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Satellite-Based Systems for Flood Monitoring and Warning

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25.1 Introduction

Major flood events with substantial damages are observed across the United States every year. Climate change and variability affect the magnitude and the frequency of these events. Nowadays extreme meteorological events are more destructive and more frequent. In 2008, for instance, much of central and eastern Iowa was affected by a 500-year flood, which was classified as the worst in the history of the region [45]. Many other similar events have occurred in the United States and around the world. The recent major flood in Pakistan in 2010 is another example. It is therefore important to develop an accurate and clear understanding of the dynamics of extreme hydrological events.

Three main elements are necessary for a reliable forecast and monitoring of hydrological processes, namely, good-quality precipitation data, accurate characterization of surface conditions, and robust, accurate, and detailed HyMODs. This chapter addresses these three elements and analyzes their role in delivering reliable forecast of hydrological events. A particular focus is placed on satellite-based land surface and precipitation products and their integration into operational HyMODs through data assimilation systems. The following questions will be addressed:

How could satellite-based precipitation products improve the performance of flood monitoring and forecasting systems?

Is it possible to accurately determine surface conditions and hydraulic parameters from space?

What is the impact of integrating satellite-based products into flood monitoring and warning systems?

In the United States, NOAA National Weather Service (NWS) issues on a daily basis maps of Flash Flood Guidance (FFG) that include the amount of rainfall that is necessary to produce a flash flood at a given location and for a specific duration of rainfall. NWS via its River Forecast Centers (RFCs) develops FFG maps for each county within the RFC domain for three durations: 1, 3, and 6 h. US Geological Survey (USGS), on the other hand, has established a vast network to observe and monitor hydraulic conditions in several rivers across the country. Discharge and water level in rivers and lakes are routinely observed and made available for end users. NOAA National Climate Data Record provides the community with satellite, radar, and rain gauge precipitations. In addition, the NOAA NSSL is developing techniques for high-resolution application over the United States and is involved in the development of global hydrological forecast systems.

Despite the investment of tremendous efforts to monitor and forecast hydrological processes and mitigate the impact of extreme events on the society, these events continue to impact larger areas and occur on regional and local scales. The extent and the dynamic of extreme events suggest using remote-sensing-based techniques to monitor them and understand their dynamic.

Remote-sensing data and particularly passive microwave (MW) images have been largely used to monitor inundation and major hydrological events [39]. Passive MW observations have appeared as
Satellite imagery has been used to determine water levels in lakes and reservoirs, discharge in rivers, and even surface conditions like roughness and relief. So, it is possible to determine from space key hydrological parameters and force HyMODs with appropriate, up-to-date information on surface conditions. Hence, the integration of satellite-based products has been tested and implemented in rural and large watersheds as well as small and urban basins. The overall performance of these models still depends, however, on the quality of the precipitation product, which is the main driver of flood monitoring and forecasting systems.

The observation of the space/time variability of precipitation globally is vital for understanding global water and energy cycle. In terms of precipitation measurements, it is critical to have locally collected data over a global domain to capture spatiotemporal variability of precipitation in micro, meso, and synoptic scales. Precipitation is the most important driving force in HyMODs as it impacts the soil moisture and other important soil or land surface parameters. QPE and QPF are the application of science and technology to either estimate or predict the rainfall rate for a specified time and a given location. QPE and QPF algorithms incorporate satellite-based atmospheric observations (e.g., visible [VIS], infrared [IR], and MW channels) to retrieve rainfall rate for the current or future time(s) [49].

Hence, remote sensing of hydrometeorological variables, such as precipitation, soil moisture, water levels in large bodies of water, areal extent of inundation, and river discharge, has provided great potential to monitor and forecast flooding in many ungauged basins in the world. Such satellite-based products are derived from different observations and a number of sensors. They are generated at different spatial resolutions and derived from observations taken at different overpass times. The indirectness of the observations to the desired measured variable, limited resolution in space and time, and retrieval errors all must be considered when applying remote-sensing data for flood applications. Assessing the exact impact of the integrating remote-sensing-based products into flood forecasting systems is crucial.

This chapter comprises three sections: The first section of this chapter includes further details about the use of satellite imagery to characterize land surface conditions and determine relevant surface and subsurface parameters that can be integrated in HyMODs. The second section presents in more details satellite-based precipitation products and their use to forecast as QPF or monitor as QPE rainfall events. The third section presents results on error modeling of satellite-based rainfall estimates, HyMOD calibration that considers the pixel resolution of the rainfall product, and the use of the ensemble square root filter (EnSRF) to assimilate a proxy for river discharge based on passive MW brightness temperature signals with the overall aim of improving flood forecasts in ungauged basins.

## 25.2 Satellite Data for Hydrological Modeling

The detection of flooded regions typically comes from trained spotter reports collected by the NWS or from USGS stream gauges. Both sources are woefully inadequate to capture the spatial extent of flooding, particularly in sparsely populated regions. Satellite imagery greatly enhances the observational aspects of flooding and thus enables refined initialization and evaluations of distributed HyMOD outputs. Several sensors have been used to delineate flooded areas. They fall into one of the two categories. First, VIS and IR sensors, often onboard polar-orbiting satellites, provide images on a daily basis like Moderate Resolution Imaging Spectroradiometer (MODIS), VIIRS, and AVHRR at moderate spatial resolution ranging from 250 to 1000 m. Under this category, we may also find high-resolution sensors like Landsat and ASTER. Despite their long revisit cycle (16 days in the case of Landsat) that is not appropriate to monitor rapid processes like flooding events, these sensors provide images with a spatial resolution that can reach 30 m. The major disadvantage of this category of sensors is their sensitivity to clouds that hampers their use to monitor flooding conditions that often occur under cloudy sky. So, the second category of sensors, namely, MW sensors, which are capable of penetrating clouds, has been utilized as an alternative. Under this category of sensors, we may find two types of sensors,
namely, passive and active MW sensors. They both penetrate through clouds. They are only sensitive to atmosphere at higher frequencies, above 19 GHz. Several passive MW sensors like special sensor microwave/imager (SSM/I), Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E), and Advanced Microwave Sounding Unit (AMSU) have been utilized to monitor flooding events and delineate inundated areas particularly on a regional scale because of the coarse spatial resolution of passive MW observations. On the other hand, active MW sensors commonly known as radar like Radarsat, ERS, and QuickSAT can deliver images at higher spatial resolution. For instance, in the case of Radarsat-1, images captured in the fine mode have a spatial resolution of 12 m. However, the extent of scenes captured at such high spatial resolution is limited and does not provide a comprehensive coverage of flooding events that usually occurs on a watershed scale. Because of the limitation of each individual sensor, the use of a multi-sensor approach has been investigated [37]. Recent advances in sensor development and data manipulation and sharing have fostered the implementation of such approaches.

In addition to delineating flooded regions, satellite imagery has been used to determine soil moisture that is a critical parameter in HyMODs as it controls the partitioning of rainfall into infiltration and runoff. Passive MW-based approaches to determine soil wetness generally fall into one of the following categories: In the first category, radiative transfer models are generally used in an inversion process that minimizes the differences between observed and simulated brightness temperatures [35]. In the second category, simplistic approaches have been developed to determine a number of wetness indices as proxies for soil moisture [3].

Recent sensors developed for soil moisture retrieval operate in the L-band frequency that minimizes the effect of vegetation and atmosphere and penetrates to deeper soil layers. Recent missions, like SMOS and AQUARIUS, have L-band radiometer onboard. The NASA SMAP mission planned for 2014 will have both radar and radiometer operating at the 1.4 GHz frequency. Despite the great interest in low frequencies such as L- and C-bands that are more appropriate for soil moisture retrieval, other studies have explored the potential of the 37 GHz channel to monitor flood conditions. Observations from AMSR-E at this frequency were used by Temimi et al. to monitor streamflow in the Mackenzie River Basin in Canada [44]. Recently, Temimi et al. have introduced a Polarization Ratio Variation Index (PRVI) that is a MW-based wetness index that was successfully tested during the major flood in Iowa in 2008 [45]. The index was expanded on global scale and implemented as flood warning system. The index showed sensitivity to flooding conditions on a global scale and was successfully verified during the major flood in Pakistan in 2010.

The use of remote sensing was not limited to sensing surface conditions, but it was expanded to determining key hydraulic variables. Brakenridge et al. have used AMSR-E 37 GHz brightness temperature to infer river discharge [6]. Their findings were in line with those by [5] that investigated the feasibility of measuring river discharge from space. A relationship was established between discharge values and the extent of flooded regions or other river and watershed parameters like the hydraulic width [10]. Temimi et al. have estimated the time of concentration of a large watershed in Upper Mississippi by determining the phase lag between the peak of discharge downstream and the timing of the maximum of water extent detected from space [45]. Smith and Pavelsky estimated the flood wave propagation speed using remote-sensing data [41].

In northern watersheds, remote-sensing-based products have been critical in determining ice coverage on lakes and rivers that significantly affect the hydraulic and hydrological processes. During the spring melting period, breaking ice raises the water in rivers and lakes to dangerous levels. Then, the breakup releases destructive flood waves. Only in the United States, the estimated cost of damages related to these processes is in the order of $100 million [52]. Moreover, the dynamic of river ice significantly affects hydropower plants management, navigation, and even transportation since ice on rivers is usually used during winter as a bridge to make the link between northern communities. VIS, IR, and MW images have been used for ice mapping over rivers and ice jam monitoring [36]. The MODIS is providing VIS/IR images at an interesting spatial resolution of 250 and 500 m. This spatial resolution is suitable for large rivers such as the Mackenzie River in northwestern Canada, the Colville River in
Alaska, and the Lena River in Russia. However, over narrower rivers the coarse spatial resolution of these images does now allow for possible monitoring on ice. Active MW, on the other hand, that is, radar images, was used in numerous studies as an interesting tool since they can penetrate cloud and provide images at higher spatial resolution. Several studies were conducted to investigate interaction between ice and backscattering radar signal [7]. These studies showed that it is possible to retrieve ice characteristics from the spectral content of backscattered signal [32]. However, these images have a limited field of view at fine mode and do not include comprehensive information on ice dynamic and flooded area particularly over large rivers.

Finally, coastal areas and wetlands play a major role in both hydrological processes and climate trends; therefore, it is crucial to understand the hydrodynamics of these systems and the interplay between the ocean, estuaries, rivers, and surrounding wetlands. Satellite images (optical and MW) have also shown an interesting potential to monitor changes that occur over long and short time scales. Active microwave sensors measure backscatters and return signal amplitude, phase, and polarization that are independent of sun angles and weather conditions (Figure 25.1).

Synthetic Aperture Radar (SAR) interferometry (InSAR) measures the corresponding phase difference resulting from the difference in distances to the same target in two SAR images. It is possible based on this concept to determine changes in water levels in coastal region and lakes and rivers as well. Combining interferometric radar observations with a digital elevation model of the river region will allow for rapid determination of water levels, especially if such assessments are done routinely. In addition, different frequency (C-, X-, L-bands) SARs provide different sensitivity and radar penetration.

**FIGURE 25.1** Coastal inundation (in dark gray) as detected by Radarsat-1 in Franklin County, FL, on January 5, 2010.
depth depending on the properties of land cover, thereby providing additional information for robust classification and morphology determination. A time series of SAR images taken over the same region at the same tide phase allows for an assessment of the morphodynamics of the study area.

### 25.3 Quantitative Precipitation Estimation/Nowcasting

The observation of the space/time variability of precipitation globally is vital for understanding global water and energy cycle. In terms of precipitation measurements, it is critical to have locally collected data over a global domain to capture spatiotemporal variability of precipitation in micro, meso, and synoptic scales. Precipitation, the most important driving force in HyMODs, impacts soil moisture and other important soil or land surface characteristics. QPE and QPF are the application of science and technology used to either estimate or predict the rainfall rate for a specified time and a given location. QPE and QPF algorithms incorporate satellite-based atmospheric observations (e.g., VIS, IR, and MW channels) to retrieve rainfall rate for the current or future time(s) [18,49].

#### 25.3.1 Satellite-Based Precipitation Estimation

The satellite remote sensing started using VIS and IR sensors first to estimate rainfall [2]. The VIS-/IR-based techniques do not measure precipitation directly. Using VIS/IR sensors, the rainfall rate would be estimated from cloud characteristics such as cloud brightness temperature [28,46]. Previous studies have shown that VIS-/IR-based algorithm works well for convective-dominated areas, and not necessarily in stratiform systems [43]. As opposed, MW sensors could penetrate into the cloud. MW-based satellite precipitation measurement has been a major milestone in QPE. Considering MW sensors' relative insensitivity to the cloud cover, they provide direct rainfall measurements. The first major step in using MW-based instrument used the SSM/I that was launched in 1987 with Defense Meteorological Satellite Program (DMSP) with sun-synchronous, near orbital, and 98.8° inclination orbit, equipped with high-frequency sensor of 19.35, 22.23, 37, and 85.5 GHz [9,43].

The Tropical Rainfall Measuring Mission (TRMM) satellite and AMSR-E launched with Earth Observing System (EOS) Aqua satellite are more recent examples [23,30,42]. The TRMM satellite includes the passive TRMM Microwave Imager (TMI) sensor and the first space-based active MW radar. The precipitation radar (PR) provides a vertical distribution of precipitation that would be used for other passive MW sensors [15,23,30]. Even though the TRMM mission was a significant step ahead, the MW-based satellites have both spatially and temporally sparse coverage. Considering all MW-based satellites, they have six to eight observations per day for a given region. Following on the TRMM mission, an international measure to launch new generation of MW-based satellite sensors called Global Precipitation Measurement (GPM) mission has been initiated. The GPM will include a constellation of satellites with passive MW and next-generation active PR. Regardless of higher accuracy and improved temporal and spatial resolution of GPM precipitation products, MW-based sensors might not have the temporal and spatial resolution required for some hydrological activities [18].

Another category of high-resolution precipitation retrieval algorithms consists of a combination of MW observations along with VIS/IR instruments [1]. There are several algorithms using MW rain rate retrievals to calibrate the VIS-/IR-based algorithms [4,16,19,24,47]. In addition, there has been also a trend to use a combination of multi-sensor or multi-satellite observations to provide the intended spatial and temporal scales (e.g., TRMM Multi-Satellite Precipitation Analysis [TMPA] [21,22,34]).

#### 25.3.2 Review of Some Operational Precipitation Retrieval Algorithms

##### 25.3.2.1 TRMM Multisatellite Precipitation Analysis

TMPA uses a wide variety of satellite-based precipitation sensors to have a best-possible estimate of global precipitation. The estimated precipitation has a relatively fine scale (0.25° × 0.25°) every 3 h.
The precipitation has been provided in both real and post-real time. Studies have shown that the finer scale has been associated with more errors and uncertainties. It is recommended to use the TMPA fine resolution data to create a time-space average that is required for each specific application [21].

25.3.2.2 Global Precipitation Measurement Mission

The GPM mission as an international network of satellites plans to estimate the precipitation every 2–4 h globally. The GPM has a “Core” observatory including advanced active and passive MW sensors in a non-sun-synchronous orbit. The GPM will be used as a calibration reference to unify rain and snow rates from a constellation of satellites [40]. The GPM Core Spacecraft will have two precipitation sensors including the GPM Microwave Imager (GMI) and the dual-frequency PR (DPR). The aforementioned sensors will be able to measure both light and heavy rain rate along with snowfall. In comparison with previous MW-based sensors (e.g., TRMM), the GPM has the new capabilities of the GMI and DPR using high-frequency channels (165.6 and 183.3 GHz) on the GMI and a new Ka-band (35.5 GHz) radar on the DPR [40].

25.3.2.3 CMORPH: High-Resolution Precipitation Product Morphing Passive Microwave and IR Satellite Sensors

The CPC MORPHing technique (CMORPH) algorithm incorporates the most desired aspect of VIS/IR sensors that is higher temporal and spatial resolution, along with passive MW precipitation retrieval sensors that has higher quality. The CMORPH algorithm uses the advection field derived from geostationary satellite IR channels to estimate the passive MW-based precipitation propagations [24]. CMORPH provides global precipitation (60 N–60 S) with (~0.10 latitude/longitude, ½ hourly) spatial and temporal resolution, respectively. This algorithm takes advantages of direct precipitation measurement from passive MW as opposed to other merging algorithms of IR and MW observations. CMORPH also has superiority to simply averaging available MW-based precipitation retrieval techniques [24].

25.3.2.4 Self-Calibrating Multivariate Precipitation Retrieval

Self-Calibrating Multivariate Precipitation Retrieval (SCaMPR) algorithm retrieves rain rate using VIS/IR and MW bands from geostationary and earth-orbiting satellites. The MW-based rain rate is used to calibrate an algorithm framework that applies optimal VIS/IR predictors along with optimal calibration coefficients in real time [27,28]. The real-time version of SCaMPR started running from November 2004 applying IR-based data (bands 3–6) from Geostationary Operational Environmental Satellite (GOES)—West and East. The newer SCaMPR version also uses VIS data from GOES (0.6 μm). SSM/I-based rain rate along with AMSU has been implemented to produce MW-based rain rates in real-time version of SCaMPR [9,50]. In 2009, the operational SCaMPR also began using TMI and PR for calibration [27,28].

25.3.2.5 Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Network Cloud Classification System

Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Network Cloud Classification System (PERSIANN-CCS) is another application of geostationary IR channels that provides high-resolution global precipitation product based on extracted cloud features. This algorithm has four consecutive steps to (1) segment images using cloud classification, (2) extract feature from IR cloud patches, (3) feature classification, and (4) rainfall estimation. The MW-based rainfall rate is used for model calibration [16]. PERSIANN-CCS provides high-resolution precipitation products (HRPPs) (0.04°×0.0.4°) with the latency between 40 min and ~2 h over the region 180° W to 180° E and 60° S to 60° N, through the UNESCO, G-WADI data server [20].

25.3.2.6 NRL-Blend High-Resolution Precipitation Product

The Naval Research Laboratory (NRL)-blend algorithm uses a real-time collection of time/space matching of pixels from all operational geostationary VIS/IR imagers and passive MW observations. From
January of 2009, the operational model uses five geostationary satellites and twelve available passive MWs and an active radar system. This algorithm produces three hourly accumulated rain rate at a gridded spatial scale of 0.25° between ±60° latitude, updated every 3 h [47,48].

It has been documented that the satellite-based real-time precipitation estimation can significantly improve the hydrological forecasting capabilities. In addition, during the last few years, there have been some activities to use the current atmospheric situation for precipitation short-term forecasting or nowcasting. The precipitation nowcasting might extend the hydrological forecasting lead time.

### 25.3.3 Satellite-Based Short-Term Quantitative Precipitation Forecasting (Nowcasting)

The nowcasting algorithms improve the predictability of hydrological extreme events [13]. Extrapolation-based or “data-driven” algorithms are capable of extracting information from the ever-increasing volume of remotely sensed data and are documented to be able to produce reliable forecasts, especially within a few hours of the analysis time [11,38,53].

Typically, a nowcasting algorithm generally includes three steps: (1) storm identification, (2) storm tracking, and (3) storm projection. The identification and tracking/matching of stormy areas at the current time \( t \) with the corresponding storm in the previous time step(s) (e.g., \( t-1, t-2, \ldots \)) is a major challenge for nowcasting. Due to the dynamic nature of storms, they change in terms of intensity, texture, and geometrical characteristics. They may also split or merge with other storms, which is a very complicated situation. To deal with this complexity, several storm identification and tracking techniques have been proposed [8,12,54]. The Storm Cell Identification and Tracking (SCIT) algorithm [25] and the Thunderstorm Identification, Tracking, Analysis, and Nowcasting (TITAN) algorithm [8] are two examples with hydrological applications. The integration of some of these algorithms into the NWS Warning Decision Support System (WDSS) has been reported [31].

Nowcasting algorithms usually have some significant limitations. Most of the nowcasting algorithms are designed either to work exclusively with ground-based radar observations or to nowcast greater and long-lived atmospheric events such as Mesoscale Convective Systems (MCSs) [8,50].

There have been multiple algorithms using high-resolution GOES observation to forecast cloud advection and evolution. As an example of newly developed object-based nowcasting algorithms, the Forecast and Tracking the Evolution of Cloud Cluster (ForTraCC) has been proposed to identify, track, and forecast MCSs over southern America [50].

### 25.3.4 Review of Operational Precipitation Nowcasting Algorithms

There are currently very few satellite-based precipitation nowcasting algorithms. A major example, the Hydro-Nowcaster (HN), provides high-resolution precipitation forecast in the next 0–3 h running on the National Environmental Satellite, Data, and Information Service (NESDIS) [29]. The HN focuses on motion of rain cells and storm cells growth and decay (GD). The HN identifies each storm, and storm will be matched together between two consecutive satellite imageries (typically 15 min). The storm position and advection will be extrapolated based on the storm tracking and matching process. The GD trend also will be used to extrapolate storm size change. Scofield et al. and Kuligowski et al. have shown the promising performance of the HN in different case studies, although the algorithm still requires more improvement [29,38].

Another recent algorithm called PERSiann-foreCAST (PERCAST) also predicts the rate of rainfall in the next 4 h using the most recent storm images to extract storm features, including advection field and changes in storm intensity and size. PERCAST algorithm is a storm nowcasting module coupled with a previously developed precipitation retrieval algorithm PERSIANN-CCS to forecast rainfall rates. The results show that, by considering storm GD trends for the prediction, the PERCAST-GD further improves the predictability of convective storms [54].
25.4 Satellite Data Assimilation in Hydrological Models

The major components of HyMODs are generally divided into forcings (i.e., rainfall, evapotranspiration), model states (e.g., soil moisture), model parameters, and outputs (i.e., streamflow). The quantification of uncertainty is required in all components because the observations are not perfect nor are the physical processes represented in the HyMOD. An ensemble approach is often preferred in modeling because it readily accommodates observed variables that have been perturbed, equally probable model parameter settings, EnSRF for state estimation, and it yields an array of forecast outcomes that can be used to derive maximum and minimum bounds, measures of central tendency (e.g., ensemble mean), and probabilistic outputs (e.g., percent chance of exceeding a threshold). The multidimensional rainfall error model called SREM2D described in Hossain and Anagnostou uses stochastic space/time formulations to characterize the spatial error structure of satellite retrievals [17]. SREM2D models the joint probability of delineating rain and non-raining areas; thus, it is capable of stochastically producing rainfall in areas where the deterministic satellite-based estimate did not detect it and removing satellite-detected rainfall in other regions. In this sense, it statistically represents missed rain detection and false alarms. A reference rainfall product, preferably gridded rainfall from ground-based radar and rain gauges, is provided to SREM2D as well as the satellite rainfall product. SREM2D then estimates parameters to arrive at an ensemble of equally probable “reference-like” rainfall products. Figure 25.2 shows an annual time series of cumulative basin-averaged rainfall estimated by three different satellite-based algorithms (TRMM 3B42RT, CMORPH, and PERSIANN) in a sub-catchment in the Tar River Basin, NC, during 2006. (Adapted from Maggioni, V. et al., J. Hydrometeorol., 2012, in review.)

**FIGURE 25.2** Cumulative rainfall from (a) TRMM 3B42RT, (b) CMORPH, and (c) PERSIANN on a sub-catchment of the Tar River Basin, NC, during 2006. ( Adapted from Maggioni, V. et al., J. Hydrometeorol., 2012, in review.)
River Basin, NC. The MPE curve corresponds to the reference rainfall that was estimated by NEXRAD radars and adjusted using rain gauges. These results illustrate how SREM2D is capable of generating a 50-member ensemble that generally encompasses the reference rainfall and yields ensemble spread that is based on the residuals between reference and satellite rainfall. Although the underestimation from CMORPH has been largely corrected, SREM2D had a tendency to overestimate rainfall during the warm season months.

HyMODs that are used for flood prediction purposes have imperfect physical representations, which generally become more evident at small basin scales. Simulated basin responses to rainfall will generally improve following the estimation of model parameters and states. Parameter estimation, also referred to as model calibration, is the process of utilizing observations of the system behavior (i.e., streamflow response to rainfall) in order to iteratively adjust parameters to yield streamflow simulations that better match observations. This process can be quite complex as it involves interactions among model parameters, different or multiple modeling objectives in terms of objective function(s) and variables, and uncertainties in the observations. When using satellite-based algorithms, another oft-ignored feature to consider is the pixel resolution of the satellite precipitation estimates. Gourley et al. evaluated a variety of rainfall estimates from ground-based radar, satellite, rain gauges, and combinations using a HyMOD on the densely instrumented Ft. Cobb basin in OK [14]. In addition to streamflow observations from a stream gauge, they made use of a reference simulation that was forced by gauged rainfall observed by a dense Micronet in the basin. This reference simulation served as a benchmark representing the most accurate simulation to be expected for the HyMOD given the high accuracy and density of the rainfall observations.

Model parameters were automatically estimated using the reference Micronet rainfall forcing at 4 km/h and then aggregated up to the 0.25°/3 h resolution corresponding to TRMM level 3 rainfall algorithms. These two models were thus calibrated with the “best” reference rainfall at two different resolutions. It turns out the HyMOD parameters were sensitive to the rainfall pixel and corresponding model grid cell resolution. It is useful to define a metric that is similar to the Nash–Sutcliffe Coefficient of Efficiency (NSCE) but provides information about the simulation skill in reference to the Micronet-forced simulation rather than the mean of the observed streamflow. The Micronet-relative efficiency (MRE) is thus defined as follows:

\[
MRE = 1 - \frac{\sum_{i=0}^{N} (Q_i^R - Q_i^{\text{obs}})^2}{\sum_{i=0}^{N} (Q_i^{\text{Micronet}} - Q_i^{\text{obs}})^2}
\]

(25.1)

where
- \(Q\) corresponds to streamflow
- the superscript R is for the different rainfall algorithms
- obs is for observed

Figure 25.3 shows the model performance relative to the simulations that used the reference Micronet rainfall forcing at the 4 km/h resolution. As expected, there is degradation in MRE when the HyMOD was forced with rainfall values that were different than the reference values used in calibration. The curves noted with “RESAMPLE” correspond to the simulations that were forced by TRMM 3B42RT and 3B42V6 into the model calibrated at the coarser satellite resolution. By considering this resolution difference, we now see the RESAMPLE simulations have improved markedly. In fact, the RT-RESAMPLE simulation has equivalent skill to the V6 forcing into the model calibrated at the finer resolution. This result indicates that the consideration of the satellite product resolution has a considerable impact on hydrological simulation, perhaps as important as the errors in the rainfall retrievals themselves.
Data assimilation methods such as variational approaches and the extended Kalman filter (EKF) are well suited for updating and improving model state estimation, such as soil moisture, and have shown great potential for improving hydrological forecasts. The technique discussed here is the EnSRF [51], which is a deterministic Monte Carlo simplification of the EKF. The EnSRF can be designed to account for uncertainties in the precipitation forcing (e.g., using a perturbations from SREM2D), in model states, and in the observed system behavior (i.e., streamflow) when generating hydrological forecasts. The variables commonly assimilated in HyMODs include soil moisture and streamflow, observed by gauges or from spaceborne instruments. The following section will focus on the assimilation of remotely sensed discharge using passive MW brightness temperature signals from AMSR-E onboard the Aqua satellite.

A time series of streamflow observed by the Rundu stream gauge and the AMSR-E signal at a collocated pixel at the basin outlet of the Cubango River located in southwest Africa was found to be very well correlated with a Pearson linear correlation coefficient of 0.94. It is noted, however, that the AMSR-E signal is in dimensionless units and shows poor sensitivity during low-flow periods. Additional procedures, such as comparing the signal to observed discharge, must be implemented in order to calibrate the signal to represent fluxes (in units of m³/s). Khan et al. introduced an alternative, called the exceedance probability approach, in hydrological modeling to normalize observations in the frequency domain by utilizing the period of recorded observations [26]. The technique can be applied to any time series data and has been recently adopted in order to assimilate AMSR-E signal data as a proxy for observed streamflow. This approach essentially converts the AMSR-E signal ratios into probability of exceedance (%), thus improving the signal’s applicability without the requirement of in situ streamflow measurements.

The dimensionless AMSR-E signal data were first converted into probability of exceedance using the available data archive. This proxy for river discharge measurements (now in the frequency domain) was subsequently used to automatically estimate parameters in the lumped, parsimonious HyMOD. This procedure required that the simulated streamflow data were converted into the frequency domain as well so that the simulated and proxy-observed data were both expressed as probability of exceedance. The conversion also enabled the assimilation of AMSR-E signals in order to update internal model states. Figure 25.4a shows simulated streamflow from the calibrated HyMOD with and without assimilation of the AMSR-E data. Simulated streamflow with data assimilation matches peak flows better...
than without data assimilation. However, there are apparently spurious AMSR-E signals during low-flow periods (i.e., November 2003) that result in degraded performance following data assimilation. The statistical performance of these experiments was compared to simulations from the HyMOD that was calibrated with streamflow observations from the Rundu gauge and also assimilated these streamflow observations; the benchmark was from a traditional gauge-calibrated HyMOD that incorporated data assimilation.

The NSCE and root-mean-square error (RMSE) with the benchmark assimilation were 0.88 and 42.0%. When the AMSR-E data were used as the streamflow proxy for calibration and assimilation, the performance dropped to 0.60 and 52.3% for NSCE and RMSE, respectively. In order to address the low-flow sensitivity problem with AMSR-E signal data, a “high-flow threshold” was applied to assimilate AMSR-E data only if the probability of exceedance was less than 30%. Figure 25.4b shows that the “assimilation” curve now performs much better during low-flow periods and is still capable of simulating the peak flows. This latter experiment had an NSCE of 0.85 and RMSE of 47.4%. These values are quite comparable to the benchmark simulation that used stream gauge observations for model

**FIGURE 25.4** Time series of gauge streamflow (shaded in gray), AMSR-E signal (short-dashed curve), simulated streamflow without data assimilation (long-dashed curve), and simulated streamflow with data assimilation (solid curve) when using the AMSR-E signal (a) all the time and (b) only when the probability of exceedance was less than 30%.
calibration and data assimilation. This study promotes the concept of precipitation estimation, model calibration, data assimilation, and flood forecasting based entirely on remote-sensing data. Provided near-global coverage of remote-sensing data, possibilities for prediction in ungauged basins are becoming increasingly viable.

### 25.5 Summary and Conclusions

This chapter includes examples of studies that demonstrate the feasibility of assessing inundation extent from space. This can be done at regional and global scales as well as local scale like coastal regions, for instance. Information on inundation extent is valuable for HyMODs. In addition, the retrieval of information on precipitation was discussed, and methodologies to QPE and QPF were addressed. Several approaches that are based on radar and satellite measurements were compared. Finally, the last section of this chapter demonstrates the important role that information on land surface parameters and precipitation have in the development of accurate understanding of hydrological processes, particularly when integrated through data assimilation processes in gridded land surface models.

### References


