Remote Sensing Data and Information for Hydrological Monitoring and Modeling

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1 Introduction

Remote sensing data and information are 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, 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, visible, infrared and microwave spectrum is commonly used in 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 microwave systems generate their own radiation, which is transmitted toward the earth surface, and measures the reflected energy.

The unique characteristics of microwave energy compared to the Visible and Infrared 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. Microwave radiation is independent of solar radiation and can be used during both night-time and day-time hours; high frequency microwaves are partially absorbed by vegetation, therefore emitted signatures contain information on vegetation properties (Ulaby et al. 1981). The microwave remote sensing data is more suitable to estimate hydrological variables including snow, soil moisture, and precipitation, can be obtained during day or night time.

There are two critical characteristics of remote sensing data that used in advancing measuring hydrological parameters are spatial and temporal resolution. 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 on definite time interval, that varies based on sensors and type of orbit. The parameters such as precipitation, is being monitored at every 15 minute interval.

2 Monitoring Hydrological Parameters

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 gauges provides an overview of approximate precipitation. However, spatial densities of these rain gauges 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 gauge field.

Precipitation retrievals from remote sensing sensors are carried out using visible (VIS), infrared (IR) and microwave (MW) wavelengths on geostationary and polar orbiting satellites. The Infrared (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 includes: NOAA GOES, European Meteosat, Russia’s Elektro–L, India’s INSAT, etc.

The Microwave (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 microwave based sensors includes: NOAA, DMSP, TRMM satellites, etc. 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 (Kummerow et al. 1998).

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 microwave sensors to be expected to launch in 2014. This mission will provide global, uniformly calibrated precipitation observations at every 2-4 hour. The GPM mission will deploy Dual-frequency Precipitation Radar (DPR) and a multi-channel 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 Defense Meteorological Satellite Program (DMSP), the EUMETSAT Polar System (EPS), the Japanese Global Change Observation Mission (GCOM), the French-Indian tropical mission Megha-Tropiques and several other that are currently being planned. During last two decades several algorithms are developed for estimating rainfall from infrared (IR) and microwave satellite observations.

The global precipitation records from point measurements are available through last century (GPCC; http://gpcc.dwd.de). However, these datasets has own inherent adequacies to quantify distribution of global precipitation to yield acceptable global climatology. The Global Precipitation Climatology Project (GPCP) was established by the World Climate Research Program (WCRP) in 1986 with an approach to merge data and information available from several sources of precipitation including: Infrared and Microwave remote sensing sensors and rain gauges (Huffman et al. 1997).

2.2 Evapotranspiration

Evapotranspiration (ET) is the largest component in terrestrial water budgets consisting of 60% of land precipitation. It modulate 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 (IPCC 2007).

The remote sensing approach to estimate ET is based on thermal infrared 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 evapotranspiration fraction can be derived from:

¿ $= R_n - G - H$

where LE is the latent heat of evaporation due to ET; Rn is net radiation absorbed by the land surface, equal to incoming solar radiation (Rs) minus outgoing shortwave and longwave radiation; H is sensible heat flux to the atmosphere; and G is 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 (LST), measured by Thermal Infrared bands on satellites such as the Landsat series (Bastiaanssen et al. 2005; Allen et al. 2007), Geostationary Operational Environmental Satellite (GOES) (Jacobs et al. 2004), the Advanced Very High Resolution Radiometer series (Loukas et al. 2005), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Galleguillos et al. 2011; Sarwar & Bill 2007), and the Moderate Resolution Imaging Spectrometer (MODIS) sensors, both on the Terra satellite (Mu et al. 2007; Mu et al. 2011). Estimates of Rn and G are available from remote sensing or ground data, allowing LE to be calculated as a residual in above equation. This approach has been applied widely to ET measurements higher accuracy in semi-arid 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 that 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 (Nagler et al. 2005). 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 (Gonzalez-Dugo et al. 2009). Duchemin et al. (2006) developed linear relationship between NDVI and crop coefficients with good accuracy to derive maps of LAI and transpiration requirements using

Landsat7-ETM+ images for agricultural area. The vegetation indices based approach is also tested successfully using AVHRR (Pan et al. 2003; Fisher et al. 2008), MODIS (Guerschman et al. 2009; Leuning et al. 2008; Cleugh et al. 2007; Nagler et al. 2005) The future designed Earth Observation Systems with higher spatial and temporal resolution would make this approaches feasible for the operational monitoring of evapotranspiration at a regional and global scale.

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 on evaporation and transpiration at the land-atmosphere boundary as well as surface energy flux (Betts et al. 1996). 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 microwave 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 microwave spectrum has the advantage of longer penetration, therefore, less atmospheric effect.

Spaceborne active microwave 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 microwave sensors provide low spatial resolutions (40 to 50 km) with a higher temporal resolution (12 to 24 hrs). Most of the applications of active microwave in soil moisture retrieval are based on the hypothesis that the signal backscattered from the observed scene is widely dependent of 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 microwave data only may face several challenges since the microwave sensors are sensitive to other land cover characteristics such as vegetation density, surface roughness, and soil texture (Engman 1995; F. G. Hall et al. 1995; Ulaby et al. 1986)

The accuracy of satellite-derived soil moisture is usually affected by the presence of vegetation which significantly modifies and attenuates the outgoing microwave 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 (Ulaby et al. 1986; Kasischke et al. 2003). The total amount of attenuation and backscatter depends on several vegetation parameters, such as vegetation height, leaf area index, and vegetation water content; and on sensor-related characteristics such as angle of incidence, frequency, and polarization.

Two microwave satellite missions, the ESA Earth Explorer SMOS (Soil Moisture and Ocean Salinity) launched on November 2009 and SMAP (Soil Moisture Active Passive) by NASA that 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 space-borne 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 in the SMAP will provide higher spatial resolution (1–3 km) soil moisture product. The EUMETSAT's Polar System METOP will be a continuation of ERS scatterometer mission carrying the Advanced Scatterometer ASCAT. The METOP satellite series, with Advanced Scatterometer onboard, will be the first operational satellite system dedicated to the retrieval of soil moisture information.

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 snowcover is projected to contract, widespread melting of snow and ice, could lead to rising global average sea level (IPCC 2007). Satellite observations in the visible and microwave 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 are well appropriate snow cover mapping due to the high albedo of snow presents a good contrast with most other natural surfaces except clouds. The two visible and infrared 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 for Northern Hemisphere. IMS product has been based primarily on visible and near infrared 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, regardless of the presence of clouds. This possible due to IMS analysts looping through sequential GOES and AVHRR images to evaluate scenes is based on integrated information (Helfrich et al. 2007; Ramsay 1998). Second, the suite of products derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) by NASA provides weekly global snow cover information. The Moderate Resolution Imaging Spectro-radiometer (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/). Snowcover products derived from MODIS are based on a band rationing of MODIS band 4 (green) (0.545–0.565 μm) and band 6 (near-infrared) (1.628–1.652 μm). These bands are used to calculate the Normalized Difference Snow Index (D. K. Hall & Riggs 2007).

The passive microwave 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 (Kelly et al. 2003; Basist et al. 1998). Microwave emission from snowpack depends on the snow grain size, density, depth, and snow water equivalent (Grody 2008). Passive microwave sensors have advantage to penetration of cloud cover unlike VIS/IR sensors. However, passive microwave data suffers from being a low resolution measurement, on the order of 25km. Therefore, an effort are being made to develop a combination of 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 microwave data (Liang et al. 2008; Foster et al. 2011; Armstrong & Brodzik 2003; Gao et al. 2010; Yu et al. 2011) .

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 levels (Prowse & Ferrick 2002). Freeze-up and break-up dates of the ice in rivers and lakes causes the seasonal hydrograph changes result from 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 (Latifovic & Pouliot 2007).

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. Visible and infrared channels onboard of polar orbiting satellites are capable of 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 & 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 with in-situ observations successfully with high accuracy.

Active microwave synthetic aperture radar (SAR) data is also used successfully in conjunction with visible and infrared 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 limits their use for climate change studies and operational monitoring (Duguay & Lafleur 2003). Using SAR data (ERS-2 and RADARSAT-1), Nolan et al (2003) were able to determine dates for lake ice formation, snowmelt, and ice melt to within a few days for four winter seasons.

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 that 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 microwave signals and the Global Positioning System. GRACE generates maps of gravity anomalies at approximately monthly time resolution and ~250 km spatial resolution

(Sean Swenson & John Wahr 2006).

Over land, GRACE products show seasonal wet-dry cycles in areas such as the Amazon and Mississippi basins (Schmidt et al. 2006). 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 to unsustainable groundwater withdrawals in regions such as northern India (Tiwari et al. 2009) 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 snow water equivalent over boreal river basins. Syed et al. (2008) compared water storage variability inferred from GRACE with that given by the Global Land Data Assimilation System (GLDAS). 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 model's simulations of river discharge and groundwater levels (Zaitchik, Matthew Rodell, et al. 2008; Lo et al. 2010; Werth & Güntner 2010). 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 (Sahoo et al. 2011), 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 (Becker et al. 2011). 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 (Krakauer & Temimi 2011). 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.

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 includes: suspended solids, algae (chlorophylls), chemicals, dissolved organic matter, thermal releases, aquatic vascular plants, pathogens, and oils. Monitoring and assessing the water quality is 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 on-site by empirical or analytical models. The empirical approach is based on using experimental data sets 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 parameters (Moses et al. 2009). The selection of spectral channel is depends upon type and concentration water quality parameters.

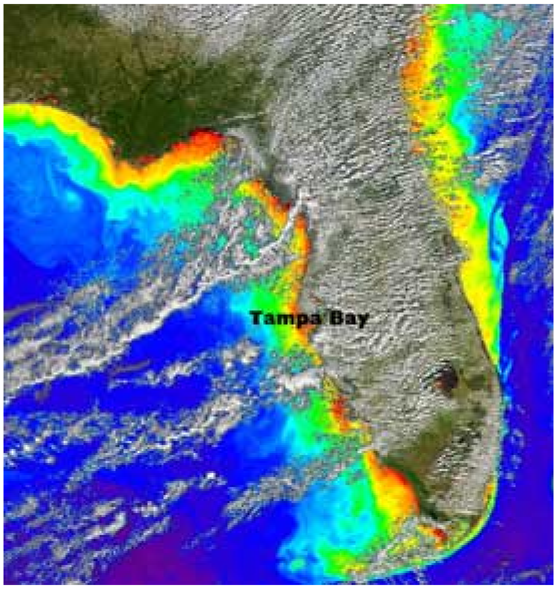

Figure : High concentrations of microscopic plants called phytoplankton (red regions) along the Florida coast and in Tampa Bay are an indicator of ocean health and change as seen in this SeaWiFS image from October 2004 (Source: NASA).

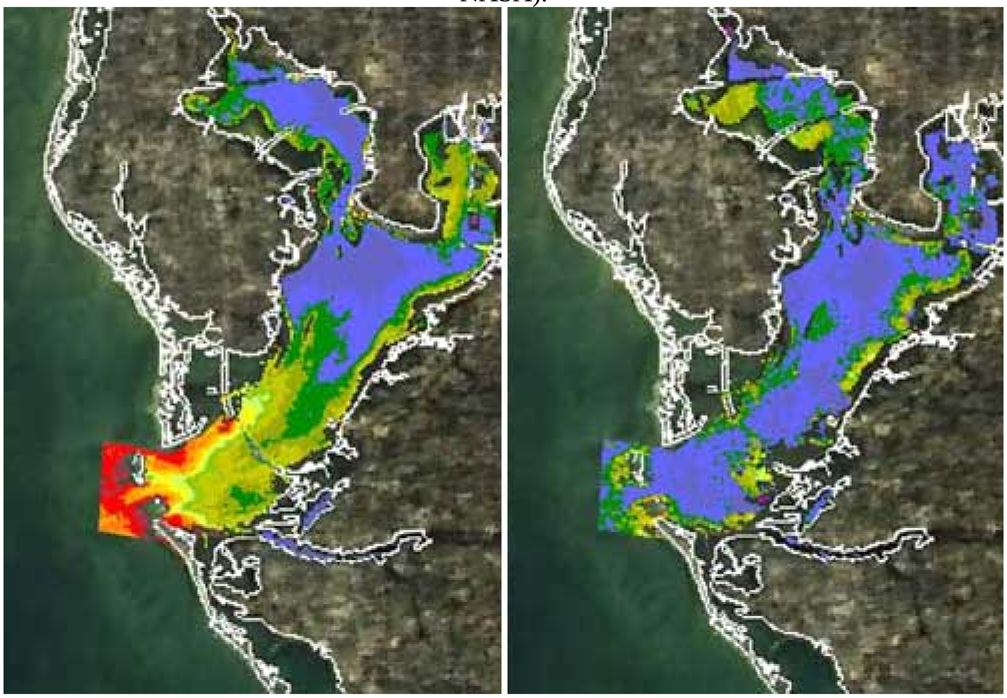

Figure : MODIS imagery has shown that water quality of Florida's Tampa Bay decreases in winter months compared to summer. More particles suspended in the water, a measure called turbidity, show up as yellow, orange and red in December (left image) than in July (right). Images are composites of turbidity data collected in December and July, respectively, over a span of three years (Source: NASA/USF)

Most of 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) (Allan et al. 2011; Brezonik et al. 2005), Total Suspended Solids and Inorganic Suspended Solids (Giardino et al. 2010; Katlane et al. 2011;

Volpe et al. 2011; Kishino et al. 2005), absorption by Colored Dissolved Organic Matter (Kutser et al. 2005) and indicators of water clarity such as turbidity (Graves et al. 2004; Potes et al. 2011). High resolution Landsat Enhanced Thematic Mapper (ETM) was used to estimate chlorophyll a (chlÂa) concentrations using band ratios for lakes (Allan et al. 2011; Brezonik et al. 2005) and coastal sewage outfall area (Forster et al. 1993). The Medium Resolution Imaging Spectrometer (MERIS) onboard ESA's Envisat is used successfully to estimate algal bloom and colored dissolved oxygen (Gons et al. 2008; Matthews et al. 2010; Campbell et al. 2011). MODIS remote sensing data in conjunction with logarithmic band ratio model has shown its capability to monitor the impact of hurricane impact on chlorophyll-a concentration in Pensacola Bay system (Huang et al. 2011). Estimation of water quality parameters from remote sensing have proved to be useful and successful and are being investigated for operational use.

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 information on land cover and land cover changes over time is necessary for hydrological modeling. Remote sensing is powerful and cost-effective tools for assessing the spatial and temporal dynamics of land use and land cover to evaluate deforestation, biodiversity loss and climate change (Rogan & D. Chen 2004; Pyke & Andelman 2007). Therefore, information on land use and land cover change is critical for decision-making of environmental and water resources management and future planning. Multi-temporal images provided by remote sensing sensors for same location are being used in conjunction with Geographical Information System (GIS) to effectively determine the land use and land cover changes over time (Joshi et al. 2009). 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 post classification, have been used wildly to evaluate land use and land cover changes using remote sensing satellite data (He et al. 2011; Kintz et al. 2006; De Jong et al. 2000) In pre-classification approach, procedures such as image differencing (Bindschadler et al. 2010) band rationing (Bahadur K C 2009) change vector analysis (Baker et al. 2007), principle component analysis (Cakir et al. 2006) 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 post-classification method, the comparison was done over independently classified land cover data. Despite the difficulties associated with post-classification comparisons, this technique is the most widely used for identifying land use and land cover changes (Dewan & Yamaguchi 2009).

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.

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 was not developed (as for e.g. precipitation) (Kalnay et al. 1996). This has improved to some extent in recent years -- e.g. the North American Regional Reanalysis (Mesinger et al. 2006) ingested land and sea snow/ice cover products based on remote sensing, and precipitation gauge 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 (M Rodell et al. 2004; J. Zhang et al. 2008; Gottschalck et al. 2005), 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 microwave is typically only for a surface layer rather than for the entire soil column (Sabater et al. 2007; S.-W. Zhang et al. 2010).

Preliminary work has also sought to assimilate both thermal and microwave 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 (Zaitchik, M Rodell, et al. 2008). 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 to improve intermediate to seasonal range weather forecasts through better capturing land-atmosphere feedbacks (Mishra & Singh 2011; Koster et al. 2000; Brunet et al. 2010).

1.1 Flash Flood Guidance and Forecasting

Climate change and variability increases 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 flash flood guidance. The FFG 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 model that portrays 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 (NWS) issues a daily national map of Gridded Flash Flood Guidance (GFFG) is produced based on surface soil moisture deficit and threshold runoff estimates. Similarly, the Central America Flash Flood Guidance System (CAFFG, a regional flash flood guidance 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 uses 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 Soil Moisture and Ocean Salinity (SMOS) satellites mission and future Soil Moisture Active and Passive (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 European Space Agency (ESA) and launched in November 2009.

4 Future Perspective

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