

Space – based methods for hydro-meteorological measurements

Dr. SP Aggarwal
Head, Water Resources Department
Indian Institute of Remote Sensing

Introduction:

A major concern in the Water Resources Management is the inadequate and timely available field data. Imaging from space provides near real time hydrologic information within few hours to few days with spatial resolution of 1 Meter to few km. and Synoptic coverage of 25 km to 2000 km. Remote Sensing (RS) has emerged as a powerful tool for providing information in spatial and temporal domain (digital form, high resolution) in contrast to traditional point measurements. Presently there are many satellites available in different orbits launched by ISRO and other space agency of USA, Europe, Japan etc. Geostationary satellites are used widely for telecommunication as well as utilized for monitoring weather phenomena.

Kalpan-1 and INSAT 3D are two important Indian Geostationary satellite which provides continuous information about cloud, cloud top temperature, water vapour etc. Polar orbiting satellites are used for mapping and monitoring of Natural resources viz. forest, agriculture, water, geology, marine and urban area. The resolution of images obtained from these satellites ranges from 40 cm to 1km. For water resources management it is necessary to monitor many parameters viz. Rainfall, Snow cover, Land use land cover, Evapo-transpiration. Space based imaging is extensively utilized in Flood mapping, monitoring and damage assessment, irrigation water management, drought monitoring and watershed management in India.

Rainfall

Recognizing the practical limitations of rain gauges for measuring spatially averaged rainfall over large areas and inaccessible areas, hydrologists have increasingly turned to remote sensing as a possible means for quantifying the precipitation input, especially in areas where there are few rain gauges. Direct measurement of rainfall from satellites for operational purposes has not been generally feasible because of the presence of clouds prevent observation of the precipitation directly with visible, near infrared and thermal infrared sensors. However, improved analysis of rainfall can be achieved by combining satellite and conventional gauge data. Useful data can be derived from satellites used primarily for meteorological purposes, including polar orbiters such as the National Oceanographic and Atmospheric Administration (NOAA) series and the Defense Meteorological Satellite Program (DMSP) and from geostationary satellites such as Global Operational Environmental Satellite (GOES), Geosynchronous Meteorological Satellite (GMS) and Meteosat, and Indian Satellite (INSAT) series which includes Kalpana 1 and INSAT 3D. The visible and infrared bands are used to estimate rain indirectly by thresholding and index techniques. However microwave remote sensing have great potential for measuring precipitation directly.

The GOES Precipitation Index (Arkin, 1979), derived from thresholding the infrared brightness temperature of cloud tops has been used to study the distribution of tropical rainfall. Spencer et.al., (1988) have shown that the DMSP Special Sensor Microwave / Imager (SSM/I) data can identify rain areas and Adler et.al., (1992) has used a cloud based

model with 85 and 37 GHz SSM/I data to estimate rain rates. Ground-based radar, which is a remote sensing technique, has advanced to an operational stage for locating regions of heavy rain, and for estimating rainfall rates also. The accurate measurement of the spatial and temporal variation of tropical rainfall around the globe remains one of the critical unsolved problems of meteorology. Tropical Rainfall Measuring Mission (TRMM) is a joint venture of US NASA and Japan Aerospace Exploration Agency (JAXA). TRMM consist of five sensors namely Precipitation RADAR (PR), TRMM Microwave Imager (TMI), Visible and Infrared Scanner (VIRS), Cloud and earth radiant energy sensor (CERES) and Lighting Imaging Sensor (LIS). Out of all precipitation radar is one of the most important sensor which provide 3-D rain structure.

Snow

Snow is one of the form of precipitation, however, in hydrology it is treated differently because of the lag between when it falls and when it produces runoff. Remote sensing is a valuable tool for obtaining snow data for predicting snowmelt runoff as well as climate studies. Rango (1992) presents a good review of the status of remote sensing in snow hydrology. Depending on the need, one may like to know the areal extent of the snow, snow water equivalent, grain size, snow density, albedo and emissivity.

Microwave remote sensing offers great promise for future applications to snow hydrology because it provides information on the snowpack properties such as snow cover area, snow water equivalent (or depth) and the presence of liquid water in the snowpack which signals the onset of melt (Kunzi et.al., 1982). Snow density and snow water equivalent are also determined using microwave data.

Early use of remote sensing for snow melt runoff forecasting focused on empirical relationships between snow cover area or percent snow cover and monthly or accumulated runoff (Rango et.al., 1977, Ramamoorthi, 1987). Optical remote sensing data is widely used to determine snow cover area, snow depletion curve as input to Snowmelt Runoff Model (SRM) (Martinec et.al., 1983). SRM has been extensively tested on basins of different sizes and regions of the world (Rango 1992, WMO 1992). Although SRM is a degree day model that uses only snow cover as remote sensing derived input, energy balance models (Leavesley and Stannard, 1990 and Marks and Dozier, 1992) are able to use additional remote sensing data such as albedo and other energy balance parameters.

Space based precipitation estimation methods

The space based precipitation methods are categorized in four types:

- Visible-Infrared range
- Passive Microwave Radiometers
- Ground based Doppler radars
- Space based Active Microwave Radars

Cloud Indexing Method for Precipitation Estimation

At any time it is possible that different types of clouds are prevalent in the given area in which case the formula used is

$$R = (K_1 A_1 + K_2 A_2 + K_3 A_3 + \dots) / A_T$$

Where, R is the mean areal rainfall, A_i is the area of i type of cloud cumulonimbus, cumulus, and/or stratus and K_i is the empirical coefficient. A_T is total area of clouds.

- **Precipitation estimation Algorithms using passive microwave**

At present, precipitation estimates are used from various passive microwave sensor types on 8 platforms:

- AMSU-B (NOAA 15,16,17,18)
 - SSM/I (DMSP 13,14,15)
 - TMI (TRMM – NASA/Japan)
 - AMSR-E (Aqua)
 - SSMIS
 - WindSat (ocean only)
- } NOAA/NESDIS

“CMORPH”: Mostly used precipitation estimation method, “CMORPH” is *not* a precipitation estimation technique but rather a method that creates spatially & temporally complete information using existing precipitation products that are derived from passive microwave observations.

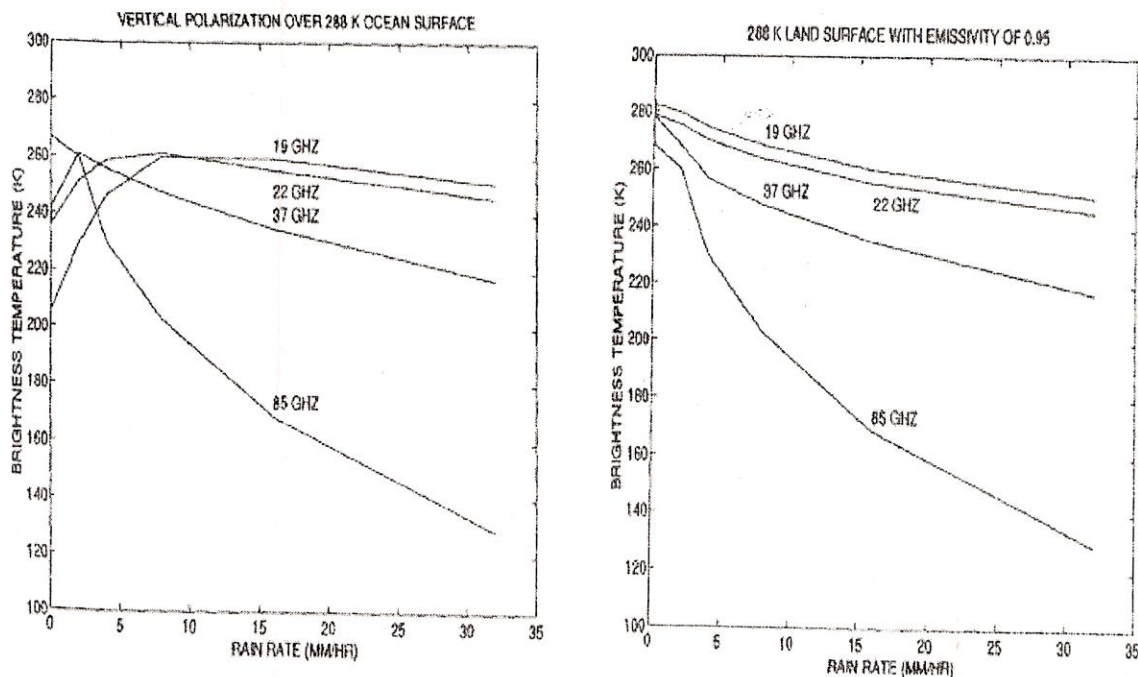


Fig 1: BT vs rain rate at land and ocean surface with passive MW frequencies

Rainfall Retrieval Algorithm using passive MW:

$$SI = a_0 + a_1 T_{19V} + a_2 T_{22V} + a_3 T_{22V}^2 - T_{85V}$$

$$R = a * SI * b; \text{ PRODUCT: RAIN RATE (mm/hr)}$$

Where, SI: Scattering index; R: Rainfall rate, T_{XP} : Brightness temperature in given frequency 'x' and polarization 'p'; a and b are empirical constants.

• Ground based Radar Measurement of Rainfall

The meteorological radar is a powerful instrument for measuring the area extent, location and movement of rainstorms. Further, the amount rainfall over large areas can be determined through the radar with a go degree of accuracy. The radar emits a regular succession of pulses of electromagnetic radiation in a narrow beam. When raindrops intercept a radar beam, it has be shown that

$$P_r = \frac{C Z}{r^2}$$

where P_r = average echo power, Z = radar-echo factor, r = distance target volume and C = a constant. Generally the factor Z is related to the intensity of rainfall as

$$Z = a I^b$$

Where, a and b are coefficients and I = intensity or rainfall in mm/h. The values a and b for a given radar station have to be determined by calibration with the help of recording raingauges. A typical equation for Z is

$$Z = 200 I^{1.60}$$

Meteorological radars operate with wavelengths ranging from 3 to 10 cm, the common values being 5 and 10 cm. For observing details of heavy flood-producing rains, 10 cm radar is used while for light rain and snow a 5-em radar is used. The hydrological range of the radar is about 200 km. Thus a radar can be considered to be a remote-sensing super gauge covering an areal extent of as much as 100,000 km². Radar measurement is continuous in time and space. Present-day developments in the field include (i) On-line processing of radar data on a computer and (ii) Doppler-type radars for measuring the velocity and distribution of raindrops.

The WMO *Guide to hydrological practices* (1994) explains that

Radar permits the observation of the location and movement of areas of precipitation, and certain types of radar equipment can yield estimates of rainfall rates over areas within range of the radar.

The important rain characteristics for radar measurement are:

- i) Rain cell size distribution
- ii) Rain cell separation and
- iii) Rain cell height

Space based Active Microwave Radars

The unique features of radar are well recognized, unlike LIDAR, it can penetrate through rain and cloud: unlike the radiometer, it can vertically profile the rain and its sensitivity is not degraded by the high emissivities of a land background.

• Tropical Rainfall Measuring Mission (TRMM)

The Tropical Rainfall Measuring Mission, TRMM, is the first mission dedicated to measuring tropical and subtropical rainfall. Measurements from TRMM are used to find out where it's raining, and how hard it's raining including 3-D structure of Storm and clouds.

Payloads of TRMM are

- Precipitation Radar (PR)
- TRMM Microwave Imager (TMI)
- Visible Infrared Scanner (VIRS)
- Clouds and the Earths Radiant Energy System (CERES)
- Lightning Imaging Sensor (LIS)

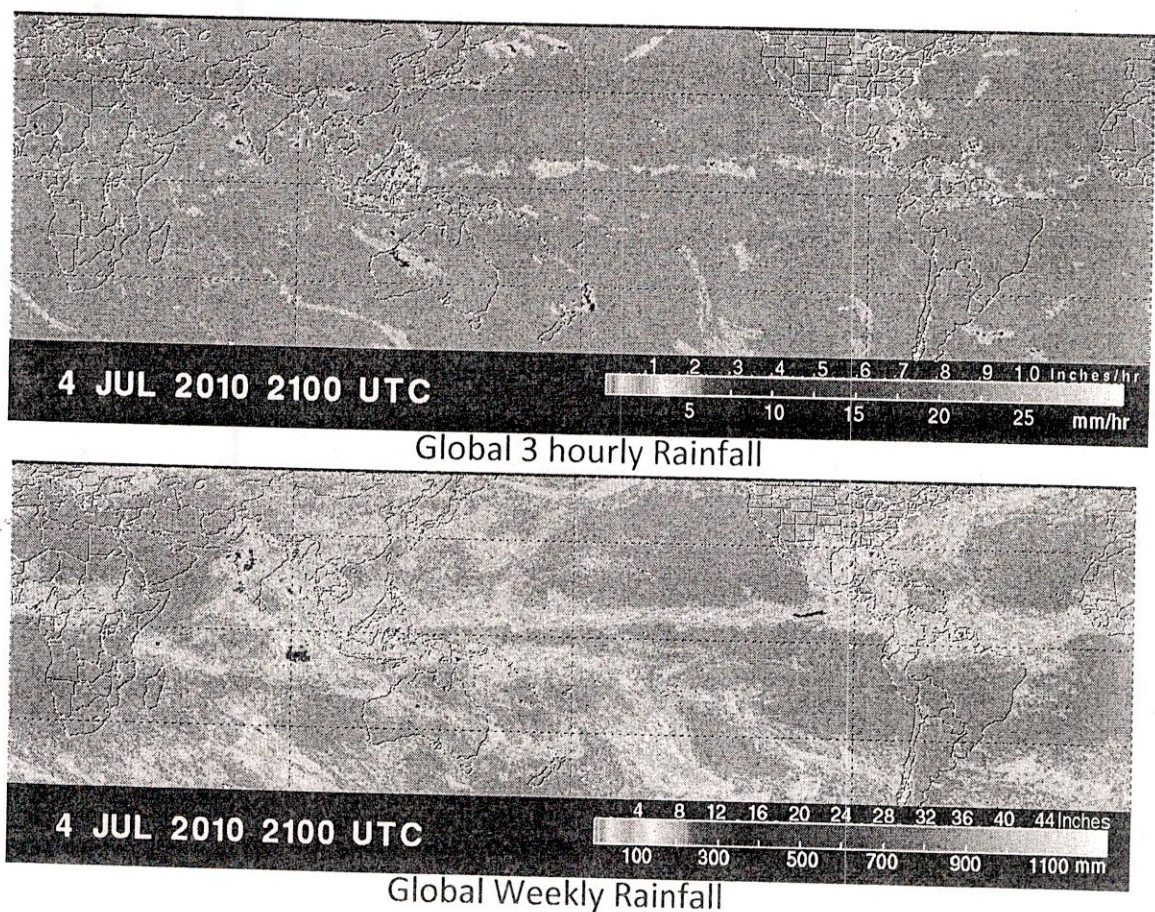
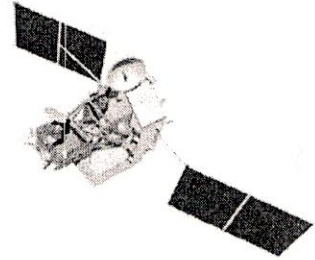


Fig. 2: Global 3 Hourly and weekly rainfall from TRMM and other satellites

http://trmm.gsfc.nasa.gov/affinity/affinity_3hrly_rain.html

(a) Backscattering methods

$$P(r) = C |KW|^2 |Z_e| / r^2$$

Where r is the radar range, C is the radar constant and Z_e is the equivalent reflectivity factor. From this equation and a knowledge of C and r , Z , can be obtained from an estimate of the mean return power, P , at each range gate.

The factor Z is related to the intensity of rainfall as: $Z = aI^b$, where a & b are constants determined by calibration with the help of recording rain gauges. I is rainfall intensity in mm/h. A typical equation for Z is: $Z = 200I^{1.60}$

b) Dual Wavelength Methods

To make the wavelength dependence of the radar equation explicit, we write:

$$P(\lambda_i, r) = C(\lambda_i) |K\omega|^2 Z_e(\lambda_i, r) \exp\left(-0.46 \int_0^r K(\lambda_i, s) ds\right) / r^2$$

For dual wavelength radar, an estimate of the differential attenuation in the range interval from r_k to r_j is

$$A = \int_{r_k}^{r_j} [K(\lambda_1, s) - K(\lambda_2, s)] ds = -5 \log(P_{12} / Z_{12})$$

If Z_{12} is equal to unity, then the differential attenuation, A , can be expressed in terms of the measured quantity P_{12} . This condition is satisfied exactly if either the radar reflectivity factors are independent of wavelength at r_k and r_j , or if the reflectivity factor at each wavelength is uniform in range.

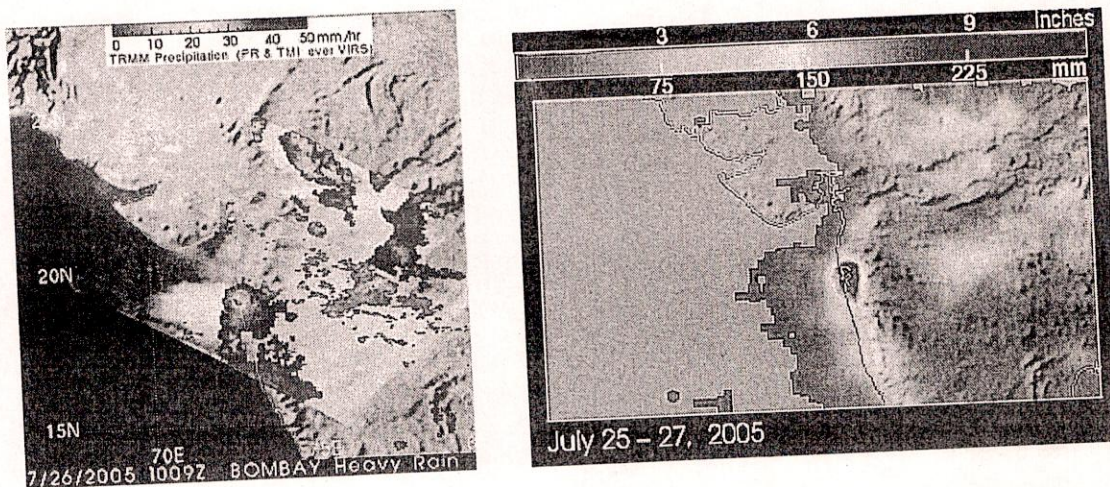


Fig. 3 TRMM based rainfall estimate of 2005 Mumbai extreme rainfall event

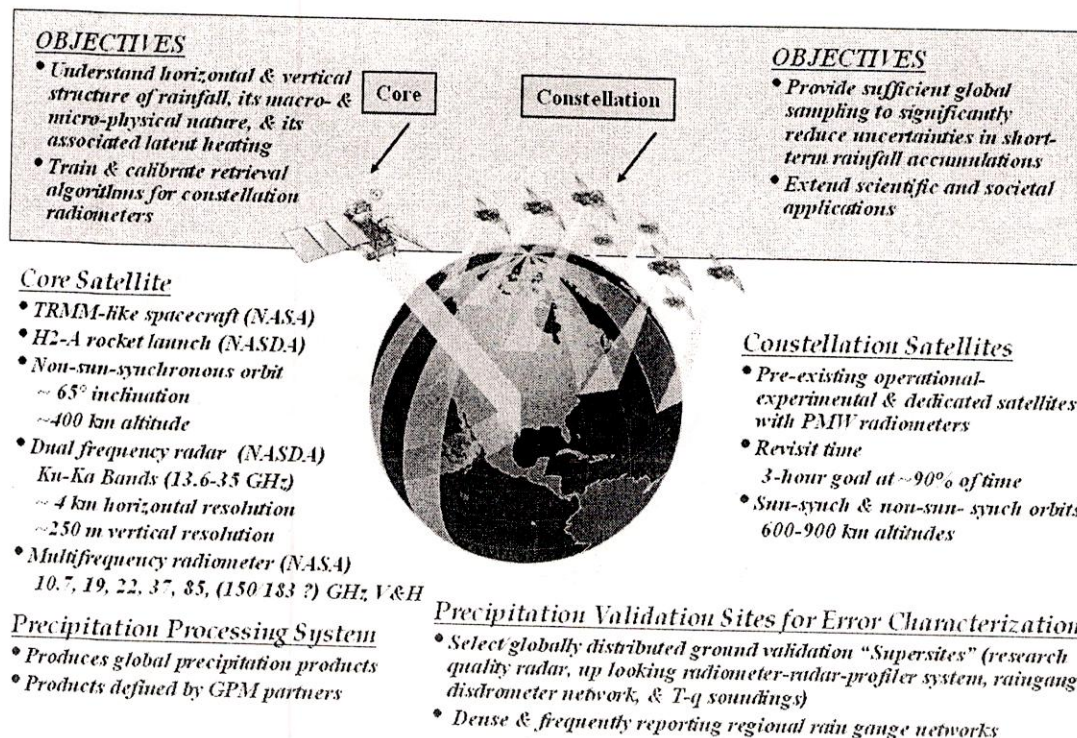


Fig. 4: GPM Reference Concept, Source; GSFC, NASA

Measuring surface water from space: Altimetry for surface water studies

- The requirements for the measurement of surface water from space have been reviewed by Alsdorf and Lettenmaier (Science, 301, 2003).
- Water level measurement by satellite altimetry has been developed and optimized for open oceans. Nevertheless, the technique is now applied to obtain water levels of extensive inland seas, lakes, rivers, floodplains and wetlands. Several satellite altimetry missions have been launched since the early 1990s: ERS-1 (1991-1996), Topex/Poseidon (1992-), ERS-2 (1995-), GFO (2000-), Jason-1 (2001-), ENVISAT (2002-) and Saral-Altika (2013-). We have developed a global data base of water level time series over lakes and rivers based on satellite altimetry.
- The spatial and temporal signature of climate variability on water levels, systematic use of satellite altimetry in large river basins might support initialization and verification of models used in forecasts of hydrological variability, and, possibly, estimates of river discharge where rating curves can be established by surface-based methods.
- These requirements include monitoring the water level to centimetric accuracy with a spatial resolution on the order of 100 meters; imaging of fresh water bodies with a similar spatial scale; determining the slope of rivers with an accuracy of about 1cm/1km; temporal sampling which varies from weekly, for arctic rivers, to a few weeks, for tropical rivers like the Amazon. In this work, we review the ability current remote sensing technology to meet these requirements.
- Among the technologies examined will be radar altimeters, such as the NASA TOPEX altimeter, lidars, such as IceSat, and interferometric radars, such as SRTM or the forthcoming Wide-Swath Ocean Altimeter.

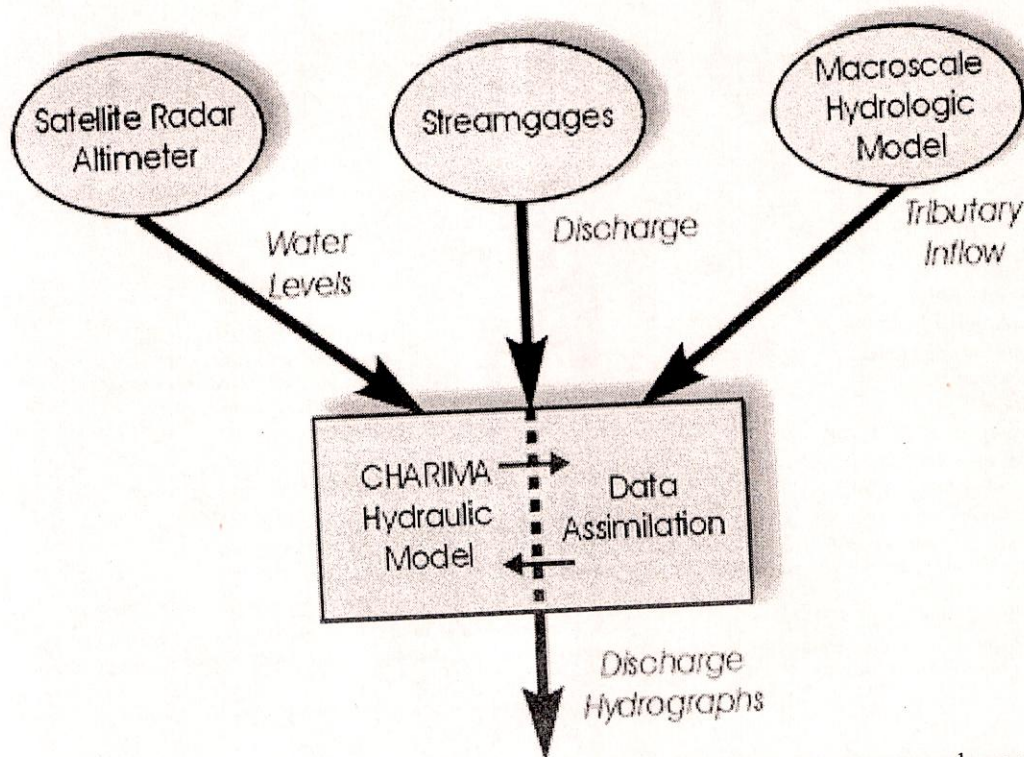


Fig.5 Flowchart showing the proposed river discharge estimation system, where water level information from satellite radar altimetry and other information on flows is integrated into the hydraulic model using a data assimilation approach.

Estimation of channel cross section geometry & discharge

With the unavailability of rating curves this width elevation data can be used to estimate channel cross section geometry. The approaches that can be followed are:

1. Assume a channel cross section shape –e.g, Parabolic, which is often assumed for natural channels. The equation for such a cross section is given by,

$$(W/2)^2 = 4 * K * (Z - Z_0)(3)$$

$$Z = Z_0 + W^2 / (16 * K)(4)$$

where K is constant and Z₀ is the elevation of the deepest point of channel (centre)

2. Surface Water and Ocean Topography (SWOT) will make successive observation of $W/\cos(q)$ and Z, where q is the angle between the ground path and the perpendicular to the channel. q can be determined by reference to maps and ancillary information such as DEMs, LIDAR or other satellite observations of land surface elevations. Thus we have concurrent values of W and Z.
3. Using these concurrent values, we can regress Z vs W² to find least square estimates of Z_{0a} and K.
4. The maximum channel depth $Y_{max} = Z - Z_0$. For a parabolic channel, the average depth, $Y = 2 * Y_{max} / 3$. Thus we have now estimates of Y and W for each observation

5) To find Q , we turn to the empirical equation developed by Dingman and Sharma (1997), which gives Q as a function of cross-sectional area ($A = W \cdot Y$), hydraulic radius slope, we could use estimates of channel/floodplain slope in the equation. Such slope estimation can be derived from the same ancillary source.

SWOT: PROPOSED ALTIMETER FOR INLAND WATER APPLICATIONS

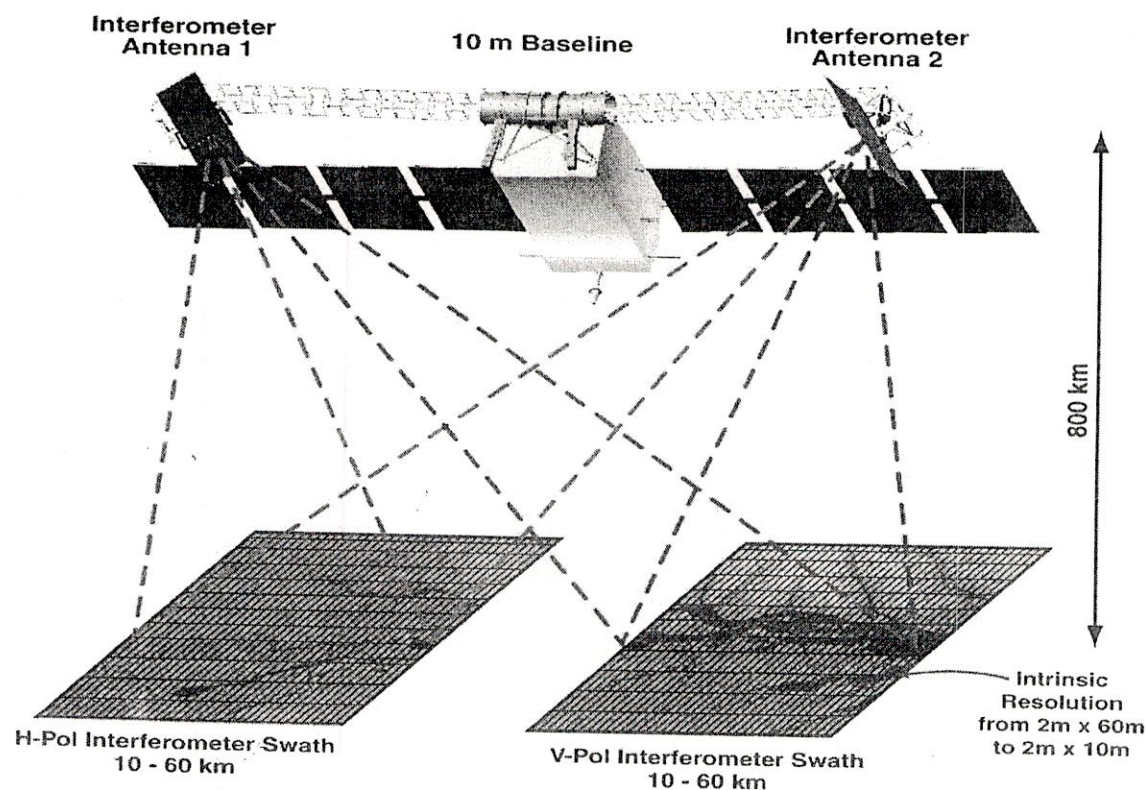


Fig.6: Proposed SWOT (WATER HM) Mission Concept

The major objectives of this mission are:

Primary:

- To determine the spatial and temporal variability in freshwater stored in the world's terrestrial water bodies.

Secondary (potentially):

- Inundation area provides carbon fluxes at air-water boundary (e.g., CO_2)
- High resolution h images allow plume and near shore studies
- Calculation of ocean water slopes for bathymetry and ocean circulation
- Differences between sea ice and water surface allow ice-freeboard calculations, thus thickness.
- Repeated topographic measurements for floodplains, glacial ice, etc.

Table 1: Geophysical Parameters and Products from SWOT

Target location	Number of sites	products	sensor	units	accuracy
Lake/Reservoirs ^a	1400	Stage	Altimeter	m	+0.05m
		Area	Imager ^b	Km ²	+5%
		Δ volume	Computed	Km ³	+5%
Wetlands	1000	Stage	Altimeter	M	+0.05m
		Area	Imager ^b	Km ²	+5%
		Δ volume	Computed	Km ³	+5%
Rivers ^a	2000	Stage	Altimeter	M	+0.05m
		Width	D.P. ^c	M	+1-5m
		Velocity	Lidar ^d	m/s	+0.20m/s
		Discharge	Computed	M ³ sec-1	+10%

a based on 100 km² minimum area, minimum eligible river width for altimetric stage retrievals is 0.25km

b Radar imager such as from proposed cryospheric mission, ERS-2, Jason, ENVISAT.

c D.P.=Along-track Doppler Processing.

d Doppler Lidar

- Satellite radar altimeters have successfully retrieved echo information over inland water bodies. The primary priorities of current (T/P, ERS-2) and future (Jason-1, ENVISAT) radar altimeter mission lie with vegetation, ocean or ice studies
- Therefore a new satellite SWOT (Surface Water and Ocean Topography), a surface water mission dedicated to the near-real time monitoring of rivers, lakes, reservoirs and wetlands.
- The aim of the satellite is to retrieve stage, surface velocity and along track target widths for the determination of river discharge and inland water body volumes.
- Satellite based on i) Radar remote sensing system with day/night and all weather capability for river and lake stage and along track width. ii) A Doppler Lidar system for measurement of surface velocities day or night with a target of 50% of all weather capability.

Space-Based Measurement of River Runoff

Observations of river inundation areas, water levels, and flow variability from orbital sensors have the potential to directly measure the runoff component of the Earth's hydrologic cycle [Birkett et al., 2002; Brakenridge et al., 1998; Sippel et al., 1994, 1998; Townsend, 2001]. A remote-sensing-based measurement strategy for rivers and streams is emerging: Surface

water data can be collected, their accuracy evaluated, and the results disseminated without regard to political boundaries. The results can be used to address a wide variety of applications.

Discharge Estimation

If adequate floodplain topographic data are available, bank-full and various overbank river stages can be measured on higher resolution data by determining the elevation of the water/land boundaries. This provides a path forward to inferring discharge in the absence of in situ gaging stations. First, the imaged inundation pattern at the upstream and downstream ends of the reach are compared with topography. This results in two stage estimates for each reach image, as well as the longitudinal water surface slope. Then, hydraulic geometry equations such as those of *Bjerklie et al.* [2003] are applied to the imaged flow parameters and the channel and floodplain characteristics (including slope and resistance-to-flow), in order to derive reasonable discharge estimates. The process is repeated for a variety of flow conditions, resulting in empirical area/stage and stage/discharge relations similar to those constructed for in situ gaging stations. Alternatively, two-dimensional hydraulic modeling methods can be employed [*Bates et al.*, 1992]. Without direct velocity measurements, the calibration of surface area to discharge will be less accurate than that obtained for stage at gaging stations. However, the surface water time series itself can be used in many types of analyses, and it becomes increasingly valuable as the period of record lengthens. Also, if flow velocities can be obtained, even intermittently, and if channel bathymetry can be observationally constrained (via lidar or other techniques), then the accuracy of the area/discharge calibration can be much improved. The overall strategy is to use one kind of sensor for frequent repeat imaging of a defined river reach, and other, higher spatial resolution sensors and ancillary data to assist in accurate discharge inference at such measurement sites.

MODIS data can be used to obtain time series of water surface areas at several hundred gaging reaches worldwide. This optical sensor provides a daily opportunity for new data, but it is constrained by cloud cover. Experimental work indicates that microwave sensors, working at relatively coarse spatial resolutions, can also record reach water surface area variations: for example, by changes in reach-averaged polarization ratios, where $!VV$ and $!HH$ are the vertically and horizontally polarized backscatter. Microwave sensors can thereby detect the onset of flooding in response to intense or prolonged rainfall without interference by cloud cover. Many rivers exhibit seasonal variation in flow in response to monsoons or snowmelt: Such seasonal cycles can be observed and their timing and intensity can be measured. The ability of microwave sensors to obtain new data over a reach in a predictable manner and at daily or higher revisit frequencies makes these sensors potentially useful also as operational flood warning tools.

Evapotranspiration estimation from space

The most common algorithms used to estimate ET from space based observations is Surface energy balance based models. In the Surface Energy Balance Algorithm for Land (SEBAL) model, ET is computed from satellite images and weather data using the surface energy balance as illustrated in Figure 1. Since the satellite image provides information for the overpass time only, SEBAL computes an instantaneous ET flux for the image time. The ET flux is calculated for each pixel of the image as a "residual" of the surface energy budget equation:

$$\lambda ET = R_n - G - H$$

where; λET is the latent heat flux (W/m^2), R_n is the net radiation flux at the surface (W/m^2), G is the soil heat flux (W/m^2), and H is the sensible heat flux to the air (W/m^2). The surface energy budget equation is further explained in part 4 of this section.

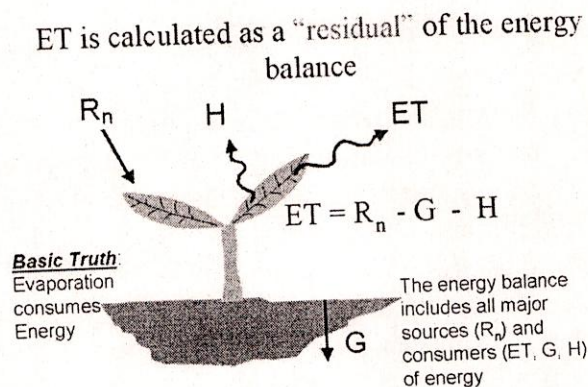


Figure 7. Surface Energy Balance

Remote sensing has great potential for improving irrigation management, along with other types of water management by providing ET estimations for large land surface areas using a minimal amount of ground data.

The net radiation flux at the surface (R_n) represents the actual radiant energy available at the surface. It is computed by subtracting all outgoing radiant fluxes from all incoming radiant fluxes (Figure 2). This is given in the surface radiation balance equation:

$$R_n = RS_{\downarrow} - \alpha RS_{\downarrow} + RL_{\downarrow} - RL_{\uparrow} - (1 - \epsilon_0)RL_{\downarrow}$$

where; $RS_{\downarrow}$ is the incoming shortwave radiation (W/m^2), α is the surface albedo

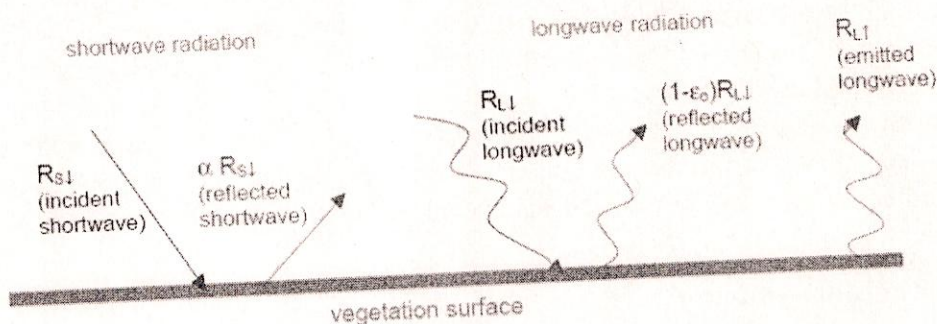


Figure 8. Surface Radiation Balance

(dimensionless), $RL_{\downarrow}$ is the incoming longwave radiation (W/m^2), $RL_{\uparrow}$ is the outgoing longwave radiation (W/m^2), and ϵ_0 is the surface thermal emissivity (dimensionless).

In Equation (2), the amount of shortwave radiation ($RS_{\downarrow}$) that remains available at the surface is a function of the surface albedo (α). Surface albedo is a reflection coefficient defined as the ratio of the reflected radiant flux to the incident radiant flux over the solar spectrum. It is calculated using satellite image information on spectral radiance for each satellite band. The incoming shortwave radiation ($RS_{\downarrow}$) is computed using the solar constant, the solar incidence angle, a relative earth-sun distance, and a computed atmospheric transmissivity. The incoming longwave radiation ($RL_{\downarrow}$) is computed using a modified Stefan-Boltzmann equation with atmospheric transmissivity and a selected surface reference temperature. Outgoing longwave radiation ($RL_{\uparrow}$) is computed using the Stefan-Boltzmann equation with a calculated surface emissivity and surface temperature. Surface temperatures are computed from satellite image information on thermal radiance.

The surface emissivity is the ratio of the actual radiation emitted by a surface to that emitted by a black body at the same surface temperature. In SEBAL, emissivity is computed as a function of a vegetation index. The final term in Equation (2), $(1-\epsilon_0)RL_{\downarrow}$, represents the fraction of incoming longwave radiation that is lost from the surface due to reflection. The radiation balance equation is explained in detail in part 3 of this section.

In Equation (1), the soil heat flux (G) and sensible heat flux (H) are subtracted from the net radiation flux at the surface (R_n) to compute the "residual" energy available for evapotranspiration (λET). Soil heat flux is empirically calculated using vegetation indices, surface temperature, and surface albedo. Sensible heat flux is computed using wind speed observations, estimated surface roughness, and surface to air temperature differences. SEBAL uses an iterative process to correct for atmospheric instability due to the buoyancy effects of surface heating.

Once the latent heat flux (λET) is computed for each pixel, an equivalent amount of instantaneous ET (mm/hr) is readily calculated by dividing by the latent heat of vaporization (λ). These values are then extrapolated using a ratio of ET to reference crop ET to obtain daily or seasonal levels of ET. Reference crop ET, termed ET_r , is the ET rate expected from a well-defined surface of full-cover alfalfa or clipped grass and is computed in the SEBAL process using ground weather data.

SEBAL can compute ET for flat, agricultural areas with the most accuracy and confidence.

Soil Moisture measurement from Space

Soil moisture is an important variable in land surface hydrology. Soil moisture has very important implications for agriculture, ecology, wildlife, and public health and is probably (after precipitation) the most important connection between the hydrological cycle and life—animal, plant, and human. Land surface hydrology is a well-studied portion of the terrestrial water cycle. The main variables in land-surface hydrology are soil moisture, surface temperature, vegetation, precipitation, and streamflow. Of these, surface temperature, vegetation, and precipitation are currently observed using satellites, and streamflow is

routinely observed at in situ watershed locations. Soil moisture remains the only variable not observed (or observed very sparsely) either in situ or via remote sensing. Due to this very reason, in the past decade, satellite soil moisture has been increasingly used in hydrological, agricultural, and ecological studies due to its spatial coverage, temporal continuity, and (now) easiness of use.

The NASA soil moisture active passive (SMAP) mission [33], is set for launch in 2014. SMAP will utilize a very large antenna and combined radiometer/radar measurements to provide soil moisture at higher resolutions than radiometers alone can currently achieve. SMAP [33] consists of both passive and active microwave sensors. The passive radiometer will have a nominal spatial resolution of 36 km and the active radar will have a resolution of 1 km. The active microwave remote sensing data can provide a higher spatial resolution observation of backscatter than those obtained from a radiometer (order of magnitude: radiometer ~40 km and radar ~1 km or better). Radar data are more strongly affected by local roughness, microscale topography, and vegetation than a radiometer, meaning that it is difficult to invert backscatter to soil moisture accurately, thus limiting the development of such algorithms. Therefore, it can be difficult to use radar data alone. SMAP will use high-resolution radar observations to disaggregate coarse resolution radiometer observations to produce a soil moisture product at 3 km resolution. The soil moisture has been retrieved from radiometer data successfully using various sensors and platforms and these retrieval algorithms have an established heritage [29, 34].

There have been methods integrating the use of active sensors that have a higher spatial resolution to downscale passive microwave soil moisture retrievals [35–37]. Recent studies have addressed the soil moisture downscaling problem using MODIS sensor derived temperature, vegetation, and other surface ground variables. The major publications in this area of study include the following. (i) A method based on a “universal triangle” concept was used to retrieve soil moisture from Normalized Difference Vegetation Index (NDVI) and land surface temperature (LST) data [31]. (ii) A relationship between fractional vegetation cover and soil evaporative efficiency was explored for catchment studies in Southeastern Australia by Merlin et al., 2010 [30] while Merlin et al., 2008 [31], developed a simple method to downscale soil moisture by using two soil moisture indexes: evaporative fraction (EF) and the actual EF (AEF) [38]. (iii) A sequential model which used MODIS as well as ASTER (Advanced Scanning Thermal Emission and Reflection Radiometer) data was proposed for downscaling soil moisture [32, 39, 40].

REFERENCES

1. Balakrishnan, P., 1986. A technical report on issues in Water Resources Development and Management and the role of Remote Sensing. ISRO-NNRMS-TR67-86.
2. Berkowicz, R., and L.P. Prahm. 1982. Sensible heat flux estimated from routine meteorological data by the resistance method. *Journal of Applied Meteorology* 21: 1845-1864.

3. Bhargava, D.S. and Mariam, D.W., (1990). Spectral Reflectance Relationships to Turbidity Generated by Different Clay Material, Photogrammetric Engineering and Remote Sensing, 56: 225-229.
4. Calder, I.R. 1977. A model of transpiration and interception loss from a spruce forest in Plynlimon, central Wales. *Journal of Hydrology* 33 : 247-265.
5. Calder, I.R. 1978. Transpiration observations from a spruce forest and comparisons with predictions from an evaporation model. *Journal of Hydrology* 38:33-47.
6. Charbonneau, R. (1981), Problems of modeling a high mountainous drainage basin with predominant snow yields, *Hydrological Sciences Bulletin*, Vol. 26, pp.345-361.
7. Dolman, A.J., J.B. Stewart, and J.D. Cooper. 1988. Predicting forest transpiration from climatological data. *Agricultural and Forest Meteorology*. 42:337-353.
8. Engman, E.T. and Gurney, R.J., (1991). *Water Quality, Remote Sensing in Hydrology*, Great Britain: Cambridge Press, 175-192.
9. Engman, E. T. and Gurney, R. J. (1991). *Remote Sensing in Hydrology*, Chapman and Hall, London.
10. Gitelson, A.A., (1992). The Peak Near 700 nm on Radiance Spectra of Algae and Water: Relationships of Its Magnitude and Position With Chlorophyll Concentration, *International Journal of Remote Sensing*, 13: 3367-3373.
11. Jain, S.K., Dash, K.K., and Ranvir Singh, (1996). "GIS for estimation of direct runoff potential." *IWRS journal*.
12. Jensen, M.E., Burman, R.D., and Allen, R.G. (ed). (1990). "Evapotranspiration and Irrigation Water Resuirements." ASCE Manuals and Reports on Engineering Practices No. 70., Am.Soc.Civil Engrs., New York, NY, 360p.
13. K.H.V.Durga Rao, Roshn Pradhan (1998). "Remote Sensing and GIS in Hydrological Modelling of Ungauged watersheds", *International Conference on watershed Management and Conservation*, 8-10 December 1998, New Delhi, pp-402-409.
14. Lemeur, R., and L. Zhang, (1980). "Evaluation of three evapotranspiration models in terms of their applicability for an arid region." *Journal of Hydrology* 114:395-411.
15. Lindroth, A. (1985). Canopy conductance of coniferous forests related to climate. *Water Resources Research* 21:297-304.
16. Lillesand M. Thomas, Kieffer W. Ralph and Chipman W. Jonathan (2004). *Remote Sensing and Image Interpretation*. John Wiley & Sons.
17. Lodhi, M.A., Rundquist, D.C., Han, L. and Kuzila, M.S., "The Potential for Remote Sensing of Loess Solis Suspended in Surface Waters", *Journal of American Water Resources Association*, 33: 111- 117, 1997.
18. Martinec, J. (1985), Time in hydrology, In: J. C. Rodda (Editor), *Facets of Hydrology*, Vol.II, Wiley, Chichester, pp. 264-277.
19. Mather, J. R., 1978, "The Climatic Water Budget in Environmental Analysis"
20. Penman, H.L. (1948). "Natural evaporation from open water, bare soil, and grass." *Royal Society of London Proceedings, Series A*, 193:120-145.
21. Rasamee Suwanwerakamtorn, (1994). "GIS and hydrological modelling for the management of small watersheds." *ITC journal*, 4, 343-348

22. Schultz, G. A. and Engman, E. T. (2000). Remote Sensing in Hydrology and Water Management, Springer-Verlag, Berlin, Germany.
23. Shiklomanov, I.A., and A.A. Sokolov. (1983). "Methodological basis of world water balance investigation and computation." In New Approaches in Water Balance Computations. International Association for Hydrological Sciences Publication No. 148, (Proceedings of the Hamburg Symposium).
24. Stewart, J.B., and L.W. Gay, 1989. Preliminary modelling of transpiration from the FIFE site in Kanas. *Agricultural and Forest Meteorology* 48:305-315.
25. Thangaraj C. (1997), Remote Sensing and GIS applications in Hydrological Modelling and Water Resources Planning, Jr. Indian water works association, 7-15.
26. Thornthwaite, C.W. and Mather, J.R. (1957), Instructions and tables for computing potential evapotranspiration and water balance, Laboratory of Climatology, Publication No. 10, Centerton, NJ.
27. Thornthwaite, C.W. 1948 An approach toward a rational classification of climate. *Geographical Review* 38:55-94.
28. Viollier, M., Deschamps, P.Y. and Lecomte, P. (1978). Airborne remote sensing of chlorophyll content under cloudy sky as applied to the tropical waters in the Gulf of Guinea. *Remote Sens. Environ.*, 7: 235-248.
29. E. G. Njoku and D. Entekhabi, "Passive microwave remote sensing of soil moisture," *Journal of Hydrology*, vol. 184, no. 1-2, pp. 101-129, 1996.
30. O. Merlin, A. Al Bitar, J. P. Walker, and Y. Kerr, "An improved algorithm for disaggregating microwave-derived soil moisture based on red, near-infrared and thermal-infrared data," *Remote Sensing of Environment*, vol. 114, no. 10, pp. 2305-2316, 2010.
31. M. Piles, A.Camps, M.Vall-llossera et al., "Downscaling SMOS derived soil moisture using MODIS visible/infrared data," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 9, pp. 3156-3166, 2011.
32. O. Merlin, A. Al Bitar, J. P. Walker, and Y. Kerr, "A sequential model for disaggregating near-surface soil moisture observations using multi-resolution thermal sensors," *Remote Sensing of Environment*, vol. 113, no. 10, pp. 2275-2284, 2009.
33. D. Entekhabi, E. G. Njoku, P. E. O'Neill et al., "The soil moisture active passive (SMAP) mission," *Proceedings of the IEEE*, vol. 98, no. 5, pp. 704-716, 2010.
34. T. Schmugge, P. Gloersen, T. Wilheit, and F. Geiger, "Remote sensing of soil moisture with microwave radiometers," *Journal of Geophysical Research*, vol. 79, no. 2, pp. 317-323, 1974.
35. U. Narayan, V. Lakshmi, and T. J. Jackson, "High-resolution change estimation of soil moisture using L-band radiometer and radar observations made during the SMEX02 experiments," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, no. 6, pp. 1545-1554, 2006.
36. U.Narayan and V. Lakshmi, "Characterizing subpixel variability of low resolution radiometer derived soil moisture using high resolution radar data," *Water Resources Research*, vol. 44, no. 6, Article IDW06425, 2008.
37. N. N. Das, D. Entekhabi, and E. G. Njoku, "An algorithm for merging SMAP radiometer and radar data for high-resolution soil-moisture retrieval," *IEEE*

- Transactions on Geoscience and Remote Sensing*, vol. 49, no. 5, pp. 1504–1512, 2011.
38. O. Merlin, A. Al Bitar, V. Rivalland, P. B'eziat, E. Ceschia, and G. Dedieu, "An analytical model of evaporation efficiency for unsaturated soil surfaces with an arbitrary thickness," *Journal of Applied Meteorology and Climatology*, vol. 50, no. 2, pp. 457–471, 2011.
 39. O. Merlin, F. Jacob, J.-P. Wigneron et al., "Multidimensional disaggregation of land surface temperature using high resolution red, near-infrared, shortwave-infrared, and microwave-L bands," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 5, pp. 1864–1880, 2012.
 40. O. Merlin, C. Rudiger, A. Al Bitar et al., "Disaggregation of SMOS soil moisture in Southeastern Australia," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 5, pp. 1556–1571, 2012.

BOOKS FOR FURTHER READING

1. Application of Remote Sensing to Agrometeorology edited by F. Toselli, ISPRA courses on Remote Sensing, Klemmer Academic Publishers.
2. Issues in Water Resources Development and Management the role of the remote sensing by P. Bala Krishnan.
3. Manual of Remote Sensing, Vol. II Chapter on "Water Resources Assessment", American Society of Photogrammetry.
4. Remote Sensing in Hydrology and Water Management (2000). Schultz, G. A. and Engman, E. T., Springer-Verlag, Berlin, Germany.
5. Remote Sensing: The quantitative approach (1978). Philip, Swain and Shirley M. Davis. McGraw Hill, Inc.
6. Remote Sensing in Hydrology by Engman & Gurian.
7. Satellite Remote Sensing for Operational Hydrology. E.C. Barret.