediction System.

Surfacewater. Surfacewater refers to ponding or slow moving floodwater in flat terrain that overlies the soil surface. This water is potentially 'observable' by remote sensing. Cf. 'runoff'.

SWE. Snow Water Equivalent.

SWIR. ShortWave InfraRed (portion of the electromagnetic spectrum).

SWDR. Short-Wave Downward Radiation reaching the earth's surface.

TRMM. Tropical Rainfall Measuring Mission.

TUW. Technische Universität Wien (Vienna University of Technology).

TIROS. Television InfraRed Observation Satellite program (the first successful weather satellite, launched in April 1960).

UKF. Unscented Kalman Filter (a sequential method of data assimilation from the EKF class).

VIC. Variable Infiltration Capacity (a macro-scale hydrologic model).

VIIRS. Visible/Infrared Imager/Radiometer Suite.

VUA. Vrije Universiteit Amsterdam (The Free University of Amsterdam).

WADA. West Australian Departments of Agriculture.

WaterCAST. Water and Constituent Accounting Simulation Tool (one of the eWater CRC Product Development Programs, designed for long-term planning and decision support for water resources management agencies).