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Remote Sensing Data and Information for Hydrological Monitoring and Modeling

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PREFACE

Advances in remote sensing techniques provide capabilities for the estimation of hydrological parameters at different spatial and temporal scales not necessarily possible with traditional field measurement techniques. This chapter provides an overview of how remote sensing techniques have been used over recent decades to estimate hydrological parameters including precipitation, evapotranspiration (ET), soil moisture, snow, lake ice, land use, and land cover. The sensors used are electromagnetic (in the visible [VIS], infrared [IR], or microwave [MW] sections of the spectrum) or gravitational, and may be passive or active. Case studies are presented to illustrate the use of remote sensing–based parameters in distributed hydrological models, for example, for flash flood forecasting, and for environmental studies.

24.1 Introduction

Remote sensing data and information have shown great potential in supplying relevant spatial data and parameters at the appropriate scale for use in distributed hydrological models for water resource applications. In contrast with many conventional data normally represented by point measurements, AQ1 remote sensing–based measurements are spatially averages over the pixels can appropriate for distributed hydrological model. Furthermore, remote sensing enables data access from remote areas, where data are typically sparse. Remote sensing technology used electromagnetic spectrum in the range of wavelengths of different radiations reflected or emitted by objects. Although remote sensing spectrum varies from 0.03 nm to 100 cm, VIS, IR, and MW spectra are commonly used in the retrieval of hydrological parameters.

There are two main types of remote sensing: passive remote sensing and active remote sensing. The passive systems are based on the measurement of the natural thermal emission in the form of brightness temperature from the earth surface. On the other hand, the active MW systems generate their own radiation, which is transmitted toward the earth surface, and measure the reflected energy.

The unique characteristics of MW energy compared to the VIS and IR remote sensing systems are the ability to penetrate the atmosphere under various conditions including clouds, light rain, snow, and smoke, as well as the ability of low frequency to penetrate vegetation up to a certain level. MW radiation is independent of solar radiation and can be used during both nighttime and daytime hours; high-frequency MWs are partially absorbed by vegetation; therefore, emitted signatures contain information on vegetation properties [82]. The MW remote sensing data, which are more suitable to estimate hydrological variables including snow, soil moisture, and precipitation, can be obtained during day- or nighttime.

There are two critical characteristics of remote sensing data that used in advancing measuring hydrological parameters are spatial and temporal resolutions. Remote sensing obtains spatially distributed information of hydrological variables that is important and helps to understand the spatial variability of watershed properties, to be included in modeling analysis. These datasets can be obtained in one definite time interval, which varies based on sensors and type of orbit. The parameters such as precipitation are being monitored at every 15 min interval. AQ2 AQ3

24.2 Monitoring Hydrological Parameters

24.2.1 Precipitation

Precipitation is a crucial parameter that drives the hydrological cycle, thus helps to improve weather and climate predictions. Improving hydrologic forecasting requires accurate quantitative precipitation measurements at higher temporal and spatial scales. The old and usually reliable network of rain gages provides an overview of approximate precipitation. However, spatial densities of these rain gages are the limiting factor to accurately capture the highly varied nature of precipitation. In such cases, remote sensing–based precipitation provides a spatially continuous gridded dataset, using area-averaged remotely sensed information rather than strictly an interpolated point-based rain gage field.

Precipitation retrievals from remote sensing sensors are carried out using VIS, IR, and MW wavelengths on geostationary and polar orbiting satellites. The IR sensor aboard detects radiation within the IR wavelengths that is emitted from the nearest surface beneath the satellite. This radiation is converted to a temperature and may be then correlated to surface-based rainfall based on an assumption such as that colder cloud temperatures indicate clouds of higher vertical extent and thus may be producing more rainfall. The currently operated IR sensors include National Oceanic and Atmospheric Administration (NOAA) Geostationary Operational Environmental Satellite (GOES), European METEOSAT, Russia's Elektro-L, and India's INSAT.

The MW sensors estimate rainfall based on a radiation emitted from sources such as liquid water droplets or suspended ice particles. Surface-based rainfall is thus correlated to the extent and composition of actual water in the atmosphere. The examples of MW-based sensors include NOAA, Defense Meteorological Satellite Program (DMSP), and TRMM satellites. The TRMM precipitation radar (PR) is an active sensor that measures the change between emitted and returned radiation due to atmospheric water particles and relates this to previously determined surface rainfall intensity [51].

The GPM is an international mission by JAXA and NASA as well as other international agencies that aims to unify and advance global precipitation measurements using MW sensors to be expected to be launched in 2014. This mission will provide global uniformly calibrated precipitation observations at every 2–4 h. The GPM mission will deploy dual-frequency precipitation radar (DPR) and a multichannel GPM Microwave Imager (GMI) with high-frequency capabilities. The GMI will serve as a reference standard for the constellation radiometers by means of an advanced calibration system, and the DPR will provide microphysical measurements such as particle size distribution and vertical structure of precipitating cloud systems. This system will be used in conjunction with cloud-resolving models for the creation of a common cloud-radiation database for precipitation retrievals from both the GMI and the constellation radiometers. The constellation members in GPM will be represented by existing or future satellites of opportunity such as those of the US DMSP, the EUMETSAT Polar System (EPS), the Japanese Global Change Observation Mission, the French–Indian tropical mission Megha-Tropiques, and several others that are currently being planned. During the last two decades, several algorithms are developed for estimating rainfall from IR and MW satellite observations.

The global precipitation records from point measurements are available through last century (GPCC; http://gpcc.dwd.de). However, these datasets have own inherent adequacies to quantify the distribution of global precipitation to yield acceptable global climatology. The Global Precipitation Climatology Project was established by the World Climate Research Program in 1986 with an approach to merge data and information available from several sources of precipitation including IR and MW remote sensing sensors and rain gages [38].

24.2.2 Evapotranspiration

ET is the largest component in terrestrial water budgets consisting of 60% of land precipitation. It modulates land surface energy budget and constitutes an important source of water vapor to the atmosphere. However, atmospheric water vapor is the most significant greenhouse gas and thus plays a fundamental role in weather and climate [39].

First, the remote sensing approach to estimate ET is based on thermal IR spectrum wavelength, by solving simplified form of surface energy balance model. In this approach, the radiometric surface temperature is used for estimating the sensible heat flux (H) and obtaining ET as a residual of the energy balance. The latent heat flux (LE) representing the ET fraction can be derived from

$$\mathrm{LE} = \mathrm{R_n} - \mathrm{G} - \mathrm{H} \tag{24.1}$$

where

LE is the latent heat of evaporation due to ET

R_n is the net radiation absorbed by the land surface, equal to incoming solar radiation (R_s) minus outgoing shortwave and longwave radiations

H is the sensible heat flux to the atmosphere

G is the heat flux to the soil

In this equation, variables are expressed in energy units (W m^{-2}). ET can be calculated from LE by the amount of energy needed to evaporate water at a given temperature and pressure. If heat transfer coefficients are known or can be estimated, H can, in theory, be calculated from the difference between air temperature at reference height and the land surface temperature, measured by thermal IR bands on satellites such as the Landsat series [2,7], GOES [40], the Advanced Very High Resolution Radiometer series [58], the Advanced Spaceborne Thermal Emission and Reflection Radiometer [24,77], and the Moderate Resolution Imaging Spectrometer (MODIS) sensors, both on the Terra satellite [63,64]. Estimates of R_n and G are available from remote sensing or ground data, allowing LE to be calculated as a residual in the earlier equation. This approach has been applied widely to ET measurements with higher accuracy in semiarid regions.

The second approach to estimate ET is based on vegetation indices derived from canopy reflectance data. In this approach, the crop coefficients are estimated, which are further used to convert reference ET to actual crop ET. The crop coefficients are modified for water demands by irrigated crops. The crop coefficients are empirical ratios relating crop ET to a calculated reference-crop ET that is based on atmospheric water demand over a crop cycle or to actual ET measurements [65]. A time series of vegetation indices is correlated with measured ET to develop a curve over the crop cycle. This approach requires local meteorological and soil data to maintain a water balance in the root zone of the crop [28]. Duchemin et al. (2006) developed linear relationship between NDVI and crop coefficients with good accuracy to derive maps of leaf area index (LAI) and transpiration requirements using Landsat7-(Enhanced Thematic Mapper) ETM+ images for agricultural area. The vegetation indices–based approach is also tested successfully using AVHRR [21,68] and MODIS [16,32,54,65]. The future design of earth observation systems with higher spatial and temporal resolutions would make these approaches feasible for the operational monitoring of ET at a regional and global scale. AQ4

24.2.3 Soil Moisture

Soil moisture is a very important variable in hydrology because its variations influence the evolution of weather and climate. The soil moisture controls runoff, affects vegetation growth, and plays a significant role in evaporation and transpiration at the land–atmosphere boundary as well as surface energy flux [9]. However, conducting ground-based measurements of soil moisture consistently and regionally is difficult. Remote sensing provides an opportunity without the limitation of time and area. Active and passive remote sensing systems and especially those operating in the MW region of the electromagnetic spectrum have shown the ability to measure the soil moisture content since it is very sensitive to the dielectric properties of the soil. Low-frequency MW spectrum has the advantage of longer penetration and, therefore, less atmospheric effect.

Spaceborne active MW sensors are able to provide high spatial resolution (up to 10 m), but have low temporal resolution and are more sensitive to surface characteristics than passive systems. However, passive MW sensors provide low spatial resolutions (40–50 km) with a higher temporal resolution (12–24 h). Most of the applications of active MW in soil moisture retrieval are based on the hypothesis that the signal backscattered from the observed scene is widely dependent on the dielectric contrast that exists between wet and dry soils. Indeed, under the same land cover condition, the stronger radar backscattering values are observed for high soil moisture. However, soil moisture estimation based on active MW data only may face several challenges since the MW sensors are sensitive to other land cover characteristics such as vegetation density, surface roughness, and soil texture [20,34,83].

The accuracy of satellite-derived soil moisture is usually affected by the presence of vegetation, which significantly modifies and attenuates the outgoing MW radiation of the soil and makes the retrieval of realistic soil moisture from satellite-based sensors difficult and inaccurate. Soil moisture estimation by active remote sensing involves the measurement of backscattering, which may be affected by both vegetation canopy and soil moisture. The vegetation canopy may affect the backscattered energy by contributing to the volume backscatter of the observed scene and by attenuating the soil component of the total backscatter [44,83]. The total amount of attenuation and backscatter depends on several vegetation parameters, such as vegetation height, LAI, and vegetation water content, and on sensor-related characteristics such as angle of incidence, frequency, and polarization.

Two MW satellite missions, the European Space Agency (ESA) Earth Explorer Soil Moisture and Ocean Salinity (SMOS) launched in November 2009 and Soil Moisture Active Passive (SMAP) by NASA, which has been proposed to launch in 2015, take advantages of low frequency in soil moisture retrievals. SMOS mission has been designed to observe soil moisture over the global land with the first-ever polar-orbiting spaceborne radiometer. This novel technique of the SMOS mission will provide operational monitoring of water in soils. SMAP mission will overlap with the SMOS mission in time so that it will enable intercalibration and intercomparison of their respective data. Moreover, the synthetic aperture radar (SAR) in the SMAP will provide higher spatial resolution (1–3 km) soil moisture product. The EPS METOP will be a continuation of ERS scatterometer mission carrying the advanced scatterometer ASCAT. The METOP satellite series, with advanced scatterometer on board, will be the first operational satellite system dedicated to the retrieval of soil moisture information.

24.2.4 Snow

The storage of water in snowpack affects the surface runoff and soil moisture and is therefore important at the regional scale for various applications such as flood prediction and water resource management. The rising in air temperature over land and at most high northern latitudes, where snow cover is projected to contract, widespread melting of snow and ice could lead to rising global average sea level [39].

Satellite observations in the VIS and MW spectral range have been used for the global monitoring of snow cover properties for more than three decades.

Remote sensing sensors in VIS/IR spectrum that are well-appropriate snow cover mapping due to the high albedo of snow present a good contrast with most other natural surfaces except clouds. The two VIS- and IR-based snow products are widely used for large-scale climate research. The interactive multisensor snow and ice mapping system (IMS) by NOAA provides daily snow cover information AQ5 for Northern Hemisphere. IMS product has been based primarily on VIS and near-IR observations, judged and mapped manually and covers the period from late 1998 to present, is being continues to undergo, improvements and refinements. IMS snow cover product is being produced every day regard- AQ6 less of the presence of clouds. This possible due to IMS analysts looping through sequential GOES and AQ7 AVHRR images to evaluate scenes is based on integrated information [36,72]. Second, the suite of products derived from the MODIS by NASA provides weekly global snow cover information. The MODIS snow products are provided as a sequence of products beginning with a swath product and progressing, through spatial and temporal transformations, to an 8 day global-gridded product (http://modis-snow-ice.gsfc.nasa.gov/). Snow cover products derived from MODIS are based on a band rationing of MODIS band 4 (green) (0.545–0.565 μm) and band 6 (near-IR) (1.628–1.652 μm). These bands are used to calculate the normalized difference snow index [33].

The passive MW remote sensing sensors, the Scanning Multichannel Microwave Radiometer (SMMR, 1978–1987), Special Sensor Microwave/Imager (SSM/I, 1987–present), and the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) on board the Aqua satellite (2002–2011), provided opportunity to global snow cover and snow water equivalent (SWE) mapping [6,46]. MW emission from snowpack depends on the snow grain size, density, depth, and SWE [31]. Passive MW sensors have the advantage of penetrating the cloud cover unlike VIS/IR sensors. However, passive MW data suffer from being a low-resolution measurement, on the order of 25 km. Therefore, an effort is being made to develop a combination of the two products to provide a significant improvement of snow cover and SWE product with high spatial resolution from the VIS/IR data and cloud transparency from the MW data [3,23,25,56,86].

24.2.5 River and Lake Ice

An effect of ice in river and lake produces an increased hydraulic resistance by growing ice and storage of frozen winter precipitation that can readily be seen in dramatic short-term changes in flow and water AQ8 levels [70]. Freeze-up and break-up dates of the ice in rivers and lakes cause the seasonal hydrograph changes, which result in the storage and later release of significant quantities of water within river channels. Variability and trends in river and lake ice dynamics can serve as indicators of climatic change, as climate influences the timing of lake ice melt and freeze onset, ice duration, and lake thermal dynamics that feedback to the climate system initiating further change [53].

In the past decade, the use of satellite data has gradually developed to the point that today remote sensing–based techniques are the main tool in lake and river ice observation and monitoring. VIS and IR channels on board of polar orbiting satellites are capable of the visualization of the lake and river ice and location under cloud-free condition. Polar orbiting satellites such as MODIS, AVHRR, and Landsat were extensively being used due to their higher spatial resolution. Latifovic and Pouliot (2007) proposed a profile feature extraction technique for lake ice phenology from historical satellite records acquired by the series of AVHRR sensors and then compared them with in situ observations successfully with high accuracy.

Active MW SAR data are also used successfully in conjunction with VIS and IR channels in order to monitor the ice extent, growth, and thickness even in the presence of cloud. However, temporal resolution (5–6 days) of current radar sensors and the short period for which measurements are available limit their use for climate change studies and operational monitoring [19]. Using SAR data (ERS-2 and RADARSAT-1), Nolan et al. (2003) were able to determine dates of lake ice formation, snowmelt, and ice melt to within a few days for four winter seasons [67].

24.2.6 Water Storage

Changes in terrestrial surface water storage affect the gravity field, where the added water mass exert a slight additional attraction. Precise measurements of changes in the gravity field sensed by orbiting satellites give information about seasonal and interannual shifts in the surface mass distribution. Over land, the filling and emptying of water pools, including soil and aquifers, is the main contributor to gravity changes, though hydrologically irrelevant contributions such as glacial rebound of the lithosphere exists and must be subtracted from the total gravity signal to estimate the change in water storage. While gravimetric remote sensing cannot distinguish between different surface water pools at a given location, subtracting known changes in pools (such as lakes and snowpack) permits inference of changes in otherwise poorly observed regional pools (such as groundwater).

Gravity Recovery and Climate Experiment (GRACE) is a pair of NASA satellites launched in March 2002, which measure earth's gravity field from orbits at about 500 km height. Small changes in the distances between the satellites, due to gravity field variations, are measured via onboard K-band MW signals and the global positioning system. GRACE generates maps of gravity anomalies at approximately monthly time resolution and ~250 km spatial resolution [79].

Over land, GRACE products show seasonal wet–dry cycles in areas such as the Amazon and Mississippi basins [78]. Interannual variability in water storage can be used to quantify drought and pluvial episodes. Regional decreasing trends in water storage over the observation period have been found, due to ice sheet melting over parts of Greenland and Antarctica and due to unsustainable groundwater withdrawals in regions such as northern India [81] and California's Central Valley.

The constraints provided by GRACE data for hydrological variability have been used in various ways to test and improve hydrological models. For example, Niu et al. (2007) subtracted modeled soil moisture and groundwater variability from total water storage change inferred from GRACE to deduce SWE over boreal river basins [66]. Syed et al. (2008) compared water storage variability inferred from GRACE with that given by the Global Land Data Assimilation System [80]. Assimilation of water storage information from GRACE into regional hydrologic models, combined with other data such as streamflow, has been shown to improve the realism of these models' simulations of river discharge and groundwater levels [57,85]. On the scale of large river basins, GRACE storage changes have been used together with precipitation, evaporation, and streamflow estimated from remote sensing and/or ground observations to test whether these estimates are good enough to close the water budget [76], and the correlation of GRACE water storage with observed streamflow has been used to extend water storage estimates to times where GRACE data are not available [8]. GRACE water storage has also been compared to streamflow in small watersheds (tens of square km) in order to clarify the consistency of the relationship between streamflow and watershed storage [50]. Bloom et al. (2010) correlated GRACE water storage with anomalies in column atmospheric methane, inferring that tropical moisture status is the leading contributor to interannual variability in methane emissions [11].

24.2.7 Water Quality

Water quality is a general descriptor of water properties in terms of physical, chemical, thermal, and/or biological characteristics that are suitable for human consumption. Major factors affecting water quality in water bodies include suspended solids, algae (chlorophylls), chemicals, dissolved organic matter, thermal releases, aquatic vascular plants, pathogens, and oils. Monitoring and assessing the water quality are critical for managing and improving its quality. Polar orbiting, high spatial resolution hyperspectral remote sensing sensors are being used increasingly as a tool for monitoring water quality conditions in inland and near-coastal waters. Remote sensing techniques to estimates these water quality parameters are based on changes in the spectral signature from water bodies and relate these measured changes onsite by empirical or analytical models. The empirical approach is based on using experimental datasets and statistical regression techniques to generate algorithms relating the water reflectance or radiances at the sensor in specific spectral bands or band ratios/combinations to the observed in situ water quality

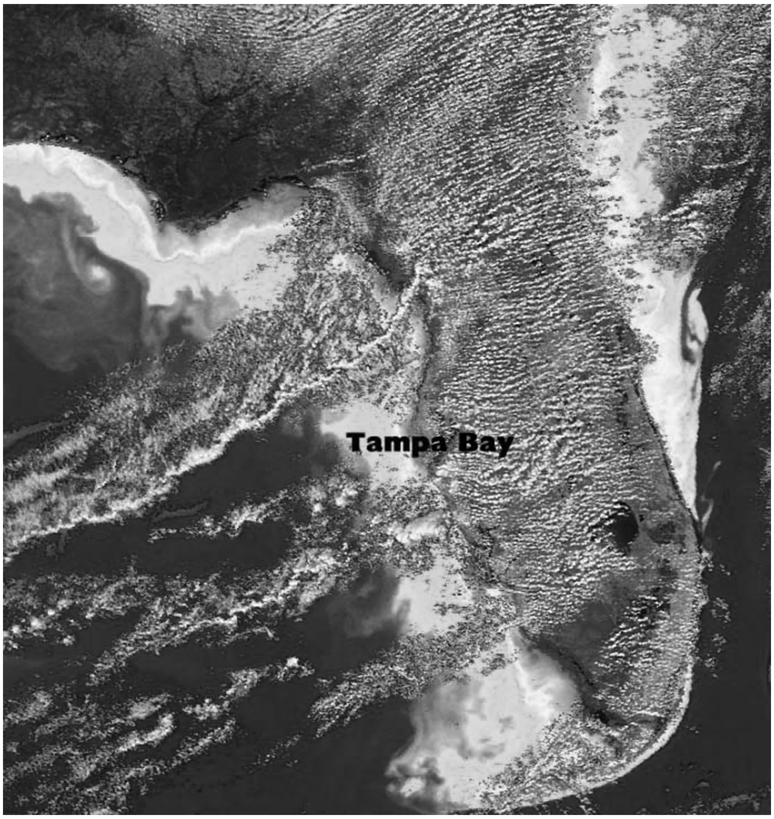

FIGURE 24.1 High concentrations of microscopic plants called phytoplankton (red regions) along the Florida coast and in Tampa Bay are an indicator of ocean health and change as seen in this SeaWiFS image from October 2004. (Photo courtesy of NASA, Washington, DC.)

AQ9 parameters [62]. The selection of spectral channel depends upon type and concentration water quality
AQ10 parameters (Figures 24.1 and 24.2).

Most of the research for water quality using remote sensing sensors has been carried out for chlorophyll content estimation, which is then used as an estimate for observing algal content and hence water quality. Commonly detected water quality parameters include the concentrations of phytoplankton pigments chlorophyll a (Chl a) [1,12,62], total suspended solids and inorganic suspended solids [26,45,48,55,84], absorption by colored dissolved organic matter [52], and indicators of water clarity such as turbidity [30,69]. High-resolution Landsat ETM was used to estimate chlorophyll a (Chl a) concentrations using band ratios for lakes [1,12] and coastal sewage outfall area [22]. The Medium Resolution Imaging Spectrometer (MERIS) on board ESA's ENVISAT is used successfully to estimate algal bloom and colored dissolved oxygen [15,27,59]. MODIS remote sensing data in conjunction with logarithmic band ratio model have shown its capability to monitor the impact of hurricane impact on chlorophyll-a concentration in Pensacola Bay system [37]. Estimation of water quality parameters from remote sensing has proved to be useful and successful and is being investigated for operational use.

24.2.8 Land Use–Land Cover

The vegetation or land cover plays critical part in hydrological processes including interception and transpiration, which are sink or loss term in water balance model. The runoff curve number uses land use/land cover condition with soil texture to estimate runoff from precipitation. Therefore, accurate

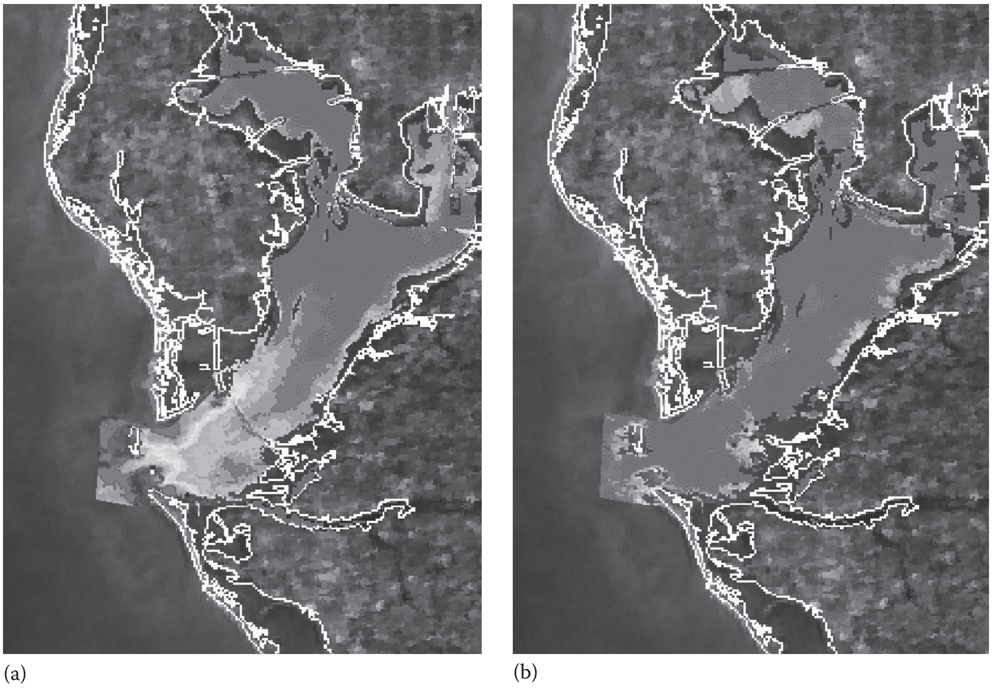

FIGURE 24.2 MODIS imagery has shown that water quality of Florida's Tampa Bay decreases in winter months compared to summer. More particles suspended in the water, a measure called turbidity, show up as yellow, orange, and red in December (a) than in July (b). Images are composites of turbidity data collected in December and July, respectively, over a span of 3 years. (Photo courtesy of NASA/USF, Washington, DC.) AQ11

information on land cover and land cover changes over time is necessary for hydrological modeling. AQ12 Remote sensing is a powerful and cost-effective tool for assessing the spatial and temporal dynamics of land use and land cover to evaluate deforestation, biodiversity loss, and climate change [71,74]. Therefore, information on land use and land cover changes is critical for the decision making of environmental and water resources management and future planning. Multitemporal images provided by remote sensing sensors for same location are being used in conjunction with geographical information system to effectively determine the land use and land cover changes over time [42]. In addition, retrospective and consistent synoptic coverage over 40 years from remote sensing satellites is greatly benefited to assess the historic or long-term land cover changes for climate studies.

Change detection methods including pre- and postclassification have been used wildly to evaluate land use and land cover changes using remote sensing satellite data [35,41,47] In preclassification approach, procedures such as image differencing [10], band rationing [4], change vector analysis [5], and principal component analysis [14] have been developed and used. These techniques are developed on basic approach to estimate the differences in the pixel reflectance values between the dates of interest. However, while these techniques are effective for identifying change, they cannot identify the nature of change. On the other hand, in postclassification method, the comparison was done over independently classified land cover data. Despite the difficulties associated with postclassification comparisons, this technique is most widely used for identifying land use and land cover changes [17].

24.3 Remote Sensing in Hydrological Modeling

The emergence of distributed hydrological model provides a powerful tool for water resource management under changing environments. Distributed hydrological models are commonly physically based water balance/water transport model that requires large amounts of high-resolution input data. The constant improvement of remote sensing data availability made it possible to meet data needs in distributed hydrological simulation. Compared with the conventional observation method, remote sensing can periodically obtain grid-based ground observations within a certain period, so as to elevate the temporal–spatial resolution of data.

24.3.1 Land Surface Modeling

Historically, regional and global analyses and reanalyses used for weather forecasting or for diagnosing climate variability and change did not directly use observations of many water fluxes and stores, either due to lack of observations (as for, e.g., soil moisture) or because the assimilation techniques for using these variables were not developed (as for, e.g., precipitation) [43]. This has improved to some extent in recent years, for example, the North American Regional Reanalysis [60] ingested land and sea snow/ice cover products based on remote sensing, and precipitation gage observations over land as well as precipitation information from satellites (CMAP) over oceans. In numerical weather forecasting models, there is a fundamental need to incorporate those physical processes in the analysis that are linked to atmospheric moisture and dynamics. NASA's Land Data Assimilation System project has used observation-based forcing (precipitation, temperature, radiation) datasets to drive land surface models over recent decades, helping elucidate trends and variability in soil moisture [29,73,88], but still does not use available observations of soil moisture or many other land surface variables.

Several recent pilot studies have showed encouraging results in assimilating remotely sensed soil moisture into land surface models in reanalysis mode, taking into account that soil moisture information based on MW is typical only for a surface layer rather than for the entire soil column [75,89].

Preliminary work has also sought to assimilate both thermal and MW information on moisture status in order to better constrain soil moisture at different depths. Additional data streams to assimilate include observed streamflow, which could in some cases be estimated from remote sensing, and GRACE water storage change [87]. Improvements in analyzed hydrology resulting from making full use of earth observing satellite observations promise to not only result in more accurate retrospective estimates of regional-to-global hydrological variability and change, but also improve intermediate-to-seasonal range weather forecasts through better capturing land–atmosphere feedbacks [13,49,61].

24.3.2 Flash Flood Guidance and Forecasting

Climate change and variability increase the probability of frequency, timing, intensity, and duration of flood events. After precipitation, soil moisture is the most important factor dictating flooding, since rainfall infiltration and runoff are based on the saturation of the soil. Flash flood guidance (FFG) systems provide lead-time for emergency responders to evacuate citizens and deploy resources to assess flood damage. Remote sensing technologies have proved to be valuable tools to support effective early flood warning system for disasters. There are few FFG systems that have the capability to indicate the likelihood of flooding of small streams or rivers over large regions by using bias-corrected remotely sensed precipitation estimates and real-time soil moisture estimates to produce FFG. The FFG systems have the potential to provide advance warning of situations likely to lead to floods and thus provide additional lead-time for emergency managers to monitor the situation and provide improved flood forecasting services. The FFG models are commonly water balance models that portray the grid-based runoff generation process, using grid-based inputs including precipitation, evaporation, soil moisture, soil type, vegetation, and other underlying surface information.

Currently, National Weather Service issues a daily national map of gridded flash flood guidance, which is produced based on surface soil moisture deficit and threshold runoff estimates. Similarly, the Central America Flash Flood Guidance System (a regional FFG system) has been in operation since 2004. These systems use real-time remotely sensed precipitation datasets from NOAA satellites. However, these systems are limited by real-time observations of soil moisture and hence use model-derived soil moisture information. Improved flash flood forecasting requires accurate and high-resolution soil surface information. Recent development in soil moisture estimation using remote sensing shows potential in flash flood application. The already launched SMOS satellite's mission and future SMAP mission are two potential sources of remotely sensed soil moisture data. SMAP is a directed mission within the NASA Earth Systematic Mission Program and is planned to launch in 2015, while SMOS is a Living Planet Programme from the ESA and launched in November 2009.

24.4 Summary and Conclusions

Advances in remote sensing techniques provided many advantages in the estimation of hydrological parameters at different spatial and temporal scales over traditional field measurement techniques reliably with sufficient accuracy. Over the last 10 years, use of remote sensing techniques in hydrology has advanced greatly with the launch of research platforms such as Terra and Aqua, TRMM, and operational platforms such as GOES and the DMSP series, as well as many other satellite platforms, and with the development of more sophisticated retrieval algorithms.

Currently, remote sensing data are being used operationally for the estimation of hydrological variables including precipitation, soil moisture, snow, and ice at varying spatial and temporal resolutions and accuracy via remote sensing. In the next decade, significant progress is expected in measuring other variables including albedo measurements, ET, sediment loads, erosion, and groundwater, to be operationally available for hydrological models. In some cases, current operational remote sensing–based techniques are used in only limited areas due to restriction from heavy forest or higher elevation mountains, but their use is expected to expand in the future. However, these problems can be solved through additional research and development.

Using passive MW remote sensing for measuring snow, soil moisture, and precipitation has been used operationally; however, one of the limitations in measuring these parameters is lower spatial scale. Much effort is needed to develop a framework to integrate multifrequency remote sensing information to produce high-resolution hydrological products that can be used over a range of spatial scales, from field, farm, and watershed, up to regional scales. In case of precipitation, there are many remote sensing possibilities including ground-based radar, VIS and thermal IR satellite imagery, and MW satellite data. However, development of hybrid solutions to combine the benefits of satellites and ground observations (e.g., ground radars and gage networks), and advanced multispectral algorithms to improve the accuracy and spatial resolution of satellite precipitation is needed.

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AUTHOR QUERIES

[AQ1] Please check the part "spatially averages over the pixels can appropriate" for correctness and sense.
[AQ2] Please check the sentence starting with "There are two critical characteristics…" for sense.
[AQ3] Please check if edit to the sentence starting with "These datasets can be obtained…" is okay.
[AQ4] Please check if edit to the sentence starting with "The future design of…" is okay.
[AQ5] Please check the sentence starting with "IMS product has been…" for sense.
[AQ6] Please check the sentence starting with "This possible due to IMS…" for sense.
[AQ7] Consider including the term "first" in appropriate sentence for better clarity.
[AQ8] Please check if edit to the sentence starting with "Freeze-up and break-up…" is okay.
[AQ9] Please check the sense of the phrase "concentration water quality."
[AQ10] Please check the inserted citations of Figures 24.1 and 24.2.
[AQ11] Figures are to be set in grayscale. Please rephrase the mention of color in the caption of Figures 24.1 and 24.2.
[AQ12] Please check if "land cover and land cover" should be "land use and land cover" in the sentence "Therefore, accurate information…."
[AQ13] Please provide complete details for Refs. [3,30].
[AQ14] Please provide in-text citation for Ref. [18].
[AQ15] Please provide the volume number and page range in Refs. [45] and [87].
[AQ16] Please provide all the authors' names or 7 authors plus et al. if the total number of author is more than 11.